DISCUSSION PAPER SERIES

No. 4438

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INTERNATIONAL TRADE

Centre for Economic Policy Research

www.cepr.org

Available online at: **www.cepr.org/pubs/dps/DP4438.asp**

ISSN 0265-8003

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Discussion Paper No. 4438
June 2004

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CEPR Discussion Paper No. 4438

June 2004

ABSTRACT

Cities and Cultures*

We investigate the existence of wage premium due to cultural diversity across US cities. Using census data from 1970 to 1990, we find that at the urban level richer diversity is systematically associated with higher average nominal wages for white US-born males. We measure cultural diversity in a city using the variety of languages spoken by city-residents. While the positive correlation between wages and diversity survives a battery of robustness checks, it seems to be larger once foreign cultures have been assimilated. Finally, instrumental variable estimation hints at causation going from diversity to wages. Comparing real and nominal wages across cities, we interpret these results as evidence that diversity enhances productivity.

JEL Classification: F10, O40 and R00
Keywords: cultural diversity, metropolitan areas, productivity and wages

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*We are grateful to Alberto Alesina, Ed Glaeser, Eliana LaFerrara, Dino Pinelli, Vernon Henderson, and workshop participants at FEEM Milan and UBC Vancouver for helpful discussions. We thank Elena Bellini for outstanding research assistance. Financial support from Bocconi University and FEEM is gratefully acknowledged.

Submitted 21 April 2004

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 (2003): "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 the economic point of view, the question is whether a culturally homogeneous society is more efficient than a culturally diversified one. The answer is not obvious. On the one hand, cultural diversity generates potential costs as it may entail conflicts of preferences, not to mention racism and prejudices, leading to a suboptimal provision of private and public goods (Alesina, Baqir, and Easterly, 1999; Alesina, Baqir, and Hoxby, 2004). On the other hand, cultural diversity creates potential benefits by increasing the variety of goods, services and skills available for consumption and production (Lazear, 1999a,b; O'Reilly, Williams and Barsade, 1998). By bringing together complementary skills and alternative approaches to problem solving, it may also boost innovation (Berliant and Fujita, 2003).

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 such a thing as a *diversity wage premium* in US cities? Do identical workers earn higher or lower wages in urban environments that are identical to others in all respects except their richer cultural diversity? Is the diversity premium associated with different productivity or different consumption amenities?

In so doing, we use data from 160 metropolitan areas for three census years, 1970, 1980 and 1990. US metropolitan areas represent a natural laboratory to investigate cultural diversity under many respects. First, the US have a long standing tradition as a favorite immigrant destination from both developed and developing countries. During the period of observation most immigrants have targeted urban rather than rural areas. This has made US cities a 'melting pot' of different cultures within a rather homogeneous institutional framework. Second, the US is arguably the most advanced market economy and the largest fully integrated marketplace. In the US prices reflect preferences and costs better than in any other place. In particular, in the US people are quite mobile. For instance, census data reveal that 36 per cent of the population moved from one state to another between 1985 and 1990. As people respond to changes in the local working and living environment, we may expect them to 'vote with their feet' thus seizing (and revealing) consumption and wage gains wherever they arise (Blanchard and Katz, 1992). Last but not least, the availability and quality of data are better in the US than anywhere else.

We focus on linguistic groups as carriers of cultural identity and on US-born white individuals as our

reference group. In other words, we investigate whether and how linguistic diversity affects the wage of US-born white males aged between 40 and 50 years. This has two advantages. First, it avoids composition effects in our dependent variable. Second, it highlights the effects of immigrants on the well-being of the dominant and most integrated group of natives. We choose linguistic diversity as our central explanatory variable because it captures not only the place of birth but also its associated traditions. In addition, language allows us to capture cultural identity beyond the first generation of immigrants. Other dimensions of diversity, such as race and skills, are used as controls.

The effect of diversity on aggregate economic performance has been mainly studied by means of growth regressions using racial fragmentation as the key explanatory variable. At the cross country level, Easterly and Levine (1997) find that, ceteris paribus, in countries characterized by more racial fragmentation income grows less than in more homogeneous ones. Collier and Gunning (1999) explain such behavior in terms of mutual distrust among ethnic groups, which makes it difficult to build social capital and to share productive public goods. However, when comparing countries, institutions do play a role. Collier (2001) finds that democracies are better at coping with ethnic diversity. More generally, Easterly (2001) 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, using population growth rather than income growth as dependent variable. The reason is that people are much more mobile across cities in the same country than across countries so that migration tends to arbitrage out income differences. This approach is due to Glaeser, Scheinkman and Shleifer (1995) who find that racial fragmentation has a positive impact on population growth only when matched by segregation. According to Alesina and La Ferrara (2003), that may be due to the fact that segregation makes it possible to enjoy the benefits of diversity in production without paying its costs in terms of social conflicts over public goods provision. Florida (2002a,b) argues that segregation is not the only way to fence off social unrest as a consequence of diversity. He shows that tolerant cities, where tolerance is instrumented by the presence of artists, bohemians, and other creative people, are the most active in human capital accumulation and innovation. Finally, several contributions focus on the issue of new immigrants into the US and their effect on native workers (see, e.g. Borjas, 1994 and 1995; Card, 1990 and 2001) analyze the effects of new immigrants on the locations and wages of native workers. These works reveal a small negative impact of new immigrants on the wages of low-skilled natives.

A different empirical approach to the study of diversity in cities is adopted by Ottaviano and Peri (2004). Following Roback (1982), they develop a model of a multicultural system of open cities that allows them to use the observed variations of wages and rents of US-born workers to identify the nature of the externalities associated with cultural diversity. Their main finding is that, on average, US-born citizens attribute a dominant production amenity value to cultural diversity. The present paper complements our previous work

under two respects. First, we propose a more detailed model of the production side of the economy. In so doing, we adapt the set-up by Alesina, Spolaore, and Wacziarg (2000) to design a theoretical model of aggregate production where mobile workers belonging to different cultural groups contribute different services but exchanges among them are hampered by cultural diversity. We find that in such model total factor productivity is positively related to cultural diversity and negatively on the average cultural distance between groups. Thus, differently from Alesina and La Ferrara (2003), we stress the costs of communication among different groups rather than suboptimal public goods provision as the main cost of diversity. Second, we follow Glaeser and Mare (2001) in netting out and interpreting the impact of diversity on wages in the presence of mobile and heterogeneous workers.

