Multiculturalism and Growth: Skill-Specific Evidence from the Post-World War II Period*

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Abstract

This paper empirically revisits the impact of multiculturalism (as proxied by indices of birthplace diversity among immigrants and by epidemiological terms) on the macroeconomic performance of US states over the 1960-2010 period. We test for skill-specific effects of multiculturalism, controlling for standard growth regressors and a variety of fixed effects, and accounting for the age of entry and legal status of immigrants. To identify causation, we compare various instrumentation strategies used in the existing literature. We provide converging and robust evidence of a positive and significant effect of diversity among college-educated immigrants on GDP per capita. Overall, a 10% increase in high-skilled diversity raises GDP per capita by 6.2%. On the contrary, diversity among less educated immigrants has insignificant effects. Also, we find no evidence of a quadratic effect or a contamination by economic conditions in poor countries.

Keywords: Immigration, Culture, Birthplace Diversity, Growth.

JEL codes: F22, J61

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1 Introduction

Patterns of international migration to industrialized countries have drastically changed since World War II (WW2). On average, the share of foreigners in the population of high-income countries increased from 4.9 to 11.7% between 1960 and 2010 (Özden *et al.*, 2011).[1] This phenomenon has similarly affected the United States (from 5.4 to 13.6%), the members of the European Union (from 3.9 to 12.2%), Canada and Australia (from 15 to 22%). In addition, this change has been predominantly driven by immigration from developing countries; the share of South-North immigrants in the population of high-income countries increased from 2.0 to 8.7% in half a century.[2] This growing inflow of people coming from geographically, economically and culturally distant countries raises specific issues, as it has conceivably brought different skills and abilities, but also different social values and norms, or different ways of thinking. Although a large body of literature has focused on the size and skill structure of immigration flows, the macroeconomic effects of multiculturalism, as well as the channels through which they materialize, are still uncertain.

This paper empirically revisits the impact of multiculturalism on the macroeconomic performance of US states (proxied by their level of GDP per capita) in the aftermath of WW2. Our analysis combines three distinctive features. First, we rely on panel data available for a large number of regions over a long period. Our sample covers all US states over the 1960-2010 period in ten-year intervals. The use of panel data allows us to better deal with unobserved heterogeneity and endogeneity issues. This is crucial because economic prosperity and the degree of diversification of production are likely to attract people from different cultural origins. Multiculturalism is thus likely to respond to changes in the economic environment (see Alesina and La Ferrara, 2005), implying that causation is hard to establish in a cross-sectional setting. To control for unobserved heterogeneity and reverse causation biases, our paper uses a great variety of geographic and time fixed effects, and combines various instrumentation strategies that have been used in the existing literature. Second, we systematically investigate whether the economic effect of multiculturalism is heterogeneous across skill groups. The costs and benefits from multiculturalism are likely to vary

[1] This is not the case in developing countries, where the average immigration rate has decreased by half (from 2.3 to 1.1%) since 1960. Although the worldwide stock of international migrants increased from 91.6 to 211.2 million, the worldwide share of international migrants has been fairly stable since 1960, fluctuating around 3%. This is only 0.3 percentage points above the level observed in the early 20th century (McKeown, 2004).

[2] Immigration from developing countries accounts for 98% of the 1960-2010 rise in immigration to high-income countries, for 80% in the European Union, for 120% in the United States, and for 150% in Australia and Canada. Trends in immigration to the US are presented in the supplementary appendix.

with the levels of task complexity and interaction between workers; meanwhile, high-skilled and low-skilled immigrants are likely to heterogeneously propagate social values and norms across borders. We account for this by using skill-specific measures of multiculturalism. In addition, taking advantage of the availability of microdata, we compute our indices of multiculturalism for different groups of immigrants (by age of entry or by legal status). Third, we jointly test for different technologies of transmission. We follow Alesina *et al.* (2016) and proxy multiculturalism with indices of birthplace diversity, measuring the probability that two randomly-drawn individuals from a particular state have different countries of birth. In alternative specifications, we allow for non-linear effects, and include epidemiological (or contamination) forces, as well as an index of birthplace polarization of the workforce.

Our paper belongs to a recent and increasing strand of literature which considers that culture can be a feature which differentiates individuals in terms of their attributes, that this differentiation may have positive or negative effects on people's productivity, and that culture is affected by the country of birth (which determines the language and social norms individuals were exposed to in their youth, the education system, etc.). On the one hand, homogenous people are more likely to get along well, which implies that multiculturalism may reduce trust or increase communication, cooperation and coordination costs. Moreover, birthplace diversity can also be the source of epidemiological effects, as argued by Collier (2013) and Borjas (2015): by importing their "bad" cultural, social and institutional models, migrants from developing countries may contaminate the entire set of institutions in their country of adoption, influencing the world distribution of technological capacity. On the other hand, cultural diversity also enhances complementarities across diverse productive traits, stimulating innovations and the collective capacity to solve problems; a more diverse group is likely to spawn different cultures with various solutions to the same problem. Evidence of such costs and benefits has been found in micro studies. For example, Parrotta *et al.* (2014) investigate the effect of different forms of diversity (by education, age group, and nationality) on the productivity of Danish firms, using a matched employer-employee database. They find a negative effect of workers' diversity by nationality on productivity. On the contrary, Ozgen *et al.* (2014) find that birthplace diversity increases the likelihood of innovations using Dutch firm-level survey data, and Boeheim *et al.* (2012) find a positive effect of diversity on productivity using Austrian data. Finally, Kahane *et al.* (2013) find a positive effect of diversity on hockey team performance using data from the NHL (the North American National Hockey League).

Contrary to the firm-level approach, the analyses conducted at the macro level account for interdependencies between firms, industries, and/or regions. Existing studies have identified significant and positive effects of multiculturalism on comparative development and on disparities in economic performance across modern societies.[3] Ottaviano and Peri (2006) use US data by metropolitan area over the 1970-1990 period. In their (log of) wage regressions, the coefficient of diversity varies between 0.7 and 1.5. Ager and Brückner (2013) use US data by county during the 1870-1920 period: the coefficient of diversity in the output per capita regressions varies between 0.9 and 2.0. In these two studies, endogeneity issues are solved by using a shift-share method, i.e. computing the diversity index on the basis of predicted immigrant stocks. More precisely, the change in immigration to a region is predicted as the product of the global change in immigration to the US by the regional share in total immigration in the initial year. A more recent study accounting for the education level of immigrants is that of Alesina *et al.* (2016); it is the most similar to ours. They use cross-sectional data on immigration stocks by education level for a large set of countries in the year 2000, and develop a pseudo-gravity first-stage model to predict migration stocks and birthplace diversity indices. They also identify a positive effect of birthplace diversity in countries with GDP per capita above the median, and a stronger effect for diversity among college-educated workers. The effect of diversity on the log of GDP per capita is around 0.1 when computed on low-skilled workers, while the effect of diversity among the highly skilled varies between 0.2 and 0.3. Similarly, Suedekum *et al.* (2014) use annual German data by region from 1995 to 2006. Over this short period, they find a lower effect of diversity on the log of German wages (about 0.1 for diversity among high-skilled foreigners, and 0.04 for diversity among the low skilled) when fixed effects and IV methods are used.

Our empirical analysis relies on high-quality US census data by state over the 1960-2010 period. The choice of this period is guided by the 1965 amendments to the Immigration and Nationality Act, which led to an upward surge in U.S. immigration and diversity (as in (Ottaviano and Peri, 2006)). Birthplace diversity is almost perfectly correlated with the state-wide proportion of immigrants, which has increased threefold since 1960 in all skill groups. It is thus statistically impossible to disentangle the effects of birthplace diversity from those of the size of immigration. For this reason, we opt for a benchmark model that includes the immigration rate and a birthplace diversity index pertaining to the immigrant

[3] Ashraf and Galor (2013) use the concept of genetic diversity (capturing within-group heterogeneity in genomes between regions), and find that it explains about 25% of the different development outcomes (as proxied by population density) around the year 1500, i.e. before the age of mass migration. They identify an inverted-U shape relationship, suggesting that there is an optimal level of diversity for economic development. On the contrary, the empirical literature on ethnic and linguistic fractionalization identifies negative effects on economic growth (at least in developing countries).

population. In line with Alesina *et al.* (2016) and Suedekum *et al.* (2014), we find that diversity among college-educated immigrants is positively associated with the level of GDP per capita; however, diversity among less educated immigrants has insignificant (or weakly significant) effects. Another remarkable result is that the estimated coefficient is divided by four when geographic and year fixed effects are included. Overall, a 10% increase in high-skilled diversity raises GDP per capita by 6.2%. These results are robust to the exclusion of some census years, to the set of US states included in the sample, to the measurement of diversity, and to the definition of a high-skilled immigrant. The results hold true when we eliminate states with the greatest or smallest levels of immigration share, states located on the Mexican border, and states with the lowest proportions of immigrants. They are also valid when we exclude undocumented immigrants and those who arrived in the US at a young age. In addition, we find no evidence of an inverted-U shaped relationship as found by Ashraf and Galor (2013) for genetic diversity, or of a negative epidemiological effect *a la* Collier (2013) and Borjas (2015). On the contrary, we find that immigrants from richer countries have a smaller effect on GDP per capita than those from poorer countries; we interpret this as a confirmation that diversity among college-educated immigrants matters more than the economic conditions at origin. Finally, birthplace diversity is negatively correlated with the index of polarization in the immigrant population. If, instead of diversity, a high-skilled polarization index is used, we obtain a highly significant and negative effect on GDP per capita.

To address endogeneity issues, we combine Placebo tests with IV regressions; as far as the latter are concerned, we consider two instrumentation strategies that have been used in the related literature. The first one is a shift-share strategy *a la* Ottaviano and Peri (2006) which includes the predicted diversity indices based on total US immigration stocks by country of origin, and the bilateral state shares observed in 1960. The second strategy consists in instrumenting diversity indices, using the immigration predictions of a pseudo-gravity regression that include interactions between year dummies and the geographic distance between each country of origin and each state of destination (in line with Feyrer (2009) or Alesina *et al.* (2016)). In both cases, diversity among college-educated migrants remains highly significant, while diversity among the less educated is insignificant or weakly significant. In the preferred specification, the coefficient of high-skilled diversity is equal to 0.616. At first glance, this seems important because the average diversity index among college-educated immigrants equals 0.937 in 2010; hence, increasing diversity from zero to 0.937 increases GDP per capita by 58%. However, in 2010, the high-skilled diversity index ranges from 0.797 to 0.976. If all

US states had the same level of diversity as the District of Columbia (0.976), the average GDP per capita of the US would be 2.33% larger, the coefficient of variation across states would be 2.37% smaller, and the Theil index would decrease by 3.45%, only. By comparison, if all US states had the same average level of human capital as the District of Columbia, the average GDP per capita of the US would be 8.32% larger, the coefficient of variation across states would be 9.77% smaller, and the Theil index would decrease by 16.06%. Although diversity has non-negligible effects on cross-state disparities, its macroeconomic implications are rather limited.[4] We reach the same conclusion when using the longitudinal dimension of the data. The US-state average level of diversity among college-educated migrants increased by 7 percentage points between 1960 and 2010; this explains a 3.5% increase in macroeconomic performance (i.e. only one fiftieth of the total change in the US level of GDP per capita).

The remainder of the paper is organized as follows. Section 2 describes our main diversity measures and documents the global trends in cultural diversity in the aftermath of WW2. Section 3 describes our empirical strategy. The results are discussed in Section 4. Finally, Section 5 concludes.

2 Diversity in the Aftermath of WW2

Following Ottaviano and Peri (2006), Ager and Brückner (2013), Suedekum *et al.* (2014) and Alesina *et al.* (2016), we consider that the cultural identity of individuals is mainly determined by their country of birth. The rationale is that the competitiveness of modern-day economies is closely linked to the average level of human capital of workers and to the complementarity between their skills. Workers originating from different countries were trained in different school systems and are more likely to bring complementary skills, cognitive abilities and productive traits. In our benchmark model, our key explanatory variable is an index of birthplace diversity (or birthplace fractionalization), which can be computed for each US state and for the high-skilled and low-skilled populations separately. In subsection 2.1, we first define various measures of birthplace diversity, establish links between them, and discuss their statistical correlation with the average immigration rate. In subsection 2.2, we then document the global US trends in cultural diversity observed in the aftermath of WW2.

[4] The GDP per capita of Hawaii (diversity index of 0.797) would be 11.66% larger if Hawaii had the same diversity index as the District of Columbia; the difference in high-skilled diversity explains about 4.7% of the total income gap between these two states in 2010.

2.1 The Birthplace Diversity Index

In line with existing studies, we first define a Herfindahl-Hirschmann index of birthplace diversity, $TD^S_{r,t}$, which can be computed for the skill group $S = (L, H, A)$ (L for the low skilled, H for the high skilled, and A for both groups), for each region $r = (1, ..., R)$ and for each year $t = (1, ..., T)$. Our index measures the probability that two randomly-drawn individuals from the type-S population of a particular region originate from two different countries of birth. As shown by Alesina *et al.* (2016) in a cross-country setting, the birthplace diversity index is poorly correlated with genetic or ethnolinguistic fractionalization indices. The index is defined as:

$$TD^S_{r,t} = \sum_{i=1}^{I} k^S_{i,r,t}(1 - k^S_{i,r,t}) = 1 - \sum_{i=1}^{I}(k^S_{i,r,t})^2, \tag{1}$$

where $k^S_{i,r,t}$ is the share of individuals of type S, born in country i, and living in region r, in the type-S resident population of the region at year t. Computing the birthplace diversity index requires collecting panel data on the structure of the population by region of destination, by country of origin, and by education level. Our sample includes all US states (including the District of Columbia) between 1960 and 2010 in ten-year intervals, i.e. $r = (1, ..., 51)$ and $t = (1960, ..., 2010)$. Our choice to conduct the analysis at the state level is guided by the availability of long-term data series on macroeconomic performance, and by the comparability with cross-country results. We identify a common set of 195 countries of origin, including the US as a whole.[5] In the Appendix, we conduct the analysis at the level of US Commuting Zones, using wage proxies as dependent variables.[6]

Building on Alesina *et al.* (2016), the additive decomposition of the diversity index allows to distinguish between the *Between* and the *Within* components of the diversity index, $TD^S_{r,t} = BD^S_{r,t} + WD^S_{r,t}$. On the one hand, the *Between* component $BD^S_{r,t}$ measures the probability that a randomly-drawn pair of type-S residents includes a native and an immigrant, irrespective of where the immigrant comes from:[7]

$$BD^S_{r,t} = 2k^S_{r,r,t}(1 - k^S_{r,r,t}).$$

[5] We disregard heterogeneity between US natives born in different states (e.g. a Texan native is considered identical to a Californian one). See subsection 2.2 for a detailed description of the data.

[6] Table A12 describes the results obtained for Commuting Zones and for the 1970-2010 period. Commuting Zones are designed to better capture local labor market conditions. We use the data described in Dorn (2009). They cover all US regions and are fully comparable across periods.

[7] In our specific case, $k^S_{r,r,t}$ represent the share of US natives of type S living in region r at time t.

On the other hand, the residual *Within* component $WD^S_{r,t}$ measures the probability that a randomly-drawn pair of type-S residents includes two immigrants born in two different countries:

$$WD^S_{r,t} = \sum_{i \neq r}^{I} k^S_{i,r,t}(1 - k^S_{i,r,t} - k^S_{r,r,t}).$$

In the US context, the evolution of the birthplace diversity index among residents is almost totally driven by the change in the *Between* component of diversity, $BD^S_{r,t}$, which only depends on the proportion of immigrants. The median share of the *Between* component in total diversity, $BD^A_{r,t}/TD^A_{r,t}$, equals 0.98% and its quartiles are equal to 0.92% and 0.97%. Similar findings are found for the low-skilled and high-skilled populations. Consequently, birthplace diversity in group S is almost perfectly correlated with the region-wide proportion of immigrants.[8] On average, the Pearson correlation between $TD^S_{r,t}$ and the total share of immigrants in the population, $m^S_{r,t} = (1 - k^S_{r,r,t})$, equals 0.99 for all S. It is thus impossible to statistically disentangle the effects of diversity from those of immigration. For this reason and in line with existing works, our empirical specification distinguishes between the size of immigration and the variety of immigrants.

To capture the variety effect, we start from the *Within* component of the diversity index. The *Within* component can be expressed as the product of the square of the immigration rate (the probability that two randomly-drawn individuals are immigrants) by an index of diversity among immigrants, $MD^S_{r,t}$. The latter measures the probability that two randomly-drawn immigrants from region r originate from two different countries of birth. We have:

$$\begin{aligned} WD^S_{r,t} &= (1 - k^S_{r,r,t})^2 MD^S_{r,t} \\ &= (1 - k^S_{r,r,t})^2 \sum_{i \neq r} \widehat{k}^S_{i,r,t}(1 - \widehat{k}^S_{i,r,t}), \end{aligned} \tag{2}$$

where $\widehat{k}^S_{i,r,t} = k^S_{i,r,t}/(1 - k^S_{r,r,t})$ is the share of immigrants from origin country i in the total immigrant population of region r. Contrary to the total index of diversity and to its *Between* and *Within* components, the correlation between $MD^S_{r,t}$ and the total immigration rate, $m^S_{r,t}$, is small (on average, -0.19). This allows us to simultaneously include these two variables in the same regression without fearing collinearity problems.

[8] This is shown in Table A13 in the Appendix, which provides correlations between diversity indices, and between diversity and the immigration rate.

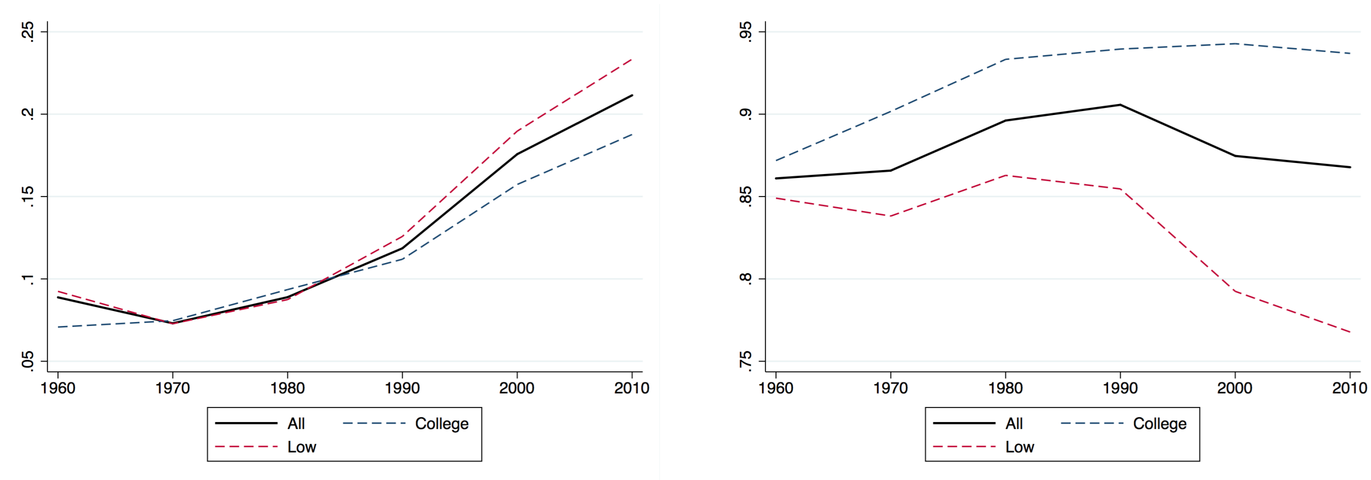
2.2 Diversity in the US states

Population data at the state level for the US are available from the Integrated Public Use Microdata Series (IPUMS). IPUMS data are drawn from the federal census of the American Community Surveys. For each census year, they allow characterizing the evolution of the American population by country of birth, age, level of education, and year of arrival in the US, among others. We extracted the data from 1960 to 2010 in ten-year intervals, using the 1% census sample for the years 1960 and 1970, the 5% census sample for the years 1980, 1990 and 2000, and the American Community Survey (ACS-1%) sample for the year 2010. Regarding the origin countries of immigrants, we consider the full set of countries available in 2010, although some of them had no legal existence in the previous census years. Hence, for the years 1960 to 1990, data for the former USSR, former Yugoslavia and former Czechoslovakia are split using the country shares observed in the year 2000. In addition, we treat five pairs of countries as a single entity; this is the case of East and West Germany, Kosovo, Serbia and Montenegro, North and South Korea, North and South Yemen, and Sudan and South Sudan. Finally, we allocate individuals with a non-specified (or an imperfectly specified, respectively) country of birth proportionately to the country shares in the US population (or to the country shares in the US population originating from the reported region, respectively).

In our benchmark regressions, we restrict our micro sample to all individuals aged 16 to 64, who are likely to affect the macroeconomic performance of their state of residence. We distinguish between two skill groups. Individuals with at least one year of college are classified as highly skilled, whereas the rest of the population is considered as low skilled. We define as US natives all individuals born in the US or in US-dependent territories such as American Samoa, Guam, Puerto Rico, the US Virgin Islands and other US possessions. Other foreign-born individuals are referred to as immigrants.

In alternative regressions, we only consider immigrants who arrived in the US after a certain age, or immigrants who are likely to have a legal status. As for the age-of-entry correction, we sequentially eliminate immigrants who arrived before the age of 5, 6, ... , 25. In order to proxy the number of undocumented immigrants, we follow the "residual methodology" described in Borjas (2016), and use information on the respondents' characteristics (such as citizenship, working sector, occupation, whether they receive public assistance, etc.).

