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Journal of Urban Economics 58 (2005) 304–337

JOURNAL OF Urban Economics

www.elsevier.com/locate/jue

Cities and cultures

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Received 23 April 2004; revised 17 June 2005

Available online 18 August 2005

Abstract

We investigate whether cultural diversity across US cities (measured as the variety of native languages spoken by city residents) is associated with any effect on their productivity. Diversity of cultures may imply diversity of production skills, of abilities and of occupations that enhances the productive performance of a city. On the other hand transaction costs and frictions across groups may hurt productivity. Similarly, diversity in available goods and services can increase utility but distaste for (or hostility to) different cultural groups may decrease it. Using census data from 1970 to 1990, we find that wages and employment density of US-born workers were systematically higher, ceteris paribus, in cities with richer linguistic diversity. These positive correlations reveal a net positive effect of diversity on productivity that survives robustness checks and instrumental variable estimation. This effect is found to be stronger for highly educated workers and for white workers. We also show that better 'assimilated' non-native speakers, i.e. those who speak English well and have been in the US for more than five years, are most beneficial to the productivity of US-born workers.

JEL classification: O4; R0; F1

Keywords: Cultural diversity; Productivity; Wages; Employment; Cities

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0094-1190/$ – see front matter
doi:10.1016/j.jue.2005.06.004

1. Introduction

> "Global civilization could never be anything other than the coalition at global levels of cultures, each of them retaining its originality." (Claude Lévi-Strauss)

Recent world developments are bringing the issue of cultural diversity to the forefront. Indeed, as argued by Alesina and La Ferrara [1]: "In a more integrated world, the question of how different people can peacefully interact is the critical problem for the next many decades" (p. 29). From an economic perspective, the most salient question is whether a culturally homogeneous society can be more productive and affluent than a culturally diversified one. The answer is not obvious. On the one hand, cultural diversity can generate costs from potential conflicts of preferences, hurdles to communication, or outright racism, prejudice or fear of other groups, leading to a sub-optimal provision of private and public goods (Alesina et al. [2]; Alesina et al. [3]). On the other hand, cultural diversity can create potential benefits by increasing the variety of goods, services and skills available for consumption and production (Lazear [25,26]; O'Reilly et al. [29]). Moreover, by bringing together complementary skills, different abilities and alternative approaches to problem solving, diversity may also boost creativity, innovation and ultimately growth (Berliant and Fujita [6], Florida [20,21]).

The aim of the present article is to investigate the impact of cultural diversity on the economic life of US cities. Specifically, we tackle the following questions: Is there a *wage premium for diversity* in US cities? Do identical workers earn higher or lower wages in urban environments that are identical to others in all respects except their cultural diversity? And by qualifying the first question, a second question arises: Is such a wage premium a consequence of a *positive effect of diversity on productivity* (accompanied therefore by higher productive density), or a compensation for a *distaste of workers for diversity* (accompanied therefore by lower productive density)?

We first present a simple theoretical framework to think about effects of diversity in production and consumption and then we use data from 160 US metropolitan areas for three census years, 1970, 1980 and 1990 to discriminate between a net positive or negative effect of diversity on wages and employment. US metropolitan areas represent natural laboratories for investigating cultural diversity in many respects. First, the US has a long standing tradition of being a favorite destination for migrants from both developed and developing countries. During this period most immigrants have settled in urban rather than rural areas. This has made US cities 'melting pots' of different cultures. Second, the US is arguably both the most advanced market economy and the largest fully integrated marketplace in the world. As such, wages and prices reflect preferences and costs better than any other place. Moreover, people are highly mobile within the US. For instance, census data reveal that 36 percent of the population moved from one state to another between 1985 and 1990. As people respond to changes in their local working and living environments, we may expect them to 'vote with their feet,' thus seizing (and revealing) consumption and wage gains wherever they arise (Blanchard and Katz [7]). Last but not least, the availability and quality of data are better in the US than anywhere else.

We focus on different linguistic groups as the carriers of cultural identity, and use US-born individuals as our reference group. In other words, we investigate whether linguistic diversity affects the wage of the average US-born, and we also qualify the effect on particular sub-groups of the US population (black workers versus white workers, more educated versus less educated). Linguistic diversity, identified as the index of fractionalization of the mother tongues of workers, serves as a proxy for cultural diversity. We choose linguistic diversity as our central explanatory variable because it captures particularly well the culture of reference of individuals, and it is associated with traditions, values and habits that may affect individual productivity. Language allows us to capture cultural identity beyond merely the first generation of immigrants. At the same time linguistic diversity has a clear "communication" cost, due to the imperfect communication between groups.[1] While ethnicity is of course another important component of diversity, we do not focus on it in our work. One reason for this is that ethnicity is self-assessed, and therefore is more subject to endogeneity and measurement errors. Another reason is that the impact of ethnic diversity is likely to be dominated by the discrimination, segregation and disadvantages experienced by the African American community. These issues are important and deserve a more specific and separate analysis.[2]

The effects of diversity on aggregate economic performance have been previously studied mainly through cross-countries growth regressions that use racial fragmentation as the key explanatory variable. At the cross country level, Easterly and Levine [19] find that, ceteris paribus, income grows less in countries characterized by more racial fragmentation than in more homogeneous ones. Collier and Gunning [17] explain such behavior in terms of mutual distrust among ethnic groups, which makes it difficult to build social capital and share productive public goods. However, when comparing countries, institutions will also play a role. Collier [16] for example finds that democracies are better at coping with ethnic diversity. More generally, Easterly [18] stresses the importance of good institutions in mitigating the negative impact of diversity on growth.

Growth regressions have also been used at the city level. In those regressions population growth takes the place of income growth as dependent variable, because people are much more mobile across cities within the same country so that migration tends to arbitrage out income differences. Glaeser et al. [22] use this approach, and find that racial fragmentation has a positive impact on population growth only when accompanied by segregation. According to Alesina and La Ferrara [1], this may be due to the possibility that segregation can produce the benefits of diversity in production without any costly social conflicts over public goods provision. On the other hand, Florida [20,21] argues that segregation is not the only way to fence off social unrest arising from diversity. He shows that tolerant cities (where tolerance is instrumented by the presence of artists, bohemians, and other creative people) consist of the most innovative and educated people. Several authors, along similar lines, have argued that the functioning and thriving of urban clusters relies on the variety of people, factors, goods and services within them. Examples abound in the urban studies literature. Jacobs [24] views economic diversity as the key factor of a city's success. Sassen [33] studies 'global cities' and their strategic role in the development of activities

[1] Within the US, however, the overwhelming majority of non-native speakers report to understand English well (90% according to the 1990 census); thus problems of verbal communication, which would increase the cost of diversity, are, in general, not extremely severe.

[2] See Alesina and La Ferrara [1] for a review of this literature and Sparber [34] for a recent contribution.

that are central to world economic growth and innovation. A key feature of these cities is the cultural diversity of their populations. Similarly, Bairoch [5] sees cities and their diversity as the engines of economic growth. Such diversity, however, has been seen mainly in terms of the diversified provision of consumer goods and services, as well as productive inputs (see, e.g., Quigley [31]; Glaeser et al. [23]). The positive 'production value' of diversity has also been stressed in the literature on the organization and management of teams. Here the standard assumption is that higher diversity can lead to more innovation and creativity by increasing the number of ways groups frame problems, thus producing a richer set of alternative solutions and consequently better decisions. Lazear [25] provides an attempt to model team interactions. He defines the 'global firm' as a team whose members come from different cultures or countries. Combining workers whose countries of origin have different cultures, legal systems, and languages imposes costs on the firm that would not be present if all the workers had similar backgrounds. However, complementarity between workers, in terms of skills, can more than offset the costs of cross-cultural interaction. Finally, several contributions have focussed on the issue of new immigrants into the US and their effects on native workers. For example, Borjas [8,9], Card [13,15] analyze the effects of immigration on the locations and wages of native workers. These works reveal a small negative impact of immigration on the wages of natives, especially the low-skilled ones.

A different approach to the study of diversity within cities is adopted by Ottaviano and Peri [30] and further developed in this article. Following Roback [32] our previous work developed a model of a multicultural system of open cities implying that we could use the observed variations in wages and rents of US-born workers to identify the nature of the effects associated with cultural diversity. Our main finding was that, on average, there is a positive production value of cultural diversity to US-born citizens. The present paper complements and expands that work in two main respects. First, we propose a more detailed model of the production and consumption side of the economy. We provide some explanation and formalization of how (and through which channels) diversity affects utility and productivity. Second, we use a different identification strategy in the empirical analysis. Specifically, we adapt the set-up by Alesina et al. [4] to design a theoretical model of aggregate production where the diversity of the workforce contributes different services (skills) but hampers worker exchange because of transaction costs. We complement the production side of the model with agents' utility functions that also exhibit a positive effect of diversity, through taste for variety in consumption, as well as a negative effect of diversity on utility, potentially created by aversion to different cultures. Allowing agents to move across cities in order to equate their utility and allowing firms to locate across cities in order to eliminate profit differentials, we obtain the equilibrium conditions on wages and employment. In particular, as we are interested in the effect of diversity on productivity and utility, the equilibrium conditions of the model provide the relationship between diversity, employment and wages that we can estimate empirically. The identification strategy produced by the model relies on the estimation of a wage and an employment (density) equation. This is close to the approach followed by the literature assessing the effects of immigration on US natives (such as Card [15]). In our empirical implementation we assume that we may identify an exogenous shifter of the amount of diversity across cities, which is based on different immigration rates across cities. Migration alters the linguistic diversity of cities and, by analyzing jointly the net employment changes and net wage (productivity) changes of natives, we infer the net effect of linguistic diversity.

Implementing this strategy we find evidence in support of a *diversity wage premium*: richer diversity is associated with higher wages for natives. This positive effect seems strongest for highly skilled workers, although it is present for the unskilled as well. This association, which is both economically and statistically significant, can be interpreted in terms of higher productivity, for we also find a positive association between linguistic diversity and the employment of natives in a city. Moreover the benefits do not fall exclusively to the highly skilled. These results are compatible with the idea that different cultures provide different skills to production, beyond the formal schooling of their members (a 'horizontal' type of skill diversity). This is confirmed by the fact that the positive effect remains even after controlling for the years of schooling of non-native speakers.

