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Original Article

The 'Paradox of Diversity': Economic Evidence from US Cities 1980–2010

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Abstract

We evaluate the economic significance of linguistic barriers to communication in 226 US cities from 1980 to 2010. We address the question: to what extent do linguistic barriers across social groups inhibit the benefits of knowledge exchange? The empirical results show that linguistic, racial and composite diversity increase *the average income of working age population in American cities. This positive effect of diversity, however, diminishes the higher is the proportion of foreign-born population who lack English fluency. We call this the 'paradox of diversity'. Overall, our findings provide important policy insights about how social diversity may enhance economic performance within cities.*

Key words: diversity, economic performance, wages, cities, immigrants
JEL Classification: C33, C36, J61, R11

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1. Introduction

In a seminal paper, Lucas (1988) emphasized the role of cities as engines of economic growth and built on earlier insights of Marshall and others. Lucas acknowledged his debt to Jacobs (1970) who had earlier observed that city regions generate their own growth by facilitating trade and innovation across diverse agents. Jacobs (1984), in particular, observed '… cities are unique in their abilities to shape and reshape the economics of other settlements, including those far removed from them geographically.'

In this article, we empirically investigate the role of diversity and the economic performance of cities and then respond to the possible policy implications. Our data is for a single country, the United States. Nevertheless, our analysis offers insights to city regions such as Sydney and Melbourne in Australia; Manchester and London in the United Kingdom; and other nations whether there is a plethora of social and economic diversities. Our analysis focuses on the economic effect of social diversity as measured by the effect of diversity on the average income of the working age population. In particular, we test whether *linguistic barriers to communication* (*LBC*) have a statistically significant impact on the economic performance of American cities.

Large American cities like New York, Los Angeles or Miami are highly diverse in terms of demographic characteristics, skill compositions and the abilities of their inhabitants. We argue that social diversities within such cities are economically productive, but paradoxically, they also have the potential to retard the process of knowledge exchanges across different social groups due to barriers in communication. Here, we define the percentage of foreign-born population who are not fluent in English as a barrier to communication and test the hypothesis that it reduces the positive economic outcome of social diversity. Our findings are of interest to researchers and policy-makers because these effects of diversity are not fully recognized either in the literature, or in practice, in terms of public policy.

We use a panel dataset for US cities and find that linguistic diversity enhances average income, but barriers to communication offset the positive effects of linguistic diversity. If this were to be the case, this would be a paradox of diversity such that although diversity supports improved economic performance in cities, greater diversity in terms of lack of fluency in English diminishes these benefits. In other words, if social diversity contributes to the economic performance of cities this may be conditional on the ability of people to exchange ideas and knowledge with a common language. A possible explanation for such a finding could be that tacit knowledge (Polanyi 1967), and the transmission of 'know-how', depends substantially on face-to-face communication and where a common language is critically important. Thus, where people are unable to communicate in a mutually comprehensible language, much of the benefits from the exchange of different ideas and experiences are likely to be moderated.

In Section 2, we briefly review key parts of the relevant literature. Section 3 describes the data and variables and outlines the econometric model we employ. Section 4 analyses the ordinary least squares (OLS) results and the findings from our instrumental variables estimation (IVE), while in Section 5, we offer concluding remarks.

2. Economics of Social Diversity: A Review

In this section, we provide a link between two strands of literature on the economic impacts of diversity. First, we draw from cross-country studies (and in some cases, studies across other geographical areas) that identify fractionalization indexes as causal factors for differences in economic performance. Second, we review studies that link social diversity to economic outcomes in regional and/or urban areas within a country.

2.1. Diversity and Economic Performance

One of the first studies to identify the negative economic impacts of ethno-lingual fractionalization was research by Easterly and Levine (1997). They argued that a higher level of ethno-lingual fractionalization, which is a measure of social diversity, leads to conflicts of preferences, and also sub-optimal decision-making. As a consequence, this results in a lower level of economic growth. Easterly and Levine further find that 'a movement from complete heterogeneity to complete homogeneity is associated with a productivity increase of 2.5 times and an increase in capital per worker of 9.2 times'. Subsequently, Alesina et al. (2003) developed an alternative set of fractionalization measures that provided support for the earlier findings of Easterly and Levine, namely, that a higher level of social fragmentation reduces long-term economic growth.