Figure 1: Trends in birthplace diversity in US states, 1960-2010



(a) Total diversity ($TD^S_{r,t}$) (b) Diversity among immigrants ($MD^S_{r,t}$)

Notes: Diversity among residents is defined as in Eq. (1), whereas diversity among immigrants is defined as in Eq. (2). Source: Authors' elaboration on IPUMS data.

We use IPUMS data to identify the bilateral stocks and shares of international migrants, $k^S_{i,r,t}$, in the population of each state r, by country of origin i and by education level S in the year t. We thus construct comprehensive matrices of "Origin $\times$ State $\times$ Skill" stocks and shares from 1960 to 2010 in ten-year intervals.[9] Missing observations are considered as zeroes, even if a positive number of immigrants is identified for an adjacent year.[10] The evolution of the average index of cultural diversity is described in Figure 1, whereas Figure 2 represents differences in the average level of diversity across US states.

Figure 1(a) describes the evolution of the birthplace diversity index computed for the resident population, $TD^S_{r,t}$ for all S, between 1960 and 2010. Looking at the average of all US states, the birthplace diversity index among residents increased from about 0.09 in 1960 to 0.21 in 2010, reflecting the general rise in immigration to the US. A large portion of this change occurred after 1990. Nevertheless, this average trend conceals important differences between US states and between skill groups. As far as cross-state differences are concerned, the number of immigrants drastically increased in states such as California (+195%) or New York (+91%); on the contrary, the number of foreign-born individuals

[9] We distinguish between 195 countries of birth and 50 US states plus the District of Columbia. Countries and states are listed in Appendix A2. Descriptive statistics by state are provided in Table A3.

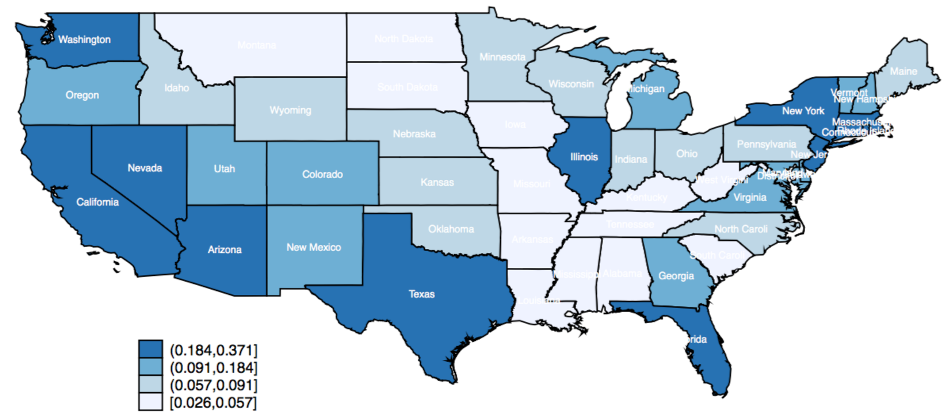
[10] The number of zeroes equals 33,145 out of a sample of 59,670 observations (55.5%). The missing values are mostly concentrated in the years 1960 and 1970.

remained small and stable in other states such as Montana or Maine. Regarding differences between skill groups, changes in immigration rates were larger for the low skilled than for college graduates, particularly after the year 1980. This is mainly due to the large inflows of low-skilled Mexicans observed during the last three decades, which drastically affected the level of diversity in states located on the West Coast and along the US-Mexican border, as illustrated by Figure 2(a).

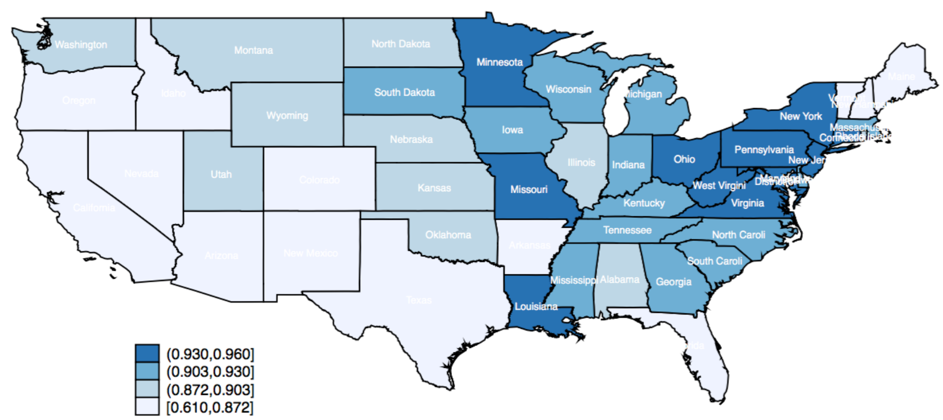
Second, Figure 1(b) describes the evolution of the diversity index computed for the immigrant population, $MD_{r,t}^{S}$ for all S. It shows that on average, the level of diversity in the immigrant population varies across skill groups. Diversity among college-educated immigrants has always been greater than diversity among the less educated. This might be due to the fact that college-educated migrants are less prone to concentrate in regions where large migration networks exist; they consider moving to more (geographically) diversified locations. Differences between skill groups drastically increased after 1960. On the one hand, diversity among high-skilled immigrants increased during the sixties and seventies, possibly due to the the Immigration and Nationality Act of 1965. Changes have been smaller since 1980 despite the Immigration Act of 1990, which allocated 50,000 additional visas (in the form of a lottery) to people from non-typical origin countries. On the other hand, diversity among low-skilled immigrants has fallen since 1980. Again, the latter decline is mainly explained by the large inflows of low-skilled Mexicans. Along the Mexican border and on the West Coast, the probability that two randomly-drawn immigrants were born in two different countries decreased as the share of Mexicans increased. This is also illustrated in Figure 2(b), which reveals important cross-state differences in the long-run average level of diversity among immigrants.

In sum, the evolution of diversity among immigrants varies across US states and over time. Figure A2 in the Appendix reveals that diversity among immigrants decreased in states located along the US-Mexican border and on the West Coast. A rise in diversity was observed in other states (such as Maine or Vermont). Our panel data analysis takes advantage of these intra-state and inter-state variations to identify a causal effect of diversity on macroeconomic performance.

Figure 2: Cross-state differences in birthplace diversity, 1960-2010 average index



(a) Diversity among residents ($TD^{A}_{r,t}$)



(b) Diversity among immigrants ($MD^{A}_{r,t}$)

Notes: Diversity among residents is defined as in Eq. (1), whereas diversity among immigrants is defined as in Eq. (2). The two maps present the average birthplace diversity observed between 1960 and 2010. Alaska and Hawaii are not represented. Source: Authors' elaboration on IPUMS data.

3 Empirical Strategy

Our goal is to identify the effect of multiculturalism on the macroeconomic performance of US states.[11] The level of macroeconomic performance is measured by the log of the Gross

[11]In the supplementary Appendix, a complementary analysis is conducted on the 34 OECD member states, using population data from Özden *et al.* (2011). The first drawback of the database is that it does

Domestic Product (GDP) per capita. In subsection 3.1, we present the benchmark specification in which multiculturalism is proxied by the skill-specific indices of birthplace diversity described in Section 2. In subsection 3.2, we conduct a large set of robustness checks, considering alternative sub-samples, alternative measures of birthplace diversity, and alternative technologies of transmission of cultural shocks. Subsection 3.3 explain how we deal with endogeneity issues. We rely on Placebo and IV regressions, combining two instrumentation strategies. Finally, subsection 3.4 presents the data sources used to construct our control variables and instruments.

3.1 Benchmark Specification

Our benchmark empirical model features the log of GDP per capita as the dependent variable. In line with Ottaviano and Peri (2006), Ager and Brückner (2013), Suedekum *et al.* (2014) and Alesina *et al.* (2016), we use the following specification:

$$log(y_{r,t}) = \beta_1 MD^S_{r,t} + \beta_2 m^S_{r,t} + \boldsymbol{\lambda}'\boldsymbol{X}_{r,t} + \gamma_r + \gamma_t + \varepsilon_{r,t}, \tag{3}$$

where $log(y_{r,t})$ is the log of GDP per capita in region r at year t, $MD^S_{r,t}$ is the type-S birthplace diversity among immigrants (proxy for the variety of immigrants), and $m^S_{r,t}$ is the proportion of immigrants in the working-age population of type S. The latter variable captures the other channels through which the level of immigration affects macroeconomic performance (e.g. labor market, fiscal or market-size effects). We opt for a static specification and assume that changes in diversity fully materialize within 10 years. This spares us from dealing with the endogeneity of the lagged dependent, an important issue in dynamic models with a short-panel dimension (Nickel, 1981).[12]

The coefficient β_1 is our coefficient of interest. It captures the effect of diversity on macroeconomic performance. Using skill-specific measures of cultural diversity and immigration, $S = (L, H, A)$, we can identify whether the level and significance of β_1 vary across skill groups. We first estimate Eq. (3) using pooled OLS regressions, bearing in mind that such regressions raise a number of econometric issues that might generate inconsistent estimates.

not report the educational structure of migration stocks. To capture skill-specific effects, we combine it with the 1990-2000 estimates of the bilateral proportion of college graduates provided in Artuc *et al.* (2015). The second drawback is that it relies on imputation techniques to fill the missing bilateral cells. Despite the lower quality of the data, our fixed-effect analysis globally confirms the results obtained for US states.

[12]Nevertheless, Tables A19 and A20 in the Appendix provide the results of dynamic GMM regressions with internal or external instruments, and with different lag structures. In these regressions, the lagged dependent is insignificant or weakly significant, which reinforces the credibility of our static benchmark specification. In addition, the effect of diversity is similar to that obtained in the static model.

The key issue when using pooled OLS regressions is the endogeneity of the main variable of interest, the index of diversity. Endogeneity can be due to a number of reasons. These reasons include the existence of uncontrolled confounding variables causing both dependent and independent variables, the existence of a two-way causal relationship between these variables, or a measurement problem.

To mitigate the possibility of an omitted variable bias, the benchmark model includes a vector $\boldsymbol{X}_{i,t}$ of time-varying covariates. It includes the log of population, the log of the region-wide average educational attainment of the working-age population (as measured by the years of schooling or highest degree completed), and the log of the urbanization rate. In addition, our specification includes a full set of region and year fixed effects, γ_r and γ_t, which allows us to better account for unobserved heterogeneity (including initial conditions in 1960). To solve the reverse causation and measurement problems, we use Placebo tests and two methods of instrumental variables described in subsection 3.3.

3.2 Alternative Specifications

Our benchmark specification Eq. (3) assumes linear effects of the level of immigration and of the variety of immigrants on the log of GDP per capita. The literature on multiculturalism suggests that the technology of transmission of cultural shocks can be different.[13]

First, looking at the effect of genetic diversity on economic development, Ashraf and Galor (2013) and Ashraf *et al.* (2015) consider a quadratic specification, which allows them to identify an optimal level of diversity. In our context, cultural diversity may also induce costs and benefits, implying that its effect on macroeconomic performance could be better captured by an inverted-U shape relationship. We thus naturally extend our benchmark specification in sub-section 4.2 by adding the square of the birthplace diversity index.

Second, another strand of the literature focuses on migration-induced transfers of norms, and tests for potential epidemiological or contamination effects. Transfers of norms from origin to destination countries have been examined by a limited set of studies.[14] Comparing

[13]The birthplace diversity index $MD^S_{r,t}$ does not account for the cultural distance between origin and destination countries. It assumes that all groups are culturally equidistant from each other. Another extension consists therefore in multiplying the probability that two randomly-drawn immigrants were born in two different countries by a measure of cultural distance between these two countries. For the latter, we use the database on genetic distance between countries, constructed by Spolaore and Wacziarg (2009). Genetic distance is based on blood samples and proxies the time since two populations had common ancestors. It is worth noticing that our results are robust to the use of an augmented diversity index and are reported in the supplementary Appendix.

[14]More studies focus on emigration-driven contagion effects, i.e. the effects of migrants' destination-country characteristics on outcomes at origin. The most popular study is that of Spilimbergo (2009), which

the economic performance of US counties from 1850 to 2010, Fulford *et al.* (2015) show that the country-of-ancestry distribution of the population matters, and that the estimated effect of ancestry is governed by the sending country's level of economic development, as well as by measures of social capital at origin (such as trust and thrift). Putterman and Weil (2010) study the effect of ancestry in a cross-country setting, and find that the ancestry effect is governed by a measure of state centralization in 1500. More recently, debates about the societal implications of diversity have been revived in the migration literature. Collier (2013) and Borjas (2015) emphasize the social and cultural challenges that movements of people may induce. Their reasoning is the following: by importing their "bad" cultural, social and institutional models, migrants may contaminate the set of institutions in their country of adoption, influencing the world distribution of technological capacity. To account for such epidemiological effects, we supplement our benchmark specification with $MY^S_{r,t}$, the weighted average of the log of GDP per capita in the origin countries of type-S immigrants to region r (weights are equal to the bilateral shares of immigrants). The epidemiological term is defined as:

$$MY^S_{r,t} = \sum_{i \neq r}^{I} \widehat{k}^S_{i,r,t} log(y_{i,t}). \quad (4)$$

On average, the correlation between this term and the diversity index is small (around -0.17 across US states), so that both variables can be tested jointly. Similarly, the correlation with the immigration rate is rather small (-0.26). Alesina *et al.* (2016) control for such epidemiological terms and find insignificant effects. Compared to them, we consider several variants of Eq. (4) in the Appendix, and we also instrument epidemiological terms.

3.3 Identification Strategy

Although our benchmark specification includes time-varying covariates and a full range of fixed effects, the positive association between diversity and macroeconomic performance can be driven by reverse causality. As argued by Alesina and La Ferrara (2005), diversity is likely to respond to changes in the economic environment. In particular, economic prosperity and the degree of diversification of production are likely to attract people from different cultural origins. Causation is hard to establish with cross-sectional data. Two methods are used in this paper.

investigates the effect of foreign education on democracy. Beine *et al.* (2013) and Bertoli and Marchetta (2015) use a similar specification to examine the effect of emigration on source-country fertility. Lodigiani and Salomone (2012) find that emigration to countries with greater female participation in parliament increases female participation in the origin country.

On the one hand, we augment our benchmark specification with natives' migration rates (denoted by $n^S_{r,t}$), and measures of diversity computed for the native population (denoted by $ND^S_{r,t}$). More precisely, we use the IPUMS data to identify the state of birth and the state of residence of each American citizen, and we compute internal migration rates and indices of diversity by state of birth for both skill groups. The latter index measures the probability that two randomly-drawn Americans from the type-S population of a particular state originate from two different states of birth. If diversity responds to economic prosperity, we expect a positive correlation between $ND^S_{r,t}$ and GDP per capita. On the other hand, we use a two-stage least-square estimation method. We compare the results obtained under alternative sets of instruments, and show that our IV results are robust to the instrumentation strategy. We consider two different sets of instruments that have been used in the existing literature.

Our first IV strategy is a shift-share strategy *a la* Ottaviano and Peri (2006) or Ager and Brückner (2013). The set of instruments includes an index of remoteness, as well as predicted diversity indices based on total US immigration stocks by country of origin, and bilateral shares observed in 1960. Following the shift-share methodology, we predict the skill-specific bilateral migration stocks for each state using the residence shares of natives and immigrants observed in 1960. Then, we use these shares to allocate the new immigrants by state of destination. The predicted stock of migrants at time t is:

$$\widehat{Stock^S}_{i,r,t} = Stock^S_{i,r,1960} + \phi^S_{i,r}(Stock^S_{i,t} - Stock^S_{i,1960}), \tag{5}$$

where $Stock^S_{i,r,t}$ is the type-S stock of immigrants from country i residing in region r at year t. The term $\phi^S_{i,r}$ is the time-invariant share that we use to allocate the variation in the bilateral migration stocks observed between the years 1960 and t. More precisely, we allocate changes in bilateral migration stocks using the 1960 skill-specific shares of US natives and immigrants from the same origin country. These shares capture both origin- and skill-specific network effects, and the concentration of type-S workers in 1960. We have:

$$\phi^S_{i,r} = \frac{Nat^S_{r,1960} + Stock^S_{i,r,1960}}{\sum_r (Nat^S_{r,1960} + Stock^S_{i,r,1960})}, \tag{6}$$

where $Nat^S_{r,1960}$ is the number of US natives residing in region r at year 1960. Using the predicted stock of migrants (who are less likely to be affected by the economic performance of each state), we compute the predicted diversity indices.

In line with Feyrer (2009) or Alesina *et al.* (2016), our second IV strategy consists in instrumenting diversity indices using the predicted migration stocks obtained from a "zero-stage", pseudo-gravity regression. The latter regression includes interactions between year dummies and the geographic distance between each country of origin and each US state. In line with the shift-share strategy, the identification thus comes from the time-varying effect of geographic distance on migration, reflecting gradual changes in transportation and communication costs. The pseudo-gravity model is written:

$$\log(Stock_{i,r,t}) = \beta_t \log(Dist_{i,r}) + Bord_{i,r} + Lang_{i,r} + \gamma_r + \gamma_i + \gamma_t + \varepsilon_{i,r,t}, \tag{7}$$

where $Bord_{i,r}$ is a dummy equal to one if country i and region r share a common border, $Lang_{i,r}$ is a dummy equal to one if at least 9% of the populations of i and r speak a common language, γ_r, γ_i, and γ_t are the destination, origin and year fixed effects. In the pseudo-gravity stage, the high prevalence of zero values in bilateral migration stocks gives rise to econometric concerns about possible inconsistent OLS estimates. To address this problem, we use the Poisson regression by pseudo-maximum likelihood (see (Santos Silva and Tenreyro, 2006)). Standard errors are robust and clustered by country-state pairs.

Although commonly used in the literature, each of these IV strategies has some drawbacks. The augmented shift-share and internal methods are imperfect if potential regressors exhibit strong persistence. In addition, the relative geography variables used in the strategy *a la* Feyrer (2009) can affect macroeconomic performance through other channels such as trade, foreign direct investments or technology diffusion (not measurable at the state level for the 1960-2010 period). Nevertheless, we can reasonably support a careful causal interpretation of our results if these strategies yield consistent and converging results.

3.4 Data Sources

The sources of our migration data were described in Section 2. In this subsection, we describe the data sources used to construct our dependent variables, the set of control variables, and the set of instruments. Table 1 summarizes the descriptive statistics of our main variables. More details on our data sources and variable definitions are available in Table A1 in the Appendix. The data for GDP ($y_{r,t}$) are provided by the Bureau of Economic Analysis for US states. The population data by age are taken from the IPUMS database. We consider the population aged 15 to 64 ($Pop_{r,t}$) in the regressions. The US Bureau of Census also provides the data on urbanization rates for US states ($Urb_{r,t}$); the urbanization rate measures the percentage of the population living in urbanized areas, and urban clusters are defined in terms of population size and density. As for human capital ($Hum_{r,t}$), we compute the

Table 1: Summary statistics 1960-2010

	Mean	s.d.	Min	Max
$TD^A_{r,t}$	0.126	0.105	0.006	0.548
$MD^A_{r,t}$	0.879	0.099	0.342	0.974
$m^A_{r,t}$	0.068	0.061	0.003	0.347
$TD^H_{r,t}$	0.116	0.087	0.007	0.478
$MD^H_{r,t}$	0.921	0.054	0.610	0.976
$m^H_{r,t}$	0.061	0.049	0.003	0.281
$TD^L_{r,t}$	0.134	0.121	0.006	0.592
$MD^L_{r,t}$	0.827	0.141	0.293	0.967
$m^L_{r,t}$	0.074	0.073	0.003	0.417
$log(y_{r,t})$	9.534	1.018	7.587	12.058
$log(Pop_{r,t})$	14.390	1.068	11.831	17.042
$log(Urb_{r,t})$	4.201	0.245	3.472	4.605
$log(Hum_{r,t})$	1.806	0.156	1.360	2.072

Source: Authors' elaboration on IPUMS-US data.

average educational attainment of the working-age population using the IPUMS database.

As far as the set of instruments is concerned, the data on geographic distance between origin countries and US states are computed using the latitude and the longitude of the capital city of each US state and each country. Such data are available from the Infoplease and Realestate3d websites which have allowed us to compute a bilateral matrix of great-circle distances between US state capital cities and countries.[15]

4 Results

Our empirical analysis follows the structure explained in Section 3. In subsection 4.1, we investigate the effect of birthplace diversity among immigrants using pooled OLS regressions; we produce separate results for the three skill groups of immigrants. Then, we test for the existence of epidemiological effects, and we control for unobserved heterogeneity, including a full set of state and year fixed effects (FE). In subsection 4.2, we show that the FE estimates are robust to sub-samples with the exclusion of states with the greatest or smallest immigration rates, or states sharing a common border with Mexico. We also show that our results are stable when controlling for the share of the ten largest groups of immigrants, when considering alternative education categories, or when using alternative diversity indices. In other robustness checks, we take into account the legal status and the age of entry of migrants,

[15]See `http://www.infoplease.com/ipa/A0001796.html` and `http://www.realestate3d.com/gps/latlong.htm` (accessed on July 4, 2016).

and we test for possible non-linear effects of birthplace diversity. Finally, in subsection 4.3, we address endogeneity issues using Placebo and IV regressions; the latter rely on two instrumentation strategies frequently used in the existing literature, i.e a shift-share strategy *a la* Ottaviano and Peri (2006) and a gravity-like strategy *a la* Feyrer (2009).