Some of our findings may seem at odds with some of the previous literature. We investigate in greater detail this apparent incompatibility. This allows us to qualify our results in three respects. First, we highlight the importance of the adoption of a core of shared norms ('assimilation') for fruitful multicultural interactions, by showing that the impact of recent immigration on productivity is mildly negative, consistent with what is suggested by Borjas [8,9], while overall diversity has a positive effect. This fact is consistent with the idea that assimilation and the benefits of diversity may take some time to emerge. Second, differently from most of the labor literature that has looked at the shift of relative wages across different skill groups (e.g. Borjas [10,11], Card [15]) we focus on the average (overall) effect of diversity on wages of US-natives. Finally we clarify the different effects of diversity on the private and public sectors, by showing that the impact of diversity on the provision of public goods is indeed negative as argued in Alesina et al. [2,3].[3]

The paper is organized in five sections after the introduction. Section 2 presents the data set and some descriptive statistics. Section 3 derives the theoretical model that will be used to guide the empirical analysis. This is implemented in Section 4, which describes the main wage and employment regressions, along with a battery of robustness checks, and proposes an instrumental variable strategy to reduce the endogeneity problem. Section 5 compares our findings with related studies focussing on the impact of recent immigration and the provision of public goods. Section 6 concludes.

2. Descriptive statistics: cultures in US cities

We begin our analysis of the effects of cultural diversity on wages and employment in US cities by presenting the data set and some descriptive statistics.

2.1. Data on US cities

Our unit of observation is the Metropolitan Statistical Area (MSA). Data at the MSA level for the US are available from different sources. We use mostly the Census Public

[3] Specifically, in the provision of public goods ethnic diversity seems to play a significant negative role while linguistic diversity has no significant impact. Alesina et al. [2,3] analyze only the effect of ethnic diversity.

Use Microdata Sample (PUMS) data (the 5% Form the Metro sample for 1970 and the 1% Metro Samples for 1980 and 1990) that allow for the most detailed analysis when calculating average values and shares across groups. We also include data from the 'County and City Data Book' from several years in order to obtain some aggregate variables such as aggregate employment, income, population, spending for local public goods, and some indices of cultural composition. We consider 160 MSAs that are identified in each of the three census years considered. From the PUMS we have around 1,200,000 individual observations for 1990, 900,000 for 1980, and 500,000 for 1970. We use these to construct aggregate variables and indices at the MSA level. The reason for focussing on MSAs is twofold. First, MSAs constitute closely connected economic units within which interactions are intense. Thus, they fit the theoretical model presented in Section 3, in which local services are used to produce final output. Second, they exhibit a higher degree of linguistic diversity than the rest of the country, as new immigrants and their offspring traditionally settle down in larger cities.

We measure average labor productivity as hourly wage. This is calculated as yearly salary divided by weeks worked in the year, and then by hours worked during the week.[4] Such a measure is not contaminated by the variations in individual labor supply. We select working individuals between 16 and 65 years of age as our workforce. In order to identify the average city-specific wage and estimate its dependence on cultural diversity, we select only US-born workers in a MSA and then control for their composition. In particular, we control for average schooling, average experience (and its square), the share of women, the share of blacks and the share of native Americans in the city. The residual variation of average wages of US-born workers in city c in year t, $\overline{w}_{ct}$, is therefore not affected by the demographic composition of the city. Its correlation with linguistic diversity can be used to capture co-movements between a city's productivity and its diversity.

Cultural diversity is a multi-dimensional concept. It could stem not just from groups with different languages or ethnicities, but also from groups with different skills or regional origins. Nonetheless, 'cultural diversity,' as it is commonly referred to, mostly involves ethno-linguistic differences. Ethnicity and language (with religion a possible third candidate) are probably the most important characteristics for the identification of a sub-group (or sub-culture) within the US. Indeed, especially in the US, apart from black-white issues, most debates about diversity are strongly related to issues such as the 'Latino identity' or the 'Chinese-American community,' which are identifiable with linguistic groupings. In this paper we choose to focus on the concept of linguistic diversity as a crucial and measurable dimension of the broader concept of cultural diversity.[5] Measures of diversity based on ancestry, race and regional origins will be used as controls in order to verify the robustness of our results.

The theoretical model of Section 3 suggests a specific index of diversity, stemming from the 'taste of variety' embedded in the aggregate production function (5) and utility function (3): the sum of the population shares of the different groups raised to the power of α. Since in (5) α represents the wage share of aggregate income, we follow common

[4] As hours worked in a week and weeks worked in a year are coded as categorical variables for 1970 we choose the median point of the range to impute the hours of a single individual.

[5] Recently, Sparber [34] analyzes the impact of racial diversity on productivity.

practice by setting $\alpha = 0.66$ for the US economy. Formally, we define our own index of linguistic diversity of city c in year t as:

$$div\,Lang_{ct} = \sum_j \left(l_j^c\right)_t^{0.66} \tag{1}$$

where *Lang* labels the variable 'language' and $(l_j^c)_t$ is the share of the group speaking language j (at home) in the total population of workers of city c in year t. If all city residents are in the same linguistic group, the index takes on its minimum value of 1. The more equal is the distribution of citizens across groups, the larger is the index.

In order to check that our results do not depend too strongly on the particular form chosen for the diversity index, we also consider, however, a more standard measure of diversity, namely, the so called 'index of fractionalization.' This index, popularized in cross-country studies by Mauro [28] and widely used thereafter, captures the probability that two individuals, taken at random from a universe made of different groups, belong to the same group. The index of fractionalization is calculated as 1 minus the Herfindahl index of concentration across groups. Formally, we define the fractionalization index of linguistic diversity of city c in year t as:

$$frac(Lang_{c,t}) = 1 - \sum_j \left(l_j^c\right)_t^2. \tag{2}$$

This index is an increasing measure of both the cultural 'richness' of a city (i.e. the number of groups) and its cultural 'diversity' (i.e. the evenness of the groups' sizes). It reaches its minimum value 0 when all individuals speak the same language, and its maximum value 1 when there are no individuals speaking the same language. Intuitively, when all individuals share the same language, the probability that two randomly selected individuals belong to different linguistic groups is 0, whereas it equals 1 when all individuals speak different languages. On the other hand, for a given number of linguistic groups M (i.e. controlling for 'richness'), the index reaches its maximum at $(1 - 1/M)$ when individuals are uniformly distributed across groups.[6]

In addition to its usefulness for robustness checks, fractionalization also allows us to get a feeling of the extent of diversity in US cities by comparing their linguistic diversity with those calculated in cross-country studies. Note that the correlation between the two indices, $div\,Lang_{ct}$ and $frac(Lang_{c,t})$, across the 160 MSAs is about 0.85, which confirms that the two indices are indeed capturing the same features of linguistic diversity across cities.

2.2. Diversity in US cities

Table 1 reports the summary statistics on the shares of the five main linguistic groups after merging all other groups together. Columns 1 and 3 report the averages in 1970 and 1990 for each share across the 160 metropolitan areas, while columns 2 and 4 report the standard deviations in 1970 and 1990. A linguistic group is defined as those people prevalently speaking a particular language at home. For parsimony, the table includes very few

[6] See Maignan et al. [27] for details.

Table 1
Main linguistic shares in 160 US metropolitan areas

Language shares	Average 1970	Std. Dev. 1970	Average 1990	Std. Dev. 1990
English	0.800	0.123	0.789	0.120
German	0.033	0.032	0.006	0.004
Italian	0.017	0.024	0.006	0.004
Spanish	0.039	0.091	0.132	0.110
Chinese	0.001	0.013	0.015	0.010
Other	0.129	0.071	0.052	0.020
Fractionalization Index of language	0.333	0.150	0.180	0.133

Source: Authors' calculations on Census PUMS Data 1970 and 1990.

Table 2
Linguistic shares in some metropolitan areas, 1990

City	English	German	Italian	Spanish	Chinese	Other	Fractionalization
Atlanta, GA	0.934	0.005	0.001	0.026	0.004	0.030	0.137
Chicago, IL	0.804	0.009	0.008	0.094	0.006	0.079	0.355
Cincinnati, OH-KY-IN	0.962	0.008	0.002	0.009	0.001	0.018	0.080
Dallas, TX	0.850	0.004	0.001	0.112	0.005	0.029	0.265
El Paso, TX	0.322	0.009	0.001	0.656	0.002	0.011	0.473
Indianapolis, IN	0.963	0.005	0.001	0.014	0.001	0.016	0.070
Los Angeles, CA	0.570	0.005	0.003	0.300	0.025	0.097	0.591
New York, NY	0.645	0.007	0.028	0.177	0.032	0.111	0.550
Philadelphia, PA-NJ	0.922	0.007	0.009	0.026	0.003	0.034	0.148
Pittsburgh, PA	0.958	0.005	0.008	0.008	0.002	0.020	0.080
San Francisco, CA	0.679	0.009	0.006	0.107	0.087	0.112	0.620
Washington, DC-MD-VA-WV	0.857	0.007	0.003	0.053	0.009	0.071	0.278

Source: Authors' calculations on Census PUMS Data, 1990.

specific linguistic groups, even though other groups are important in certain cities. The fractionalization index reported in the last row of the table is calculated, instead, using all 29 groups listed in Appendix A. Besides English speakers we report the average shares of German, Spanish, and Italian speakers (corresponding to the most largely represented European languages), as well as Chinese speakers. Table 1 displays a tendency for linguistic diversity to decrease between 1970 and 1990, for the index of fractionalization falls significantly. In particular, while the share of English speakers remains stable, other European languages become less relevant, while Spanish turns into the second most common linguistic group in the country. The share of Chinese speakers slightly increases as well. The diversity of European languages, still present to a certain extent in 1970, gives way to a single large Spanish speaking minority by 1990.

Table 2 reports the fractionalization index of some representative MSAs in 1990. The two largest metropolises, New York and Los Angeles, are the most diverse cities along the linguistic dimension. Both cities have very large Spanish speaking communities (in L.A. they represent 30% of the population, while in N.Y. they reach 17%) and a non negligible Chinese speaking group. The third most diverse city in our group is San Francisco. Cities in the Midwest such as Cincinnati and Indianapolis rank very low in diversity. The fact that in general larger cities are associated with more diversity implies that we will have to control for some measure of city size when analyzing the impact of diversity on productivity. To put into context the extent of diversity in US cities, their linguistic fractionalization can be compared with the cross-country values reported by the Atlas Narodov Mira and published in Taylor and Hudson [35] for the year 1960. Those values have been largely used in the growth literature (see, e.g., Easterly and Levine [19], and Collier [16]). A diversified city such as San Francisco has a linguistic fractionalization equal to 0.62, which is the level of Malawi or Pakistan. Afghanistan, well known for hosting many different ethnicities, reaches a value of 0.66 that is only slightly higher. More homogeneous cities such as Cincinnati and Pittsburgh have a level of fractionalization equal to 0.08, which is the same as that of very homogeneous Sweden. Between these extremes US cities span a range of linguistic diversity that is about two thirds of the range spanned by the countries of the world.[7]

Finally, Fig. 1 presents a partial scatter-plot of the average wage change for US-born workers during the period 1970–1990 against the change in the index of linguistic diversity, $divLang_{c1990}$. Each variable is 'cleaned' of the effects of changing city demographics,