We find evidence in favour of a diversity wage premium: richer diversity is associated with higher white wages, while keeping other factors - such as average schooling and employment - constant. This association, which is both economically and statistically significant, can be interpreted in terms of higher productivity. As such finding seem to clash with the literature cited above, we investigate in greater detail such superficial incompatibility. This allows us to qualify our results under two respects. On the one hand, we emphasize the different effects of diversity on the private and the public sectors, by showing that the impact of diversity on the provision of public goods is indeed negative as in Alesina, Baqir, and Easterly (1999) as well as Alesina, Baqir, and Hoxby (2004). On the other hand, 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 immigrants on productivity is negative as in Borjas (1994, 1995), while overall diversity has a positive effect.

The paper is organized in five sections after the introduction. Section 2 presents the dataset 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 regression and a battery of robustness checks. Section 5 compares our findings with related studies focusing on the provision of public goods and the impact of recent immigrants. Section 6 concludes.

2 Descriptive Statistics: Cultures in US Cities

We start our analysis of the effect of cultural diversity on wages in US cities by presenting the dataset and some descriptive statistics.

2.1 Data on US Cities

Our unit of observation is the Standard Metropolitan Statistical Area (SMSA). Data at SMSA level for the US are available from different sources. We use mostly the Census Public Use Microdata Sample (PUMS)

data (1971, 1981 and 1991) 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 employment, income, population, spending for local public goods, and some indices of cultural composition. We consider 160 SMSAs that are identified in each of the three census years considered. We have around 1,200,000 individual observations for 1991, 900,000 for 1981, and 500,000 for 1971. We use them to construct aggregate variables and indices at the SMSA level. The reason for focusing on SMSAs is twofold. First, SMSAs constitute closely connected economic units within which interactions are intense. Thus, they seem to fit the theoretical model presented in section 3 in which local services are used to produce the final output. Second, they exhibit a higher degree of linguistic diversity than the rest of the country as new immigrants and their offsprings 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 in the week. Such measure is not contaminated by the variations in labor supply such as the length of the working week. We select working individuals between 16 and 65 years of age as our universe. In order to identify an average city-specific level of wage and estimate its dependence on cultural diversity, we try to minimize the composition effects. Accordingly, we consider a large and homogeneous group within each city, namely the one consisting of white US-born male non-agricultural workers aged between 40 and 50 who are heads of households. The average hourly wage constructed using this procedure for city c, call it $\overline{w}_c$ with $c = 1, ..., 160$, is neither affected by composition effects nor distorted by potential discriminatory factors (across cultures). In particular, the construction of $\overline{w}_c$ is not affected by the degree of diversity of a city, as it considers only the wage of one (the largest) group.

Cultural diversity is a multidimensional concept. It could stem from different ethnic or linguistic groups but also from different skills or US regional origins. Nonetheless, 'cultural diversity' as it is commonly referred to, mostly involves ethno-linguistic differences. Ethnicity and language, together with religion as 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, most debates about diversity are strongly related to issues such as the 'Latino identity' or the 'Chinese-American Community' (i.e., linguistic grouping). For these reasons we choose measures of linguistic diversity as our favorite empirical correlates of the broader concept of cultural diversity. Measures of diversity in skills, 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 (6): the sum of the population shares of the different groups raised to the power of α. Since in (6) α represents the labor share of aggregate income, we follow common practice by setting $\alpha = 0.66$ for the US economy. Formally, we define the our own index of linguistic

diversity of city c in year t as:

$$divLang_{ct} = \sum_j (l_j^c)_t^{0.66} \tag{1}$$

where $Lang$ labels the 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. The index has its minimum value at 1, if all city residents are from the same linguistic group. The more equal 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 indices, however, we also consider a more standard measure of diversity, namely, the so called 'index of fractionalization'. Such index, popularized in cross-country studies by Mauro (1995) and largely 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 Herfindal index of concentration across groups. Formally, we define the fractionalization index of linguistic diversity. of city c in year t as:

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

This index reaches its maximum value 1 when each individual is in a different group, and its minimum value 0 when all individuals belong to the same group. In addition to its usefulness for robustness checks, fractionalization also allows us to get a feeling of the extent of diversity of US cities by comparing their linguistic diversity with those calculated in cross-country studies. Note that the correlation between the two indices, $divLang_{ct}$ and $frac(Lang_{c,t})$, across the 160 SMSA's 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. Column 1 and 3 report the averages in 1970 and 1990 for each share across the 160 metropolitan areas, column 2 and 4 report the standard deviation in 1970 and 1990. A linguistic group is defined as speaking prevalently a certain language at home. For parsimony, the table includes only very few specific linguistic groups even though other groups are important especially in some cities. The fractionalization index reported in the last row of the table is calculated, instead, using all the (29) groups that are listed in the Data Appendix. 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 of linguistic diversity to decrease between 1970 and 1990: the

index of fractionalization decreases significantly. In particular, while the share of English speakers remains stable, other European Languages become less relevant, while Spanish turns into the second 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, gave way to a single large Spanish speaking minority in 1990.

Table 2 reports the fractionalization index of some representative SMSAs in 1990. The two largest metropolis, New York and Los Angeles, are the most diverse cities along the linguistic dimension. Both cities have a very large Spanish speaking community (in L.A. it represents 30% of the population, while in N.Y it reaches 17%) and a non negligible Chinese speaking group. The third most diverse city in our group is San Francisco. Cities in the mid-west 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 (1972) for year 1960. Those values have been largely used in the growth literature (see, e.g., Easterly and Levine, 1997, and Collier, 2001). 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 homogenous cities such as Cincinnati and Pittsburgh have a level of fractionalization equal to 0.08, which is the same as that of very homogenous Sweden. Between these extremes US cities span a range of linguistic diversity that is about two thirds of the range spanned by countries in the world.

Finally, Figure 1 presents a partial scatterplot of the nominal average wage for year 1990 against the index of linguistic diversity, $divLang_{c1990}$. We use the (zero-mean) residuals of nominal wages after controlling for population in the city as city-density could be correlated both with wages and diversity. Figure 1 reveals the presence of a diversity premium: nominal wages are higher in more diverse cities. In particular, the estimated slope of the fitted line is both positive (equal to 5.5) and significant (with a t-statistic of 4.4). To check the robustness of such correlation and to understand its determinants is the objective of the following sections.

3 A Model of Multicultural Production

We consider an open system of a large number C of non-overlapping cities, indexed by $c = 1, ..., C$. There is one factor of production, labor. There are L workers and they are perfectly mobile between and within cities and we call L^c the number of workers located in city c. We assume that intercity commuting costs

are prohibitive so that for any worker the cities of work and residence coincide. We also ignore intra-city commuting costs, which allows us to focus on the intercity allocations of workers. Workers are differentiated by 'culture' across M groups with L_i^c measuring the number of residents of city c in group $i = 1, ..., M$. Following Glaeser and Mare (2001), workers belonging to different groups may also differ in terms of their endowments of efficiency units of labor.