4.1 Pooled OLS and FE Regressions

Table 2 describes the pooled OLS and FE estimates. We produce separate results for the three skill groups, $S = (A, L, H)$, under the same set of control variables, including the skill-specific immigration rate, $m^S_{r,t}$, the log of population, $log(Pop_{r,t})$, the log of urbanization, $log(Urb_{r,t})$, and the log of the average educational attainment of the working-age population, $log(Hum_{r,t})$. In all cases, our standard errors are clustered at the state level in order to correct for heteroskedasticity and serial correlation.

The pooled OLS estimates are reported in col. 1, 3 and 6. We find that the effect of birthplace diversity on GDP per capita is skill-specific. Insignificant effects are obtained when diversity is computed using the low-skilled or the total immigrant populations.[16] On the contrary, the association between GDP per capita and birthplace diversity among college-educated immigrants is positive and significant at the 1% level. The coefficient is large, implying that a 10% increase in high-skilled diversity is associated with a 27.2% increase in GDP per capita.[17]

In col. 2, 4 and 7, we present the benchmark results, introducing state and year fixed effects in order to mitigate the omitted variable bias. The state fixed effects account for all time-invariant state characteristics that could jointly affect productivity and diversity; the year fixed effects account for time-varying sources of change in GDP per capita that are common to all US states. In the FE regressions, the R-squared is above 0.99. The effect of diversity remains highly significant for college-educated immigrants, and remains insignificant for the less educated. Interestingly, the inclusion of fixed effects leads to a drop in our estimated diversity coefficient. The coefficient of high-skilled diversity is divided by four compared to the pooled OLS regression. This demonstrates that accounting for unobserved heterogeneity is crucial when addressing such an issue. As for our control variables, human capital and urbanization rates are significantly and positively associated with GDP

[16]When computing the diversity index on the total immigrant population, the effect is significant at the 1% level in the FE regression. This is because high-skilled diversity influences this index.

[17]One could be concerned that some of our controls are endogenous inducing a bias in the coefficient of diversity. We show in Table A9 in the Appendix that our results still hold when removing our controls variables.

Table 2: Pooled OLS and FE regressions
Results by skill group (Dep= $log(y_{r,t})$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	FE	OLS	FE	FE	OLS	FE	FE
	$S=A$	$S=A$	$S=L$	$S=L$	$S=L$	$S=H$	$S=H$	$S=H$
$MD^S_{r,t}$	0.416	0.318***	0.019	0.141	0.104	2.719***	0.616***	0.531***
	(0.329)	(0.114)	(0.184)	(0.086)	(0.085)	(0.719)	(0.160)	(0.159)
$m^S_{r,t}$	2.632***	0.582*	1.901***	0.481*	0.412	4.383***	0.614*	0.388
	(0.615)	(0.341)	(0.485)	(0.282)	(0.283)	(1.018)	(0.315)	(0.366)
$MY^S_{r,t}$					-0.104**			-0.133*
					(0.042)			(0.069)
$log(Pop_{r,t})$	0.070	-0.172**	0.079*	-0.166**	-0.146*	0.011	-0.155**	-0.080
	(0.047)	(0.079)	(0.047)	(0.081)	(0.082)	(0.044)	(0.075)	(0.065)
$log(Urb_{r,t})$	-0.407*	0.385**	-0.367	0.329**	0.312*	-0.563**	0.285**	0.156
	(0.238)	(0.156)	(0.254)	(0.163)	(0.173)	(0.229)	(0.135)	(0.138)
$log(Hum_{r,t})$	5.752***	0.695***	5.817***	0.807***	0.802***	5.288***	0.759***	1.007***
	(0.157)	(0.197)	(0.147)	(0.205)	(0.196)	(0.182)	(0.197)	(0.299)
Constant	-0.697	7.529***	-0.728	7.662***	8.379***	-0.584	7.348***	7.492***
	(0.890)	(1.254)	(0.914)	(1.263)	(1.317)	(0.890)	(1.262)	(1.273)
Observations	306	306	306	306	306	306	306	306
Nb. states	51	51	51	51	51	51	51	51
R-squared	0.879	0.993	0.878	0.993	0.993	0.889	0.993	0.993
Time fixed effects	No	Yes	No	Yes	Yes	No	Yes	Yes
States fixed effects	No	Yes	No	Yes	Yes	No	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. The specification is described in Eq. (3). Pooled OLS results are provided in col. 1, 3 and 6; FE results are provided in col. 2, 4, 5, 7 and 8. Results for all immigrants are provided in col. 1 and 2; results for low-skilled immigrants are provided in col. 3, 4 and 5; results for college-educated immigrants are provided in col. 6, 7 and 8. The sample includes the 50 US states and the District of Columbia from 1960 to 2010. The set of control variables includes the immigration rate ($m^S_{r,t}$), the log of population ($log(Pop_{r,t})$), the log of urbanization ($log(Urb_{r,t})$) and the log of the average educational attainment of the working-age population ($log(Hum_{r,t})$). We supplement our benchmark specification in col. 5 and 8 with the epidemiological effect ($MY^S_{r,t}$).

per capita. On the contrary, the correlation between GDP and population size is negative. More interestingly, immigration rates are always positively associated with GDP per capita, and the correlation is always greater for college graduates.[18]

[18]Our results hold when using a measure of cultural polarization. In Ager and Brückner (2013), Montalvo and Reynal-Querol (2003) and Montalvo and Reynal-Querol (2005), the index of polarization captures how far the distribution of a population is from the bimodal distribution. It is defined as: $TP^S_{r,t} = 1 - \sum_{i=1}^{I} \left((0.5 - k^S_{i,r,t})/0.5\right)^2 k^S_{i,r,t}$. The rationale is that a more polarized population can be associated with increased social conflict and a reduction in the quality and quantity of public good provision. Applied to the immigrant population (i.e. using $\widehat{k}^S_{i,r,t}$ instead of $k^S_{i,r,t}$ in the previous equation, the index $MP^S_{r,t}$ is maximized when there are two groups of immigrants which are of equal size (i.e. 50%). For US states, the polarization index exhibits a correlation of -0.89 with the fractionalization index, drammatically high in comparison to Ager and Brückner (2013) due to the high level of diversity in our sample in comparison

In sum, we find that diversity is positively associated with the level of GDP per capita, but only when diversity is computed on workers performing complex or skill-intensive tasks. On the contrary, diversity among less educated immigrants does not have a significant effect on macroeconomic performance. According to our fixed-effect estimates, a 10% increase in high-skilled diversity (i.e. in the probability that two randomly-drawn, college-educated immigrants originate from two different countries of birth) is now associated with a 6.2% increase in GDP per capita. Expressed differently, a one-standard-deviation increase in high-skilled diversity is associated with a 3.2% increase in GDP per capita. This implies that, if all US states had the same level of diversity as the most diverse state in 2010, i.e. the District of Columbia (0.976), the average GDP per capita of the US would be 2.3% larger, the coefficient of variation across states would be 2.4% smaller, and the Theil index would decrease by 3.5%. By comparison, if all US states had the same average level of human capital as the District of Columbia, the average GDP per capita of the US would be 8.3% larger, the coefficient of variation across states would be 9.8% smaller, the Theil index would decrease by 16.1% and the GDP per capita of Hawaii, the least diverse state in 2010 (0.797), would be 11.7% larger. In addition, the US-state average level of diversity among college-educated migrants increased by 7 percentage points between 1960 and 2010; this explains a 3.5% increase in macroeconomic performance (i.e. only one fiftieth of the total change in the US level of GDP per capita). Although diversity has significant effects on cross-state disparities, its macroeconomic implications are rather limited.

Finally, we supplement the benchmark model with epidemiological effects *a la* Collier (2013) and Borjas (2015) in col. 5 and 8. Interpreting the coefficient of the epidemiological term is not straightforward. On the one hand, if immigrants originating from poor countries contaminate the total factor productivity or the quality of institutions at destination, we should find a positive and significant relationship between our epidemiological term ($MY^S_{r,t}$) and macroeconomic performance. On the other hand, if attracting immigrants from economically or culturally distant countries generates more complementarities in skills and ideas than immigrants from richer countries, we should find a negative and significant relationship. Moreover, reverse causality is a serious source of concern as macroeconomic performance affects the attractiveness of states and the variety of their immigrant population. Our database reveals that richer states attract more people, including immigrants from poorer countries. This selection issue pushes the correlation between GDP per capita and the epidemiological

to their data. Hence, including these two variables in the same regression is risky. The results obtained when using the polarization index are reported in Table A8 in the Appendix.

term downwards.[19] This reverse causality issue will be addressed in subsection 4.3.[20] As far as low-skilled immigrants are concerned, controlling for epidemiological effects in col. 5 , we find a negative and significant coefficient (at the 5% level). Although we suspect that the negative relationship between the epidemiological term and US state level of GDP per capita can be driven by reverse causality, the negative sign suggests that low-skilled immigrants from richer countries generate fewer complementarities with US natives than immigrants from poorer countries, and/or that greater economic growth in a state attracts more immigrants from poorer countries. As far as high-skilled immigrants are concerned, we find no clear evidence of contamination effects driven by high-skilled immigration in col. 8. The epidemiological effect is insignificant, whereas the coefficient of birthplace diversity is hardly affected. Overall, we find no evidence of a significant contamination mechanism.[21]

4.2 Robustness checks

This subsection investigates the robustness of our previous results. Tables 3 and 4 summarize the results for high-skilled and low-skilled immigrants, respectively. These two tables only report the main results for all the robustness checks that have been done. All models include the full vector of controls (not shown) with the log of population ($log(Pop_{r,t})$), the log of urbanization ($log(Urb_{r,t})$) and the log of the average educational attainment of the working-age population ($log(Hum_{r,t})$) as well as time and state fixed effects. Complete tables are provided in Tables A4 to A11 in the Appendix .

Robustness by subsample. – In Tables 3 and 4, the benchmark results of Table 2 are reported in col. 1. In col. 2, we limit our sample to the 1970-2000 period, eliminating possible sources of variation prior to the 1965 amendments to the Immigration and Nationality Act, as well as variations driven by the recent evolution of diversity.[22] Then, in col. 3 and 4, we

[19]Figure A1 in the Appendix confirms this presumption. When we keep the levels of GDP per capita constant for all origin countries (at their 1960-2010 average), we observe that the US state level of GDP per capita is negatively correlated with the epidemiological term.

[20]We also consider alternative specifications for the epidemiological term in the Appendix Table A15. We first compute $MY^S_{r,t}$ by keeping the immigration shares $(\widehat{k}^S_{i,r,t})$ constant, at their 1960-2010 average levels. Then, we keep the levels of GDP per capita at origin $(log(y_{i,t}))$ constant, at their 1960-2010 average level. Finally, we combine annual data on GDP per capita at origin with individual data on the year of arrival in the US; each immigration share is multiplied by the average level of GDP per capita prevailing in the year of immigration to the US. The latter specification allows us to capture the norms and values that immigrants bring with them when they migrate. Due to data limitations, this variable cannot be computed for the year 1960.

[21]We obtain the same conclusion when the epidemiological term in Eq. (4) is based on democracy levels at origin, instead of GDP per capita. We use the Polity2 index of democracy. These unreported results are available upon request.

[22]Remember that Figure 1(b) shows that the average high-skilled diversity index slightly decreased between

Table 3: Robustness of FE regressions for high-skilled diversity
(Dep= $log(y_{r,t})$)

		Sub-Samples (A4)				
	(1)	(2)	(3)	(4)	(5)	(6)
	Full-Sample	1970-2000	No Top5	No Bot5	No Mex	No Q1
$MD^H_{r,t}$	0.616***	0.870***	0.725***	0.672***	0.630***	0.596**
	(0.160)	(0.321)	(0.174)	(0.170)	(0.170)	(0.288)
$m^H_{r,t}$	0.614*	1.140**	1.317**	0.613*	0.541	0.765**
	(0.315)	(0.459)	(0.529)	(0.323)	(0.397)	(0.365)
Observations	306	204	276	276	282	228
Nb. states	51	51	46	46	47	38
R-squared	0.993	0.990	0.993	0.993	0.993	0.995

	10 Largest (A6)	Quadratic (A8)	Educ. levels (A10)		Legal Status (A11)	
	(7)	(8)	(9)	(10)	(11)	(12)
			Ph.D	Tertiary	Docum.	Undoc.
$MD^H_{r,t}$	0.617***	-0.131	0.262**	0.369***	1.009**	-0.153
	(0.169)	(1.954)	(0.103)	(0.136)	(0.473)	(0.127)
$m^H_{r,t}$	0.726*	0.622*	0.256	0.372	0.959*	4.426**
	(0.365)	(0.314)	(0.266)	(0.298)	(0.535)	(2.140)
$(MD^H_{r,t})^2$		0.453				
		(1.202)				
Observations	306	306	306	306	204	204
Nb. states	51	51	51	51	51	51
R-squared	0.993	0.993	0.993	0.993	0.979	0.979

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. A-indexed numbers in parentheses refer to full Tables provided in the Appendix. All models include the full vector of controls (not shown) with the log of population ($log(Pop_{r,t})$), the log of urbanization ($log(Urb_{r,t})$) and the log of the average educational attainment of the working-age population ($log(Hum_{r,t})$) as well as time and states fixed effects.

examine whether the impact of diversity is driven by the size of the immigrant population: we drop the five US states with the greatest or the smallest immigration rates in 2010, respectively.[23] In col. 5, we investigate whether our results are driven by the Mexican diaspora, which represented 30% of the whole immigrant population of the US in 2010. We drop the states located on the US-Mexican border, which host 62% of all Mexican immigrants

2000 and 2010.

[23]The states with the greatest immigration rates are California, New York, Hawaii, New Jersey, and Florida. The states with the smallest rates are West Virginia, Mississippi, Kentucky, South Dakota, and Alabama.

to the US.[24] Remember that these states have experienced a drastic decrease in their diversity index (-40% in low-skilled diversity between 1960 and 2010), which is totally due to the rising inflows from Mexico. Finally, in col. 6, we exclude the states in the first quartile (i.e. below Q1) of the 2010 distribution by immigrant population size. Overall, we show that our FE results are robust to sample selection. In Table 3, the coefficient of high-skilled diversity is always positive, significant, and of the same order of magnitude as the benchmark estimates in col. 1. The positive impact becomes even larger when reducing the time span (0.87) or after excluding the states with the highest immigration rates (0.73). This suggests that high-skilled diversity could generate non-linear effects on macroeconomic performance (e.g. a decreasing marginal impact); we will explore this hypothesis in col. 8. As for Table 4, it shows that low-skilled diversity is insignificant in all specifications but one. It only becomes significant in col. 3, when the most diverse states are excluded, but only at the 5% level.

Controlling for large groups. – We now investigate whether the effect of birthplace diversity does is not driven by the presence of large diasporas characterized by specific productivity levels (this generalizes what we did when excluding states located on the US-Mexican border). To do so, we control for the state-specific shares that the ten largest origin countries in the US immigrant population. In col. 7 of the two tables, we only report the coefficient for diversity. As far as high-skilled migrants are concerned, controlling for the size of the largest immigrant groups neither affects the significance nor the magnitude of our coefficients of interest. As for low-skilled diversity, the diversity coefficient becomes significant but its magnitude is small.

Quadratic specification. – In col. 8, we supplement our benchmark specification with the squared index of birthplace diversity. If an optimal level of diversity exists, we should find a positive coefficient for the linear term, and a negative coefficient for the squared term. As far as high-skilled immigrants are concerned, we find no evidence of a quadratic effect of birthplace diversity. The coefficient for the squared index of diversity is insignificant in Table 3. Hence, this regression rejects the existence of an optimal level of diversity among college-educated immigrants. As far as low-skilled immigrants are concerned, the coefficient for the quadratic term is negative and significant, but only at the 10% level in Table 4, while the linear term is significant at the 5% level. We cannot reject the possibility of an inverted-U-shaped relationship, with an optimal level of diversity equal to $MD^L_{r,t} = 0.90$, but the interval of confidence of the quadratic effect is large.[25]

[24] These include California, Texas, New Mexico, and Arizona.

[25] Note that $MD^L_{r,t} = 0.90$ corresponds to the median of the distribution. The US states with a low-skilled diversity index around the optimal level in 2010 are Rhode Island (0.891) and Michigan (0.903).

Table 4: Robustness of FE regressions for low-skilled diversity
(Dep= $log(y_{r,t})$)

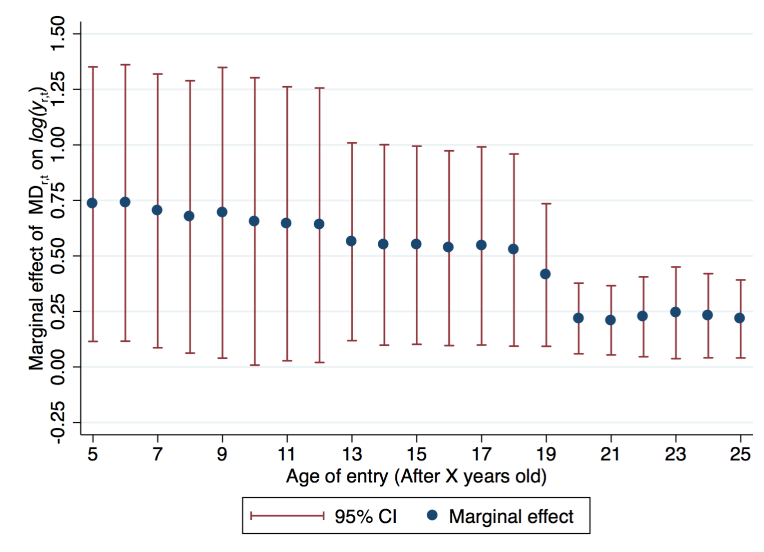
		Sub-Samples (A5)				
	(1)	(2)	(3)	(4)	(5)	(6)
	Full-Sample	1970-2000	No Top5	No Bot5	No Mex	No Q1
$MD^H_{r,t}$	0.141	0.130	0.228**	0.128	0.109	0.015
	(0.086)	(0.097)	(0.093)	(0.092)	(0.091)	(0.115)
$m^H_{r,t}$	0.481*	0.691**	0.938**	0.448	0.474	0.647**
	(0.282)	(0.272)	(0.418)	(0.288)	(0.392)	(0.276)
Observations	306	204	276	276	282	228
Nb. states	51	51	46	46	47	38
R-squared	0.993	0.989	0.993	0.993	0.993	0.993

	10 Largest (A7)	Quadratic (A8)	Educ. levels (A10)			Legal Status (A11)	
	(7)	(8)	(9)	(10)	(11)	(12)	(13)
			No School	Primary	Secondary	Docum.	Undoc.
$MD^H_{r,t}$	0.276**	0.705**	0.038	0.033	0.120	0.043	-0.017
	(0.104)	(0.293)	(0.032)	(0.061)	(0.101)	(0.112)	(0.045)
$m^H_{r,t}$	0.058	0.504*	0.152	0.165	0.432	1.107**	3.482*
	(0.274)	(0.281)	(0.100)	(0.101)	(0.301)	(0.424)	(1.795)
$(MD^L_{r,t})^2$		-0.391*					
		(0.218)					
Observations	306	306	306	306	306	204	204
Nb. states	51	51	51	51	51	51	51
R-squared	0.994	0.993	0.993	0.993	0.993	0.979	0.979

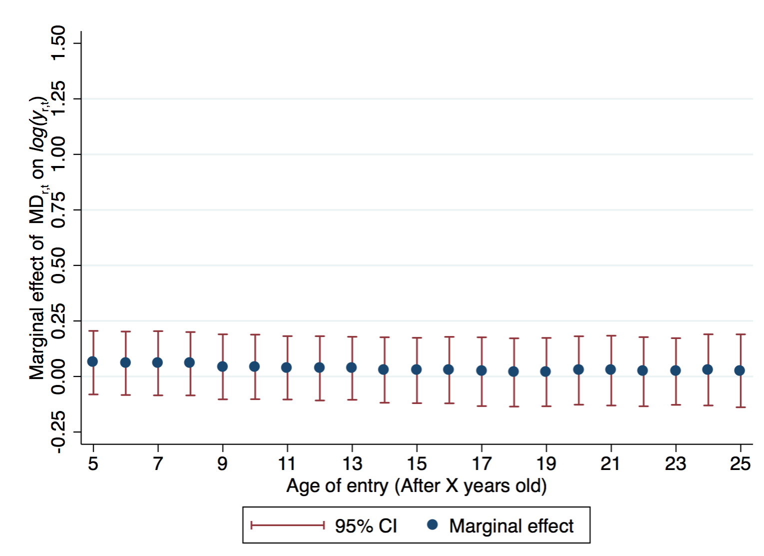
Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. A-indexed numbers in parentheses refer to full Tables provided in the Appendix. All models include the full vector of controls (not shown) with the log of population ($log(Pop_{r,t})$), the log of urbanization ($log(Urb_{r,t})$) and the log of the average educational attainment of the working-age population ($log(Hum_{r,t})$) as well as time and states fixed effects.

Robustness by skill group. – One might be concerned that the positive effect of high-skilled diversity is driven by the presence of immigrants at the very top of the skill distribution. Similarly, it can be suspected that the insignificant effect of low-skilled diversity is due to the the prevalence of immigrants with very low levels of education. We investigate these issues in col. 9 and 10 of Table 3 and in col. 9 to 11 in Table 4. As far as high-skilled diversity is concerned, we find insignificant differences when computing diversity on PhD graduates, or on other college-educated immigrants. As for low-skilled diversity, the effect remains insignificant when computing the diversity index on the immigrant populations with no schooling, primary education or secondary education.