Based on the similar rationalization of conflicting preferences over resource allocation, Alesina et al. (1999) showed that US metropolitan areas and counties with higher social fragmentation allocate less on 'productive public goods' such as education or infrastructure. This finding is of particular interest to us because Collier (2000) argued that the optimal allocation of resources is intricately linked with the political environment of a country. This, in turn, determines whether social diversity has a positive or negative impact on aggregate economic indicators. Consequently, according to Collier (2000), social diversity is detrimental for economic growth in societies that lack political rights such as in dictatorships.

Alesina and La Ferrara (2005) evaluated the effect of social diversity on economic growth across countries, and examined the economic outcome of diversity. Given the positive and statistically significant coefficient of the interaction variable between fractionalization and income per capita, they concluded that the productivity enhancing effect of diversity might only be realized at higher stages of economic growth.

Grafton et al. (2004) and Grafton et al. (2007) outlined two contrasting economic impacts of diversity by focusing on social barriers to communication. They argued that the positive effect of diversity is reduced due to a lack of inter-group communication and that such interaction is essential for knowledge spill over and productivity growth. Their empirical estimations for 110 countries provided cross-country evidence that higher linguistic fractionalization reduced Total Factor Productivity (TFP) growth.

Unlike the work of Alesina and La Ferrara (2005), Grafton et al. (2004, 2007), and others, which were based on cross-country comparisons, we evaluate the economic impact of social diversities and the consequent barriers to communication across cities or metropolitan areas in the United States, proxied by percentage of population who are not fluent in English. Given that city-level US data allows us to control for a range of institutional factors that would, typically, differ across countries we contend that our analyses provide a better test for the effect of social diversity on economic performance. The closest analysis to our work here is Ratna et al. (2012) that used state/province level data, but not at a city level, from the United States and Canada to evaluate the effects of diversity on state per capita gross domestic product. In their study, they found that the economic payoff from diversity diminishes as the level of fluency in the official language diminishes.

2.2. Diversity, Human Capital and Regional Growth

Unlike the mixed economic consequences of diversity at an aggregate or national level, the link between urban agglomeration and diversity is frequently viewed as overwhelmingly positive. Beginning with Alfred Marshall (1920) the economics literature has stressed that labour market externalities generated by localization and cities are a result of skill concentrations and employment diversity. Subsequent literature on economic geography has focused on human capital externalities in urban growth centres created via complementarity in skills, knowledge sets and abilities (Glaeser et al. 1992, Jacobs (1970) cited in Fu 2007).

In the urban economics literature, cities are considered diverse in terms of types of capital and demographic characteristics, irrespective of the stages of economic development of a country. Consequently, cities relative to towns, villages or rural areas provide greater opportunity for knowledge spillover and innovation that, in turn, can promote economic growth. Florida (2002) further extended the notion of knowledge spillovers by incorporating the role of creative capital. In this work, the 'creative class' is a combination of two groups of people, that is, 'professionals' such as doctors or academics, and 'bohemians' such as artists or musicians. Introducing a measurement termed the Bohemian index, this empirical analysis provided evidence that a high concentration of 'Bohemians' provide a positive synergy to the concentration of a high level of human capital and high technology industries.

Niebuhr (2010) evaluated the impact of cultural diversity on innovation for different regions in Germany. In her analysis, she used employment data instead of population data to measure three diversity indices: Herfindahl, Theil and Krugman index. Based on an extensive set of robustness checks, Neibuhr concluded that the productivity effect of cultural diversity outweighs the negative effect of transaction costs. She also showed that the number of patents per capita is higher for regions where R & D workers are more diverse. Cheng and Li (2012) tested whether an increase in social diversity leads to additional newly created business using US county level data for 10 sectors with a Theil index for cultural and racial diversity. Their estimated coefficients were statistically significant for broad service sectors such as professional and business services, education and health care, and leisure and hospitality. While the estimated coefficients to evaluate the indirect effects of social diversities to neighbouring counties are statistically significant for only manufacturing sector,[1] their study established the significance of the spatial dimensions of knowledge spillovers.