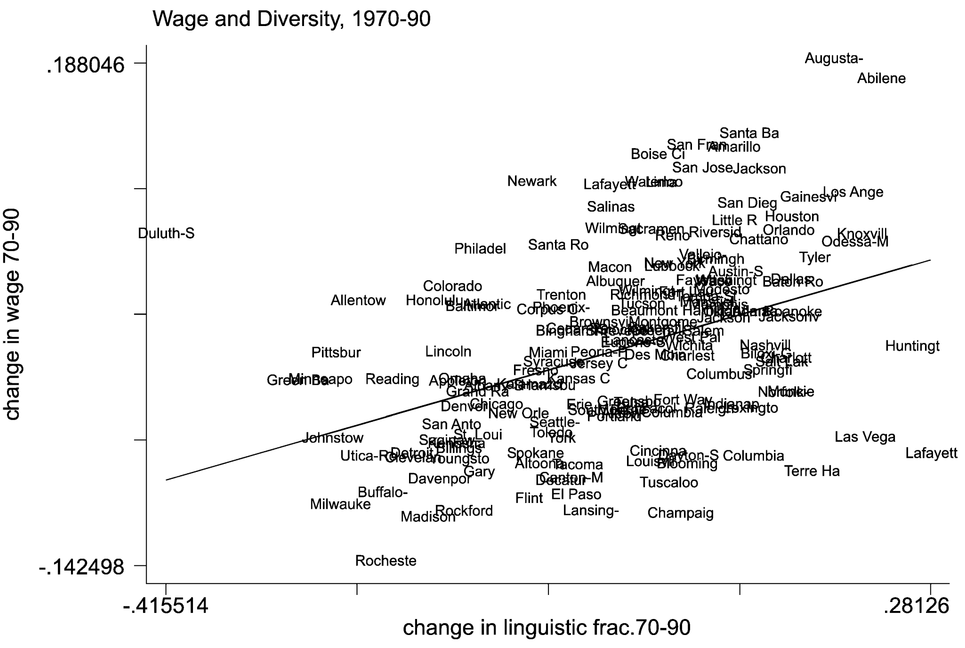

Fig. 1. Wage and diversity.

[7] Given the properties of the fractionalization index discussed above, this evidence shows that, when jointly measured, the linguistic richness and diversity of some US cities are very close to those of very rich and diverse countries. However, the comparison across different countries have to be taken with a grain of salt as the range spanned by the fractionalization index depends on the total number of groups.

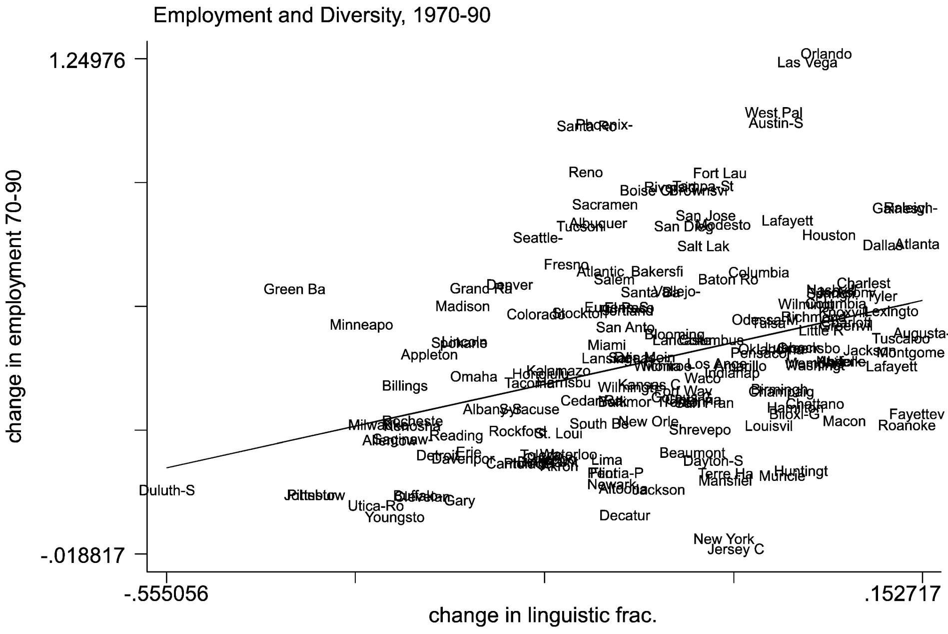

Fig. 2. Employment and diversity.

by controlling for average schooling, experience (and its square), the share of women and the share of blacks. Similarly Fig. 2 shows the partial correlation between the change in city employment of US-born workers and the change in the index of linguistic diversity. Figure 1 reveals the presence of a diversity premium: wages increase more in cities where diversity grows faster. In particular, the estimated slope of the fitted line is both positive (equal to 0.21) and very significant (with a t-statistic of 6.9). Similarly employment density grows faster in cities experiencing higher increases in diversity. The coefficient of the regression line in Fig. 2 is 0.6 and highly significant (t-statistic is 4.7). As argued in the next section, the prima facie evidence of a jointly positive effect on wages and employment speaks in favor of a positive productivity effect of linguistic diversity. The rest of the article qualifies more precisely this effect and checks its robustness.

3. A model of multicultural cities

We model a scenario in which diversity is good for utility and productivity thanks to the variety of goods and services it supports but it also has transaction-type costs on utility and productivity, so that its net effect may be ambiguous. Before illustrating these different effects in a formal model let us provide some intuition for each one of them. First, foreign-born workers and US-born ones provide differentiated services and skills to production. One reason is that, for given observable skills, US and foreign born workers tend to choose different "occupations" (see Card [15] for more detail). Among less educated, for instance, foreign born are highly over-represented in professions like tailors (54% were foreign-born in 1990) and plaster-stucco masons (44% were foreign-born in 1990) while US-born are over-represented, say, among crane operators (less than 1% were foreign-born) and sewer-pipe cleaners (less than 1% foreign-born). If those services are not perfect substitutes increased cultural diversity would imply increased variety of available services. Among highly educated the same is true. Foreign-born are, for instance, highly over-represented in scientific and technological fields (45% of medical scientists and 33% of computer engineers were foreign-born) while US-born are largely over-represented among lawyers (less than 4% are foreign-born) or museum curators and archivists (less than 3% are foreign-born). Even within the same occupation often US and foreign-born provide different services and benefit from complementing each other. Among less educated, for instance, a Chinese cook and a US-born cook or an Italian tailor and a US-born tailor do not provide the same services. Similarly, among highly educated professionals a German-trained physicist (more inclined to theory) is not perfectly substitutable with a US-trained one (more inclined to experimental approach). As long as the overall production benefits from larger diversity of skills and services, cultural diversity will have a positive impact on it. Diversity, however, can also have negative effects on production due to difficult interactions (‘communication’) between different cultures, incompatible behaviors, lack of shared values and norms or sheer antipathy. Similarly, on the consumption side, while variety in available foods, crafts, entertainment shows, styles of design (clearly correlated with cultural diversity) has a positive utility value, diversity may also generate various utility losses. Individuals may need a (costly) diversified cultural background to fully enjoy a variety of cultural goods and services and, more simply, diversity may generate fear of losing national identity and reactions against ‘aliens’ such as reciprocal distaste if not outright aversion and conflict. These costs and benefits depend on the number and relative sizes of cultural groups living in the city. Finally, the costs of interaction could also depend on the time of arrival of the different cohorts of immigrants: interactions are likely to be easier when groups have had enough time to assimilate a common set of norms and habits from the host society. We will come back to these points later in the empirical analysis.

3.1. Preferences and technologies

We consider an open system of a large number C of non-overlapping cities, indexed by $c = 1, \dots, C$. There are two primary factors of production, labor and land. There are a total of L workers who are perfectly mobile between and within cities, while L^c is the number of workers located in city c. We assume that inter-city commuting costs are prohibitive, so that for each worker, their cities of work and residence coincide. We also ignore intra-city commuting costs, which allows us to focus on the inter-city allocations of workers. Workers are differentiated by ‘culture’ (language) across M groups, with L_i^c measuring the number of residents of city c belonging to group $i = 1, \dots, M$. Land is owned by absentee landlords. We call K^c the land endowment of city c and K the total land available in the economy. Land is homogeneous across alternative uses (residential and productive). Workers demand two goods, Y (tradable and homogeneous) and D (non-tradable and differentiated), as well as land K for residential purposes. Utility is assumed to be Cobb–Douglas with expenditures shares η, γ, and $1 - \eta - \gamma$ going to Y, D and K respectively:

$$U_i^c = \left(K_{u,i}^c\right)^{1-\eta-\gamma}\left(Y_i^c\right)^{\eta}\left(D_i^c\right)^{\gamma}, \tag{3}$$

where $K_{u,i}^c$ and Y_i^c denote individual consumptions of land and good Y by a typical member of group i in city c. In addition, D_i^c is a CES sub-utility defined on the set of different varieties of good D:

$$D_i^c = \left(1-\tau^c\right)\left[\sum_{j=1}^{M}\left(D_{j,i}^c\right)^{\alpha}\right]^{1/\alpha}, \quad 0<\alpha<1 \tag{4}$$

with $D_{j,i}^c$ labeling the consumption of variety j. The sub-utility function (4) exhibits 'love for variety' in that for a given total amount of consumption it is preferable to distribute it across all available varieties than to concentrate it on a single variety. Thus, utility is higher the larger the number of available varieties and the more balanced their supply. The CES aggregator D_i^c is supposed to capture utility from those goods/services (such as restaurants, specialty food, entertainment, hair stylists) that are supplied in different varieties by people of different cultures (think of Chinese food, French hair-stylists or Italian Opera-singers) and are non tradable. Low values of α (determining low elasticity of substitution between different cultural groups, defined as $\varepsilon \equiv 1/(1-\alpha)$) magnify the "love of variety" effect. The term τ^c measures the utility loss ('disamenity') of diversity: the larger τ^c the lower the utility derived from the differentiated good. We think of τ^c as an increasing function of diversity but we leave this dependence implicit to simplify notation.[8]

The production side is modeled by adapting the multi-regional trade model by Alesina et al. [4] to a multi-cultural set-up with freely mobile workers. Product and input markets are perfectly competitive. Land is homogeneous whereas labor is horizontally differentiated across groups. Each worker contributes one unit of her group-specific labor inelastically. Labor may be supplied only within the city of residence.

The differentiated good D is supplied using labor only with productivity equal to A. Such good is freely traded within cities but non-traded between them. Each variety is produced employing workers of a specific group, hence there is a one to one relation between groups and varieties. Accordingly, the output of variety i is $D_i^c = AL_{i,D}^c$, where $L_{i,D}^c$ is labor supply of group i to sector D.