Figure 3: Marginal effect of $MD^S_{r,t}$ on $log(y_{r,t})$
Results for different age-of-entry thresholds (1970-2010)



(a) High-skilled



(b) Low-skilled

Source: Authors' elaboration on IPUMS data. Notes: The two graphs report the marginal effect of $MD^S_{r,t}$ on $log(y_{r,t})$ when the immigrant population is restricted to individuals who arrived in the US after age X. Marginal effects are obtained using our main specification Eq. (3) which includes state and year fixed effects, as well as the immigration rate ($m^S_{r,t}$), the log of population ($log(Pop_{r,t})$), the log of urbanization ($log(Urb_{r,t})$) and the log of the average educational attainment of the working-age population ($log(Hum_{r,t})$).

Robustness by legal status. – We also investigate the role of undocumented migration in governing the skill-specific effects of diversity. The US census counts every person regardless of immigration status. Hence, undocumented immigrants influence our diversity index. This can be a source of concern as undocumented migrants are likely to be less educated than the legal ones and to contribute differently to GDP, either because their productive activities are not recorded in the official GDP or because they are employed in jobs/sectors where skill complementarities are smaller. This could explain why the effect of low-skilled diversity is insignificant in most of our regressions. To explore this hypothesis, we use the "residual methodology" proposed by Borjas (2016) to identify the number of legal and undocumented immigrants by skill group. It consists in using individual characteristics to proxy the legal status of US immigrants. In this work, we use five characteristics (citizenship, employment industry, occupation, whether the individual receives any assistance, and the spouse's legal status) and, due to data availability, we apply the residual methodology to the census years 1980 to 2010. We obtain similar results as in Borjas (2016). For the year 2010, our estimated proportions of undocumented immigrants are equal to 23% in California, 7% in New York, and 15% in Texas; for the same states in the year 2012, Borjas (2016) also obtains 23%, 7%, and 15%. Moreover, the observable characteristics of our undocumented population are also similar. We identify 50% of males and 36% of college graduates; Borjas (2016) obtains 55% and 40%, respectively. As a robustness check, we thus compute the diversity indices on the legal and undocumented immigrant populations, and include them separately in our FE regressions. Col. 11 and 12 in Table 3 and Col. 12 and 13 in Table 4 give the results for the two skill groups. As far as high-skilled immigrants are concerned, distinguishing between legal and undocumented immigrants yields different effects. Diversity among undocumented immigrants has no significant effect, while diversity among legal immigrants has a positive and significant effect at the five percent level. On the contrary, controlling for the legal status of low-skilled immigrants does not modify our conclusions. It confirms that the insignificant effect of low-skilled diversity cannot be attributed to the greater proportion of undocumented migrants in this group (on average, 17% for the US in 2010).

Robustness by age of entry. – The diversity indices used in our benchmark regressions are computed for the total population of working-age immigrants, whatever their age of entry in the US. As birthplace diversity conceivably reflects complementarities between individuals trained in different countries, it can be argued that immigrants who arrived in the US at different ages generate different levels of complementarity in skills and ideas with the native workforce. However, the role of the age of entry is unclear. On the one hand, immigrants with a longer foreign education are likely to bring more complementarities. On the other hand, immigrants who were partly educated in the US may have more transferable skills and a greater potential to interact with natives. To investigate this issue, we compute the diversity index using various samples of immigrants, and we include these alternative indices in Eq. (3). More precisely, we exclude from the immigrant population the individuals who arrived in the US before a given age threshold, which ranges from 5 to 25 in one-year intervals. For each skill group, Figure 3 reports the marginal effect of diversity and its confidence interval as a function of the age-of-entry threshold.[26] As information on age of entry is not available in the 1960 census, our sample covers the 1970-2010 period. For this time span, the coefficients of the benchmark FE regressions (without controlling for age of entry) are equal to 0.835 for high-skilled diversity (significant at the 1% level), and to 0.088 for low-skilled diversity (insignificant). Whatever the age-of-entry threshold, the effect of low-skilled diversity is insignificant. Nevertheless, the age of entry matters for college graduates. Although the coefficient of high-skilled diversity is always positive and significant, the largest effects are obtained when the immigrant population includes individuals who arrived before age 20. Considering three age thresholds (12, 18, and 22), Alesina *et al.* (2016) show that the positive effect of birthplace diversity slightly decreases when eliminating children immigrants, but always remains large and significant. Conversely, our results suggest that the greatest levels of complementarity are obtained when immigrants acquired part of their secondary education abroad and their college education in the US.

4.3 Dealing with endogeneity

In this section, we investigate the likelihood that reverse causality drives our results. We use Placebo and IV regressions to deal with the endogeneity of birthplace diversity, the immigration rate and the epidemiological term.

Placebo regressions. – If diversity increases with economic prosperity, we expect a positive correlation between birthplace diversity among American workers and GDP per capita, as explained in Section 3. Table 5 reports the results of our Placebo tests. We augment the benchmark model with two additional control variables, namely the natives' migration rates ($n^S_{r,t}$) and the measures of diversity computed for the native population ($ND^S_{r,t}$). It comes out that internal immigration rates are positively correlated with GDP per capita. However, the native diversity index is insignificant (or weakly significant in col. 3). Although these Placebo

[26] Comprehensive regression results are provided in Table A18 in the Appendix.

Table 5: $MD_{r,t}$ v.s diversity among "native immigrants" $ND_{r,t}$
Results by skill group (Dep= $log(y_{r,t})$)

	(1) $S=H$	(2) $S=H$	(3) $S=H$	(4) $S=L$	(5) $S=L$	(6) $S=L$
$MD^S_{r,t}$	0.616***		0.432**	0.141		0.156*
	(0.160)		(0.168)	(0.086)		(0.082)
$m^S_{r,t}$	0.614*		1.008***	0.481*		0.642**
	(0.315)		(0.347)	(0.282)		(0.278)
$ND^S_{r,t}$		0.968	1.183*		0.456	0.513
		(0.654)	(0.662)		(0.570)	(0.563)
$n^S_{r,t}$		0.376**	0.428**		0.059	0.218
		(0.167)	(0.203)		(0.242)	(0.244)
$log(Pop_{r,t})$	-0.155**	-0.135*	-0.176**	-0.166**	-0.120*	-0.169**
	(0.075)	(0.068)	(0.073)	(0.081)	(0.067)	(0.073)
$log(Urb_{r,t})$	0.285**	0.294*	0.316**	0.329**	0.266	0.304*
	(0.135)	(0.159)	(0.149)	(0.163)	(0.164)	(0.172)
$log(Hum_{r,t})$	0.759***	0.557**	0.477**	0.807***	0.677**	0.505*
	(0.197)	(0.213)	(0.217)	(0.205)	(0.271)	(0.269)
Constant	7.348***	6.829***	6.810***	7.662***	7.193***	7.712***
	(1.262)	(1.450)	(1.443)	(1.263)	(1.048)	(1.088)
Observations	306	306	306	306	306	306
Nb. states	51	51	51	51	51	51
R-squared	0.993	0.993	0.993	0.993	0.993	0.993
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
States fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. Source: Authors' elaboration on IPUMS-US data. $ND^S_{r,t}$ is computed as the diversity among natives born in a different state than the r state where they reside. $n_{r,t}$ is the immigration rate in the state r where immigrants are natives born in a different state than r.

tests do not necessarily imply that diversity among foreign immigrants is not affected by macroeconomic performance, they mitigate the risk of a strong reverse causation relationship.

IV regressions. – Table 6 the results of our 2SLS regressions. In col. 1, 2, 6 and 7, we first only instrument our main variable of interest, $MD^S_{r,t}$, and use the two IV strategies detailed in subsection 3.3. The first one is a shift-share strategy, which uses the predicted diversity index based on the 1960 geographic structure of each bilateral diaspora. The second one is the gravity-like strategy *a la* Feyrer (2009). First-stage estimates are provided in Tables A16 and A17 in the Appendix. Then, in the remaining columns, we deal with the endogeneity of two other important regressors, the immigration rate ($m^S_{r,t}$) and the epidemiological term

($MY^{S}_{r,t}$). To do so, we use the gravity-like strategy *a la* Feyrer (2009) only.

Table 6 confirms our previous findings for diversity among high-skilled migrants when only $MD^{H}_{r,t}$ is instrumented in col. 1 and 2. The effect of $MD^{H}_{r,t}$ is always positive and highly significant. When using the shift-share strategy in col. 1 , the magnitude of the coefficient is close to that of our FE regressions. The coefficient becomes larger under the gravity-like strategy *a la* Feyrer (2009) in col. 2 even if both are not significantly different from the FE estimates. It is worth noticing that the instruments used in our IV regressions are valid. In particular, the Kleibergen-Paap F-stat of our second stage is always very large, and satisfies the Stock-Yogo critical values related to 10% maximal IV size. In addition, the F-test of the first stage is always above the critical value of 10. After instrumenting with the shift-share strategy, a 10% change in diversity induces a 5.1% change in GDP; equivalently, a one-standard-deviation change in high-skilled diversity increases GDP per capita by 2.8%, which is close to our benchmark results. As for low-skilled diversity, we find insignificant or weakly significant effects in col. 6 and 7.

We conduct additional IV regressions to deal with the endogeneity of the immigration rate and of the epidemiological term in the remaining columns of Table 6. As the shift-share strategy does a poor job at predicting the immigration rate,[27] we only use the gravity-like strategy *a la* Feyrer (2009). Different combinations of endogenous regressors are considered, without changing our conclusions. In all specifications, the instrumental variables are strong. Our estimates for $MD^{H}_{r,t}$ are robust, and the magnitude of the coefficient is similar to the FE estimates. The effect of low-skilled diversity is always insignificant from col. 8 to 10. Under some specifications, we obtain a negative and significant epidemiological effect for both college-educated and low-skilled immigrants. Again, we find no evidence of a contamination effect. On the contrary, our epidemiological results are more in line with the effect of diversity; attracting immigrants from economically and culturally distant countries is beneficial for economic growth. Overall, our IV regressions support the view that increasing birthplace diversity among college-educated immigrants causes a rise in GDP per capita at destination.

5 Conclusions

This paper empirically investigates the impact of multiculturalism (as measured by birthplace diversity among immigrants, birthplace polarization indices or immigration-driven epidemiological norms) on GDP per capita. To do so, we use a large sample of US states and take

[27]The same problem arises in Alesina *et al.* (2016).

advantage of the availability of panel data. Compared to existing studies, our analysis relies on panel data available for a long period of fifty years, and systematically tests for skill-specific effects of cultural diversity. Using a full set of fixed effects and combining various instrumentation strategies, we find that diversity among college-educated immigrants positively affects macroeconomic performance. On the contrary, diversity among less educated immigrants has insignificant effects (neither positive nor negative), and this is not due to the higher fraction of undocumented migrants in this group. These results are highly robust to measurement, specification and instrumentation hypotheses. Furthermore, we find no evidence of a quadratic effect, or of a contamination by the bad economic conditions in poor countries.

Overall, a 10% increase in diversity among college-educated immigrants raises GDP per capita by 6.2%. Albeit non-negligible, the macroeconomic implications of diversity are limited. High-skilled diversity only explains 3.5% of the output rise between 1960 and 2010 in the US, and about 4% of the current output gap between the least and most diverse states.

Table 6: 2SLS regressions under different IV strategies.
(Dep= $log(y_{r,t})$)

	(1) Shift-Share $S=H$	(2) Feyrer $S=H$	(3) Feyrer $S=H$	(4) Feyrer $S=H$	(5) Feyrer $S=H$	(6) Shift-Share $S=L$	(7) Feyrer $S=L$	(8) Feyrer $S=L$	(9) Feyrer $S=L$	(10) Feyrer $S=L$
$MD_{r,t}$	0.511**	1.035***	0.853***	0.444**	0.726***	0.276*	0.186	0.089	0.105	0.096
	(0.213)	(0.308)	(0.278)	(0.200)	(0.259)	(0.157)	(0.132)	(0.142)	(0.089)	(0.151)
$m_{r,t}$	0.548*	0.878**	0.481	0.079	0.289	0.623*	0.527*	0.373	0.404	0.388
	(0.306)	(0.387)	(0.533)	(0.504)	(0.573)	(0.326)	(0.278)	(0.390)	(0.396)	(0.421)
$MY_{r,t}$			-0.122*	-0.208**	-0.215**			-0.106***	-0.098*	-0.099*
			(0.074)	(0.098)	(0.096)			(0.040)	(0.055)	(0.056)
$log(Pop_{r,t})$	-0.153**	-0.163**	-0.145*	-0.130*	-0.137*	-0.174**	-0.169**	-0.143*	-0.146*	-0.145*
	(0.074)	(0.073)	(0.076)	(0.078)	(0.078)	(0.080)	(0.076)	(0.076)	(0.083)	(0.075)
$log(Urb_{r,t})$	0.285**	0.283**	0.277**	0.276**	0.276**	0.378**	0.345**	0.307*	0.313*	0.309*
	(0.135)	(0.125)	(0.123)	(0.131)	(0.124)	(0.170)	(0.161)	(0.178)	(0.167)	(0.177)
$log(Hum_{r,t})$	0.772***	0.709***	0.705***	0.737***	0.702***	0.711***	0.776***	0.807***	0.801***	0.806***
	(0.190)	(0.199)	(0.193)	(0.186)	(0.192)	(0.210)	(0.218)	(0.211)	(0.191)	(0.210)
Endogenous regressors:										
$\widehat{MD^S_{r,t}}$	√	√	√		√	√	√	√		√
$\widehat{MY^S_{r,t}}$				√	√				√	√
$\widehat{m^S_{r,t}}$			√	√	√			√	√	√
Observations	306	306	306	306	306	306	306	306	306	306
Nb. states	51	51	51	51	51	51	51	51	51	51
R-squared	0.993	0.993	0.993	0.993	0.993	0.993	0.993	0.993	0.993	0.993
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
States fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P F-$Test^{\dagger}$	439.9	103.9	43.65	69.68	48.14	91.14	70.12	33.89	75.88	18.11
Stock Yogo	29.18/16.23	16.38/8.96	7.03/4.58	7.03/4.58	N.A	29.18/16.23	16.38/8.96	7.03/4.58	7.03/4.58	N.A

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. The specification is described in Eq. (3) and includes all fixed effects. We estimate it with 2SLS and rely on two IV strategies (the augmented shift-share and the gravity-like strategy *a la* Feyrer (2009)) to instrument the birthplace diversity index. Col. 1, 2 and 3 report estimates for high-skilled diversity; col. 4, 5 and 6 report estimates for low-skilled diversity. †Kleinbergenn-Paap F-statistic tests for weak identification (critical values from Stock-Yogo (2005) are given for 10%/15% maximal IV size). First-stage results are reported in Table A16 and A17in the Appendix. Zero-stage regressions with instrumentation *a la* Feyrer (2009) are provided in Table A14 in the Appendix. The sample includes the 50 US states and the District of Columbia from 1960 to 2010. The set of control variables includes the immigration rate ($m^S_{r,t}$), the log of population ($log(Pop_{r,t})$), the log of urbanization ($log(Urb_{r,t})$) and the log of the average educational attainment of the working-age population ($log(Hum_{r,t})$).

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A1: List of variables

Table A1: Variables: Source and definition.

Variable	Description	Definition	Source
$y_{r,t}$	Gross Domestic product	Gross domestic product (GDP) per capita.	Bureau of Economic Analysis.
$TD^S_{r,t}$	Birthplace diversity among residents	Probability that two randomly-drawn residents in region r have different countries of birth.	Authors' calculation on IPUMS-US data.
$MD^S_{r,t}$	Birthplace diversity among immigrants	Probability that two randomly-drawn immigrants in region r have different countries of birth.	Authors' calculation on IPUMPS-US data.
$MY^S_{r,t}$	Immigration-driven norm among immigrants	Weighted average outcome y in immigrant's origin countries where the weights are immigrants' share in the total immigrants' population in the destination region r.	Authors' calculation on IPUMS-US data.
$TP^S_{r,t}$	Polarization index among residents	Index that captures how the birthplace distribution in a population is far from the bimodal distribution.	Authors' calculation on IPUMS-US data.
$MP^S_{r,t}$	Polarization index among immigrants	Index that captures how the birthplace distribution in a immigrant's population is far from the bimodal distribution.	Authors' calculation on IPUMS-US data.
$k^S_{i,r,t}$	Share of immigrants	Number of individuals born in country i and living in region r as percentage of the total population of region r at year t.	IPUMS-US data.
$\widehat{k}^S_{i,r,t}$	Share of immigrants	Share of immigrants from origin country i in the total immigrant population of region r.	IPUMS-US data.
$m^S_{r,t}$	Immigration rate	Ratio of the total stock of foreign-born individuals to the total population of region r at year t.	Author's calculation on IPUMS-US.
$Hum_{r,t}$	Average education	Average education level.	Authors' calculation IPUMS data.
$Pop_{r,t}$	Population	Population of region r at year t.	IPUMS-US data.
$Urb_{r,t}$	Urbanization	Urban Percentage of the Population for States.	U.S. Census Bureau.
Gravity model:			
$Stock_{i,r,t}$	Stock of immigrants	Number of individuals born in country i and living in region r at year t.	IPUMS-US data.
$Distance_{i,r}$	Distance	Great-circle distance between the capital city of the origin countries i and the capital of the destination region r for US states.	Authors' calculation.
$Bord_{Canada,r}$	Common border	Dummy equal to 1 if Canada and State r share a common border and 0 otherwise.	Authors' elaboration.
$Bord_{Mexico,r}$	Common border	Dummy equal to 1 if Mexico and State r share a common border and 0 otherwise.	Authors' calculation.

Source: Authors' calculation.

A2: List of origin countries and US states

Table A2: List of origin countries (195).

Afghanistan, Albania, Algeria, Andorra, Angola, Antigua-Barbuda, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bhutan, Bolivia, Bosnia, Botswana, Brazil, Brunei, Bulgaria, Burkina Faso, Burma (Myanmar), Burundi, Cambodia, Cameroon, Canada, Cape Verde, Central African Republic, Chad, Chile, China, China, Hong Kong SAR, China, Macao SAR, Colombia, Comoros, Congo, Dem. Rep. of the, Congo, Rep. of the, Costa Rica, Cote d'Ivoire, Croatia, Cuba, Cyprus, Czech Republic, Denmark, Djibouti, Dominica, Dominican Republic, East Timor, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Estonia, Ethiopia, Fiji, Finland, France, Gabon, Gambia, Georgia, Germany, Ghana, Greece, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana/British Guiana, Haiti, Holy See (Vatican City), Honduras, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kiribati, Korea, Kuwait, Kyrgyzstan, Laos, Latvia, Lebanon, Lesotho, Liberia, Libya, Liechtenstein, Lithuania, Luxembourg, Macedonia, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshall Islands, Mauritania, Mauritius, Mexico, Micronesia, Moldova, Monaco, Mongolia, Morocco, Mozambique, Namibia, Nauru, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Occupied Palestinian Territory, Oman, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russia, Rwanda, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Samoa, San Marino, Sao Tome and Principe, Saudi Arabia, Senegal, Serbia and Montenegro, Seychelles, Sierra Leone, Singapore, Slovakia, Slovenia, Solomon Islands, Somalia, South Africa, Spain, Sri Lanka, Sudan, Suriname, Swaziland, Sweden, Switzerland, Syria, Taiwan, Tajikistan, Tanzania, Thailand, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Tuvalu, Uganda, Ukraine, United Arab Emirates, United Kingdom, Unites States, Uruguay, Uzbekistan, Vanuatu, Venezuela, Vietnam, Yemen, Zambia, Zimbabwe.