The closest analysis to our own in terms of the data employed is the work of Ottaviano and Peri (2005, 2006). They employed a panel dataset for the period 1970 to 1990 and concluded that US-born or native workers are more productive in cities that are more diverse. They defined cultural diversity as a linguistic fractionalization index and estimated its impact on wages and employment density (Ottaviano & Peri 2005) and rents (Ottaviano & Peri 2006) of US-born workers. Similar findings have also been reported by Manacorda et al. (2006) and D'Amuri et al. (2010) for Britain and Germany, respectively. Bellini et al. (2009) also adopted the same theoretical framework as Ottaviano and Peri (2006), and obtained a similar result using data from 12 countries[2] in the EU region. Notwithstanding this rich body of work, as far as we are aware, there has been no test for the paradox of diversity or the possibility that where people are unable to communicate in a mutually comprehensible language, the economic benefits from social exchange diminish.

2.3. Rationale for Our Investigation

The existing literature suggests that social diversity can be either positive or negative in terms of economic outcomes. Although studies have used different theoretical approaches, the cross-country empirical studies largely report negative economic consequences of social diversity while urban or city-focused studies within the United States (or a specific country or region) largely report positive economic outcomes. In this article we ask, what ways can social diversity contribute to economic performance at the city level? And, how might this be conditioned by low barriers to communication to support the exchange of tacit knowledge across diverse social groups?

To our knowledge, Ratna et al. (2012) is the only study that has attempted to analyze the paradox of diversity, but they used state-level for the United States and province-level data for Canada. We contend that in very diverse societies, such as Canada and the United States, the wide variation in measures of diversity across cities of the same state/province can fail to evaluate the economic impact of diversity because of the use of aggregate data. Further, cross-country results and comparisons (United States and Canada) where immigration policies and support for migrants differ markedly are difficult to interpret in terms of whether or not the potential economic benefits of social diversity are moderated by *LBC*.

Following Jacobs (1984), we employ cities or metropolitan areas as the unit of economic analysis. We make three contributions. First, we capture the linguistic barrier for inter-group communication at a city level and hypothesize and then test that, in the absence of a common language, multicultural or highly socially diverse cities are constrained by reduced social interactions among workers with different linguistic backgrounds. As a result, the knowledge exchange, especially of tacit knowledge, is less likely to happen or to occur less effectively, contributing to lower level of average wage for cities with higher linguistically isolated population. Our empirical analysis uses the average wage of working age population as an indicator of economic performance at the unit of analysis. We define the variable (*LBC*) as the percentage of foreign-born population who lack proficiency in English.

Our second contribution is that in testing for a paradox of diversity, we use the most recent and comprehensive datasets available. In particular, we include more cities than any other study using the US data at a city level for testing city-level effects on economic performance.

Third, we employ a new diversity measure, a *Composite Diversity Index (CDI),* to aggregate the effects of diversity in different aspects including language, birth country and race to a common index. To date, the literature has

1. The cultural diversity is statistically significant for the wholesale and retail sector, and racial diversity is statistically significant for fire and leisure and hospitality sector.
2. The countries included in the analysis are: Austria, Belgium, Denmark, France, former West Germany, Ireland, Italy, The Netherlands, Portugal, Spain, Sweden and the United Kingdom.

typically focused on one aspect among the many dimensions of diversity such as culture, ethnicity, race, country of birth, language or religion.

We use *CDI*, in addition to three single-measures of diversity, to test for the paradox of diversity. Although multiple single dimensional indexes can capture the complexity of multicultural societies, as we have performed in this study, a composite index can provide a useful comparison.