3.1 Labor Supply

Workers' utility is homothetic and defined over the consumption of a freely tradable good Y as well as over a set of non-tradables produced under constant returns to scale and perfect competition using land as their only input. Landowners are absentee. Since workers are freely mobile, in equilibrium each of them expects to earn the same real wage wherever located:

$$\frac{w_i^c}{P^c} = \frac{w_i^{c'}}{P^{c'}}, \ \forall c, c' = 1, ..., C \tag{3}$$

where w_i^c is the nominal wage of a typical worker of group i in city c, and P^c is the local price index inclusive of traded and non-traded goods.

Groups may differ in terms of efficiency units and we call ϕ_i^c the endowment of efficiency units of a typical worker of group i in city c. Accordingly, the average wage in city c may reflect two effects: a group-wise composition effect and a cost-of-living effect. Indeed, if one defines W_i^c as the wage per efficiency unit of group i in city c, i.e. $w_i^c = W_i^c \phi_i^c$, the average of the nominal wage can be decomposed as:

$$\widetilde{w}^c = \widetilde{W}^c + \widetilde{\phi}^c \tag{4}$$

where $\widetilde{w}^c \equiv \sum_{i=1}^{M} \ln w_i^c / L^c$ is a geometric mean. Similar definitions apply to the other variables in (4).

Noticing that (3) also implies the equalization of real wages per efficiency unit allows us to write:

$$\widetilde{W}^c - \widetilde{W}^{c'} = \ln \frac{P^c}{P^{c'}}$$

which, together with (4), gives:

$$\widetilde{w}^c - \widetilde{w}^{c'} = \widetilde{\phi}^c - \widetilde{\phi}^{c'} + \ln \left(\frac{P^c}{P^{c'}} \right) \tag{5}$$

for all $c, c' = 1, ..., C$. Thus, the free mobility of workers implies that differences in nominal wages across cities are driven by different compositions across groups or different costs of living or both.

To check the relative importance of these two effects we compare the scatterplot of nominal wages in

Figure 1 with the analogous plot of real wages in Figure 2. In each city the corresponding real wage is calculated as the ratio of the nominal wage to the cost of living in 1990, as published quarterly by the American Chamber of Commerce Research Association (ACCRA). As mentioned above, Figure 1 reveals the presence of a diversity premium: nominal wages are higher in more diverse cities. Figure 2, however, shows that, once we control for the local cost of living, the wage premium disappears: nominal wage differences are exactly matched by local price differences. In fact, a slightly (non significant) negative correlation appears. Then (5) implies that compositional differences are negligible: the diversity premium is likely not to be the result of omitted ability bias. In what follows, we use this result to simplify the model by neglecting cross-group differences in efficiency units. In particular, we normalize the number of efficiency units per worker to one.

3.2 Labor Demand

The production side is modeled by adapting the multi-regional trade model by Alesina, Spolaore, and Wacziarg (2000). The tradable good Y is produced using an array of differentiated intermediate inputs X. Both are produced under perfect competition. Each group $i = 1, ..., M$ supplies one and only one intermediate input using its group-specific endowment of labor ('culture'). Due to our normalization of efficiency units, each group member contributes one unit of labor and the i-group's resource yields L_i units of the corresponding intermediate good. Thus, M is also the number of intermediate inputs ('services') available and L_i is both the amount of intermediate input supplied by and the number of workers belonging to group i.

Final production by group i in city c is given by:

$$Y_i^c = A\left(K_i^c\right)^{1-\alpha} \sum_{j=1}^{S} \left(X_{ji}^c\right)^{\alpha}, \ 0 < \alpha < 1 \tag{6}$$

where X_{ji}^c denotes the amount of intermediate input produced by group j and used by group i, K_i^c is physical capital used by group i and A is total factor productivity. Capital is freely mobile within and between cities at rental rate r. Notice that (6) exhibits 'love of variety' in terms of intermediates: it is more productive to spread a given total amount of intermediate consumption across all available inputs than to concentrate that same amount on a single input. The more so the lower the value of α (i.e. the lower the elasticity of substitution between intermediates $\varepsilon = 1/(1-\alpha)$).

The final good is freely traded both within and between cities. Intermediates are only traded within cities and such trade incurs iceberg transaction costs. Of one unit shipped between groups only a fraction $(1-\tau^c)$ reaches destination. This can be widely interpreted as the resource cost of interaction ('communication')

between groups. These costs may depend on the exact identities of the groups living in the city: interactions are likely to be more difficult when the groups of citizens are very different (e.g., Japanese and Italians) than when they are rather homogenous (e.g., Italians and Spanish). The costs of interaction may also depend on the time from 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 in the empirical analysis.

Let P_Y be the price of the final good and let this good be the numeraire (hence $P_Y = 1$). Call P_{ji}^c the price per unit shipped ('mill price') of an intermediate produced by group j and sold to group i in city c. Recalling that, when Z_{ji}^c units are shipped, only $(1-\tau^c)Z_{ji}^c$ units arrive at destination, we have that the amount of intermediate available for final production is $X_{ji}^c = (1-\tau^c)Z_{ji}^c$. Then, given (6), pricing at marginal cost implies that the mill price of one unit of intermediate shipped from group j to group i in city c is:

$$A\left(K_i^c\right)^{1-\alpha}(1-\tau^c)^{\alpha}\alpha\left(Z_{ji}^c\right)^{\alpha-1} = P_{ji}^c \text{ for } i \neq j \tag{7}$$

$$A\left(K_j^c\right)^{1-\alpha}(1-\tau^c)^{\alpha}\alpha\left(Z_{jj}^c\right)^{\alpha-1} = P_{jj}^c \text{ for } i = j \tag{8}$$

Since the mill price of an intermediate has to be the same whatever the buyer, we have $P_{ji}^c = P_{jj}^c$. Thus, by (7) and (8), the ratio of within-group to between-group shipments can be written as:

$$\frac{Z_{ji}^c}{Z_{jj}^c} = \frac{K_i^c}{K_j^c} \tag{9}$$

This result can be used to substitute for Z_{ji}^c in the resource constraint for group j's specific resource:

$$\sum_{i=1}^{M} Z_{ji}^c = L_j^c \tag{10}$$

which can then be solved for within-group shipments:

$$Z_{jj}^c = L_j^c \frac{K_j^c}{K^c} \tag{11}$$

where $K^c = \sum_{i=1}^{M} K_i^c$ is the total capital stock in the city. By (9), the associated between-groups shipments are then:

$$Z_{ji}^c = L_j^c \frac{K_i^c}{K^c} \tag{12}$$

Recalling that $X_{ji}^c = (1-\tau^c)Z_{ji}^c$ and plugging (11) as well as (12) into (6) yields the group i's final

output:

$$Y_i^c = K_i^c A(1-\tau^c)\alpha \left(K^c\right)^{-\alpha} \sum_{j=1}^{M} \left(L_j^c\right)^{\alpha} \tag{13}$$