Table A3: List of US States (51) and descriptives statistics

States	$log(y_{r,t})$	$MD^A_{r,t}$	$MD^H_{r,t}$	$MD^L_{r,t}$	$m^A_{r,t}$	$log(Pop_{r,t})$	$log(Urb_{r,t})$	$log(Hum_{r,t})$
Alabama	9,256	0,900	0,923	0,846	0,021	14,715	4,060	1,722
Alaska	10,053	0,894	0,880	0,882	0,064	12,561	4,071	1,855
Arizona	9,484	0,690	0,906	0,554	0,107	14,440	4,428	1,806
Arkansas	9,209	0,871	0,914	0,811	0,024	14,154	3,930	1,706
California	9,731	0,845	0,941	0,734	0,221	16,618	4,519	1,839
Colorado	9,616	0,872	0,934	0,778	0,071	14,490	4,393	1,888
Connecticut	9,759	0,940	0,952	0,928	0,116	14,518	4,402	1,856
Delaware	9,847	0,930	0,932	0,889	0,055	12,919	4,303	1,827
District of Columbia	10,564	0,960	0,968	0,903	0,106	13,016	4,605	1,893
Florida	9,424	0,869	0,889	0,856	0,143	15,675	4,431	1,794
Georgia	9,458	0,909	0,939	0,854	0,052	15,174	4,164	1,741
Hawaii	9,657	0,745	0,828	0,711	0,172	13,347	4,457	1,846
Idaho	9,336	0,811	0,869	0,714	0,046	13,299	4,057	1,824
Illinois	9,675	0,883	0,947	0,792	0,109	15,807	4,438	1,816
Indiana	9,501	0,917	0,950	0,852	0,032	15,066	4,197	1,784
Iowa	9,476	0,909	0,945	0,856	0,029	14,379	4,077	1,826
Kansas	9,470	0,878	0,940	0,791	0,044	14,237	4,219	1,849
Kentucky	9,369	0,905	0,930	0,859	0,019	14,640	3,953	1,690
Louisiana	9,501	0,948	0,958	0,925	0,028	14,728	4,229	1,721
Maine	9,319	0,656	0,796	0,590	0,047	13,481	3,812	1,802
Maryland	9,592	0,955	0,960	0,938	0,088	14,872	4,389	1,836
Massachusetts	9,700	0,930	0,951	0,911	0,122	15,148	4,461	1,873
Michigan	9,561	0,927	0,928	0,910	0,060	15,568	4,290	1,809
Minnesota	9,580	0,938	0,950	0,907	0,046	14,789	4,222	1,855
Mississippi	9,119	0,917	0,898	0,879	0,015	14,242	3,820	1,701
Missouri	9,490	0,939	0,950	0,913	0,028	14,969	4,232	1,785
Montana	9,344	0,873	0,877	0,859	0,029	13,113	3,973	1,845
Nebraska	9,510	0,895	0,937	0,838	0,039	13,792	4,164	1,846
Nevada	9,759	0,863	0,923	0,802	0,125	13,342	4,439	1,818
New Hampshire	9,470	0,809	0,887	0,772	0,057	13,315	4,028	1,843
New Jersey	9,717	0,949	0,951	0,941	0,159	15,394	4,509	1,832
New Mexico	9,477	0,660	0,893	0,509	0,071	13,655	4,278	1,796
New York	9,805	0,954	0,964	0,944	0,189	16,276	4,453	1,827
North Carolina	9,475	0,905	0,948	0,845	0,039	15,232	3,929	1,737
North Dakota	9,362	0,873	0,834	0,857	0,029	12,886	3,889	1,817
Ohio	9,531	0,951	0,951	0,940	0,037	15,732	4,320	1,799
Oklahoma	9,360	0,883	0,942	0,796	0,036	14,445	4,193	1,798
Oregon	9,511	0,866	0,920	0,788	0,072	14,342	4,262	1,852
Pennsylvania	9,505	0,945	0,952	0,933	0,046	15,844	4,287	1,796
Rhode Island	9,478	0,888	0,931	0,858	0,109	13,346	4,477	1,790
South Carolina	9,273	0,903	0,924	0,857	0,028	14,548	3,981	1,716
South Dakota	9,326	0,911	0,901	0,893	0,021	12,971	3,868	1,809
Tennessee	9,375	0,916	0,943	0,863	0,025	14,920	4,099	1,720
Texas	9,569	0,610	0,917	0,452	0,113	16,091	4,385	1,764
Utah	9,450	0,883	0,925	0,822	0,066	13,739	4,432	1,880
Vermont	9,387	0,754	0,852	0,679	0,053	12,690	3,570	1,839
Virginia	9,560	0,953	0,952	0,940	0,070	15,132	4,201	1,802
Washington	9,709	0,897	0,912	0,853	0,098	14,862	4,331	1,870
West Virginia	9,248	0,933	0,915	0,910	0,013	13,958	3,700	1,700
Wisconsin	9,504	0,909	0,946	0,849	0,038	14,910	4,194	1,818
Wyoming	9,755	0,885	0,894	0,818	0,033	12,513	4,134	1,844

Note: Average from 1960 to 2010. Source: Authors' elaboration on IPUMS-US data.

A3: Robustness Checks

Table A4: Robustness of FE regressions for high-skilled diversity.
Alternative sub-samples (Dep= $log(y_{r,t})$)

	(1) Full Sample	(2) 1970-2000	(3) No Top5	(4) No Bot5	(5) No Mex	(6) No $Q1$
$MD^H_{r,t}$	0.616***	0.870***	0.725***	0.672***	0.630***	0.596**
	(0.160)	(0.321)	(0.174)	(0.170)	(0.170)	(0.288)
$m^H_{r,t}$	0.614*	1.140**	1.317**	0.613*	0.541	0.765**
	(0.315)	(0.459)	(0.529)	(0.323)	(0.397)	(0.365)
$log(Pop_{r,t})$	-0.155**	0.002	-0.187**	-0.160**	-0.158*	-0.182**
	(0.075)	(0.075)	(0.082)	(0.073)	(0.088)	(0.074)
$log(Urb_{r,t})$	0.285**	0.290	0.260*	0.300**	0.295**	0.198
	(0.135)	(0.187)	(0.140)	(0.147)	(0.138)	(0.151)
$log(Hum_{r,t})$	0.759***	1.251***	0.692***	0.945***	0.731***	0.797***
	(0.197)	(0.310)	(0.213)	(0.183)	(0.224)	(0.233)
Constant	7.348***	4.309***	7.870***	7.030***	7.373***	8.107***
	(1.262)	(1.584)	(1.387)	(1.250)	(1.398)	(1.313)
Observations	306	204	276	276	282	228
Nb. states	51	51	46	46	47	38
R-squared	0.993	0.990	0.993	0.993	0.993	0.995
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
States fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. The specification is described in Eq.(3) and includes all fixed effects. Col. 1 reports the results from Table 2. In col. 2, we exclude observations for the years 1960 and 2010. In col. 3 and 4, we exclude the five US states with the greatest or smallest immigration shares. In col. 5, we exclude US states located on the US-Mexican border. In col. 6, we exclude the lowest quartile in terms of immigrant population. The set of control variables includes the immigration rate ($m^S_{r,t}$), the log of population ($log(Pop_{r,t})$), the log of urbanization ($log(Urb_{r,t})$) and the log of the average educational attainment of the working-age population ($log(Hum_{r,t})$).

Table A5: Robustness of FE regressions for low-skilled diversity. Alternative sub-samples (Dep= $log(y_{r,t})$)

	(1) Full Sample	(2) 1970-2000	(3) No Top5	(4) No Bot5	(5) No Mex	(6) No $Q1$
$MD^L_{r,t}$	0.141	0.130	0.228**	0.128	0.109	0.015
	(0.086)	(0.097)	(0.093)	(0.092)	(0.091)	(0.115)
$m^L_{r,t}$	0.481*	0.691**	0.938**	0.448	0.474	0.647**
	(0.282)	(0.272)	(0.418)	(0.288)	(0.392)	(0.276)
$log(Pop_{r,t})$	-0.166**	0.004	-0.200**	-0.169**	-0.157	-0.197**
	(0.081)	(0.086)	(0.090)	(0.080)	(0.095)	(0.076)
$log(Urb_{r,t})$	0.329**	0.323	0.315*	0.341*	0.313*	0.360**
	(0.163)	(0.200)	(0.165)	(0.182)	(0.168)	(0.166)
$log(Hum_{r,t})$	0.807***	1.309***	0.743***	0.964***	0.785***	0.919***
	(0.205)	(0.343)	(0.212)	(0.204)	(0.215)	(0.264)
Constant	7.662***	4.738***	8.183***	7.439***	7.660***	7.971***
	(1.263)	(1.514)	(1.370)	(1.259)	(1.429)	(1.158)
Observations	306	204	276	276	282	228
Nb. states	51	51	46	46	47	38
R-squared	0.993	0.989	0.993	0.993	0.993	0.996
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
States fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. The specification is described in Eq.(3) and includes all fixed effects. Col. 1 reports the results from Table 2. In col. 2, we exclude observations for the years 1960 and 2010. In col. 3 and 4, we exclude the five US states with the greatest or smallest immigration shares. In col. 5, we exclude US states located on the US-Mexican border. In col. 6, we exclude the lowest quartile in terms of immigration rate. The set of control variables includes the immigration rate ($m^S_{r,t}$), the log of population ($log(Pop_{r,t})$), the log of urbanization ($log(Urb_{r,t})$) and the log of the average educational attainment of the working-age population ($log(Hum_{r,t})$).

Table A6: Robustness of FE regressions for high-skilled diversity.
Ten largest US immigrants group in 2010 (Dep= $log(y_{r,t})$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
i	Mexico	India	Philippines	China	Vietnam	El Salvador	Cuba	Korea	Dominican Rep.	Guatemala	10 largest
$MD^H_{r,t}$	0.649***	0.616***	0.602***	0.577***	0.615***	0.613***	0.627***	0.617***	0.607***	0.621***	0.617***
	(0.176)	(0.161)	(0.164)	(0.149)	(0.160)	(0.156)	(0.158)	(0.160)	(0.156)	(0.163)	(0.169)
$m^H_{r,t}$	0.673**	0.743**	0.626*	0.638**	0.615*	0.500	0.631**	0.628*	0.550	0.649**	0.726*
	(0.316)	(0.349)	(0.315)	(0.311)	(0.315)	(0.303)	(0.301)	(0.336)	(0.338)	(0.322)	(0.365)
$\widehat{k}^H_{i,r,t}$	0.214	-0.628*	-0.126	0.403	-0.035	2.033	0.063	-0.158	0.354	-0.813	
	(0.260)	(0.352)	(0.199)	(0.280)	(0.458)	(1.483)	(0.237)	(0.425)	(0.712)	(1.313)	
$log(Pop_{r,t})$	-0.166**	-0.174**	-0.150**	-0.144*	-0.155**	-0.157**	-0.155**	-0.156**	-0.151*	-0.156**	-0.169**
	(0.078)	(0.075)	(0.074)	(0.079)	(0.076)	(0.074)	(0.075)	(0.076)	(0.079)	(0.075)	(0.083)
$log(Urb_{r,t})$	0.282**	0.278**	0.283**	0.292**	0.286**	0.271*	0.285**	0.289**	0.296**	0.287**	0.282*
	(0.136)	(0.139)	(0.139)	(0.134)	(0.138)	(0.139)	(0.136)	(0.136)	(0.145)	(0.138)	(0.162)
$log(Hum_{r,t})$	0.807***	0.852***	0.743***	0.766***	0.758***	0.760***	0.766***	0.753***	0.752***	0.759***	0.895***
	(0.218)	(0.196)	(0.198)	(0.198)	(0.205)	(0.196)	(0.202)	(0.199)	(0.198)	(0.195)	(0.233)
Constant	7.404***	7.506***	7.328***	7.173***	7.349***	7.442***	7.327***	7.352***	7.263***	7.356***	7.341***
	(1.263)	(1.212)	(1.248)	(1.338)	(1.266)	(1.240)	(1.272)	(1.266)	(1.354)	(1.262)	(1.360)
Observations	306	306	306	306	306	306	306	306	306	306	306
Nb. states	51	51	51	51	51	51	51	51	51	51	51
R-squared	0.993	0.993	0.993	0.993	0.993	0.993	0.993	0.993	0.993	0.993	0.993
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
States fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. $\widehat{k}^H_{i,r,t}$ is the share of high-skilled immigrants from origin country i in the total immigrant population of state r. The sample includes the 50 US states and the District of Columbia from 1960 to 2010. Col. 11 includes $\widehat{k}^H_{i,r,t}$ for the 10 largest immigrant groups in the US. Coefficients for all the countries are not reported in col. 11 for space limitations.

Table A7: Robustness of FE regressions for low-skilled diversity.
Ten largest US immigrants group in 2010 (Dep= $log(y_{r,t})$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
i	Mexico	India	Philippines	China	Vietnam	El Salvador	Cuba	Korea	Dominican Rep.	Guatemala	10 largest
$MD^L_{r,t}$	0.294**	0.149*	0.159	0.213**	0.127	0.133	0.131	0.148	0.147*	0.142*	0.276**
	(0.111)	(0.086)	(0.097)	(0.093)	(0.093)	(0.082)	(0.089)	(0.090)	(0.086)	(0.085)	(0.104)
$m^L_{r,t}$	0.652**	0.454*	0.252	0.483*	0.484*	0.211	0.446	0.482*	0.500*	0.443	0.058
	(0.290)	(0.266)	(0.266)	(0.260)	(0.282)	(0.249)	(0.283)	(0.281)	(0.293)	(0.291)	(0.274)
$\widehat{k}^L_{i,r,t}$	0.173*	-1.781	-1.472*	-1.394*	0.250	0.620***	-0.232	-0.103	-0.087	0.351	
	(0.089)	(1.159)	(0.803)	(0.831)	(0.364)	(0.209)	(0.209)	(0.295)	(0.414)	(0.399)	
$log(Pop_{r,t})$	-0.187**	-0.172**	-0.151**	-0.190**	-0.161*	-0.127	-0.164**	-0.166**	-0.169*	-0.162*	-0.129*
	(0.078)	(0.079)	(0.071)	(0.075)	(0.084)	(0.077)	(0.080)	(0.081)	(0.086)	(0.082)	(0.069)
$log(Urb_{r,t})$	0.335*	0.307*	0.308**	0.317**	0.312*	0.320*	0.325**	0.336**	0.328*	0.329**	0.256*
	(0.167)	(0.163)	(0.147)	(0.153)	(0.174)	(0.162)	(0.161)	(0.153)	(0.164)	(0.162)	(0.149)
$log(Hum_{r,t})$	0.792***	0.839***	0.681***	0.810***	0.804***	0.733***	0.808***	0.801***	0.808***	0.777***	0.622***
	(0.203)	(0.209)	(0.217)	(0.207)	(0.202)	(0.211)	(0.200)	(0.204)	(0.206)	(0.207)	(0.218)
Constant	7.804***	7.786***	7.768***	7.999***	7.683***	7.292***	7.655***	7.637***	7.698***	7.659***	7.665***
	(1.273)	(1.229)	(1.166)	(1.172)	(1.267)	(1.097)	(1.254)	(1.262)	(1.326)	(1.261)	(0.975)
Observations	306	306	306	306	306	306	306	306	306	306	306
Nb. states	51	51	51	51	51	51	51	51	51	51	51
R-squared	0.993	0.993	0.993	0.993	0.993	0.993	0.993	0.993	0.993	0.993	0.994
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
States fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. $\widehat{k}^L_{i,r,t}$ is the share of low-skilled immigrants from origin country i in the total immigrant population of state r. The sample includes the 50 US states and the District of Columbia from 1960 to 2010. Col. 11 includes $\widehat{k}^L_{i,r,t}$ for the 10 largest immigrant groups in the US. Coefficients for all the countries are not reported in col. 11 for space limitations.

Table A8: Robustness of FE estimates to alternative specifications. Results by skill group (Dep= $log(y_{r,t})$)

	(1) Quadratic. $S=H$	(2) Polarization $S=H$	(3) Quadratic $S=L$	(4) Polarization $S=L$
$MD^S_{r,t}$	-0.131		0.705**	
	(1.954)		(0.293)	
$(MD^S_{r,t})^2$	0.453		-0.391*	
	(1.202)		(0.218)	
$MP^S_{r,t}$		-0.291***		-0.025
		(0.090)		(0.072)
$m^S_{r,t}$	0.622*	0.596*	0.504*	0.352
	(0.314)	(0.306)	(0.281)	(0.271)
$log(Pop_{r,t})$	-0.154**	-0.154**	-0.164**	-0.159*
	(0.075)	(0.074)	(0.081)	(0.082)
$log(Urb_{r,t})$	0.279*	0.254*	0.347**	0.282
	(0.143)	(0.142)	(0.159)	(0.170)
$log(Hum_{r,t})$	0.758***	0.748***	0.799***	0.894***
	(0.197)	(0.196)	(0.206)	(0.202)
Constant	7.666***	8.121***	7.388***	7.762***
	(1.571)	(1.224)	(1.284)	(1.271)
Observations	306	306	306	306
Nb. states	51	51	51	51
R-squared	0.993	0.993	0.993	0.993
Time fixed effects	Yes	Yes	Yes	Yes
States fixed effects	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. The specification is described in Eq. (3) and includes all fixed effects. Col. 1 and 3 tests for a quadratic specification in birthplace diversity with $MD^H_{r,t}$ and $(MD^H_{r,t})^2$. In col. 2 and 4, we replace birthplace diversity by a polarization index ($MP^H_{r,t}$). The sample includes the 50 US states and the District of Columbia from 1960 to 2010. The set of control variables includes the immigration rate ($m^S_{r,t}$), the log of population ($log(Pop_{r,t})$), the log of urbanization ($log(Urb_{r,t})$) and the log of the average educational attainment of the working-age population ($log(Hum_{r,t})$).

Table A9: Robustness of Pooled OLS, FE and IV regressions without controls.
Results by skill group (Dep= $log(y_{r,t})$)

	(1) OLS $S=H$	(2) Fixed-effects $S=H$	(3) Shift-Share $S=H$	(4) Feyrer $S=H$	(5) OLS $S=L$	(6) Fixed-effects $S=L$	(7) Shift-Share $S=L$	(8) Feyrer $S=L$
$MD_{r,t}^S$	7.595***	0.664***	0.418*	1.079***	0.343	0.147**	0.009	0.130
	(0.909)	(0.209)	(0.234)	(0.376)	(0.498)	(0.063)	(0.120)	(0.192)
$m_{r,t}^S$	9.912***	-0.019	-0.168	0.231	6.963***	-0.123	-0.290	-0.143
	(1.421)	(0.452)	(0.452)	(0.529)	(1.053)	(0.314)	(0.334)	(0.468)
Observations	306	306	306	306	306	306	306	306
Nb. states	51	51	51	51	51	51	51	51
R-squared	0.452	0.992	0.992	0.991	0.236	0.991	0.991	0.991
Time fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
States fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
K-P F-$Test^{\dagger}$			383.45	107.45			100.82	47.31
Stock Yogo			16.38/ 8.96	16.38/ 8.96			16.38/ 8.96	16.38/ 8.96

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. The specification is described in Eq. (3). The sample includes the 50 US states and the District of Columbia from 1960 to 2010. We estimate 2SLS relying on two IV strategies (the augmented shift-share and the gravity-like strategy *a la* Feyrer (2009)) to instrument the birthplace diversity index. †Kleinbergenn-Paap F-statistic tests for weak identification (critical values from Stock-Yogo (2005) are given for 10%/15% maximal IV size).

Table A10: Robustness of FE regressions to alternative educational levels
(Dep= $log(y_{r,t})$)

	(1) $S=H$	(2) $S=Ph.D$	(3) $S=Tertiary$	(4) $S=L$	(5) $S=No\ school$	(6) $S=Primary$	(7) $S=Secondary$
$MD^S_{r,t}$	0.616***	0.262**	0.369***	0.141	0.038	0.033	0.120
	(0.160)	(0.103)	(0.136)	(0.086)	(0.032)	(0.061)	(0.101)
$m^S_{r,t}$	0.614*	0.256	0.372	0.481*	0.152	0.165	0.432
	(0.315)	(0.266)	(0.298)	(0.282)	(0.100)	(0.101)	(0.301)
$log(Pop_{r,t})$	-0.155**	-0.158**	-0.141*	-0.166**	-0.167**	-0.160**	-0.149*
	(0.075)	(0.077)	(0.077)	(0.081)	(0.076)	(0.076)	(0.080)
$log(Urb_{r,t})$	0.285**	0.287*	0.253*	0.329**	0.207	0.287	0.311*
	(0.135)	(0.145)	(0.148)	(0.163)	(0.168)	(0.173)	(0.163)
$log(Hum_{r,t})$	0.759***	0.763***	0.779***	0.807***	0.843***	1.004***	0.831***
	(0.197)	(0.205)	(0.206)	(0.205)	(0.210)	(0.206)	(0.209)
Constant	7.348***	7.702***	7.489***	7.662***	8.205***	7.552***	7.497***
	(1.262)	(1.244)	(1.290)	(1.263)	(1.342)	(1.197)	(1.300)
Observations	306	306	306	306	306	306	306
Nb. states	51	51	51	51	51	51	51
R-squared	0.993	0.993	0.993	0.993	0.993	0.993	0.993
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
States fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. Col 1 and 4 report our benchmark specifications from Table 2.

Table A11: Robustness of FE regressions.
Results by legal status and skill group (Dep= $log(y_{r,t})$)

	(1)	(2)	(3)	(4)	(5)	(6)
	$S = H$	$S = H$	$S = H$	$S = L$	$S = L$	$S = L$
	All	Legal	Undoc.	All	Legal	Undoc.
$MD^S_{r,t}$	0.813*	1.009**	-0.153	0.038	0.043	-0.017
	(0.438)	(0.473)	(0.127)	(0.100)	(0.112)	(0.045)
$m^S_{r,t}$	0.842*	0.959*	4.426**	0.957**	1.107**	3.482*
	(0.431)	(0.535)	(2.140)	(0.377)	(0.424)	(1.795)
$ln(Population_{s,t})$	-0.029	-0.028	0.013	-0.074	-0.057	-0.088
	(0.092)	(0.094)	(0.088)	(0.105)	(0.099)	(0.112)
$ln(Urban_{s,t})$	0.129	0.129	0.050	0.093	0.090	0.079
	(0.164)	(0.166)	(0.172)	(0.167)	(0.166)	(0.180)
$ln(College_{s,t})$	2.043***	1.997***	2.296***	2.508***	2.418***	2.671***
	(0.633)	(0.622)	(0.611)	(0.690)	(0.676)	(0.724)
Constant	4.762***	4.650**	4.839***	5.450***	5.366***	5.497***
	(1.723)	(1.758)	(1.647)	(1.630)	(1.634)	(1.706)
Observations	204	204	204	204	204	204
Nb. states	51	51	51	51	51	51
R-squared	0.979	0.979	0.979	0.979	0.979	0.979
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
States fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses adjusted for clustering at the state level. Col. 1 and 4 report the coefficient of the benchmark sample over the 1980-2010 period and for high-skilled and low-skilled immigrants, respectively. In col. 2 and 5, the diversity indices are computed for the legal immigrant population only. In col. 3 and 6, we use the undocumented immigrant population only.