The homogeneous good Y is produced using labor and land. It is freely traded both within and between cities. It is chosen as numeraire, hence its price equals one. While groups do not interact in supplying the varieties of good D, they do interact in the production of good Y. This interaction entails iceberg transaction costs: of one unit supplied by any worker only a fraction $(1-\tau^c) \in (0,1)$ is available for production. Specifically, aggregate production of good Y is given by:

$$Y^c = A\left(1-\tau^c\right)^{\alpha}\left(K_Y^c\right)^{1-\alpha}\sum_{j=1}^{M}\left(L_{i,Y}^c\right)^{\alpha} \tag{5}$$

where A is total factor productivity, K_Y^c is land used by sector Y, and $L_{i,Y}^c$ is labor supplied by group i to that sector. Accordingly, $(1-\tau^c)L_{i,Y}^c$ is the fraction available for production net of transaction costs. Notice that (5) exhibits a 'love for variety' in terms of

[8] Using the notation introduced in Section 2.1 the parameter τ^c would be an increasing function of $divLang_{ct}$, formally $\tau^c(\sum_j (l_j^c)_t^{0.66})$.

labor inputs: given total amount of jobs it is more productive to distribute them across all available groups than to concentrate all of them on a single group. The CES aggregator captures the fact that different cultures provide different workers with different observable and unobservable skills choosing different occupations (as argued above) and, therefore, not perfectly substitutable for each other. Thus, productivity is higher the larger the number of available varieties and the more balanced their supply. The more so the smaller the elasticity of substitution between groups $\varepsilon \equiv 1/(1-\alpha)$.[9]

3.2. Labor demand and supply

Since workers are freely mobile, in equilibrium they must be indifferent about location, which requires each of them to enjoy the same level of utility ('real wage') wherever located. On average this implies

$$\bar{u} = \left(\frac{K_u^c}{L^c}\right)^{1-\eta-\gamma} \left(\eta \overline{w}^c\right)^{\eta} \left(\frac{D^c}{L^c}\right)^{\gamma}, \quad \forall c = 1, \dots, C \tag{6}$$

where K_u^c and D^c are aggregate consumptions of residential land and good D in city c respectively, whereas $\overline{w}^c = \sum_{i=1}^{M} w_i^c L_i^c / L^c$ is the average (nominal) wage in the city with w_i^c being the wage of group i.[10] With absentee landlords aggregate expenditures are equal to the total wage bill $\overline{w}^c L^c$, so $\eta \overline{w}^c$ represents average consumption of the numeraire good Y. Finally, $\bar{u}$ is the real average wage, which is the same in any city due to the mobility of workers. We assume that the number of cities C is large enough to make the reservation real wage $\bar{u}$ independent from city-level idiosyncrasies.

Under perfect competition, profit maximization and free entry imply that both factors are paid the value of their marginal productivity so that the value of production is split between them according to their cost shares. Moreover, for non-traded K and D, the values of production in city c equal the corresponding expenditures of local workers $\overline{w}^c L^c$. Therefore, remembering that good Y is the numeraire, we can write $\alpha Y^c = (1-\gamma)\overline{w}^c L^c$ and $\alpha r^c K^c = (1-\alpha\eta-\gamma)\overline{w}^c L^c$. This implies that the demands of group-specific labor L_i^c across sectors D and Y are linked by $L_{iX}/L_{iY} = \gamma/(1-\gamma)$. Analogously, land demands satisfy $K_u^c/K_Y^c = \alpha[(1-\eta-\gamma)]/[(1-\gamma)(1-\alpha)]$. These results can be inserted into the city resource constraints for labor and land to obtain the amounts of labor and land employed in the supply of good Y:

$$L_{i,Y}^c = (1-\gamma)L_i^c, \qquad K_Y^c = \frac{(1-\alpha)(1-\gamma)}{1-\alpha\eta-\gamma} K^c \tag{7}$$

[9] We have assumed that elasticity of substitution between different types of labor in production is the same as the elasticity of substitution between varieties in consumption. We have also assumed that the utility loss and the productivity loss due to diversity are both measured by the same function τ^c. These assumptions simplify the exposition of the model and have no bearing on our identification procedure.

[10] Mobility of workers of each type (L_i) between production of good Y and production of variety D_i implies that the wage for a type of worker (i) is equated between the two sectors.

with complementary shares of labor and land going to differentiated production and residential use respectively. Given (5), expressions (7) allows us to rewrite the free mobility condition (6) as:

$$\overline{w}^c = \frac{(\bar{u})^{1/\eta}}{\eta}\left(\frac{\alpha(1-\eta-\gamma)}{1-\alpha\eta-\gamma}\frac{L^c}{K^c}\right)^{\frac{1-\eta-\gamma}{\eta}}\left[\left(1-\tau^c\right)A\right]^{-\gamma/\eta}\left[\sum_{j=1}^{M}\left(\lambda_j^c\right)^\alpha\right]^{-\frac{\gamma}{\alpha\eta}} \tag{8}$$

where $\lambda_i^c \equiv L_i^c/L^c$ is the share of residents of city c belonging to group i. Equation (8) identifies an upward sloping labor-supply relation between employment L^c and the average wage in city c. It shows that, for a given wage, workers are willing to move to cities that have:

(i) a more balanced distribution across groups;
(ii) lower costs of interaction;
(iii) more abundant land.

The reason is that under all three counts utility ('quality of life') is higher. This, however, does not imply that workers are drawn to more diverse cities which have a richer set of varieties of good D but also higher "interaction" costs. The overall effect of diversity on labor supply depends on the relative effect of diversity on the term $(1-\tau^c)$, that captures the dis-utility effect and the term $\sum_{j=1}^{M}(\lambda_j^c)^\alpha$ that captures the positive effect from love of variety.

Lastly, under our choice of numeraire, Eq. (7) also implies that the average profit-maximizing wage $\overline{w}^c$ satisfies:

$$\overline{w}^c = \alpha A(1-\gamma)\left(\frac{(1-\alpha)}{1-\alpha\eta-\gamma}\frac{K^c}{L^c}\right)^{1-\alpha}\left(1-\tau_Y^c\right)^\alpha\sum_{j=1}^{M}\left(\lambda_i^c\right)^\alpha \tag{9}$$

which identifies a downward sloping labor-demand relation between employment and the average wage in city c. Equation (9) shows that, for a given wage, firms are willing to hire more workers in cities that have:

(i) a more balanced distribution across groups;
(ii) lower costs of interaction;
(iii) more abundant land.

The reason is that under all three counts labor productivity is higher. Nevertheless, this does not imply that firms are drawn to more diverse cities. These, in fact, offer a richer set of labor types but also higher transaction costs. Again the relative impact of diversity on $(1-\tau_Y^c)$ and on $\sum_{j=1}^{M}(\lambda_i^c)^\alpha$ will determine the net effect on the labor demand equation.

3.3. Identification: wage and employment

To prepare the model for empirical investigation, it is useful to evaluate wages and employment levels at the equilibrium allocation. This is achieved by solving labor demand (9) and labor supply (8) together, which yields, once we take logs on both sides, the following employment (density) equation:

$$\ln\left(\frac{L^c}{K^c}\right) = \text{constant}_L + \frac{\alpha\eta+\gamma}{1-\alpha\eta-\gamma}\ln\left(1-\tau^c\right) + \frac{\alpha\eta+\gamma}{\alpha(1-\alpha\eta-\gamma)}\ln div^c \tag{10}$$

and the following 'wage equation':

$$\ln\left(\overline{w}^c\right) = \text{constant}_w + \frac{\alpha(1-\eta)-\gamma}{1-\alpha\eta-\gamma}\ln\left(1-\tau^c\right) + \frac{\alpha(1-\eta)-\gamma}{\alpha(1-\alpha\eta-\gamma)}\ln div^c \tag{11}$$

where we defined, following (1) of Section 2.1, the diversity index as $div^c \equiv \sum_{j=1}^{M}(\lambda_j^c)^\alpha$. Recall that the "transaction cost" τ^c is itself an increasing function of diversity, $\tau^c(div^c)$. The model, therefore, yields ambiguous predictions on the impact of diversity on average wage and employment density, the reason being the opposing effects of diversity on both utility and productivity captured by the second and third term on the right hand sides of Eqs. (10) and (11). Depending on the relative importance of these effects in each equation we may have the four cases illustrated below.

Equations (9) and (8) can be used to identify the net impact of diversity shocks on urban performance. Those equations are depicted in Fig. 3. The vertical axis measures the logarithm of the average wage in a city (w) while the horizontal axis measures the logarithm of its employment density (l). The city index c is dropped for parsimony. The downward sloping lines are derived from Eq. (9) and depict labor demand. The upward sloping lines are derived from Eq. (8) and represent labor supply. The exact positions of demand and supply depend on city-specific characteristics. For example, suppose we observe two cities. In the first city labor demand and supply are represented by the solid lines, whose intersection identifies the local equilibrium wage and employment density (point A). Now suppose that we observe a second city with higher average wage ($w' > w$). Figure 3 shows that in principle this could be associated with either an upward shift of labor demand (point B) or an upward shift of labor supply (point C). In both cases the wage is higher but for very different reasons. The upward shift of labor demand implies that firms in this city are able to make zero profit even though they face higher wages and higher land rents due to a

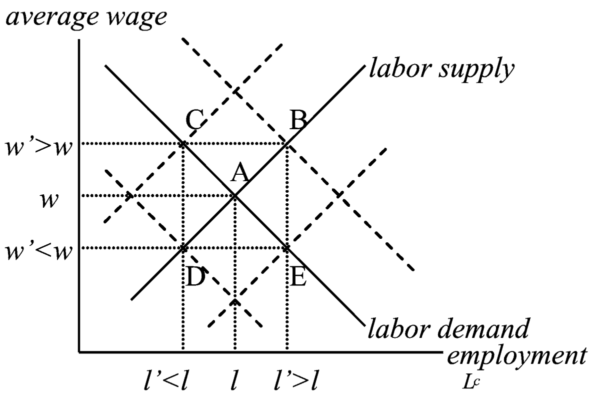

Fig. 3. Labor market equilibrium.

higher population density. This is possible only if firms are more productive in the second city than in the first one. The upward shift of labor supply implies, instead, that in order for workers to be as happy in the second city as in the first one, a higher wage has to be associated with a lower land rent stemming from lower density. This reveals the presence of a real wage premium that compensates for a poorer quality of life.