By summing up across all groups, we get the total output of the city $Y^c = \sum_{j=1}^{M} Y_j^c$:

$$Y^c = A(1-\tau^c)^{\alpha} \left(K^c\right)^{1-\alpha} \sum_{j=1}^{M} \left(L_j^c\right)^{\alpha}$$

Profit maximization then implies that the average wage in city c equals:

$$\overline{w}^c = A^{\frac{1}{\alpha}}(1-\tau^c)\alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}} r^{-\frac{1-\alpha}{\alpha}} \left[\sum_{j=1}^{M} \left(\lambda_j^c\right)^{\alpha}\right]^{\frac{1}{\alpha}} \tag{14}$$

where $\overline{w}_c \equiv \sum_{j=1}^{S} w_{jc}\lambda_{jc}$ and $\lambda_j \equiv L_j^c / \sum_{j=1}^{M} L_j^c$ is the share of citizens belonging to group j. Equation (14) can be taken in logarithm to yield:

$$\ln \overline{w}^c = \text{constant} + \ln(1-\tau^c) + \frac{1}{\alpha} \ln \sum_{j=1}^{M} \left(\lambda_j^c\right)^{\alpha} \tag{15}$$

This is our estimating equation, which implies that, due to love of variety in final production, the wage should be higher in cities that, ceteris paribus, have: (i) a more balanced distribution across groups; (ii) lower costs of interaction.

Note that $\sum_{j=1}^{M} \left(\lambda_j^c\right)^{\alpha}$ is the theoretical measure of diversity underpinning the use of (1) as explanatory variable. As pointed out by Ottaviano and Peri (2004) in the wake of Roback (1982), the sign of its estimated coefficient in single-equation regressions such as (15) should be interpreted with great care. The reason is that a positive coefficient is compatible with two very different stories. On the one hand, it could reflect a positive impact of diversity on productivity: workers are more productive in multi-cultural environments. On the other hand, it could reflect a negative impact of diversity on utility: workers dislike multi-cultural environments, so they ask for monetary compensation if they have to cope. Nonetheless, Figure 1 and 2 make us favor the first story. The reason is that the variations in the ACCRA cost of living across cities are essentially driven by the price differentials of non-trade goods, most notably land rents. Figure 1 shows that nominal wages are higher in more diverse cities. Figure 2 shows that the costs of living are equally higher in more diverse cities. Higher wages and higher prices of non-tradables are compatible with a positive correlation between diversity and productivity but incompatible with a negative correlation between diversity and utility: nobody would ever pay more in order to reside in a place she happens to dislike. Hence, when estimating various versions of (15), we will interpret the eventual finding of positive and significant coefficients

for our diversity measures as evidence of positive association between diversity and urban productivity.

4 Effects of Diversity in US Cities

We now turn to the estimation of the effects of diversity on cities' average wages using panel regression techniques. In so doing, we will address several econometric issues. In particular, we will check that our results are robust to potential omitted variable bias as well as to potential endogeneity bias. Finally we will qualify and compare our findings with reference to the existing literature.

4.1 Basic Regressions

Our basic regression analyzes the impact of diversity on the average wage using a panel of the 160 SMSAs in three census years (1970, 1980 and 1990). We control for 160 city fixed effects, α_c, and for year dummies, β_t. Therefore, we identify the effect of diversity on productivity by exploiting only the within-city variation over time. In each specification we also control for the average level of schooling of workers, the share of White, and the share of college-educated workers in the city. Based on the theoretical model presented in section 3, our basic estimating equation is:

$$\begin{aligned} \ln(\overline{w}_{c,t}) &= \alpha_c + \beta_t + \gamma_1 (\overline{s}_{c,t}) + \gamma_2 (white_{c,t}) + \gamma_3 (college_{c,t}) \\ &\quad + \gamma_4 (Lang\_diversity_{c,t}) \end{aligned} \tag{16}$$

where, on the left hand side, the dependent variable $\ln(\overline{w}_{c,t})$ is the log of the average hourly wage of white US born males between 40 and 50 years of age (see Section 2.1 for details). On the right hand side, $\overline{s}_{c,t}$ is average schooling of white US born males 40 to 50 years old in city c in year t, $white_{c,t}$ and $college_{c,t}$ are the share of white workers and the share of college-educated workers in the city, $Lang\_diversity_{c,t}$ is the index of linguistic diversity measured as either (1) or (2). The city fixed effects control for permanent differences across cities (such as size, location, proximity to the coast and to the US borders), while the time effects control for common national trends. The average years of schooling, $\overline{s}_{c,t}$, control for returns to human capital while the shares of white and college-educated workers control for composition characteristics of the city.

We estimate few variations of equation (16). The results are reported in Table 3. Columns I to III report the results obtaining by using the diversity index $divLang_{ct}$ as the measure of linguistic diversity; Column IV to VI report the results of otherwise identical specifications that uses the fractionalization index

$frac(Lang_{c,t})$ instead. Our very first specification (Column I) shows the estimates from a pooled OLS regression without city fixed effects. This specification simply shows that, even after controlling for average schooling, for the share of white workers, and for the share of college graduates, the average wage levels of white US-born workers are still positively correlated with linguistic diversity across cities. The coefficient is both significant and large. As the standard deviation of the linguistic diversity index is 0.30, the estimated coefficient implies that two cities with a difference of one standard deviation in their linguistic diversity have a 15 per cent difference in their average wages. Controlling for city fixed effects, in Column II, and for city-size, as captured by log(employment), in Column III, does not change much the estimated coefficient, which remains close to 0.4. Similarly, using the linguistic fractionalization index as measure of linguistic diversity, we still get a positive and significant coefficient. As the standard deviation of $frac(Lang_{c,t})$ in the sample is about 0.20, the quantitative effect of increasing fractionalization by one standard deviation is also a 15-to-20 per cent increase in the average wage of our reference group. The other variables included have the expected impacts. Returns to schooling are estimated around 6 per cent and the share of white population has a positive and significant effect. Nevertheless, once we control for average schooling, the share of college-graduates does not have any significant effect on the average wage.

4.2 Other forms of Diversity

The regressions in Table 4 test the robustness of the effect of linguistic diversity when other measures of diversity are introduced. Cultural diversity may simply be a proxy of skill diversity, or may be correlated with diversity of races so that the correlation found above may be the result of an omitted variable.