Table A12: Robustness of FE and IV regressions to spatial scale.
Results by skill group at the Commuting Zones level (Dep= $log(Wage_{CZs,t})$)

	(1) Fixed-effects $S = H$	(2) Fixed-effects $S = L$	(3) Shift-Share $S = H$	(4) Shift-Share $S = L$
$MD_{r,t}^S$	0.319**	0.171**	0.372***	-0.317
	(0.150)	(0.076)	(0.128)	(0.207)
$m_{r,t}^S$	1.907***	0.997***	1.913***	0.439
	(0.567)	(0.350)	(0.561)	(0.438)
Constant	5.395***	5.528***		
	(0.110)	(0.063)		
Observations	3,688	3,688	3,688	3,688
R-squared	0.895	0.894	0.895	0.891
Number of CZs	741	741	741	741
Time fixed effects	Yes	Yes	Yes	Yes
CZs fixed effects	Yes	Yes	Yes	Yes
F-test (IV)			2305	501.3

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the Commuting zones level (CZs). The specification includes all fixed effects. The sample includes the 50 US states and the District of Columbia from 1970 to 2010. The dependent variable $= log(Wage_{CZs,t})$ is logarithm of the average wage of white US natives between 40-50 which is not affected by discrimination, following Ottaviano and Peri (2006). Commuting zones are computed following Dorn (2009).

A4: Correlation between diversity measures

Table A13: Pearson correlations between diversity measures

Variables	$TD^A_{r,t}$	$MD^A_{r,t}$	$TP^A_{r,t}$	$MP^A_{r,t}$	$MD^{A,G}_{r,t}$	$MY^A_{r,t}$	$m^A_{r,t}$
$TD^A_{r,t}$	1.000						
$MD^A_{r,t}$	-0.194***	1.000					
$TP^A_{r,t}$	0.987***	-0.244***	1.000				
$MP^A_{r,t}$	0.146***	-0.892***	0.190***	1.000			
$MD^{A,G}_{r,t}$	0.314***	0.393***	0.298***	-0.449***	1.000		
$MY^A_{r,t}$	-0.261***	-0.166***	-0.253***	0.189***	-0.182***	1.000	
$m^A_{r,t}$	0.998***	-0.196***	0.977***	0.152***	0.306***	-0.256**	1.000
Variables	$TD^H_{r,t}$	$MD^H_{r,t}$	$TP^H_{r,t}$	$MP^H_{r,t}$	$MD^{H,G}_{r,t}$	$MY^H_{r,t}$	$m^H_{r,t}$
$TD^H_{r,t}$	1.000						
$MD^H_{r,t}$	0.169***	1.000					
$TP^H_{r,t}$	0.990***	0.178***	1.000				
$MP^H_{r,t}$	-0.237***	-0.968***	-0.253***	1.000			
$MD^{H,G}_{r,t}$	0.430***	0.685***	0.439***	-0.733***	1.000		
$MY^H_{r,t}$	-0.128**	-0.189***	-0.116**	0.186***	-0.094	1.000	
$m^H_{r,t}$	0.999***	0.158***	0.984***	-0.224***	0.422***	-0.130**	1.000
Variables	$TD^L_{r,t}$	$MD^L_{r,t}$	$TP^L_{r,t}$	$MP^L_{r,t}$	$MD^{L,G}_{r,t}$	$MY^L_{r,t}$	$m^L_{r,t}$
$TD^L_{r,t}$	1.000						
$MD^L_{r,t}$	-0.340***	1.000					
$TP^L_{r,t}$	0.986***	-0.413***	1.000				
$MP^L_{r,t}$	0.238***	-0.828***	0.297***	1.000			
$MD^{L,G}_{r,t}$	0.194***	0.377***	0.156***	-0.364***	1.000		
$MY^L_{r,t}$	-0.322***	-0.148**	-0.313***	0.148**	-0.283***	1.000	
$m^L_{r,t}$	0.995***	-0.349***	0.972***	0.246***	0.178***	-0.303***	1.000

Notes: *** p<0.01, ** p<0.05. Source: Authors' elaboration on IPUMS data.

A5: Gravity models *a la* Feyrer (2009)

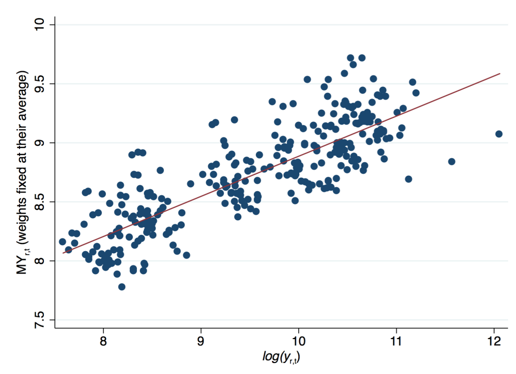
Table A14: Zero-stage estimates (PPML): gravity model *a la* Feyrer (2009)

	(1)	(2)	(3)
	$S = A$	$S = H$	$S = L$
	$log(Stock_{i,r,t})$	$log(Stock_{i,r,t})$	$log(Stock_{i,r,t})$
$log(Dist_{i,r}) \times I_{1960}$	-1.666***	-1.480***	-1.741***
	(0.32)	(0.31)	(0.34)
$log(Dist_{i,r}) \times I_{1970}$	-1.786***	-1.463***	-1.954***
	(0.33)	(0.33)	(0.35)
$log(Dist_{i,r}) \times I_{1980}$	-1.760***	-1.349***	-2.033***
	(0.35)	(0.35)	(0.36)
$log(Dist_{i,r}) \times I_{1990}$	-1.733***	-1.280***	-2.112***
	(0.35)	(0.35)	(0.36)
$log(Dist_{i,r}) \times I_{2000}$	-1.821***	-1.241***	-2.250***
	(0.35)	(0.35)	(0.36)
$log(Dist_{i,r}) \times I_{2010}$	-1.827***	-1.276***	-2.309***
	(0.35)	(0.35)	(0.36)
$Bord_{Canada,r}$	3.605***	2.710***	4.352***
	(0.84)	(0.70)	(0.95)
$Bord_{Mexico,r}$	1.153***	0.999***	1.240***
	(0.20)	(0.24)	(0.21)
Constant	18.808***	15.445***	19.162***
	(2.96)	(2.89)	(3.13)
Observations	59364	59364	59364
R-squared	0.884	0.777	0.907
Year dummies	Yes	Yes	Yes
Origin dummies	Yes	Yes	Yes
Destination dummies	Yes	Yes	Yes

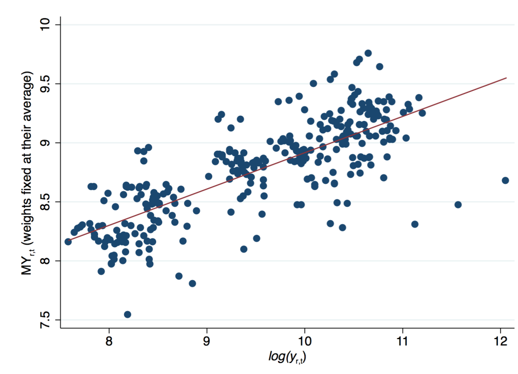
Notes: *** p<0.01, ** p<0.05, * p<0.1. Col.1 shows the results of the stocks of all migrants. Columns 2 and 3 illustrate the results for the college and low educated immigrants respectively. Standard errors in parentheses adjusted for clustering at the state/country-pair level. Source: Authors' elaboration on IPUMS data.

A6: Epidemiological effects

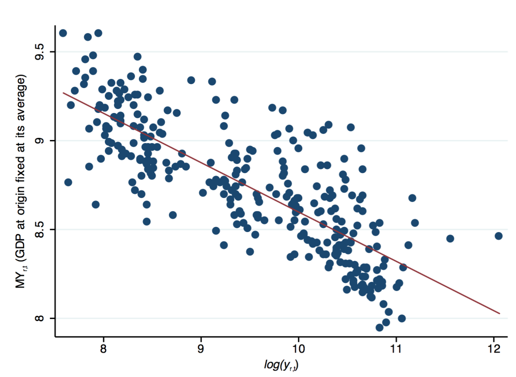
Figure A1: Cross-state correlation between the epidemiological term and GDP per capita (in logs)



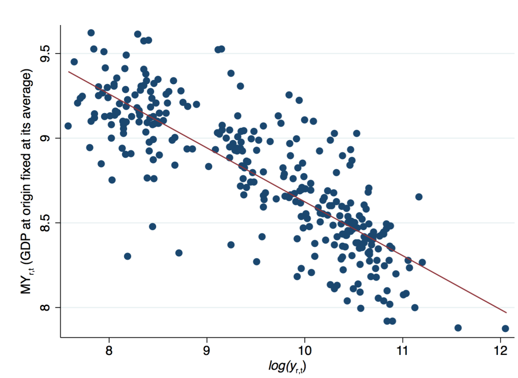
(a) High-skilled



(b) Low-skilled



(c) High-skilled



(d) Low-skilled

Source: Authors' elaboration on IPUMS data.

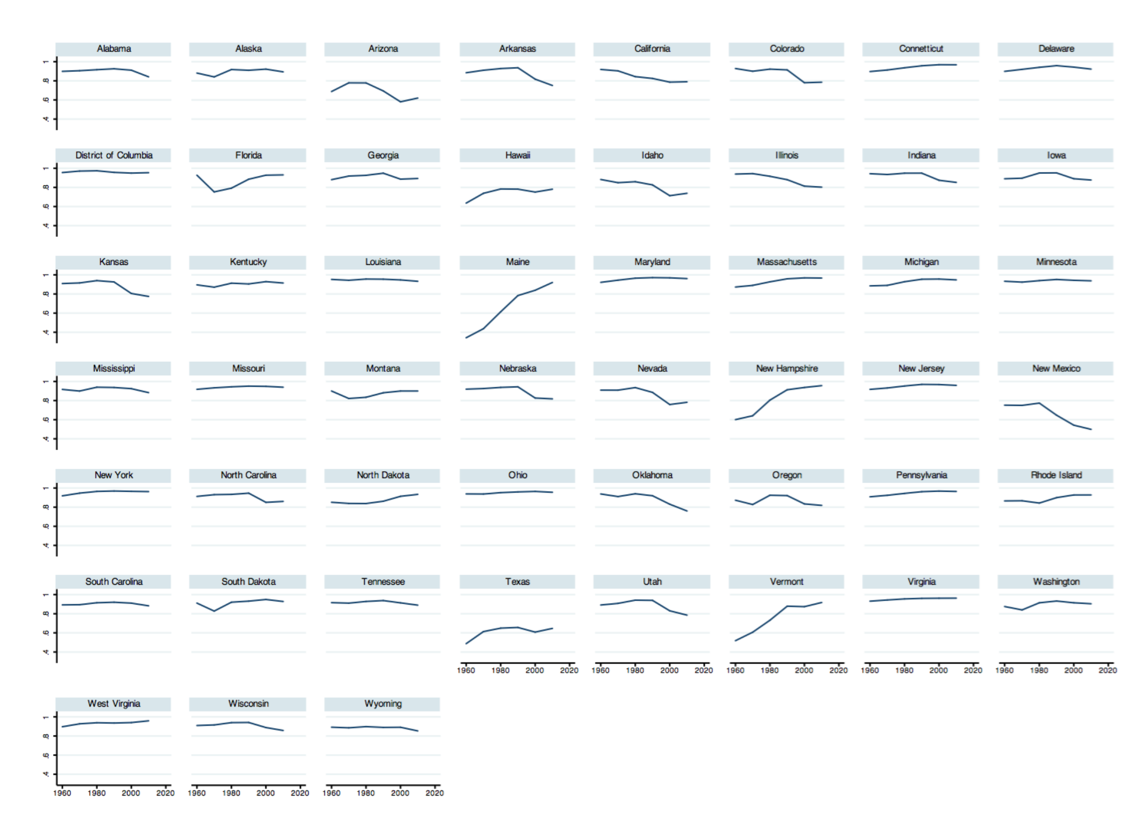
Table A15: Robustness of FE estimates to alternative definitions of the epidemiological term.
Results by skill group (Dep= $log(y_{r,t})$)

	(1) $S=H$	(2) $S=H$	(3) $S=H$	(4) $S=H$	(5) $S=L$	(6) $S=L$	(7) $S=L$	(8) $S=L$
$MD^S_{r,t}$	0.531***	0.618***	0.538***	0.725***	0.104	0.141	0.101	0.006
	(0.159)	(0.162)	(0.157)	(0.249)	(0.085)	(0.085)	(0.086)	(0.085)
$MY^S_{r,t}$	-0.133*				-0.104**			
	(0.069)				(0.042)			
$MY^S_{r,t}$ (Const. $\widehat{k}^S_{i,r,t}$)		-0.120				0.001		
		(0.255)				(0.234)		
$MY^S_{r,t}$ (Const. $y_{i,t}$)			-0.110				-0.092**	
			(0.075)				(0.044)	
$MY^S_{r,t}$ ($y_{i,Entry}$)				-0.111***				-0.146**
				(0.039)				(0.057)
$m^S_{r,t}$	0.388	0.582*	0.441	0.539	0.412	0.481*	0.443	0.530**
	(0.366)	(0.300)	(0.368)	(0.328)	(0.283)	(0.273)	(0.285)	(0.241)
$log(Pop_{r,t})$	-0.144*	-0.157**	-0.143*	-0.080	-0.146*	-0.166**	-0.151*	-0.071
	(0.080)	(0.077)	(0.082)	(0.065)	(0.082)	(0.078)	(0.084)	(0.075)
$log(Urb_{r,t})$	0.282**	0.295**	0.273**	0.156	0.312*	0.329**	0.317*	0.194
	(0.135)	(0.130)	(0.134)	(0.138)	(0.173)	(0.163)	(0.172)	(0.169)
$log(Hum_{r,t})$	0.744***	0.740***	0.762***	1.007***	0.802***	0.807***	0.801***	1.108***
	(0.189)	(0.215)	(0.192)	(0.299)	(0.196)	(0.203)	(0.199)	(0.281)
Constant	8.455***	8.341***	8.299***	7.492***	8.379***	7.651***	8.384***	8.032***
	(1.229)	(3.006)	(1.164)	(1.273)	(1.317)	(2.708)	(1.316)	(1.320)
Observations	306	306	306	255	306	306	306	255
Nb. states	51	51	51	51	51	51	51	51
R-squared	0.993	0.993	0.993	0.991	0.993	0.993	0.993	0.991
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
States fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. The specification is described in Eq. (3) and includes all fixed effects. We supplement our benchmark specifications reported in col. 1 and 5 we alternatives definition of the epidemiological term ($MY^S_{r,t}$). We compute $MY^S_{r,t}$ (Const. $\widehat{k}^S_{i,r,t}$) by keeping the immigration shares constant, at their 1960-2010 average levels. We $MY^S_{r,t}$ (Const. $y_{i,t}$) by keeping the levels of GDP per capita at origin ($log(y_{i,t})$) constant, at their 1960-2010 average level. We compute $MY^S_{r,t}$ ($y_{i,Entry}$) combining annual data on GDP per capita at origin with individual data on the year of arrival in the US. Each immigration share is multiplied by the average level of GDP per capita prevailing in the year of immigration to the US which allows us to capture the norms and values that immigrants bring with them when they migrate. Due to data limitations, this variable cannot be computed for the year 1960. The sample includes the 50 US states and the District of Columbia from 1960 to 2010. The set of control variables includes the immigration rate ($m^S_{r,t}$), the log of population ($log(Pop_{r,t})$), the log of urbanization ($log(Urb_{r,t})$) and the log of the average educational attainment of the working-age population ($log(Hum_{r,t})$).

A7: Trends in birthplace diversity by US state

Figure A2: Diversity among immigrants ($MD^A_{r,t}$) in the US states



Source: Authors' elaboration on IPUMS-US data. Diversity among residents is defined as in Eq. (1). Diversity among immigrants is defined as in Eq. (2).

A8: First-stage estimates

Table A16: First-Stage regressions High-skilled (Alternative IV Strategies)

	(1) $MD^H_{r,t}$	(2) $MD^H_{r,t}$	(3) $MD^H_{r,t}$	(3) $m^H_{r,t}$	(4) $MY^H_{r,t}$	(4) $m^H_{r,t}$	(5) $MD^H_{r,t}$	(5) $MY^H_{r,t}$	(5) $m^H_{r,t}$
$MD^H_{r,t}$(Shift-share)	0.751***								
	(0.036)								
$MD^H_{r,t}$(Feyrer)		0.304***	0.302***	-0.003			0.318***	-0.236*	-0.002
		(0.030)	(0.032)	(0.013)			(0.027)	(0.093)	(0.014)
$m^H_{r,t}$ (Feyrer)			-0.921***	1.600***	-0.189	1.483***	-0.678***	0.513	1.528***
			(0.188)	(0.141)	(0.660)	(0.141)	(0.155)	(0.709)	(0.143)
$MY^H_{r,t}$ (Feyrer)					0.349***	-0.013***	0.031***	0.323***	-0.014***
					(0.020)	(0.004)	(0.008)	(0.020)	(0.004)
$MD^H_{r,t}$					-0.919***	-0.043			
					(0.237)	(0.027)			
$m^H_{r,t}$	-0.266	-0.524***							
	(0.137)	(0.108)							
$MY^H_{r,t}$			0.007	-0.020*					
			(0.021)	(0.009)					
$log(Pop_{r,t})$	-0.004	0.009	0.020	-0.016	0.002	-0.012	0.010	-0.011	-0.013
	(0.012)	(0.015)	(0.017)	(0.010)	(0.035)	(0.009)	(0.016)	(0.039)	(0.010)
$log(Urb_{r,t})$	0.005	-0.027	-0.007	-0.035*	0.058	-0.035*	-0.008	0.059	-0.036*
	(0.022)	(0.078)	(0.081)	(0.017)	(0.068)	(0.014)	(0.075)	(0.071)	(0.015)
$log(Hum_{r,t})$	0.067	0.081	0.148	-0.119	-0.044	-0.103	0.130	-0.175	-0.111
	(0.047)	(0.072)	(0.084)	(0.062)	(0.171)	(0.055)	(0.075)	(0.204)	(0.058)
Observations	306	306	306	306	306	306	306	306	306
R-squared	0.717	0.660	0.642	0.853	0.748	0.862	0.680	0.719	0.860
Angrist-Pischke F-test	439.93	103.94	87.26	99.19	233.71	108.93	138.18	237.69	95.81

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Source: Authors' elaboration on IPUMS-US data. This table provides the results of the first-stage regressions under different IV (Shift share and Feyrer).

Table A17: First-Stage regressions Low-skilled (Alternative IV Strategies)

	(1) $MD^L_{r,t}$	(2) $MD^L_{r,t}$	(3) $MD^L_{r,t}$	(3) $m^L_{r,t}$	(4) $MY^L_{r,t}$	(4) $m^L_{r,t}$	(5) $MD^L_{r,t}$	(5) $MY^L_{r,t}$	(5) $m^L_{r,t}$
$MD^L_{r,t}$ (Shift-Share)	0.788***								
	(0.083)								
$MD^L_{r,t}$ (Feyrer)		0.416***	0.390***	0.022			0.393***	-0.177**	0.014
		(0.050)	(0.048)	(0.016)			(0.047)	(0.058)	(0.013)
$m^L_{r,t}$ (Feyrer)			-1.166***	1.379***	-0.592	1.337***	-1.150***	-0.608	1.346***
			(0.304)	(0.129)	(0.428)	(0.120)	(0.300)	(0.446)	(0.119)
$MY^L_{r,t}$ (Feyrer)					0.385***	-0.006	0.008	0.371***	-0.005
					(0.027)	(0.004)	(0.013)	(0.027)	(0.004)
$MD^L_{r,t}$					-0.213	0.014			
					(0.109)	(0.022)			
$m^L_{r,t}$	-0.863***	-0.603*							
	(0.229)	(0.232)							
$MY^L_{r,t}$			0.006	0.010					
			(0.039)	(0.014)					
$log(Pop_{r,t})$	-0.024	-0.052	-0.028	-0.008	0.180**	0.000	-0.029	0.219***	-0.003
	(0.048)	(0.040)	(0.041)	(0.013)	(0.059)	(0.010)	(0.039)	(0.061)	(0.012)
$log(Urb_{r,t})$	-0.043	-0.206	-0.164	-0.049*	-0.151	-0.050*	-0.166	-0.137	-0.050*
	(0.091)	(0.141)	(0.138)	(0.021)	(0.111)	(0.022)	(0.138)	(0.100)	(0.022)
$log(Hum_{r,t})$	0.639**	0.232	0.311	-0.145	-0.114	-0.133*	0.306	-0.070	-0.139
	(0.192)	(0.215)	(0.213)	(0.079)	(0.272)	(0.064)	(0.212)	(0.310)	(0.077)
Observations	306	306	306	306	306	306	306	306	306
R-squared	0.519	0.604	0.617	0.881	0.762	0.880	0.618	0.769	0.881
Angrist-Pischke F-test	91.14	70.12	73.14	75.92	198.22	120.62	76.08	183.86	85.90

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses. Source: Authors' elaboration on IPUMS-US data. This table provides the results of the first-stage regressions under different IV (Shift share and Feyrer).

A9: Robustness of FE regressions to age of entry

Table A18: Robustness of FE regressions to age of entry, 1970-2010.