To distinguish whether higher nominal wages signal higher productivity or a worse quality of life, additional information is therefore needed. We see in Fig. 3 that, as implied by the above argument, such information is provided by employment density: whereas higher productivity is associated with both a higher wage and a higher employment density (point B), a worsening of the quality of life is associated with a higher wage but a lower density (point C). By symmetry the foregoing arguments can be applied to downward shifts of labor demand and supply. This implies that only the parallel estimation of (9) and (8) allows one to establish which effect indeed dominates. Focussing on diversity as city-characteristic that may shift labor demand or labor supply, the analysis of Fig. 3 suggests the following four possibility.

$$\frac{\partial L^c}{\partial div^c} > 0 \text{ and } \frac{\partial \overline{w}^c}{\partial div^c} > 0 \quad \text{iff } \textit{there exists a dominant positive productivity effect},$$
$$\frac{\partial L^c}{\partial div^c} > 0 \text{ and } \frac{\partial \overline{w}_c}{\partial div_c} < 0 \quad \text{iff } \textit{there exists a dominant positive utility effect},$$
$$\frac{\partial L^c}{\partial div^c} < 0 \text{ and } \frac{\partial \overline{w}_c}{\partial div_c} < 0 \quad \text{iff } \textit{there exists a dominant negative productivity effect},$$
$$\frac{\partial L^c}{\partial div^c} < 0 \text{ and } \frac{\partial \overline{w}_c}{\partial div_c} > 0 \quad \text{iff } \textit{there exists a dominant negative utility effect}.$$

This identification procedure, based on estimating the effect of diversity on average wage and employment density is 'dual' to the one based on wages and rents that Ottaviano and Peri [30] propose following Roback [32].

4. Effects of diversity in US cities

We now turn to the estimation of the effects of diversity on average wages and employment across US cities using panel regression techniques. In so doing, we address several econometric issues. In particular, we check that our results are robust to different specifications, we qualify the effects of diversity across some important demographic groups and we address the issue of a potential endogeneity bias. Finally we qualify our results and compare them with the existing literature.

4.1. Wage and employment regressions

Our basic regressions analyze the impact of diversity on average wages and aggregate employment levels of US-born workers using a panel of the 160 MSAs in three census years (1970, 1980 and 1990). We control for 160 city fixed effects, α_c, and for three year dummies, β_t. Therefore, we identify the effect of diversity on productivity by exploiting only the within-city variation over time. Based on the theoretical model presented in Section 3, our basic wage equation is:

$$\ln(\overline{w}_{c,t}) = \alpha_c + \beta_t + \underline{\gamma}_d(\underline{d}_{c,t}) + \gamma_w(Lang\_diversity_{c,t}) + e_{c,t}. \tag{12}$$

On the left hand side, the dependent variable $\ln(\overline{w}_{c,t})$ is the log of the average hourly wage of US-born workers (age 16–65). On the right hand side, along with our fixed effects, we include in the vector $\underline{d}_{c,t}$ several demographic controls, namely the average level of schooling of workers, their average experience and its square, the share of women, the share of blacks and the share of native Americans for each city. $Lang\_diversity_{c,t}$ is the index of linguistic diversity measured either using the index defined in (1) or the one defined in (2). The coefficient γ_w captures the effect of a variation in the linguistic diversity on the average wage of US-born workers and is our primary parameter of interest. The city fixed effects control for permanent differences across cities (such as size, location, weather and so on), while the time effects control for common national trends (such as improved technology and increased openness). The term $e_{c,t}$ is a random error with zero mean and no correlation with the regressors.

The basic employment equation, similarly, is:

$$\ln(Empl_{c,t}) = \alpha_c + \beta_t + \gamma_e(Lang\_diversity_{c,t}) + u_{c,t}. \tag{13}$$

As in the previous expression the parameters α_c and β_t denote a set of city-specific and time-specific dummies, $Lang\_diversity_{c,t}$ is the measure of linguistic diversity and $u_{c,t}$ is a zero mean random error uncorrelated with the regressors. The coefficient γ_e captures the impact of linguistic diversity on the density of employment in a city.

We estimate Eq. (12) for the average US-born city worker, as well as for the average worker in several sub-groups. The results are reported in Table 3. Column I contains the basic regression that uses all US-born workers in the calculation of the average city wage and controls for their demographic characteristics. Column II considers only the group of white male workers. Column III considers only black males and column IV considers only workers with more than two years of college (skilled workers). We also run a specification that includes only unskilled workers, but we do not report it for the sake of brevity. We will however refer to it in the text. Columns I–IV use the 'diversity index' $divLang_{ct}$ as the measure of linguistic diversity. Columns V to VIII reproduce specifications I–IV but instead use the fractionalization index $frac(Lang_{c,t})$ as the measure of diversity. Table 4 reports the coefficient estimates of Eq. (13) using groups and specifications that parallel those of Table 3. In Table 4 the dependent variable that measures employment for each group is calculated using data on aggregate employment (from the city databook) multiplied by the share of each group in total city employment obtained using the PUMS data. The joint analysis of Tables 3 and 4 conveys the basic message of this paper.

Before focussing on the coefficients of interest, namely those on linguistic diversity (first row of every table) let us briefly comment on the estimated effects of demographic controls. The effect of one extra year of schooling on average wages is close to 7% for the whole population. This is close to the estimates of private returns to schooling for the US (around 6.5–8.5% as reviewed in Card [14]). Average experience has a mild positive (and concave) effect on wage. This estimate is smaller than for individual wage estimates, but a city with lower average experience may be adopting newer technologies, reducing the aggregate

Table 3
Wage regressions

Adopted measure of linguistic diversity:	$divLang_{ct} = \sum_j (l_c^j)_t^{0.66}$				$fracLang_{c,t} = 1 - \sum_j (l_c^j)_t^2$			
Specification:	I All US-born	II White males	III Black males	IV More skilled	V All US-born	VI White males	VII Black males	VIII More skilled
Linguistic diversity	0.23* (0.04)	0.22* (0.04)	−0.05 (0.20)	0.31* (0.05)	0.27* (0.04)	0.28* (0.05)	−0.07 (0.30)	0.44* (0.06)
Average schooling	0.062* (0.01)	0.067* (0.01)	0.15* (0.03)	0.12* (0.04)	0.074* (0.01)	0.071* (0.01)	0.15* (0.03)	0.14* (0.04)
Average experience	0.006 (0.02)	0.027 (0.02)	0.025 (0.015)	0.06 (0.04)	0.01 (0.02)	0.03 (0.02)	0.023 (0.015)	0.03 (0.03)
Average experience, squared	−0.0004 (0.0003)	−0.001 (0.001)	−0.0001 (0.0002)	−0.002 (0.002)	−0.004 (0.006)	−0.001 (0.0007)	−0.0001 (0.0002)	−0.001 (0.001)
Share of women	−1.08* (0.21)			−0.52* (0.20)	−1.05* (0.21)			−0.46* (0.17)
Share of black	−0.16 (0.16)			−0.12* (0.42)	−0.15 (0.16)			−0.19* (0.35)
Share of native Americans	0.15 (0.70)			0.03 (0.10)	−0.03 (0.65)			0.10 (0.10)
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Partial R^2 (excluding fixed effects)	0.10	0.06	0.07	0.04	0.10	0.05	0.07	0.04
Observations	480	480	480	480	480	480	480	480

In parentheses, heteroskedasticity-robust standard errors.
Dependent variables:
specifications I and IV: Natural logarithm of average hourly wage in the SMSA expressed in 1990 US \$, for all US-born workers aged 16–65;
specifications II and V: Natural logarithm of average hourly wage in the SMSA expressed in 1990 US \$, for white male US-born workers aged 16–65;
specifications III and VI: Natural logarithm of average hourly wage in the SMSA expressed in 1990 US \$, for black male US-born workers aged 16–65;
specifications IV and VIII: Natural logarithm of average hourly wage in the SMSA expressed in 1990 US \$, for US-born workers aged 16–65 with at least two years of college education.
* Significant at the 1% level.

positive effect of experience on productivity. The share of women in the workforce reduces the average wage significantly (this is the aggregate counterpart of a significant negative wage premium for women) while the share of blacks and that of natives have smaller effects, respectively negative and positive, on average wages. When we consider only white

Table 4
Employment regressions

Adopted measure of linguistic diversity:	$div\,Lang_{ct} = \sum_j (l_c^j)_t^{0.66}$				$frac\,Lang_{c,t} = 1 - \sum_j (l_c^j)_t^2$			
Specification:	I All US-born	II White males	III Black males	IV More skilled	V All US-born	VI White males	VII Black males	VIII More skilled
Linguistic diversity	0.61* (0.16)	0.45* (0.20)	0.50 (0.30)	0.54* (0.15)	0.77* (0.16)	0.43* (0.20)	0.55 (0.30)	0.53* (0.18)
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Partial R^2 (excluding fixed effects)	0.03	0.03	0.01	0.04	0.04	0.03	0.01	0.04
Observations	480	480	480	480	480	480	480	480

In parentheses, heteroskedasticity-robust standard errors.
Dependent variables:
specifications I and IV: Natural logarithm of employment of all US-born workers aged 16–65;
specifications II and V: Natural logarithm of employment of white male US-born workers aged 16–65. The employment is calculated by multiplying total employment figures by the share of white males in the SMSA obtained using the PUMS data;
specifications III and VI: Natural logarithm of employment of black male US-born workers aged 16–65. The employment is calculated by multiplying total employment figures by the share of black males in the SMSA, obtained using the PUMS data;
specifications IV and VIII: Natural logarithm of employment of US-born workers aged 16–65 with at least two years of college education. The employment is calculated by multiplying total employment figures by the share of workers with more than two years of college in the SMSA, obtained using the PUMS data.
* Significant at the 1% level.

males the effect of schooling is unchanged but average experience has a stronger positive and concave effect.

The estimates in the first columns of Tables 3 and 4 show that the overall effects of diversity on the wage and employment of US-native workers is positive and significant. Its magnitude is most decidedly relevant. A change in the diversity index of 0.60, comparable to the differences in diversity between Pittsburgh (a very homogeneous city) and Los Angeles (a very diverse one), is associated with a 13% increase in the average wage of US-born workers.[11] A very similar effect is obtained using the estimates of column V in Table 3, in which diversity is proxied by the index of linguistic fractionalization. The main message from the basic wage specification is that diversity is associated with a very large increase in productivity. By way of comparison, a city would need an average increase of

[11] The standard deviation of the two indices is around 0.16 so that an increase of one standard deviation implies an increase of average wages by 4% and an increase of employment by 8%.

more than one year of schooling for each worker in order to achieve the same 13% increase in productivity.