3. Data and Estimated Model

Ottaviano and Peri (2005) analyzed the impact of cultural diversity on labour productivity and aggregate employment levels of US-born workers for 160 Metropolitan Statistical Areas (MSAs), and included the most ethnically diverse cities in the United States. We add to this work by: (i) including the barrier to communication variable, *LBC,* to test for the paradox of diversity; (ii) utilizing an innovative set of instrumental variables to account for possible endogeneity in diversity fractionalizations; (iii) encompassing many more cities and by updating the data to include the 2010 census; and (iv) analyzing the impact of a composite measure of diversity, *CDI.*

Our estimated model is provided by equation (1):

$$\ln\left(\overline{w}_{c,t}\right) = \chi_c + \beta_t + \underline{\delta}_c\left(\underline{c}_{c,t}\right) + \underline{\alpha}_d\left(\underline{d}_{c,t}\right) + e_{c,t} \tag{1}$$

The explanatory variables include χ_c that represents city fixed effects (FE), $\underline{c}_{c,t}$is a vector of control variables such as educational attainment, experience and a set of demographic controls. The term $\underline{d}_{c,t}$ is a vector for diversity indexes including the variable *LBC*. Table A1, in the appendix, contains a brief definition of each of the variables used in the estimation.

Much of the city-level data, we use is sourced from the Integrated Public Use Micro-data Series (IPUMS) from Minnesota Population Centre, University of Minnesota for 226 Metropolitan Statistical Areas (listed in Table A4 in the appendix), identified in all four census years including 1980, 1990, 2000 and 2010. The dependent variable in (1) is the average wage of the working age population (age 16–64), and is treated as a proxy for economic performance. It is calculated as the total of individual 'pre-tax wage and salary income, money received as an employee for the previous years', coined as *INCWAGE* in IPUMS-USA dataset. This wage measure includes other sources of income, that is sources of 'salaries commissions, cash bonuses, tips, and other money income'. Although IPUMS-USA also reports data on other income variables, we limit our analysis to *INCWAGE* because of the availability of the data for this variable.[3]

Social diversity is multi-faceted and is difficult to define because of the challenges in identifying individuals on the basis of race, religion, language or ethnicity. Despite the dominant racial divides in the United States and consequent economic outcomes, White Americans and African Americans are likely to belong to the same mother language group, and the same region of birth. Given the definition of Bureau of Census, the race categorized as 'Asian' includes people from China as well as Pakistan, most of whom are likely to be very different in most criteria for social groupings, except region of birth. Given that, we wish to evaluate the economic impact of *social* diversity on knowledge diffusion through inter-group communication, we opt for multiple indexes. Thus, we adopt three proxies for social diversity: *Race*, *Language* and *Culture*.

To model the effect of social diversity on economic performance of cities, we use fractionalization indexes that are commonly applied in the social diversity and growth literature, as defined by:

$$\mathrm{FRAC}_i = 1 - \sum_j^n f_{ji}^2 \tag{2}$$

In equation (2), f_{ji} is defined as the share of group j ($j = 1, 2, \ldots, n$) in city i, and the sum

3. Another measure, that is, *INCEARN*, which combines wages and salaries, returns to business and farm income, did not have data for 1980. Hence was not considered for our estimation.

of its squared terms is a *Herfindahl* index or a concentration index. Fractionalization index signifies the likelihood that two people chosen at random from a diverse universe will belong to different groups defined by races, languages and cultures. The minimum value for the fractionalization index (0.00) indicates complete homogeneity, and its maximum value (1.00) represents complete heterogeneity; that is, every individual belongs to a different group (Ottaviano & Peri 2005).

Measuring fractionalization index based on race has two challenges. First, different categories of races are defined across the years. For instance, the 2,000 census employed an additional category, Native Hawaiian and Pacific Islanders (NHPI), and allowed respondents to choose from more than one category.[4] Second, there is controversy over identification of the Hispanic population. For instance, the US Bureau of Census and the US National Research Council both consider Hispanics as a separate ethnic group, but Hispanics typically identify themselves as a separate race. To address these problems, instead of a single category race variable, we use a separate variable from IPUMS-USA, termed as *RACEING*, in which Hispanics are defined as a separate category of race. Further, given the small number of respondents under NHPI in 2,000, we followed the categorization of 1990 and 1980 and counted the number of respondents identifying as Non-Hispanic Asian, NHPI together. Consequently, we are able to calculate a fractionalization index with six categories of 'race': (i) non-Hispanic white; (ii) non-Hispanic Black; (iii) non-Hispanic Asian, NHPI; (iv) non-Hispanic American Indian/Alaskan Native; (v) Hispanic; and (vi) other races.