To test that linguistic diversity has a direct correlation to average wages, we control for fractionalization along the dimensions of skills, state of birth, and race. Columns I and IV include a fractionalization index calculated on four skill groups identified in terms of schooling achievements. The groups are high school dropouts, high school graduates, college dropouts and college graduates. While skill diversity seem to have a negative impact on the wage, the impact of linguistic diversity is still positive and significant. The negative impact of skills dispersion after controlling for average schooling can be interpreted as a sign of decreasing returns to skills: it is better to have workers at the mean level of skills than dispersed skill levels around it.

Columns II and V add a measure of fractionalization based on the state of birth of urban workers. If the benefit to productivity simply came from having workers from different origins, or if it were caused by a reverse connection between high productivity and immigration in the city from other states, the coefficient of state-of-birth fractionalization should be positive. However, it turns out to be insignificant and very small.

Finally, we add an index of racial fractionalization in Columns III and VI.[1] This index is introduced

[1]The index is constructed including the following 'ethnic groups': White, Black, Native American, Japanese, Chinese,

mainly to check whether cities actually benefit from cultural diversity per se rather than from some sort of generic 'tolerance' for diversity. This last hypothesis is advanced in a series of paper by Florida 2002 (a,b) and focuses on cultural tolerance as a catalyst for innovation and creativity. While linguistic diversity is still significant after including racial diversity, this last variable has itself a positive impact on the wage. Recall, however, that we are controlling for the share of white people, so higher diversity essentially means a smaller black community relative to the other minorities. Therefore, the positive effect of racial diversity may be simply capturing the negative effect of a larger share of black citizens. For our purposes, however, what matters is that the effect of linguistic diversity remains significant and positive also after adding this control.

4.3 Robustness Checks

Table 5 presents several robustness check of our previous results. The table includes only the estimated coefficients on linguistic diversity in several possible specifications. To ease comparison, specification (1) reports the coefficient estimate on diversity in the basic regression. Specification (2) uses total income per capita, rather than wages, as dependent variable. The reason is that our theoretical model implies that the aggregate output of a city Y^c, and not only its average wage, should positively depend on diversity. Using personal income, the impact of diversity, while somewhat smaller, is still positive and significant. This could be due to the fact that personal income is a noisier measure of local economic conditions as it also includes capital income possibly earned from investment anywhere in the country.

Specification (3) considers a larger definition of cultural identity obtained by grouping the languages associated with similar cultures. This generates the following classification: Neo-Latin, Slavic, Anglo-Saxon, South-Asian, East-Asian, African, and Native languages. The objective is to capture the fact that, say, Spanish and Chinese are two cultures that are more different than Spanish and Italian. Thus, diversity between the former pair may bring higher benefits from diversity as well as higher communication costs. The estimated coefficient for linguistic diversity measured using the above large groups is both positive and highly significant. The exact value (0.53) is somewhat higher than the one in the basic specification: diversity across large groups seem to matter more.

Specification (4) controls for a 'weaker' form of cultural belonging, that is, the ancestry of individuals. People may have different relevant characteristics not only because they are from different countries but also because their ancestors and traditions are. Including the ancestry control does not change the impact of linguistic diversity. Moreover, the ancestral diversity coefficient (not reported) is not significant. Specification (5) simply controls for city population rather than employment as a better measure of density. No relevant

Filipino, Hawaiian, Korean, Others.

differences arise.

The last Specification (6) in Table 5 addresses the issue of the potential endogeneity of linguistic diversity: richer linguistic diversity may be the consequence rather than the cause of higher average wage. Indeed, fast growing cities may attract more people from outside, among them more foreign-born, so they end up with larger linguistic diversity. Short of a randomized experiment, it is hard to rule out this channel completely. One way to reduce the endogeneity bias is to resort to instrumental variable estimation. Specifically, we consider growth in wages as our dependent variable and growth in linguistic diversity as our key explanatory variable. Then we instrument the latter using the distance of each city from the international borders, from the coast, as well as from New York and Los Angeles as the main ports of entry into the US. The underlying idea is that, during the period from 1970 to 1990, the US have experienced a large increase in immigrants for reasons that are exogenous to any particular city characteristics. Just for a geographic accident, cities closer to the coast, the border or the main ports of entries have received a larger inflow of those immigrants. Presumably, these distances have no direct impact on productivity. Being exogenous to the productivity shocks of the period of observation, they can be used as instrumental variables. The full set of instruments explains about 20 per cent of the variation in linguistic diversity. Specification (6) shows that the positive correlation between linguistic diversity and wages survives the IV procedure.

To sum up, the positive correlation between wages and diversity across US cities survives a whole battery of robustness checks. Instrumental variable estimation support the view that the direction of causation goes from diversity to wages. The theoretical model allows us to describe such effect as cultural diversity boosting productivity.

5 Public Goods and Recent Immigrants

The last two subsections of this empirical analysis are devoted to clarifying and qualifying our previous results. In particular, we begin by reconciling our findings of a positive effect of linguistic diversity on productivity with previous studies that found a negative association of ethnic diversity with other measures of economic performance such as the provision of public goods. We then show that our findings are not incompatible with studies that identify a small negative impact of new immigrants on the wages of natives.

5.1 Public Goods

A recently developed strand of research analyzes the effect of racial heterogeneity on local policies, particularly policies that involve redistribution (see, e.g., Alesina and La Ferrara, 2003, for a survey). The idea is that communities with a higher degree of ethnic 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 benefit to the other ethnic groups. Such problem materializes in the underprovision of public goods because individuals do not pay the marginal cost of a service. In the case of well defined markets, where people pay the marginal cost of the service they use, there is no harm 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, Baqir, and Easterly, 1999; Alesina, Baqir, and Hoxby, 2004).

Table 6 considers whether the racial diversity of a city reduces its per capita spending for local public services after we controlling for the local level of income, the local level of education, and the city size. Again, we consider a panel estimation with city and time fixed-effects. Column I shows the impacts of linguistic and racial diversities on local spending per capita. Consistently with the existing literature, racial diversity has a negative impact. Linguistic diversity, however, has no impact whatsoever. Column II and III report the impacts of diversity on the provision of local public goods. In particular, they show that racial diversity decreases the expenditures in public education, thus confirming the findings of Alesina, Baqir, and Easterly (1999). Racial diversity also increases the expenditures in police and security, which supports the idea that ethnic diversity may generate social unrest and more need for policing. As to linguistic diversity, its effect on both variables is not significant. Thus, linguistic diversity seems to maintain its overall positive productive impact with no discernible effect on public good provision.