This average effect is very significant and forms the main focus of our analysis. This may, however, conceal different effects for different demographic groups in the native population; thus the remaining columns of Tables 3 and 4 analyze the impact of diversity on narrower groups. The effects of linguistic diversity on the wage and employment of US-born white males (columns II and VI of Tables 3 and 4) is positive and significant and, quantitatively, rather similar to the overall effect. As this is the largest group among all workers, a large part of the total effect is likely driven by the effect on this group. To the contrary, the effect on the wages of black males is negative and not significant (while the effect on the employment of black males is positive and not significant). Potentially this may arise if non-native speakers compete with blacks more than with whites for similar occupations (low-skill jobs, personal services), so that diversity harms (or at least does not help) black workers. Alternatively we may think that the composition of black workers (in terms of skills and age) is such that they are the most adversely affected by competition from non-native speakers. Columns IV and VIII provide partial support for this explanation. The positive impact of linguistic diversity on the wages of skilled US-born workers is higher than its average impact on all workers (coefficient is 0.31, significantly larger than the average of 0.23). The effect of diversity on less skilled workers (i.e. workers with less than 2 years of college education), not reported, is equal to 0.23 (standard error 0.04) when measured using the diversity index and to 0.28 (0.04) when measured using linguistic fractionalization. Thus the estimated impact of diversity on the less educated, while smaller than for the highly educated, remains positive and significant. The explanation for the insignificant effect on black workers should then arise, at least in part, from the occupational composition of the black labor force, rather than simply from their schooling. Columns IV and VIII in Table 4 show how diversity is beneficial to the employment of high skilled workers, confirming the hypothesis of a positive productivity effect on this group.

If we believe that the variation in linguistic diversity across cities is exogenous (as it is driven by exogenous migration flows) we can interpret the results of the above regressions as evidence of a strong positive effect of diversity on the productivity of average US-born workers. Moreover, there is evidence of an even stronger positive effect on the productivity of highly educated native workers, a smaller but still positive effect on the productivity of less educated native workers, while no effect (or a small negative one) is found on the productivity of black native workers. This array of correlations is compatible with the idea that non-native speakers bring a diversity of abilities that is beneficial to native speakers. Complementarities in ‘vertical skills’ may also be part of the story, as aggregate schooling levels may in part influence the benefits received by US-born workers. However, a significant part of the positive effect seems to be due to ‘horizontal differentiation’ (in the provision of occupations and abilities) which benefits skilled and unskilled alike. White workers, in aggregate, receive a beneficial productivity effect from non-native speakers (and their diversity) while black workers apparently do not receive any such gains. In the effort to better characterize the features of linguistic diversity that enhance the productivity of natives, we run a series of robustness checks before addressing the crucial issue of the potential endogeneity of linguistic diversity.

4.2. Robustness checks

The wage regressions in Table 5 (complemented by the corresponding employment regressions in Table 6) test the robustness of the effects of linguistic diversity on other measures of diversity, on characteristics of the non-native speakers and on different measures of productivity.

Our strategy consists of including sequentially a series of controls (in Tables 5 and 6) that could potentially act as relevant omitted variables and thereby generate a bias in the estimates of Tables 3 and 4. If an extra control added to a specification enters with a significant coefficient, it is maintained in the following specifications, otherwise it is dropped.

Table 5
Wage regressions: robustness checks

Specification:	I	II	III Large linguistic groups	IV	V	VI Yearly wage as dependent variable	VII Weighted regression
Linguistic diversity	0.91* (0.21)	0.28* (0.04)	0.36* (0.05)	0.91* (0.13)	0.27* (0.09)	0.20* (0.04)	0.35* (0.05)
Racial diversity	0.17 (0.21)						
State of birth diversity	0.02 (0.02)						
Ancestry diversity	0.01 (0.06)						
Diversity of schooling		0.27* (0.09)	0.30* (0.09)	0.57* (0.13)	0.28* (0.04)	0.25* (0.09)	0.29* (0.12)
percentage with good knowledge of English				0.07 (0.04)			
Average schooling of non-native speakers					0.02 (0.06)		
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	320	480	480	320	480	480	480

Dependent variable: natural logarithm of average hourly wage of US-born workers aged 16–65. Each regression includes also average schooling, average experience, average experience squared, share of women, share of black, share of native Americans in the SMSA. City- and year-fixed effects are also included.
Linguistic diversity is measured using the index $frac(Lang_{c,t})$.

* Significant at the 1% level.

Table 6
Employment regressions: robustness checks

Specification:	I	II	III Large linguistic groups	IV	V	VI Weighted regression
Linguistic diversity	1.03* (0.43)	0.79* (0.10)	0.99* (0.12)	0.91* (0.31)	0.82* (0.10)	0.76* (0.16)
Racial diversity	−0.07 (0.35)					
State of birth diversity	0.01 (0.02)					
Ancestry diversity	0.29 (0.19)					
Diversity of schooling		0.83* (0.27)	0.93* (0.27)	0.97* (0.39)	0.84* (0.27)	0.37 (0.27)
percentage with good knowledge of English				0.14 (0.18)		
Average schooling of non-native speakers					−0.04 (0.04)	
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	320	480	480	320	480	480

Dependent variable: natural logarithm of total employment of US-born workers aged 16–65. Each regression includes city- and year-fixed effects.
Linguistic diversity is measured using the index $frac(Lang_{c,t})$.
* Significant at the 1% level.

The first columns of Tables 5 and 6 include alternative indices that may proxy for 'cultural' diversity. As we wrote in the introduction, our focus on linguistic diversity is driven by the clearness of the concept: people from different countries (and their immediate descendants) refer to their own sets of traditions and values, and are easy to identify through the language they speak at home. However, vaguer concepts such as ethnicity or ancestry could also help us define identity groups. To check whether linguistic diversity uniquely influences productivity, we include in our regression indices of fractionalization based on ethnic groupings, on groupings based on 'ancestry' (this variable is available only in census 1980 and 1990), and on groupings based on the state of birth (limited to people born in the US).[12] Notice that the other indices of diversity can be very different and little correlated with linguistic diversity. For instance African Americans (who are English speakers)

[12] The index of ethnic diversity is constructed including the following five 'ethnic groups,' identifiable across censuses: White, Black, Native-American, Asian, and Others.

heavily influence our measure of ethnic diversity, while Hispanics are not even included as a separate "ethnicity" (in line with what was done in the censuses of 1970 and 1990). Similarly the diversity of one's state of birth only refers to the fraction of population that is US-born, and therefore is utterly orthogonal to measures of linguistic diversity. To convince the reader that these variables have a large amount of independent variation, note that the correlation coefficient between linguistic diversity and ethnic fractionalization is 0.09, while between linguistic diversity and fractionalization of state of birth it is 0.11. To give a concrete example of a change in the diversity index that is not highly correlated with changes of ethnic diversity and state of origin but that nonetheless has large positive effects on productivity, consider the large increases in immigration of highly skilled Europeans (eastern and western) and of low skilled Latin Americans that have characterized the 1980s and 1990s. These shocks would not be captured by the other two indices since Europeans and Latin Americans are classified as mostly white (Hispanic is not a category), and the foreign born are excluded from the state of birth index.

Our prior is that, while ethnic diversity may capture the black-white divide and so help us apprehend potential productivity losses associated with racial 'fissures,' the concepts of 'ancestry' and 'state of birth' are simply too weak to define identity or capture significant differences in abilities and skills. Thus we expect no significant effect from them. The estimated coefficients confirm our prior: linguistic diversity is the only measure having a significantly positive effect on productivity. Specifically, ethnic diversity has a negative impact on employment and a positive impact on wages, but both are insignificant. The direction of the correlations, however, may suggest that workers mildly dislike ethnic diversity and ask for a wage premium. The other two measures have insignificant effects as well. Due to some collinearity with the other variables, and to the restriction of the sample to only 1980 and 1990, the coefficient estimates on linguistic diversity (captured throughout this table with $divLang_{ct}$) become much more imprecise in the wage and employment regressions. However the magnitude of the estimates increases, and this makes us confident that the variable is capturing the type of diversity relevant for productivity. Because their coefficients are highly insignificant, and because we wish to use the whole sample, we drop the other indices of diversity in the following specifications.

The main explanation, backed by our model, for the beneficial effect of linguistic diversity is that non-native speakers provide a variety of skills complementary to those of native speakers. If this is true, there may be a 'vertical' as well as an 'horizontal' components to this diversity. It is well known (see for instance Borjas et al. [12]) that the foreign born are over-represented both among workers without a high school degree and among those with college and higher education. On the other hand, they are under-represented in the intermediate group of high-school graduates. Therefore the beneficial effects of having a more polarized distribution of skills (through complementarities) for a given average schooling may be a source of the productive impact of the foreign-born on natives (vertical differentiation). On the other hand, even within a group with homogeneous schooling, non-native speakers may have abilities different from those of natives (horizontal differentiation).

Column II in Tables 5 and 6 include a measure of the vertical diversity of skills in a city. Controlling for average schooling (as we do in all the regressions), we include the total share of workers in the two ‘extreme’ education groups (high-school dropouts and college graduates). The variable is denoted as ‘diversity of schooling’ in the tables. We find that this variable enters very significantly in the wage and employment regressions, in accordance with a positive productivity effect of vertical skill diversity (due for instance to complementarity of skills). However, linguistic diversity maintains its significance and the magnitude of the coefficient does not much differ from the baseline estimate (column I in Tables 3 and 4) . This suggests that linguistic diversity is not simply a proxy for the complementarity of observable skills, but rather captures a relevant form of horizontal, (unobservable) diversity as well.

Column III uses broader linguistic groupings to construct the diversity index, as languages with common roots (Neo-Latin, Slavic, Anglo-Saxon, South-Asian, East-Asian, African, and Native languages) may indicate similar cultures. The objective is to capture the varying *degrees* of cultural differences: for example, Spanish and Chinese cultures are arguably more different than Spanish and Italian cultures. Thus, diversity between the former pair may bring higher benefits from diversity along with higher communication costs. The estimates of the effects of diversity, both in the wage and employment regressions, increase somewhat, suggesting that the differences between large cultural groups (rather than the nuisances within a group) might be most relevant for ability and skill complementarities.

In columns IV and V we look at some characteristics of non-native speakers that may affect their contribution to productivity. Using the results of a question available only in the 1980 and 1990 censuses we can calculate what percentage of non-native speakers speaks English ‘well’ or ‘very well’ (according to a self-evaluation). This percentage provides information on whether the communication barrier (transaction costs) is relevant for non-native speakers and whether it matters for the productivity of natives. Two interesting facts should be pointed out. First this percentage is highly *negatively* correlated with the index of diversity across cities. Clearly non-natives who predominantly live with other non-natives tend to speak worse English. Second, however, the overall percentage of non-native speakers who speak English well is very high (87% in 1980 and 90% in 1990). Once we include this measure (column IV) the coefficient on linguistic diversity becomes larger, and the coefficient on English proficiency is positive in both regressions and significant at the 10% level in the wage regression. We can conclude that the effect of cultural diversity is even stronger once we control for the ability of interacting with natives. Moreover if we consider proficiency in spoken English as inversely correlated with the cost of communication across groups, our results confirm that the benefits of diversity are stronger when barriers between groups are lower. Column V includes the average schooling of non-native speakers, which does not seem to matter much. This confirms that the skill-differentiation of non-natives, rather than their average schooling, may be the most beneficial feature of diversity’s role in enhancing productivity.