Language, a linguistic fractionalization measure, is derived from Census data on *language spoken at home*. Respondents were asked if the person 'speaks a language other than English at home' and the data compiled for the population 5 years and over into four major categories: (i) Spanish; (ii) other Indo-European languages; (iii) Asian and Pacific Island languages; and (iv) all other languages. In congruence with Ottaviano and Peri (2005), we argue that languages with common linguistic roots are a good indicator of cultural proximity and define linguistic diversity based on 28 language groups in this article. For example, despite both being part of Continental Europe, substantial differences exist between Spain and, say, the Czech Republic. By contrast, Spanish and Italian cultures and languages are much more similar. Hence, we hypothesize that the cost of communication will be higher between a Spanish national and someone from the Czech Republic, than if the same information were to be exchanged between a Spanish national and an Italian, all else equal. The linguistic groups are detailed in Appendix 1.

The proxy for cultural diversity, that is, *Culture*, is a fractionalization index based on region-of-birth. Culture is a multi-layered concept and difficult to capture with one fractionalization index. Nevertheless, Ottaviano and Peri (2005) define linguistic fractionalization as a measure for cultural diversity. We recognize that language is one of the core ingredients of culture, but it is also shaped by the customs, social norms, colonial history, religious practices, geography and the social and political history of the countries and its people. Thus, while *Language* captures a major aspect of cultural proximity, we define *Culture* based on seven groups defined by region of birth: Europe, Asia, Africa, Latin America, North America (United States and Canada), Mexico and Oceania. Although our rationale should dictate North America as a single group, we separate Mexico given the differences in language, colonial history, race among others with United States and Canada.[5]

The key variable in our analysis we use to test for the paradox of diversity is the interaction variable between each of the diversity

4. The main categories for 2000 census are (i) White; (ii) Black or African American; (iii) American Indian and Alaskan native; (iv) Asian; (v) Native Hawaiian and other Pacific Islander; and (vi) some other race.

5. The correlation coefficient between this cultural diversity and cultural diversity with Mexico as a separate group, which is used in this paper is 0.746.

indices with the measure of *LBC*. It measures English fluency for people who do not speak English at home. This is derived from a self–assessed ability categorized into four groups: 'Very well', 'Well', 'Not well', and 'Not at all'. We define linguistic barriers to communication, that is, *LBC* as the percentage of foreign-born population or non-native speakers who do not speak English very well or well.

To evaluate the impact of social diversity on the average wage of 16- to 64-year-old workers, we control for their educational attainment, average age (and its square), share of female, share of Hispanics and share of African Americans. These controls are similar to those employed by Ottaviano and Peri (2005). Differences in educational attainment have been identified as a key determinant of variation in differences in economic indicators across different geographic units in the United States (Ratna et al. 2012). Here, we use a proxy for educational attainment, defined as *Education*, that is, the percentage of the working population with a bachelor degree or higher tertiary qualification. Average age (*Age*), is used as a proxy for experience of working age population. Lastly, we include three time dummies for 1990, 2000 and 2010 for three of the four census years from which we have data to capture possible time effects that remain constant across cities. Table A2 of the appendix provides the summary statistics for all variables in equation (1).

Given that different cities have historically different factors which will influence variables such as wages-age distribution, gender distribution, education levels, law enforcements, among others, we use a FE model for our estimation. However, two statistical tests were conducted to check the appropriateness of FE model. First, we undertook a Breusch Pagan (BP) Test to verify if Pooled OLS is appropriate for our estimation. The BP test generates a chi-square statistics of 492.13 with a p-value of 0.000. As the BP test rejects the null hypothesis, we do not use the Pooled OLS. Second, we conducted a Hausman Test to verify if there is a statistically significant difference in estimated coefficients from fixed effect and from random effect estimations. The Hausman Test Statistic is 112.23 (with a p-value of 0.000), rejects the null hypothesis that the random effects model is valid and, hence, supports our use of fixed effect estimation.