5.2 Recent Immigrants

Our study reveals a positive effect of linguistic diversity on the average wage at the city level. However, existing studies on immigration to the US find a moderate negative effect of inflows of immigrants on the wages of the natives (Borjas, 1994 and 1995). Such studies mostly concentrate on low-skilled wages, whereas we consider the average wage of US born workers. Nevertheless, our positive effect may seem at odds with this literature.

Those apparently conflicting findings can be reconciled. Our definition of linguistic diversity is based on the language people speak at home. That may comprise not only new immigrants but also long-time foreign-born residents and second generation immigrants as long as linguistic identity is maintained (which is quite common for some groups). Under this respect, our theoretical model can be used to explain the different 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. This implies that the costs of interaction (τ) between the groups of city dwellers may depend on the arrival time of the different cohorts of immigrants. Accordingly, in each city the gradual assimilation of old cohorts and the arrival of new ones change its τ through time, which is not captured by the city fixed effects. If such an 'assimilation effect' were relevant, we should observe a negative impact of the share of new immigrants in a city on its average wage, while linguistic diversity (due to both first and older generation of immigrants) should maintain its positive impact.

In each year we define as 'new immigrants' the foreign-born immigrated into the US within the previous five years, the reason being that the census PUMS 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 control. The corresponding results are reported in Table7. Column I shows the OLS estimates in differences (1970-1990) whereas Columns II and III report the instrumental variable estimates. As in the previous section, our instruments are the distances to the border, to the coast, and to N.Y. and L.A.. We use them as proxies of the changes in both new immigrants and linguistic diversity. Since we consider a twenty-year interval, the changes in linguistic diversity not controlled for by the changes in new immigrants are due to the changes in the number of 'old immigrants' (i.e. those who have entered the US for more than five years earlier). While linguistic diversity has still a significant and positive effect on wages, the share of new immigrants has an insignificant (almost significant in one instrumental variable estimation) negative effect on wages. Overall, our findings support the 'assimilation effect' hypothesis. Cities may face some initial costs in coping with cultural diversity: the effect of new immigrants on local wages is small and possibly slightly negative. However, once the initial costs of assimilation are incurred, the benefits of diversity for productivity materialize.

6 Conclusions

We have investigated whether immigrants into the US contribute to the economic prosperity of their host cities through the cultural diversity they bring. In particular, we have studied the effect of cultural diversity on the wages of the native population. We started with no obvious a priori. 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, heterogenous preferences may trigger social conflicts on the provision of public goods.

By studying 160 US SMAs in the period 1970-1990, we have found a significant and robust positive

correlation between cultural diversity increases and the wages of white US-born workers. By comparing the distributions of wages and costs of living across US cities, we have argued that such 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. To the best of our knowledge, these results are new.

We have finally qualified our findings under two respects. First, our data agree with previous studies in that ethnic diversity is found to be bad for the provision of local public goods as more diverse societies are less willing to pool resources for collective purposes. Second, 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) are larger than those from new immigrants. This suggests that integration and assimilation may be prerequisites for reaping the gains of cultural diversity.

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7

Data Appendix

The data on ethnic and linguistic composition of Cities have been obtained from the 1970-1990 Public Use Microdata Sample of the US Census. We selected all people in working age (16-65) in each year and we identified the city where they lived using the SMSA code for 1980 and 1990, while in 1970 we used the county group code to identify the metropolitan area. We used the variable "Language Spoken in the Home" in order to identify the linguistic identity of the person. We construct groups that can be kept homogenous 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, Other languages. Once we have grouped people in racial we use the shares of each group within a city in our sample as 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, 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, Ukrainian.

We use the Variable "Salary and Wage" to measure the yearly wage income and we divide that by the number of weeks worked in a year and then by the number of hours worker in a week in order to obtain the hourly wage. We transform the wage in real terms by deflating it for 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.

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, MI
Albuquerque, NM	Des Moines, IA	Little Rock-North Little Rock, AR	St. Louis, MO-IL
Allentown-Bethlehem-Easton, PA	Detroit, MI	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, WI	Erie, PA	Macon, GA	San Antonio, TX
Atlanta, GA	Eugene-Springfield, OR	Madison, WI	San Diego, CA
Atlantic-Cape May, NJ	Fayetteville, NC	Mansfield, OH	San Francisco, CA
Augusta-Aiken, GA-SC	Flint, MI	Memphis, TN-AR-MS	San Jose, CA
Austin-San Marcos, TX	Fort Lauderdale, FL	Miami, FL	Santa Barbara-Santa Maria-Lompoc, CA
Bakersfield, CA	Fort Wayne, IN	Milwaukee-Waukesha, WI	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, MI	Montgomery, AL	Spokane, WA
Biloxi-Gulfport-Pascagoula, MS	Green Bay, WI	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, MI	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
Chicago, IL	Johnstown, PA	Phoenix-Mesa, AZ	Vallejo-Fairfield-Napa, CA
Cincinnati, OH-KY-IN	Kalamazoo-Battle Creek, MI	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, WI	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, MI	Roanoke, VA	York, PA
Davenport-Moline-Rock Island, IA-IL	Las Vegas, NV-AZ	Rochester, NY	Youngstown-Warren, OH

Tables and Figures

Table 1
Main Linguistic Shares in 160 U.S. Metropolitan areas

language shares	Average 1970	Std. Deviation 1970	Average 1990	Std. Deviation 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

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

Table 3
Basic Panel Estimation

Specification	**I Pooled OLS**	**II Fixed Effects**	**III Fixed Effects**	**IV Pooled OLS**	**V Fixed Effects**	**VI Fixed Effects**
Index of Linguistic Diversity Used	**Div(Lang$_{c,t}$)**			**FracLang$_{c,t}$**		
Average Schooling	0.06* (0.01)	0.06* (0.01)	0.06* (0.01)	0.07* (0.01)	0.06* (0.01)	0.06* (0.01)
Share of White	0.36* (0.06)	0.49* (0.20)	0.57* (0.20)	0.30* (0.06)	0.57* (0.20)	0.52* (0.20)
Share of College	0.28 (0.27)	0.14 (0.20)	0.14 (0.20)	0.25 (0.20)	0.10 (0.20)	0.05 (0.20)
Linguistic Diversity	0.54* (0.04)	0.38* (0.10)	0.36* (0.10)	0.74* (0.11)	1.00* (0.17)	0.95* (0.17)
ln(Employment)			0.06 (0.04)			0.04 (0.03)
City Effects	No	Yes	Yes	No	Yes	Yes
R^2	0.97	0.99	0.99	0.97	0.99	0.99
Observations	480	480	480	480	480	480

Dependent Variable: natural logarithm of average hourly wage of white males 40-50 years in 1990 U.S. $.
All Regressions include time dummies, in parenthesis Heteroskedasticity-Robust Standard Errors
*significant at 5%