Columns VI and VII in Table 5 confirm these results using average yearly wages (rather then hourly) as a measure of productivity, and weighting each city observation by its size. Column V in Table 6 also shows the weighted regression for employment. No relevant differences emerge, confirming the robustness of the effect of diversity on productivity.

4.3. Endogeneity and IV

The most problematic assumption made so far in the estimation of the wage and employment regressions is the exogeneity of linguistic diversity. A positive unobservable productivity shock to a city could in fact be the cause of higher wages and employment and may, in turn, attract a wider share and variety of foreign-born workers, thereby increasing the linguistic diversity of a city. If this 'reverse' channel of causation is active, the OLS estimates of the coefficients γ_w and γ_e are upward biased. Furthermore the inclusion of other controls, as done in Tables 5 and 6, would not solve this problem.

Short of performing a randomized experiment, it is hard to rule out this channel completely. One way to reduce the endogeneity bias, however, is to resort to instrumental variable estimation. Specifically, we consider the growth of wages (and employment) in the period 1970–1990 as our dependent variable and growth in linguistic diversity as our key explanatory variable. We then instrument the latter using two sets of instruments. Notice that our sets of instruments should be correlated with the changes in linguistic diversity (rather than with their levels) so we take the time differences of the data (1970–1990) and thus estimate a cross section without fixed effects. As the estimation in differences is completely equivalent to a panel with fixed effects the results of the IV estimation are fully comparable with the previous OLS estimates.

The first set of instruments we use is the distance of each city from the international border, from the coast, and from the closest main 'gateway' into the US (i.e. New York, Los Angeles or Miami, which in total admit each year about 30% of all inbound US travelers). The underlying idea is that, during the period 1970–1990, the US experienced a large increase in immigration for reasons exogenous to the events of any particular city. Thus, simply by geographic accident, cities closer to the coast, the border or the main gateways received a larger inflow of those immigrants. Presumably, these distances have less of a direct impact on productivity if productivity shocks during the period of observation did not depend on the position of a city. Worried that the distance from New York or Los Angeles could proxy for the access to a large market (which may be a cause for larger productivity) we also use "distance from the coast" and "distance from the border" only as instruments. Tests of over-identifying restrictions (more on this below) confirm that distance from the main gateways is the most problematic variable as an instrument. The full set of instruments explains about 40 percent of the variation in linguistic diversity, while the first two variables explain 20 percent of it (see Table 7).

The second instrument was used in a previous study of ours (Ottaviano and Peri [30]), building on a work by Card [14]. It is based on a 'shift-share' methodology. We construct the variation in diversity of foreign-born workers in a city using the initial share of each group in 1970. Then we impute to each linguistic city-group the growth in population that the group experienced nationally (due to immigration) in the 1970–1990 period. In so doing we construct the imputed change in linguistic diversity that does not depend on the actual flow of non-native speakers into a city. This construction only uses national trends and should be orthogonal to city-specific shocks. The idea is that the presence of a large linguistic group attracts newcomers from the same group. As long as this effect is due to the preferences of immigrants, it should be correlated with the actual increase in diversity but not with the productivity of the city. For instance, due to the large increases in Spanish

Table 7
IV estimates, differences 1990–1970

Dependent variable	Δ Ln(Wage)				Δ Ln(Employment)			
Specification:	I	II	III	IV	V	VI	VII	VIII
Instruments:	Distance from all gateways	Distance from coast-border	Shift-share	All	Distance from all gateways	Distance from coast-border	Shift-share	All
Δ(Linguistic diversity)	0.49* (0.06)	0.68* (0.11)	0.38* (0.17)	0.55* (0.08)	1.08* (0.21)	0.96* (0.32)	1.55* (0.71)	1.02* (0.21)
R^2	0.22	0.20	0.30	0.15	0.05	0.06	0.04	0.05
First stage								
Distance from coast	−0.079* (0.022)	−0.09* (0.02)		−0.079* (0.022)	−0.079* (0.022)	−0.09* (0.02)		−0.079* (0.022)
Distance from border	−0.015 (0.01)	−0.05* (0.01)		−0.015 (0.01)	−0.015 (0.01)	−0.05* (0.01)		−0.015 (0.01)
Distance from closest major gateway	−0.011* (0.001)			−0.011* (0.001)	−0.011* (0.001)			−0.011* (0.001)
Constructed diversity of foreign-born			0.31* (0.11)	0.11 (0.11)			0.31* (0.11)	0.11 (0.11)
p-value of the test of overid. restrictions	0.42	0.21	n.a.	0.22	0.94	0.32	n.a.	0.94
Partial R^2 of instruments	0.40	0.17	0.09	0.41	0.40	0.17	0.09	0.41
Observations	160	160	160	160	160	160	160	160

Wage regressions include the usual demographic controls: average schooling, average experience, average experience squared, share of women, share of black and share of native-American in the MSA.
The variable Δ(Linguistic diversity) is the change of the index of linguistic fractionalization between 1970 and 1990.
* Significant at the 1% level.

speaking communities, a city with a large initial Spanish speaking population would be assigned a larger share of this group in 1990 and, through this channel, a larger diversity, independently of how this city attracted the foreign born. This instrument appears to satisfy the requirement of exogeneity but is rather weak. Specifically it explains slightly less than 10% of the variation in the diversity index across cities. We also use the two instruments together to increase their power. Diagnostic tests cannot reject the exogeneity of these instruments in the wage regression at any standard confidence level, but in the employment regression the exogeneity of the distance from main gateways is rejected at the 10% level (but not at the 5 or 1%).

Table 7 shows the results of instrumental variables estimation of the wage and employment regressions using different combinations of the instruments. Columns I and V use all three distance variables, columns II and VI use only distance from the coast and from the border, columns III and VII use the imputed ‘shift-share’ instrument only, and columns IV and VIII use all instruments together. Reassuringly all of the instrumental variable estimates are positive, significant and close to our OLS estimates. If anything they are slightly larger than their OLS counterparts, implying that the upward endogeneity bias of the OLS estimates cannot be too severe. The estimate that only uses the ‘imputed’ diversity as an instrument has the largest standard error (due to the weakness of that instrument) but, being based on the most exogenous instrument, is also the one we regard with the most confidence. The coefficient estimate on diversity is positively significant and very close to (possibly higher than) the OLS estimates. Overall we are reassured by the IV estimation. It successfully confirms our view that the correlation between the diversity and productivity of cities is unlikely to be only the result of reverse causation.

5. Recent immigrants and public goods

The last section of this empirical analysis is devoted to qualifying our previous results. In particular, we first show that our findings are not incompatible with studies that identify a small *negative* impact of increased immigration on the wages of natives (see Card [15]). We then reconcile our findings of a positive effect of linguistic diversity on productivity with previous studies that find a negative association of ethnic diversity with the provision of public goods.

5.1. Recent immigrants

Our study reveals a positive effect of linguistic diversity on the average wage at the city level. Some influential existing studies on US immigration, however, find a moderately negative effect of immigrant inflows on the wages of natives (Borjas [8,9], Card [15]). These studies focus on low-skilled workers, whereas we consider the average wage of all US-born workers. Given that the inflow of foreign-born is larger among low educational groups and smaller among higher educational groups a pure “relative scarcity” effect may explain the different effect when considering low skilled workers rather than the whole population. Nevertheless, our positive result may seem at odds with this literature.

These apparently conflicting findings can be reconciled. First, our definition of linguistic diversity is based on the language people speak at home. That comprises not only new immigrants but also long-time foreign-born residents and that portion of the second generation that has maintained its linguistic identity (quite large for some groups). In this respect, our theoretical model can be used to explain the contrasting results one gets when only new immigrants are considered. In particular, as discussed in Section 3, interactions are likely to be easier when groups have had enough time to assimilate a common set of norms and habits from the host society. In the language of our theoretical model (Section 3) the costs of interactions between groups as well as the “distaste” for foreigners (τ_c) may decrease as foreign-born workers assimilate into the local culture. If such an ‘assimilation effect’ were indeed relevant, we should observe a decrease in the “cost” of diversity but no decrease in benefits (due to variety of skills-services provided) as immigrant spend time in the US.

Table 8
IV estimates including new immigrants, differences 1990–1970

Dependent variable	Δ Ln(Wage)		Δ Ln(Employment)	
Instruments:	Distance from coast-border	Shift-share + distance from coast-border	Distance from coast-border	Shift-share + distance from coast-border
Δ(Linguistic diversity)	0.52* (0.19)	0.41* (0.13)	0.79* (0.38)	0.93* (0.34)
Percentage of new immigrants	−2.21 (2.75)	−3.02 (2.21)	−0.78 (0.85)	−0.65 (0.83)
Observations	160	160	160	160
R^2	0.20	0.30	0.06	0.04

Wage regressions include the usual demographic controls: average schooling, average experience, average experience squared, share of women, share of black and share of native-American in the MSA.
The variable Δ(Linguistic diversity) is the change of the index of linguistic fractionalization between 1970 and 1990.
The variable "Percentage of new immigrants" measures the foreign-born workers, as percentage of initial employment, who immigrated into the city within the last 5 years.
* Significant at the 1% level.

As a consequence the positive effect of linguistic diversity should be associated with the presence of "old" immigrants more than with the presence of "new" immigrants.

In each year we define as 'new immigrants' the foreign-born that immigrated into the US within the previous five years; the reason for this is that the censuses in 1970 and 1990 report the place of residence of individuals five years earlier. The share of new immigrants in each city is then included in our regressions as additional controls, and we perform IV estimation using the same instruments as in Table 7, excluding the distance from major gateways (as it did not survive the most stringent tests of exogeneity in the employment regression). The corresponding results are reported in Table 8. While the estimates for the effects of overall linguistic diversity on wages and employment are still positive and significant, the effects of new immigrants turn out to be mostly insignificant, however negative in sign. The impact of new immigrants is therefore more controversial than the overall impact of linguistic diversity. Our estimates however imply that a city like Dallas, with an index of linguistic diversity 0.18 higher than Pittsburgh and with 2% more new immigrants, will benefit by a 5% higher wage, even when we combine the two effects. The effects of diversity are quantitatively larger and more significant than the effects of new immigration. Overall, these findings support the 'assimilation effect' hypothesis. Cities may face some initial costs in coping with cultural diversity: the effect of recent immigration on local wages is rather variable across cities and possibly slightly negative. However, once the initial costs of assimilation are incurred, the benefits of diversity for productivity materialize.