Age of entry >	$S=H$ 5	$S=H$ 6	$S=H$ 7	$S=H$ 8	$S=H$ 9	$S=H$ 10	$S=H$ 11	$S=H$ 12	$S=H$ 13	$S=H$ 14	$S=H$ 15	$S=H$ 16	$S=H$ 17	$S=H$ 18	$S=H$ 19	$S=H$ 20	$S=H$ 21	$S=H$ 22	$S=H$ 23	$S=H$ 24	$S=H$ 25
$MD^H_{r,t}$	0.733**	0.739**	0.703**	0.676**	0.694**	0.655**	0.645**	0.638**	0.564**	0.550**	0.548**	0.535**	0.545**	0.526**	0.414**	0.218***	0.210***	0.226**	0.244**	0.231**	0.216**
	(0.308)	(0.310)	(0.307)	(0.305)	(0.326)	(0.322)	(0.307)	(0.308)	(0.222)	(0.225)	(0.222)	(0.218)	(0.222)	(0.215)	(0.160)	(0.079)	(0.078)	(0.090)	(0.103)	(0.094)	(0.087)
$m^H_{s,t}$	0.633	0.641	0.647	0.652	0.677	0.659	0.681	0.690	0.699	0.695	0.714	0.736	0.735	0.771	0.752	0.660	0.665	0.682	0.745	0.762	0.765
	(0.385)	(0.395)	(0.408)	(0.414)	(0.433)	(0.433)	(0.445)	(0.449)	(0.441)	(0.444)	(0.454)	(0.462)	(0.470)	(0.494)	(0.498)	(0.487)	(0.522)	(0.547)	(0.591)	(0.649)	(0.733)
$ln(Population_{s,t})$	-0.087	-0.090	-0.090	-0.092	-0.094	-0.091	-0.092	-0.093	-0.086	-0.085	-0.085	-0.085	-0.085	-0.086	-0.080	-0.068	-0.067	-0.066	-0.066	-0.066	-0.065
	(0.066)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.068)	(0.068)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.067)	(0.067)	(0.067)
$ln(Urban_{s,t})$	0.226	0.229	0.218	0.225	0.216	0.218	0.217	0.219	0.204	0.205	0.215	0.221	0.213	0.211	0.207	0.190	0.196	0.190	0.183	0.184	0.181
	(0.154)	(0.154)	(0.152)	(0.154)	(0.152)	(0.154)	(0.150)	(0.151)	(0.148)	(0.149)	(0.149)	(0.150)	(0.149)	(0.148)	(0.149)	(0.157)	(0.157)	(0.157)	(0.155)	(0.158)	(0.158)
$ln(College_{s,t})$	0.887***	0.881***	0.906***	0.910***	0.915***	0.921***	0.924***	0.924***	0.951***	0.956***	0.948***	0.940***	0.946***	0.958***	0.970***	1.001***	0.996***	0.997***	1.000***	0.999***	1.001***
	(0.278)	(0.278)	(0.283)	(0.283)	(0.286)	(0.286)	(0.288)	(0.288)	(0.289)	(0.289)	(0.289)	(0.288)	(0.289)	(0.293)	(0.292)	(0.291)	(0.289)	(0.292)	(0.296)	(0.295)	(0.297)
Constant	6.589***	6.618***	6.661***	6.673***	6.721***	6.702***	6.724***	6.726***	6.712***	6.704***	6.682***	6.681***	6.691***	6.706***	6.732***	6.749***	6.726***	6.727***	6.743***	6.751***	6.756***
	(1.315)	(1.313)	(1.295)	(1.294)	(1.281)	(1.288)	(1.271)	(1.269)	(1.272)	(1.276)	(1.280)	(1.283)	(1.280)	(1.268)	(1.270)	(1.280)	(1.284)	(1.284)	(1.275)	(1.283)	(1.285)
R-squared	0.991	0.991	0.991	0.991	0.991	0.991	0.991	0.991	0.991	0.991	0.991	0.991	0.991	0.991	0.991	0.990	0.990	0.990	0.991	0.990	0.990
Age of entry >	$S=L$ 5	$S=L$ 6	$S=L$ 7	$S=L$ 8	$S=L$ 9	$S=L$ 10	$S=L$ 11	$S=L$ 12	$S=L$ 13	$S=L$ 14	$S=L$ 15	$S=L$ 16	$S=L$ 17	$S=L$ 18	$S=L$ 19	$S=L$ 20	$S=L$ 21	$S=L$ 22	$S=L$ 23	$S=L$ 24	$S=L$ 25
$MD^L_{r,t}$	0.062	0.059	0.060	0.057	0.044	0.043	0.039	0.037	0.037	0.029	0.027	0.029	0.022	0.018	0.020	0.027	0.027	0.022	0.022	0.030	0.026
	(0.071)	(0.071)	(0.072)	(0.071)	(0.073)	(0.072)	(0.071)	(0.072)	(0.071)	(0.073)	(0.073)	(0.075)	(0.077)	(0.077)	(0.077)	(0.077)	(0.078)	(0.078)	(0.075)	(0.080)	(0.082)
$m^L_{s,t}$	0.462*	0.459*	0.457*	0.458*	0.443	0.444	0.437	0.441	0.452	0.444	0.439	0.457	0.470	0.482	0.520	0.534	0.570	0.601	0.637	0.683	0.733
	(0.258)	(0.258)	(0.259)	(0.262)	(0.268)	(0.270)	(0.272)	(0.275)	(0.280)	(0.284)	(0.288)	(0.300)	(0.313)	(0.330)	(0.353)	(0.379)	(0.409)	(0.443)	(0.479)	(0.518)	(0.570)
$ln(Population_{s,t})$	-0.085	-0.085	-0.084	-0.083	-0.083	-0.082	-0.081	-0.081	-0.081	-0.080	-0.079	-0.079	-0.079	-0.078	-0.078	-0.077	-0.077	-0.076	-0.076	-0.076	-0.075
	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
$ln(Urban_{s,t})$	0.242	0.242	0.241	0.240	0.233	0.233	0.232	0.232	0.232	0.229	0.228	0.228	0.226	0.225	0.226	0.228	0.229	0.228	0.229	0.230	0.231
	(0.174)	(0.174)	(0.174)	(0.174)	(0.175)	(0.175)	(0.175)	(0.175)	(0.175)	(0.176)	(0.176)	(0.176)	(0.177)	(0.177)	(0.176)	(0.176)	(0.178)	(0.178)	(0.176)	(0.175)	(0.175)
$ln(College_{s,t})$	1.038***	1.037***	1.036***	1.038***	1.049***	1.047***	1.049***	1.052***	1.053***	1.057***	1.055***	1.051***	1.054***	1.051***	1.045***	1.027***	1.023***	1.025***	1.019***	1.010***	1.010***
	(0.307)	(0.308)	(0.310)	(0.309)	(0.312)	(0.311)	(0.311)	(0.312)	(0.311)	(0.313)	(0.312)	(0.312)	(0.313)	(0.311)	(0.310)	(0.307)	(0.306)	(0.307)	(0.306)	(0.308)	(0.309)
Constant	6.858***	6.857***	6.850***	6.848***	6.857***	6.853***	6.848***	6.847***	6.841***	6.843***	6.840***	6.841***	6.850***	6.851***	6.849***	6.847***	6.850***	6.852***	6.851***	6.854***	6.845***
	(1.278)	(1.277)	(1.277)	(1.278)	(1.280)	(1.281)	(1.283)	(1.283)	(1.283)	(1.284)	(1.287)	(1.288)	(1.290)	(1.292)	(1.291)	(1.294)	(1.294)	(1.295)	(1.295)	(1.295)	(1.293)
R-squared	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990
Observations	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255
Nb. states	51	51	51	51	51	51	51	51	51	51	51	51	51	51	51	51	51	51	51	51	51
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
States fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Author's calculations on IPUMS-US data. Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses adjusted for clustering at the state level.

A10: Dynamic panel regressions

Table A19: System GMM. Internal instruments.
Results by skill group (Dep= $log(y_{r,t})$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$S=H$	$S=H$	$S=H$	$S=H$	$S=H$	$S=L$	$S=L$	$S=L$	$S=L$	$S=L$
$log(y_{r,t-10})$	0.546***	0.269	0.307*	0.314*	0.309*	0.555***	0.293*	0.338*	0.339*	0.370*
	(0.116)	(0.190)	(0.179)	(0.168)	(0.174)	(0.189)	(0.172)	(0.188)	(0.185)	(0.188)
$MD^S_{r,t}$	1.792***	1.295**	1.173**	1.088**	1.231***	0.238*	0.371***	0.358***	0.362***	0.385***
	(0.527)	(0.580)	(0.467)	(0.448)	(0.374)	(0.119)	(0.103)	(0.102)	(0.103)	(0.104)
$m^S_{r,t}$	1.325***	0.892	0.896*	0.862	0.953*	0.313	0.147	0.357	0.541*	0.574*
	(0.483)	(0.563)	(0.485)	(0.519)	(0.509)	(0.324)	(0.363)	(0.401)	(0.318)	(0.321)
$log(Pop_{r,t})$	-0.065	-0.101	-0.082	-0.082	-0.083	-0.039	-0.093*	-0.067	-0.074	-0.062
	(0.046)	(0.072)	(0.061)	(0.051)	(0.059)	(0.044)	(0.053)	(0.054)	(0.049)	(0.050)
$log(Urb_{r,t})$	0.017	0.416	0.304	0.323	0.306	0.204	0.593**	0.397	0.358	0.280
	(0.125)	(0.431)	(0.316)	(0.309)	(0.255)	(0.145)	(0.277)	(0.266)	(0.258)	(0.203)
$log(Hum_{r,t})$	0.563**	0.356	0.439	0.395	0.465	0.359	-0.148	0.095	0.315	0.302
	(0.260)	(0.436)	(0.344)	(0.321)	(0.334)	(0.266)	(0.442)	(0.416)	(0.287)	(0.324)
Constant	2.979**	5.498***	5.261***	5.280***	5.133***	2.888*	4.895***	4.567***	4.445***	4.364**
	(1.184)	(1.897)	(1.794)	(1.514)	(1.748)	(1.583)	(1.173)	(1.365)	(1.184)	(1.650)
Observations	255	255	255	255	255	255	255	255	255	255
Nb. states	51	51	51	51	51	51	51	51	51	51
Nb. instruments	56	26	31	36	41	56	26	31	36	41
Nb. lags (endogenous var.)	2	2	3	4	5	2	2	3	4	5
Collapsed matrix	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
States fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AR(1)	0.006	0.021	0.020	0.015	0.019	0.006	0.012	0.011	0.012	0.010
AR(2)	0.134	0.118	0.121	0.126	0.124	0.256	0.200	0.210	0.215	0.222
Hansen J (p-value)	0.554	0.056	0.158	0.218	0.304	0.505	0.202	0.168	0.244	0.170

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. Source: Authors' elaboration on IPUMS-US data. The lagged dependent variable is always treated as predetermined and instrumented with its own first to second lags. $MD^S_{r,t}$; $m^S_{r,t}$; $log(Pop_{r,t})$; $log(Urb_{r,t})$ and $log(Hum_{r,t})$ are treated as endogenous variables and instrumented with their own first to X lags. The number of lags X is reported in the table. From columns (2) to (5) and (7) to (10) the matrix of endogenous variable is collapsed in order to keep the number of instruments below the number of states.

Table A20: System GMM. External instruments.
Results by skill group (Dep= $log(y_{r,t})$)

	(1) $S=H$	(2) $S=H$	(3) $S=H$	(4) $S=H$	(5) $S=L$	(6) $S=L$	(7) $S=L$	(8) $S=L$
$log(y_{r,t-10})$	0.184	0.215	0.202	0.228	0.293	0.361*	0.308*	0.357**
	(0.166)	(0.144)	(0.169)	(0.153)	(0.197)	(0.201)	(0.174)	(0.171)
$MD^S_{r,t}$	1.504**	1.587***	1.675***	1.791***	0.254*	0.263*	0.435***	0.446***
	(0.686)	(0.521)	(0.466)	(0.486)	(0.131)	(0.146)	(0.116)	(0.119)
$m^S_{r,t}$	1.353*	1.543**	1.435**	1.660**	0.266	0.546	0.416	0.655
	(0.684)	(0.618)	(0.603)	(0.620)	(0.388)	(0.416)	(0.433)	(0.450)
$log(Pop_{r,t})$	-0.132**	-0.119***	-0.128*	-0.122**	-0.088	-0.069	-0.092*	-0.080*
	(0.059)	(0.044)	(0.064)	(0.052)	(0.067)	(0.058)	(0.048)	(0.042)
$log(Urb_{r,t})$	0.382	0.267	0.336	0.242	0.474	0.280	0.472*	0.348
	(0.416)	(0.298)	(0.367)	(0.291)	(0.339)	(0.300)	(0.264)	(0.237)
$log(Hum_{r,t})$	0.349	0.503	0.332	0.502	0.029	0.280	-0.215	0.054
	(0.476)	(0.407)	(0.440)	(0.392)	(0.325)	(0.263)	(0.371)	(0.316)
Constant	6.729***	6.336***	6.545***	6.143***	5.115***	4.672***	5.320***	4.811***
	(1.775)	(1.435)	(1.667)	(1.323)	(1.347)	(1.456)	(1.333)	(1.306)
Observations	255	255	255	255	255	255	255	255
Nb. states	51	51	51	51	51	51	51	51
Nb. instruments	25	33	25	33	25	33	25	33
Nb. lags (endogenous var.)	2	4	2	4	2	4	2	4
Collapsed matrix	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
States fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AR(1)	0.032	0.023	0.036	0.029	0.016	0.014	0.014	0.008
AR(2)	0.097	0.104	0.097	0.102	0.190	0.206	0.188	0.213
Hansen J (p-value)	0.189	0.306	0.202	0.272	0.145	0.189	0.232	0.303

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the state level. Source: Authors' elaboration on IPUMS-US data. The lagged dependent variable is always treated as predetermined and instrumented with its own first to second lags. $m^S_{r,t}$; $log(Pop_{r,t})$; $log(Urb_{r,t})$ and $log(Hum_{r,t})$ are treated as endogenous variables and instrumented with their own first to X lags. The number of lags X is reported in the table. The matrix of endogenous variables is collapsed in order to keep the number of instruments below the number of states. In columns (1), (2), (5) and (6), $MD^S_{r,t}$ is instrumented using the augmented shift-share strategy while in columns (3), (4), (7) and (8), $MD^S_{r,t}$ is instrumented using predictions of the gravity-like strategy *a la* Feyrer (2009).

Multiculturalism and Growth: Skill-Specific Evidence from the Post-World War II Period. Supplementary Appendix.

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SA1: US average immigration rate 1

Figure SAF1: US immigration rate, 1960-2010 1

SA2: Trends in birthplace diversity by US state 2

Figure SAF2: Global trends in birthplace diversity in the US states 2

SA3: Empirical analysis for the OECD countries 4

Figure SAF3: Trends in birthplace diversity in the OECD member states, 1960-2010 4

Figure SAF4: Diversity among immigrants in the OECD countries 4

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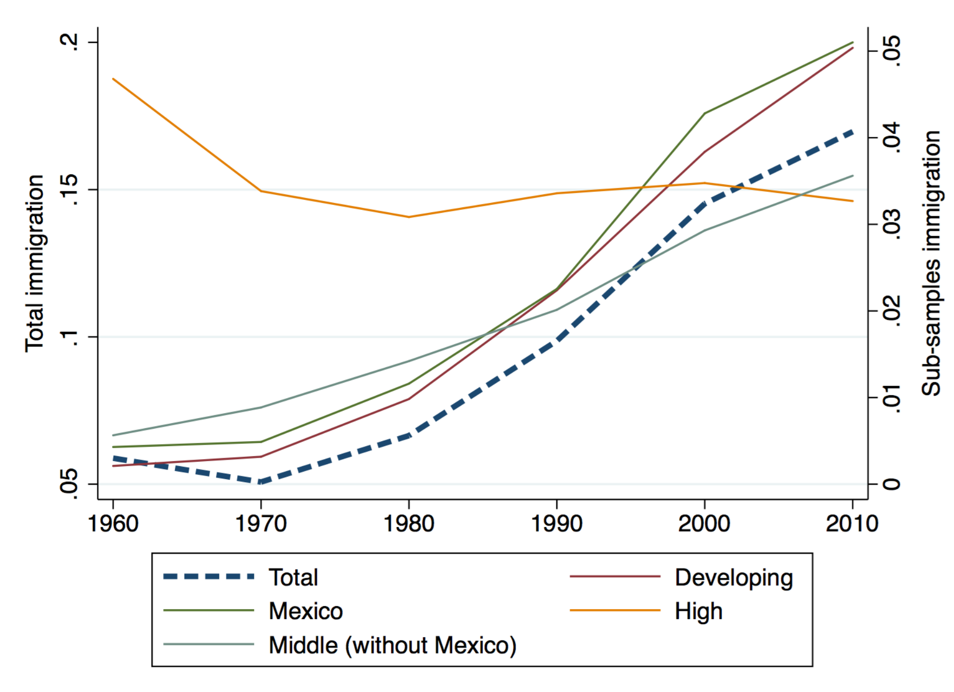
SA4: Augmented diversity index 11

Figure SAT4: Augmented diversity index 11

SA1: US average immigration rate

Figure SAF1: US immigration rate, 1960-2010 (as percentage of total population)

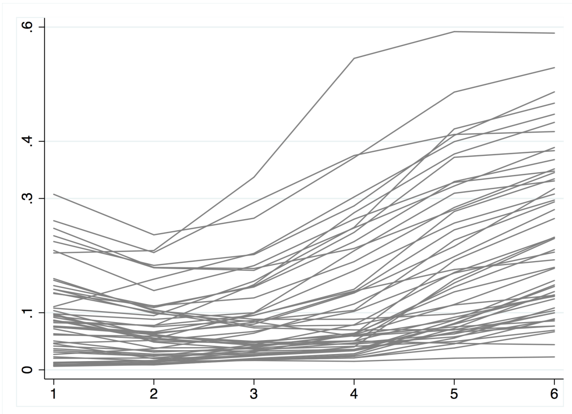


Source: Authors' elaboration on IPUMS-US data.

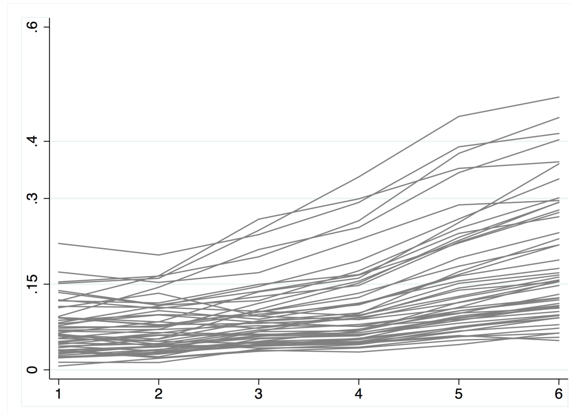
Notes: The "Total immigration rate" is defined as the ratio of the total stock of foreign-born individuals to the total population of the destination country or region. The "Immigration rate from high, developing and middle income countries" is defined as the ratio of the total stock of foreign-born individuals originating respectively from high, developing and middle countries to the total population of the destination country or region. The definition of a high, developing and middle income countries follows the World Bank classification of 2015.

SA2: Trends in birthplace diversity by US state

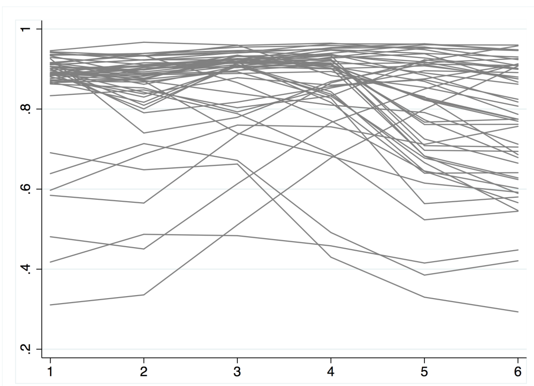
Figure SAF2: Global trends in birtplace diversity in the US states



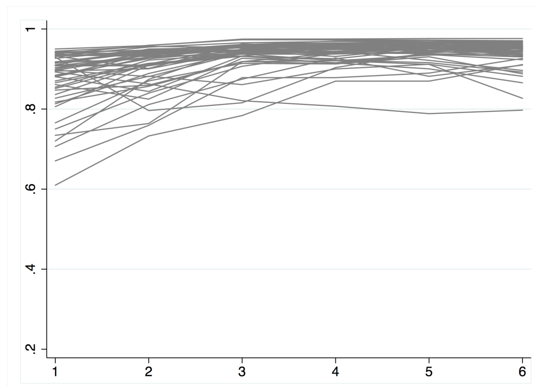
(a) $TD^L_{r,t}$



(b) $TD^H_{r,t}$



(c) $MD^L_{r,t}$



(d) $MD^H_{r,t}$

Source: Authors' elaboration on IPUMS-US data. Diversity among residents is defined as in Eq. (1) in the paper. Diversity among immigrants is defined as in Eq (2) in the paper.

SA3: Empirical analysis for the OECD countries

This appendix presents the results of a complementary analysis conducted on the 34 member states of the OECD. Despite the drawbacks of the OECD data (e.g. absence of information on the skill composition of migration stocks), we only want to verify whether the results obtained for the US states are not invalidated when using cross-country data, as the US is usually considered as one of the most attractive countries for (high-skilled) migrants.