Specification I: Basic Specification, Method of Estimation, Pooled OLS, including fixed time effects. Diversity Index used: DivLang = $\sum_j (l_c^j)_t^{0.66}$

Specification II: Basic Specification, Method of Estimation, Panel estimation with Fixed Effects, including fixed time effects. Diversity Index used: DivLang = $\sum_j (l_c^j)_t^{0.66}$

Specification III: Basic Specification, Method of Estimation, Panel estimation with Fixed Effects, including fixed time effects and ln(Employment) as controls. Diversity Index used: DivLang = $\sum_j (l_c^j)_t^{0.66}$

Specification IV: Basic Specification, Method of Estimation, Pooled OLS, including fixed time effects. Diversity Index used: FracLang = $1-\sum_j (l_c^j)_t^{2}$

Specification V: Basic Specification, Method of Estimation, Panel estimation with Fixed Effects, including fixed time effects. Diversity Index used: FracLang = $1-\sum_j (l_c^j)_t^{2}$

Specification VI: Basic Specification, Method of Estimation, Panel estimation with Fixed Effects, including fixed time effects and ln(Employment) as controls. Diversity Index used FracLang = $1-\sum_j (l_c^j)_t^{2}$

Table 4
Adding Measures of "Diversity" as Controls

Specification	**I**	**II**	**III**	**IV**	**V**	**VI**
Index of Linguistic Diversity Used	**Div(Lang$_{c,t}$)**			**FracLang$_{c,t}$**		
Average Schooling	0.06* (0.01)	0.06* (0.01)	0.06* (0.01)	0.06* (0.01)	0.06* (0.01)	0.06* (0.01)
Share of White	0.63* (0.31)	0.63* (0.31)	0.56* (0.19)	0.63* (0.31)	0.63* (0.31)	0.32 (0.33)
Share of College	0.49 (0.34)	0.49 (0.34)	0.77* (0.33)	0.49 (0.34)	0.49 (0.34)	0.59 (0.32)
Linguistic Diversity	0.33* (0.10)	0.34* (0.10)	0.49* (0.11)	0.94* (0.18)	0.94* (0.18)	0.95* (0.18)
Skills Fractionalization	-0.71 (0.38)	-0.72 (0.38)	-1.11* (0.38)	-0.83* (0.36)	-0.84* (0.33)	-0.90* (0.37)
State of Birth Fractionalization		-0.005 (0.01)	-0.004 (0.01)		-0.003 (0.01)	-0.002 (0.01)
Racial Fractionalization			0.50* (0.13)			0.26* (0.12)
ln(Employment)	0.06 (0.04)	0.07 (0.04)	0.03 (0.04)	0.06 (0.04)	0.06 (0.04)	0.03 (0.04)
City Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.99	0.99	0.99	0.99	0.99	0.99
Observations	480	480	480	480	480	480

Dependent Variable: natural logarithm of average hourly wage of white males 40-50 years in 1990 U.S. $.
All Regressions include time dummies, in parenthesis Heteroskedasticity-Robust Standard Errors
*significant at 5%

Specification I: Method of Estimation, Pooled OLS, including fixed time effects and fractionalization index for education groups. We use four education groups (High School Dropout, High School Graduates, College Dropouts and College Graduates) as skill groups.

Specification II: Method of Estimation, Pooled OLS, including fixed time effects and fractionalization index for education groups and State of birth. We use the fifty state of births as groups.

Specification III: Method of Estimation, Pooled OLS, including fixed time effects and fractionalization index for education groups, State of birth and Race. We use white, black, native American, Japanese, Chinese, Filipino, Hawaiian, Korean, others as racial groups.

Specification IV : As specification I, using FracLang $= 1 - \sum_j (l_c^j)_t^2$ as index of linguistic diversity

Specification V: As specification II, using FracLang $= 1 - \sum_j (l_c^j)_t^2$ as index of linguistic diversity

Specification VI: As specification III, using FracLang $= 1 - \sum_j (l_c^j)_t^2$ as index of linguistic diversity

Table 5
Robustness Checks

Specification	**Coefficient of Linguistic Diversity: Div($Lang_{c,t}$)**
(1) Basic	0.36* (0.10)
(2) Personal Income as Dependent Variable	0.28* (0.06)
(3) Large Linguistic Groups	0.53* (0.14)
(4) Controlling for Ancestry Diversity (1970 dropped)	0.50* (0.22)
(5) Controlling for Population	0.37* (0.10)
(6) Instrumental Variables Estimation IV: Distance from Ports of Entry	0.50* (0.11)

All Regressions include time dummies, city fixed effects average schooling, share of whites, share of college graduates and ln(Employment) as controls. Dependent Variable : ln average hourly wage of white males 40-50 years in 1990 U.S. $.
Reported is the coefficient on the Diversity index Div(Lang). In parenthesis Heteroskedasticity-Robust Standard Errors
* significant at 5%.

(1) Basic Regression, as in Column III of Table 3
(2) Using ln(personal income) in 1990 US $ as dependent variable rather than ln(wage)
(3) Grouping linguistic groups into larger "cultural groups" based on the proximity of the countries of origin of the language. Groups are listed in the Appendix
(4) Including the diversity of origin of ancestors (parents). This variable is available for 1980 and 1990 only
(5) Including ln(Population) as a control, rather than ln(Employment).
(6) Using instrumental variable for linguistic diversity. The instruments used are distance from the coast, distance from the border and distance from New York and Los Angeles, the largest port of entries in the U.S. In the first stage regression (not reported) the IV explain 20% of the variance of linguistic diversity

Table 6
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**
Ln(Income)	0.44* (0.06)	0.56* (0.12)	0.57* (0.13
Linguistic Diversity	0.14 (0.10)	-0.04 (0.09)	0.01 (0.11)
Racial Diversity	-0.22* (0.11)	-0.19* (0.10)	0.34* (0.14)
Ln(Employment)	0.10* (0.04)	-0.16* (0.05)	-0.21* (0.05)
City Effects	Yes	Yes	Yes
R^2	0.98	0.97	0.98
Observations	480	480	480

Dependent Variable: natural logarithm of real public spending per capita of local administration in 1990 U.S. $. Regressions include time dummies and city fixed effects
** significant at 5%, * significant at 10%

Specification I: Dependent Variable is natural logarithm of real total public spending per capita of local administration in 1990 U.S. $. Method of estimation is OLS.

Specification II: Dependent Variable is natural logarithm of real public spending per capita of local administration for School and Education in 1990 U.S. $. Method of estimation is OLS.

Specification III: Dependent Variable is natural logarithm of real public spending per capita of local administration for Police and Security in 1990 U.S. $. Method of estimation is OLS.