5.2. Public goods

A recently developed line of research analyzes the effects of racial heterogeneity on local policies, particularly policies that involve redistribution (see, e.g., Alesina and La Ferrara, [1], for a survey). The idea is that communities with a higher degree of ethnic

Table 9
Effects of ethnic and linguistic diversity on the provision of public goods

Specification:	I Total local spending per capita	II Local spending in education	III Local spending in police–security
Linguistic diversity	−0.14	−0.15	−0.11
	(0.10)	(0.08)	(0.10)
Racial diversity	−0.24*	−0.23*	0.27
	(0.12)	(0.11)	(0.16)
Time effects	Yes	Yes	Yes
City effects	Yes	Yes	Yes
Observations	480	480	480

Regressions include time dummies and city fixed effects. Each regression includes also the demographic controls: average schooling, average experience, average experience squared, share of black, share of women and share of native Americans in the city.
Specification I: Dependent variable is natural logarithm of real total public spending per capita of local administration in 1990 US $. Method of estimation is OLS with city and time fixed effects;
Specification II: Dependent variable is natural logarithm of real public spending per capita of local administration for School and Education in 1990 US $. Method of estimation is OLS with city and time fixed effects;
Specification III: Dependent variable is natural logarithm of real public spending per capita of local administration for Police and Security in 1990 US $. Method of estimation is OLS with city and time fixed effects.
* Significant at the 1% level.

fragmentation are less willing to pool their resources for public goods provision. Intuitively, in the presence of higher fragmentation each ethnic group cares less about the provisions granted to other ethnic groups. This causes the under-provision of public goods because individuals do not pay the marginal cost of a service. However, in the case of well defined markets, where people do pay the marginal costs of the services they use, there is no efficiency loss in having heterogeneous agents. This is why we did not consider such an effect in our model. Here, however, we want to make sure that our data are consistent with previous works showing ethnic fragmentation to be harmful for the local provision of public goods, especially education (see, Alesina et al. [2,3]).

Table 9 considers whether the racial and linguistic diversity of a city reduces its per capita spending for local public services after we control for local demographics and for city and time fixed effects. Column I shows the impacts of linguistic and racial diversity on overall local spending per capita. Consistent with the existing literature, racial diversity has a negative and significant impact on public spending. Linguistic diversity, however, has no significant impact (the point estimate of the effect is, however, negative). Columns II and III report the impact of diversity on the provision of local public goods. In particular, they show that racial diversity decreases expenditures in public education, thus confirming the findings of Alesina et al. [2]. Racial diversity also increases expenditures for police and security, which supports the idea that ethnic diversity may generate social unrest. As for linguistic diversity, its effect on both variables is not significant. This exercise shows that linguistic diversity is less harmful than ethnic diversity in fostering the under-provision of public goods. It seems that, while the costs of ethnic fragmentation are higher than those of linguistic fragmentation, the benefits to production from ethnic diversity are smaller than those from linguistic diversity. The reason for this difference may be found in the particularly disadvantaged and segregated position of the African American community.

6. Conclusions

We have investigated whether immigration into the US contributes to the economic prosperity of host cities by increasing cultural diversity. In particular, we have studied the effects of cultural diversity on the wages of the native population. We started with no obvious prior. On the production side, if different cultures contribute different skills and expertise in producing goods and services, cultural diversity may enhance productivity. However, difficulties in integration and communication across different groups of citizens may harm aggregate productivity. On the consumption side, cultural diversity may increase the variety of available goods and services. At the same time, however, heterogeneous preferences or distaste for different groups may decrease utility or trigger social conflicts.

By studying 160 US MSAs in the period 1970–1990, we find a significant and robust positive correlation between cultural diversity and the wages of white US-born workers. By comparing the distributions of wages and employment densities across US cities, we have argued that this correlation is compatible only with a dominant positive correlation between productivity and diversity. Moreover, instrumental variable estimation supports the idea of causation going from the latter to the former. These results match our previous findings in terms of wages and land rents (Ottaviano and Peri [30]).

Finally we qualify our findings in two respects. First, our analysis points out that the benefits from immigrants who have integrated (i.e. have been in the US for a longer period of time and speak English well) are larger than those from new immigrants. Second, our results agree with previous studies that find ethnic diversity to be bad for the provision of local public goods, as more diverse societies are less willing to pool resources for collective purposes. This suggests that integration and assimilation may be prerequisites for reaping the full gains of cultural diversity.

Acknowledgments

We are grateful to Jan K. Brueckner and two anonymous referees for useful comments and suggestions. Alberto Alesina, Ed Glaeser, Eliana LaFerrara, Dino Pinelli, Vernon Henderson, and workshop participants at FEEM Milan and UBC Vancouver also provided helpful discussions. We thank Elena Bellini for outstanding research assistance. A.S. Rahman provided extremely competent assistance in editing the paper. Ottaviano gratefully acknowledges financial support from Bocconi University, FEEM and MIUR. Peri gratefully acknowledges the UCLA International Institute for financial support. Errors are ours.

Table A.1
Name and state of the cities used

Abilene, TX	Dayton-Springfield, OH	Lexington, KY	Rockford, IL
Akron, OH	Decatur, IL	Lima, OH	Sacramento, CA
Albany-Schenectady-Troy, NY	Denver, CO	Lincoln, NE	Saginaw-Bay City-Midland, Ml
Albuquerque, NM	Des Moines, IA	Little Rock-North Little Rock, AR	St. Louis, MO-IL
Allentown-Bethlehem-Easton, PA	Detroit, Ml	Los Angeles-Long Beach, CA	Salem, OR
Altoona, PA	Duluth-Superior, MN-WI	Louisville, KY-IN	Salinas, CA
Amarillo, TX	El Paso, TX	Lubbock, TX	Salt Lake City-Ogden, UT
Appleton-Oshkosh-Neenah, Wl	Erie, PA	Macon, GA	San Antonio, TX
Atlanta, GA	Eugene-Springfield, OR	Madison, Wl	San Diego, CA
Atlantic-Cape May, NJ	Fayetteville, NC	Mansfield, OH	San Francisco, CA
Augusta-Aiken, GA-SC	Flint, Ml	Memphis, TN-AR-MS	San Jose, CA
Austin-San Marcos, TX	Fort Lauderdale, FL	Miami, FL	Santa Barbara-Santa Maria-Lornpoc, CA
Bakersfield, CA	Fort Wayne, IN	Milwaukee-Waukesha, Wl	Santa Rosa, CA
Baltimore, MD	Fresno, CA	Minneapolis-St. Paul, MN-WI	Seattle-Bellevue-Everett, WA
Baton Rouge, LA	Gainesville, FL	Modesto, CA	Shreveport-Bossier City, LA
Beaumont-Port Arthur, TX	Gary, IN	Monroe, LA	South Bend, IN
Billings, MT	Grand Rapids-Muskegon-Holland, Ml	Montgomery, AL	Spokane, WA
Biloxi-Gulfport-Pascagoula, MS	Green Bay, Wl	Muncie, IN	Springfield, MO
Binghamton, NY	Greensboro-Winston-Salem-High Point, NC	Nashville, TN	Stockton-Lodi, CA
Birmingham, AL	Greenville-Spartanburg-Anderson, SC	New Orleans, LA	Syracuse, NY
Bloomington-Normal, IL	Hamilton-Middletown, OH	New York, NY	Tacoma, WA
Boise City, ID	Harrisburg-Lebanon-Carlisle, PA	Newark, NJ	Tampa-St. Petersburg-Clearwater, FL
Brownsville-Harlingen-San Benito, TX	Honolulu, HI	Norfolk-Virginia Beach-Newport News, VA-NC	Terre Haute, IN
Buffalo-Niagara Falls, NY	Houston, TX	Odessa-Midland, TX	Toledo, OH
Canton-Massillon, OH	Huntington-Ashland, WV-KY-OH	Oklahoma City, OK	Trenton, NJ
Cedar Rapids, IA	Indianapolis, IN	Omaha, NE-IA	Tucson, AZ
Champaign-Urbana, IL	Jackson, Ml	Orlando, FL	Tulsa, OK
Charleston-North Charleston, SC	Jackson, MS	Pensacola, FL	Tuscaloosa, AL
Charlotte-Gastonia-Rock Hill, NC-SC	Jacksonville, FL	Peoria-Pekin, IL	Tyler, TX
Chattanooga, TN-GA	Jersey City, NJ	Philadelphia, PA-NJ	Utica-Rome, NY

(*continued on next page*)

Table A.1 (*continued*)

Chicago, IL	Johnstown, PA	Phoenix-Mesa, AZ	Vallejo-Fairfield-Napa, CA
Cincinnati, OH-KY-IN	Kalamazoo-Battle Creek, Ml	Pittsburgh, PA	Waco, TX
Cleveland-Lorain-Elyria, OH	Kansas City, MO-KS	Portland-Vancouver, OR-WA	Washington, DC-MD-VA-WV
Colorado Springs, CO	Kenosha, Wl	Raleigh-Durham-Chapel Hill, NC	Waterloo-Cedar Falls, IA
Columbia, MO	Knoxville, TN	Reading, PA	West Palm Beach-Boca Raton, FL
Columbia, SC	Lafayette, LA	Reno, NV	Wichita, KS
Columbus, OH	Lafayette, IN	Richmond-Petersburg, VA	Wilmington-Newark, DE-MD
Corpus Christi, TX	Lancaster, PA	Riverside-San Bernardino, CA	Wilmington, NC
Dallas, TX	Lansing-East Lansing, Ml	Roanoke, VA	York, PA
Davenport-Moline-Rock Island, IA-IL	Las Vegas, NV-AZ	Rochester, NY	Youngstown-Warren, OH

Appendix A. Data appendix

The data on the ethnic and linguistic composition of cities have been obtained from the 1970–1990 Public Use Microdata Sample of the US Census. We select all people of working age (16–65) in each year and identify the city where they lived using the MSA code for 1980 and 1990, while in 1970 we use the county group code to identify the metropolitan area. We use the variable 'Language Spoken in the Home' in order to identify the linguistic category of the person. We construct groups that can be kept homogeneous across census years. The linguistic groups that we identify are the following: English, Scandinavian, Dutch, French, Celtic, German, Polish, Czech, Slovac, African language, Russian, Rumanian, Indo-European, Hungarian, Yiddish, Greek, Italian, Spanish, Portuguese, Chinese, Arabic, Albanian, Persian, Hindi, Hebrew, East-Southeast Asian, Filipino, American Indian, and Other languages. Once we have grouped people, we use the shares of each group within a city in our sample as a measure of the share of the population in that city belonging to that group. In Table 4 we use the following racial groups to construct racial fractionalization: white, black, native American, Japanese, Chinese, Filipino, Hawaiian, Korean, and others. In Table 5 we use the following 15 groups of Ancestry for white people: Dutch, English, French, German, Greek, Hungarian, Irish, Italian, Norwegian, Polish, Portuguese, Russian, Scottish, Swedish, and Ukrainian.

We use the variable 'Salary and Wage' to measure the yearly wage income, and we divide this by the number of weeks worked in a year and then by the number of hours worked in a week in order to obtain the hourly wage. We transform the wage in real terms by using the GDP deflator. The data on total city employment are from the 'County and City Databook' and measure the total non-farm employment in the metropolitan area.

The list of metropolitan areas used in our study is reported in the following table.

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