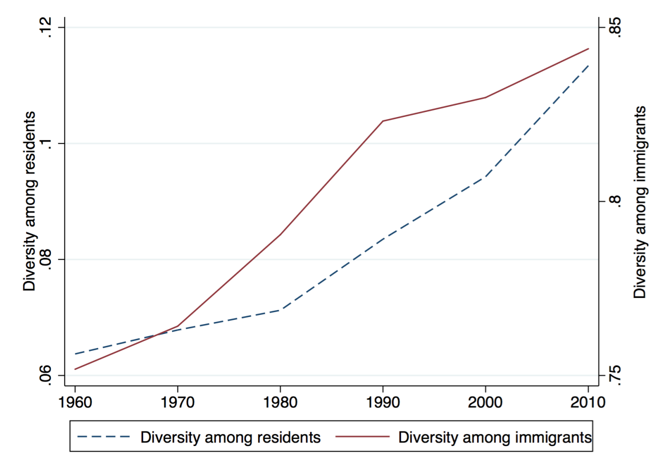
Population data at the country level for the OECD member states are available from the Global Migrant Stock database described in Özden*et al* (2011). This database documents the bilateral stocks and shares of international migrants, $k^A_{i,r,t}$, in the population of each OECD country r, by country of origin i, and by year t. Özden*et al* (2011) collected and harmonized over 1,000 censuses and population registers to construct comprehensive matrices of origin-destination stocks that correspond to the last five completed census rounds, i.e. for the period 1960-2000 in 10-year intervals. They specified a standard and common set of countries for the entire period, disaggregating data for the countries that no longer exist on the basis of more recent migration figures. There is no artificial variation due to the dislocation of the Eastern Block. We expanded the database by adding the share of native citizens, $k^A_{r,r,t}$, in order to match the total population data. We also added the year 2010 using the bilateral stock estimates of the United nations (2013).[1] Hence, our OECD database covers the same period (1960-2010) in ten-year intervals as the IPUMS data; results for the US states and for OECD countries are then comparable. Still, compared to the IPUMS data, the OECD data suffer from two drawbacks. The first drawback is that it does not report the educational structure of migration stocks. The second drawback is that many imputations were used to fill the missing bilateral cells.

We compute our indices of birthplace diversity, $TD^A_{r,t}$ and $MD^A_{r,t}$, for each OECD member state. Figure SAF3 shows that most OECD member states have experienced increasing immigration rates and total diversity indices ($TD^A_{r,t}$) in the aftermath of WW2. This is particularly the case after the year 1980.[2] Compared to the US, the average level of diversity among immigrants ($MD^A_{r,t}$) increased more strongly. Unsurprisingly, this average trend conceals important disparities across countries. Although a rise in the variety of immigrants was observed in most countries, diversity decreased in countries such as the US, Mexico or Slovakia.

[1]The list of the 34 OECD member states as well as descriptive statistics are available in Table SAT1.

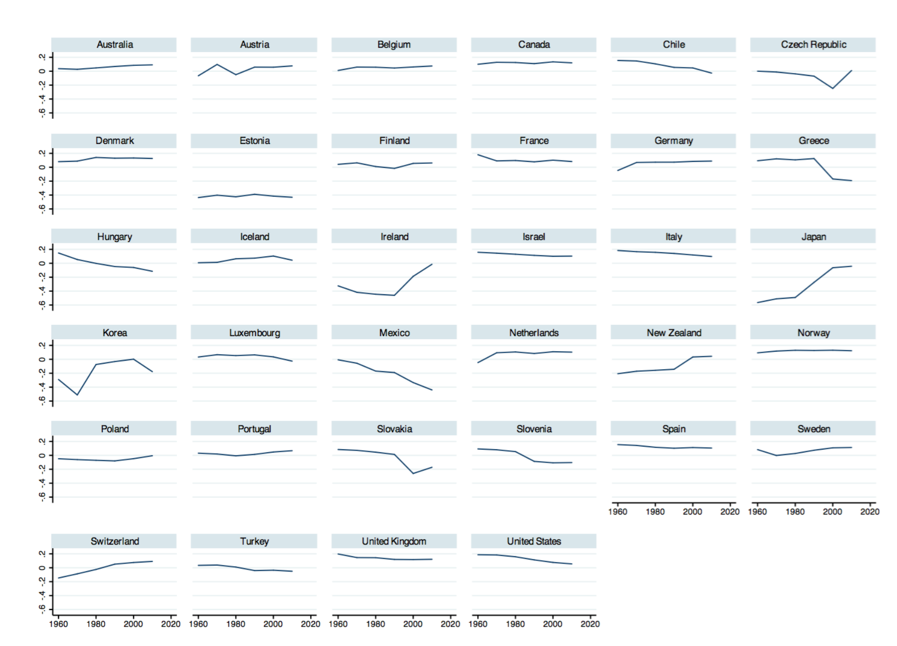
[2]Diversity trends for OECD countries are described in Figure SAF4.

Figure SAF3: Trends in birthplace diversity in the OECD member states, 1960-2010



Notes: Diversity among residents is defined as in Eq. (??), whereas diversity among immigrants is defined as in Eq. (??). Source: Authors' elaboration on ?.

Figure SAF4: Diversity among immigrants ($MD^A_{r,t}$) in the OECD countries



Source: Authors' elaboration on Özden*et al* (2011) data.

Source: Authors' elaboration on Özden*et al* (2011). Diversity among residents is defined as in Eq. (1). Diversity among immigrants is defined as in Eq. (2).

Table SAT1: Descriptives statistics for the OECD countries (34)

	$log(y_{r,t})$	$MD^A_{r,t}$	$m^A_{r,t}$	$log(Pop_{r,t})$	$log(Trade_{r,t})$	$Democ_{r,t}$	$log(Hum_{r,t})$
Australia	9.655	0.860	0.202	16.563	3.486	1.000	2.338
Austria	9.543	0.830	0.113	15.855	4.226	1.000	2.095
Belgium	9.576	0.852	0.081	16.114	4.699	0.983	2.151
Canada	9.695	0.920	0.168	17.053	3.948	1.000	2.298
Chile	8.843	0.881	0.012	16.294	3.851	0.758	1.958
Czech Republic	9.018	0.741	0.035	16.132	4.349	0.542	2.366
Denmark	9.690	0.917	0.044	15.445	4.266	1.000	2.046
Estonia	9.254	0.384	0.194	14.134	4.739	0.475	2.201
Finland	9.516	0.836	0.018	15.401	4.047	1.000	1.941
France	9.594	0.905	0.099	17.816	3.708	0.900	1.901
Germany	9.544	0.857	0.109	18.194	3.814	0.763	2.193
Greece	9.034	0.814	0.038	16.096	3.643	0.792	2.024
Hungary	8.713	0.797	0.038	16.146	4.575	0.575	2.213
Iceland	9.561	0.852	0.045	12.384	4.361	1.000	2.064
Ireland	9.290	0.492	0.071	15.057	4.685	1.000	2.186
Israel	9.286	0.926	0.395	15.217	4.169	0.975	2.305
Italy	9.465	0.945	0.035	17.831	3.646	1.000	1.898
Japan	9.465	0.476	0.010	18.550	3.121	1.000	2.191
Korea	8.607	0.620	0.003	17.443	3.881	0.708	1.965
Luxembourg	9.896	0.838	0.248	12.863	5.309	1.000	2.029
Mexico	8.628	0.601	0.005	18.107	3.459	0.508	1.512
Netherlands	9.647	0.875	0.061	16.468	4.682	1.000	2.220
New Zealand	9.492	0.700	0.162	14.998	4.047	1.000	2.396
Norway	9.655	0.921	0.049	15.244	4.299	1.000	2.256
Poland	8.632	0.748	0.043	17.379	3.973	0.533	2.114
Portugal	8.999	0.829	0.038	16.083	3.978	0.675	1.405
Slovakia	8.911	0.764	0.011	15.412	4.335	0.550	2.340
Slovenia	9.221	0.789	0.054	14.429	4.606	0.467	2.228
Spain	9.142	0.923	0.040	17.440	3.510	0.708	1.820
Sweden	9.666	0.868	0.088	15.946	4.101	1.000	2.263
Switzerland	9.855	0.794	0.197	15.691	4.398	1.000	2.352
Turkey	8.402	0.793	0.024	17.659	3.005	0.775	1.210
United Kingdom	9.587	0.942	0.066	17.859	3.885	1.000	2.162
United States	9.906	0.929	0.085	19.307	2.855	1.000	2.449

Source: Authors' elaboration on Özden *et al* (2011) .

Results of the OECD regressions are depicted in Table SAT2. The first three columns of the table show the effect of birthplace diversity among immigrants on GDP per capita, regardless of the educational structure. It is worth noticing that these estimates include the log ratio of trade to GDP, the logarithm of the population, the log of the number of years of schooling in the working-age population and the *Polity2* index of democracy as covariates. As in the US state sample, the effect of birthplace diversity on GDP per capita is strongly positive and significant at the 1% level when using pooled OLS, OLS-FE and the gravity-like IV strategy *a la* Feyrer (2009)). The magnitude of the effect is larger than in the US sample: a one standard deviation change in birthplace diversity is associated with a 13% increase in

GDP per capita. This implies that the Japanese level of GDP per capita would be 1,770 dollars greater if Japan had the same diversity index as the US in 2010.

In the remainder of the table, we combine the data of Özden*et al* (2011) with cross-sectional data on the skill structure of migration stocks. We use the database of Artuc *et al* (2015), which documents the proportion on college-educated immigrants in all OECD countries for the years 1990 and 2000. In col. 4, we add an interaction term, the product of the average birthplace diversity index by the proportion of college-educated immigrants observed in 2000. Despite collinearity with the non-interacted index, the interaction term is positive and significant, whereas the average index of diversity looses significance. This suggests that the effect of birthplace diversity increases with the educational level of migrants. At the median level of the proportion of college graduates (22%), the marginal effect of birthplace diversity on GDP per capita is significant at the 1% level, and the coefficient is almost equal to that obtained with the US state sample (0.506). The results of col. 4 are illustrated on Figure SAF5. Interestingly, this figure shows that the effect of birthplace diversity is insignificant when the bilateral migration stocks is mainly composed of low-skilled migrants. However, above 20% of college graduates, the effect of diversity becomes significant, and increases with the proportion of college graduates. Again, this suggests that the effect of birthplace diversity on macroeconomic performance is skill-specific. In the two last columns of Table SAT2, we tentatively proxy the stocks of high-skilled and low-skilled migrants using the recent shares of college-educated migrants provided in Artuc *et al* (2015). We use the 1990 skill shares to split the bilateral migration stocks observed in 1960, 1970, 1980 and 1990; we use the 2000 skill shares to split the stocks observed in 2000 and 2010. We find a positive and significant effect of birthplace diversity in both regressions, and a greater effect for high-skilled diversity. Although we should not give too much credit to these results, we confirm that the patterns obtained for the US states are not invalidated when using cross-country data.

Table SAT2: Birthplace diversity in a cross-country setting.
Regressions for the OECD member states (Dep= $log(y_{r,t})$)

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	FE	2SLS	2SLS	2SLS	2SLS
	$S = A$	$S = A$	$S = A$	$S = A$	$S = H$	$S = L$
$MD^S_{r,t}$	0.834***	0.788**	0.940***	-0.318	1.016***	0.901***
	(0.274)	(0.292)	(0.245)	(0.500)	(0.316)	(0.259)
$MD^A_{r,t} \times CollMig_{r,t}$				3.754**		
				(1.839)		
$m^S_{r,t}$	0.683	-0.291	0.148	0.020	0.107	-0.096
	(0.911)	(0.333)	(0.429)	(0.374)	(0.070)	(0.172)
$log(Pop_{r,t})$	-0.002	0.005	0.076	-0.001	0.073	0.025
	(0.027)	(0.144)	(0.143)	(0.138)	(0.145)	(0.152)
$log(Trade_{r,t})$	0.073	0.150	0.157*	0.146*	0.140	0.160*
	(0.099)	(0.089)	(0.086)	(0.080)	(0.092)	(0.083)
$log(Hum_{r,t})$	0.507***	0.370*	0.363**	0.425**	0.425**	0.347**
	(0.152)	(0.187)	(0.181)	(0.181)	(0.196)	(0.170)
$Democ_{r,t}$	0.578***	0.039	0.076	0.046	0.039	0.068
	(0.105)	(0.078)	(0.070)	(0.071)	(0.068)	(0.077)
Constant	6.420***	6.750**				
	(0.702)	(2.625)				
Total effect of $MD^A_{r,t}$				0.506***		
				(0.192)		
Observations	204	204	204	204	204	204
Nb. countries	34	34	34	34	34	34
R-squared	0.750	0.901	0.899	0.908	0.897	0.903
Time fixed effects	No	Yes	Yes	Yes	Yes	Yes
Country fixed effects	No	Yes	Yes	Yes	Yes	Yes
K-P F-$Test^\dagger$			40.89	92.66	31.64	35.18
Stock Yogo			7.03/4.58	13.43/8.18	7.03/4.58	7.03/4.58

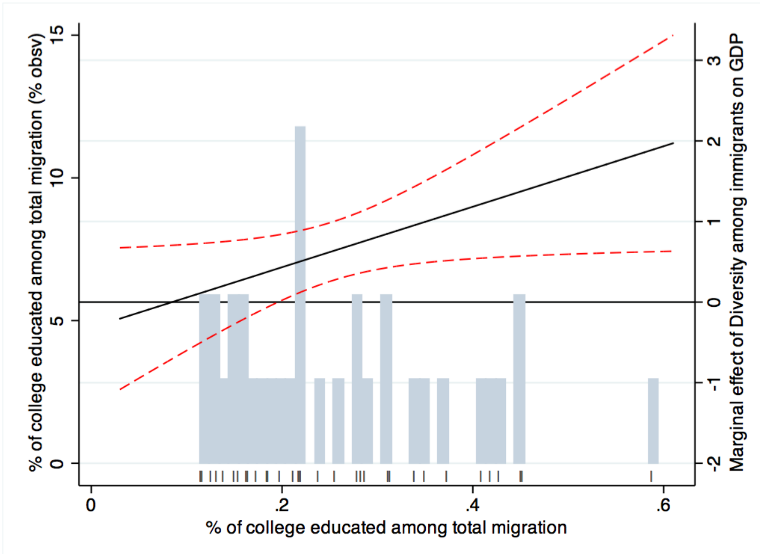
Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the country level. The $CollMig_{r,t}$ variable is the share of college-educated migrants in the total stock of immigrants of the receiving country in 2000. The total effect of diversity in col. (4) is computed for $CollMig_{r,t}$ at its median level. Diversity and immigration rates are instrumented using the gravity-like IV strategy *a la* Feyrer (2009). Zero-stage estimates are available in the appendix (Table **??**). †Kleinbergenn-Paap F-statistic tests for weak identification (critical values from Stock-Yogo (2005) are given for 10%/15% maximal IV size). The sample includes the 34 OECD member states from 1960 to 2010. The set of control variables includes the immigration rate ($m^S_{r,t}$), the log of population ($log(Pop_{r,t})$), the log of trade ($log(Trade_{r,t})$), the log of the number of years of schooling in the working-age population ($log(Hum_{r,t})$), and the Polity2 index of democracy ($Democ_{r,t}$).

Table SAT3: Zero-stage estimates (PPML): gravity model *a la* Feyrer (2009)

	(1) All OECD $log(Stock_{i,c,t})$
$log(Dist_{i,r}) \times I_{1960}$	-0.816***
	(0.155)
$log(Dist_{i,r}) \times I_{1970}$	-0.876***
	(0.151)
$log(Dist_{i,r}) \times I_{1980}$	-0.774***
	(0.139)
$log(Dist_{i,r}) \times I_{1990}$	-0.683***
	(0.131)
$log(Dist_{i,r}) \times I_{2000}$	-0.617***
	(0.125)
$log(Dist_{i,r}) \times I_{2010}$	-0.573***
	(0.124)
$Bord_{i,r}$	0.755***
	(0.219)
$Lang_{i,r}$	1.565***
	(0.218)
Constant	15.078***
	(1.322)
Observations	38964
Nb. origin	191
Nb. destination	34
R-squared	0.727
Year dummies	Yes
Origin dummies	Yes
Destination dummies	Yes

Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses adjusted for clustering at the state/country-pair level. Distances data are not available for Liechtenstein, Luxembourg and Holy See.

Figure SAF5: Marginal effect of diversity conditional to the share of college graduates in the 2000 immigrant stock



Notes: The solid line is based on col. 4 of Table SAT2. It represents the marginal effect of birthplace diversity on GDP per capita conditional on the percentage of college graduates in the total stock of bilateral migrants in 2000. The histogram indicates the percentage of observations of the modifying variable, and each mark on the vertical axis represents one OECD country. The dashed line depicts the upper and lower bounds of the 95% confidence interval.

SA4: Augmented diversity index

In this appendix, we report the results obtained when the standard index of birthplace diversity is replaced by an augmented index that accounts for the genetic distance between the countries of origin of immigrants. Indeed, the birthplace diversity index $MD^S_{r,t}$ does not account for the cultural distance between origin and destination countries. It assumes that all groups are culturally equidistant from each other. Another extension consists therefore in multiplying the probability that two randomly-drawn immigrants were born in two different countries by a measure of cultural distance between these two countries. For the latter, we use the database on genetic distance between countries, constructed by Spolaore and Wacziarg (2015). Genetic distance is based on blood sample and proxies the time since two populations had common ancestors. Spolaore and Wacziarg (2015) find a pattern of positive and significant relationships between genetic distance and various measures of cultural distance, including language, religion, values, and norms. We thus use the augmented index of cultural diversity to investigate whether the variety effect is associated with the genetic distance between countries of origin. The augmented version of the diversity index, computed for the immigrant population, is defined as:

$$MD^{S,G}_{r,t} = \sum_{i \neq r}^{I} \widehat{k}^S_{i,r,t} \sum_{j \neq i,r}^{J} \widehat{k}^S_{j,r,t} d^G_{i,j}, \tag{1}$$

where $d^G_{i,j} \in [0, 1]$ is a normalized genetic distance between population from country i and country j. The correlation between the augmented and the unweighted diversity indices is equal to 0.69 for the college-educated population, and to 0.38 for the less educated. The OLS-FE estimates point in the same direction as our benchmark regressions. The magnitude and the significance of the estimates are not statistically different from the ones reported in the previous tables. Using the gravity-like IV strategy, the effect of high-skilled diversity remains positive and significant. We lose significance under the augmented shift-share IV strategy. However, the shift-share statistics are less convincing when we introduce more complexity in the diversity index. As far as low-skilled diversity is concerned, the effect remains insignificant in OLS-FE regressions and also in IV estimates. Overall, accounting for cultural distance between countries does not add that much to our analysis.

Table SAT4: Robustness to the measure of diversity.
Accounting for genetic distance between countries (Dep= $log(y_{r,t})$)

	(1) FE OLS $S=H$	(2) 2SLS Shift-Share $S=H$	(3) 2SLS Feyrer $S=H$	(4) FE OLS $S=L$	(5) 2SLS Shift-Share $S=L$	(6) 2SLS Feyrer $S=L$
$MD^{S,G}_{r,t}$	0.658***	0.558	1.092***	0.199	0.265	0.438**
	(0.201)	(0.360)	(0.223)	(0.135)	(0.183)	(0.180)
$m^S_{r,t}$	0.298	0.287	0.346	0.413	0.440*	0.509*
	(0.326)	(0.299)	(0.346)	(0.284)	(0.255)	(0.291)
$log(Pop_{r,t})$	-0.134	-0.135*	-0.128	-0.143	-0.139	-0.127
	(0.080)	(0.079)	(0.080)	(0.088)	(0.090)	(0.092)
$log(Urb_{r,t})$	0.277*	0.278*	0.269*	0.284*	0.286*	0.291*
	(0.153)	(0.151)	(0.144)	(0.169)	(0.164)	(0.166)
$log(Hum_{r,t})$	0.818***	0.820***	0.808***	0.857***	0.840***	0.797***
	(0.207)	(0.198)	(0.214)	(0.206)	(0.207)	(0.201)
	(0.125)	(0.143)	(0.127)	(0.110)	(0.107)	(0.116)
Constant	7.436***			7.547***		
	(1.310)			(1.349)		
Observations	306	306	306	306	306	306
Nb. states	51	51	51	51	51	51
R-squared	0.993	0.993	0.993	0.993	0.993	0.993
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
States fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
K-P F-$Test$	N.A	30.90	140.6	N.A	27.64	241.0
Stock Yogo		29.18/16.23	16.38/8.96		29.18/16.23	16.38/8.96
Hansen J (p-value)	N.A	0.388	N.A	N.A	0.232	N.A

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the State level. The specification is described in Eq.(3) and includes all fixed effects. OLS-FE results are provided in col. 1 and 4 and 5; IV results are provided in col. 2, 3, 5 and 6 using the augmented shift-share and gravity-like strategies. Results for college-educated migrants are provided in col. 1 to 3; results for the low-skilled are provided in col. 3 to 6. †Kleinbergenn-Paap F-statistic tests for weak identification (critical values from Stock-Yogo (2005) are given for 10%/15% maximal IV size). The sample includes the 50 US states and the District of Columbia from 1960 to 2010. The set of control variables includes the immigration rate ($m^S_{r,t}$), the log of population ($log(Pop_{r,t})$), the log of urbanization ($log(Urb_{r,t})$) and the log of the average educational attainment of the working-age population ($log(Hum_{r,t})$).