Table 7
Cultural Diversity and New Immigrants

Specification	**I** **OLS on 70-90 differences**	**II** **Instrumental Variables Estimation (a)**	**III** **Instrumental Variables Estimation (b)**
Average Schooling	0.05* (0.01)	0.05* (0.01)	0.05* (0.02)
Linguistic Diversity Div(Lang)	0.15* (0.04)	0.33* (0.12)	0.57* (0.13)
Share of New Immigrants (5 years)	-0.25 (0.52)	-0.31 (1.02)	-2.03 (1.10)
Ln(Employment)	0.04* (0.02)	0.01 (0.02)	0.01 (0.02)
R^2	0.15	0.10	0.11
Observations	160	160	160

Dependent Variable: natural logarithm of average hourly wage of white males 40-50 years in 1990 U.S. $.

All Regressions include time dummies, in parenthesis Heteroskedasticity-Robust Standard Errors

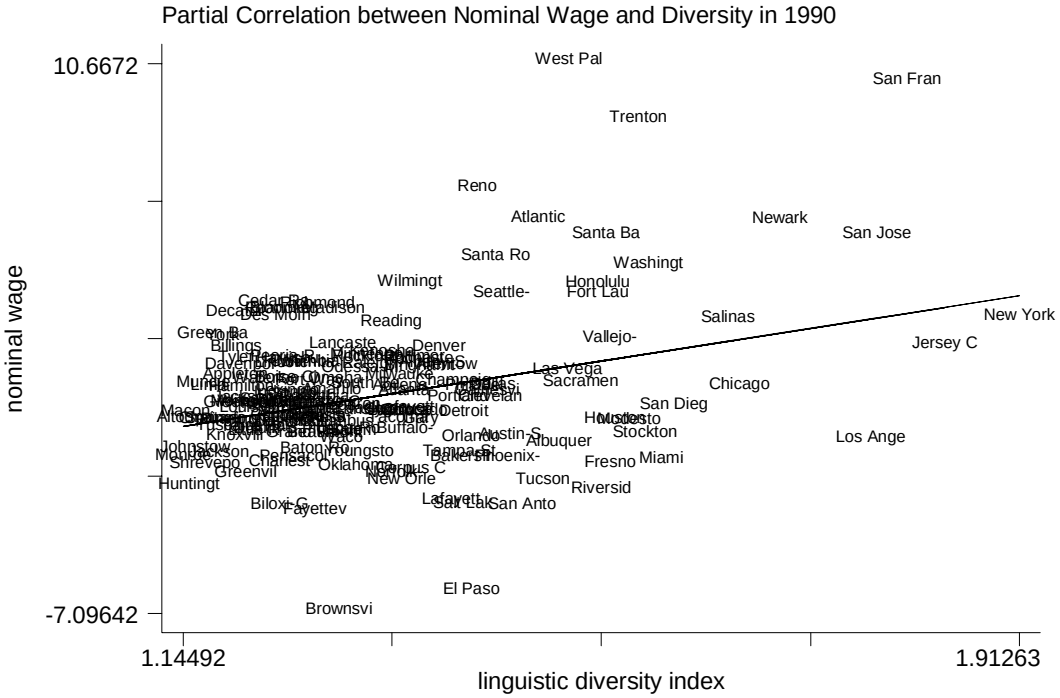
*significant at 5%

Specification I: OLS estimates on differenced variables 1970-1990. Differencing eliminates the fixed level effect and the coefficients are identified on 160 changes.

Specification II: Instrumental Variables estimation on differenced variables 1970-1990.Endogenous Variables are Div(Lang) and Share of New Immigrants Instruments are: Distance from Coast, Distance from Border, Distance from Los Angeles and Distance from New York. They explain 18% of the variation of Linguistic diversity and 16% of the variation of share of new immigrants.

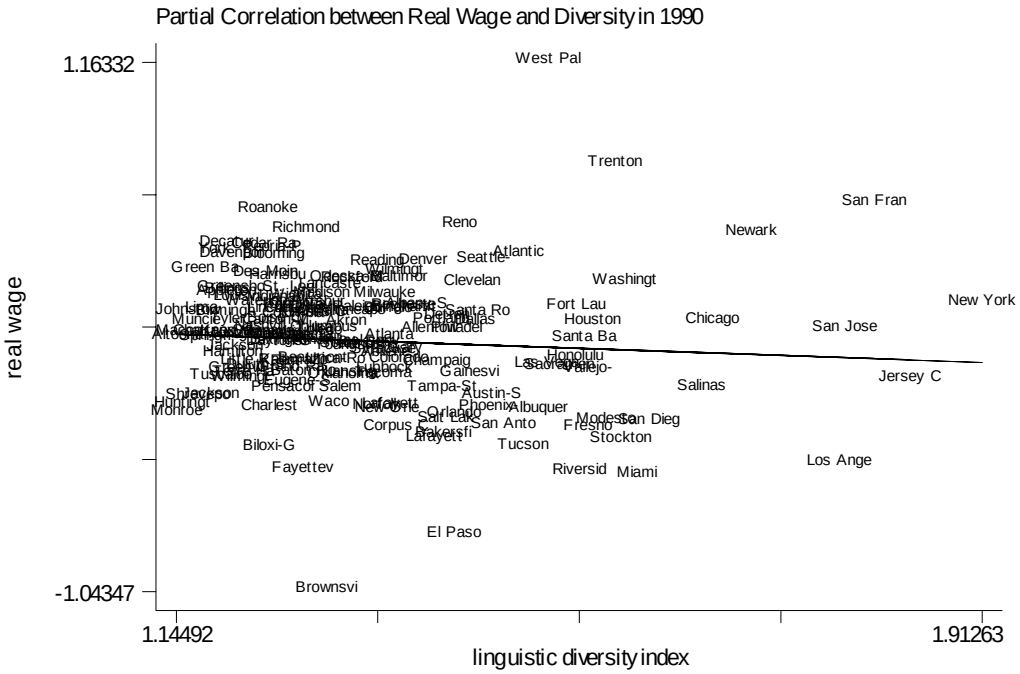
Specification III: Instrumental Variables estimation on differenced variables 1970-1990.Endogenous Variables are Div(Lang) and Share of New Immigrants Instruments are: Distance from Coast, Distance from Border. They explain 16% of the variation of Linguistic diversity and 10% of the variation of share of new immigrants.

Figure 1 – Nominal Wages and Diversity in US Cities, 1990



slope: 5.5 (s.e. 1.2) t-stat= 4.4

Figure 2 – Real Wages and Diversity in US Cities, 1990



slope: -1.15 (s.e. 1.14) t-stat= -1.04