4. Estimation Results

Our empirical estimates comprise two parts. First, we derive OLS estimates of the FE model, as specified in equation (1), with different indexes for social diversities. Second, we test the robustness of OLS results with results from Instrumental Variable Estimation (IVE).

4.1. Diversity and Wages: Fixed Effects Model

Results of OLS estimation of equation (1), with standard errors, are presented in Regression 1 of Table 1. The estimated coefficients for *Culture* and *Language* are positive, but are not statistically significant at conventional levels with a p-value of 0.122 and 0.139, respectively. The estimated coefficient for racial diversity is negative and has a p-value of 0.954. None of the interaction variables is statistically significant at the conventional level.

Regression 1, Table 1 reports that the estimated coefficient for *Education* has the hypothesized positive sign and is statistically significant at the 1 per cent level of significance. The estimated coefficients for both variables related to experience, that is, *Age* and *AgeSq*, have their expected signs, positive and negative, respectively, and are also significant at the 1 per cent level of significance. Among the demographic control variables, the estimated coefficients for the share of Hispanics and share of African American are negative and statistically significant at the 1 per cent level of significance. The model's time dummies are all statistically significant at the 1 per cent level of significance.

To test the robustness of the effect of race on the average wage of the working age population in US cities, we estimated equation (1) with the variable *Race*1 which is defined as a fractionalization index calculated from five groups, defined by the US Bureau of Census as: (i) White; (ii) Black; (iii) American

Table 1 Wage and Diversity: OLS

Variable	*Regression 1*	*Regression 2*	*Regression 3*
Language	0.227	0.243*	
	(0.153)	(0.148)	
Race	−0.006		
	(0.112)		
Race 1		0.100	
		(0.156)	
Culture	0.386	0.345	
	(0.249)	(0.265)	
CDI			0.676***
			(0.131)
*LBC** *Language*	0.745 (0.756)	0.294 (0.640)	
LBC Race*	−0.356	−0.226	
	(0.262)	(0.241)	
LBC Culture*	−0.572	−0.394	
	(0.952)	(0.942)	
LBC CDI*			−0.378
			(0.286)
Education	0.790***	0.789***	0.765***
	(0.110)	(0.110)	(0.108)
Hispan	−0.452***	−0.440**	−0.389***
	(0.140)	(0.143)	(0.130)
Black	−0.599***	−0.725***	−0.785***
	(0.186)	(0.224)	(0.148)
Female	−0.211	−0.211	−0.256
	(0.302)	(0.303)	(0.296)
Age	0.221***	0.223***	0.226***
	(0.049)	(0.049)	(0.048)
AgeSq	−0.003***	−0.003***	−0.003***
	(0.001)	(0.001)	(0.001)
Time dummies			
Y1990	0.499***	0.497***	0.498***
	(0.020)	(0.020)	(0.020)
Y2000	0.954***	0.952***	0.949***
	(0.024)	(0.024)	(0.024)
Y2010	1.098***	1.093***	1.087***
	(0.037)	(0.036)	(0.036)
N	904	904	904
R^2	0.889	0.889	0.885

***, ** and * indicate significance level of 1, 5 and 10 per cent, respectively.

Note: 1. Standard errors are presented in parentheses. 2. LBC × Race in Regression 2 indicates interaction between LBC and Race1.

Indian/Alaskan Native; (iv) Asian and Pacific Islander; and (v) other races. Regression 2, Table 1 reports that coefficients for *Language* (with a p-value of 0.100) and *Culture* (with a p-value of 0.193) are positive. The estimated coefficient for *Race*1 is positive, but statistically insignificant at the standard levels of significance. The estimated coefficients for interaction variable, other control variables and time dummies are similar to those in Regression 1 of Table 1. Table A3 of the appendix provides the correlation matrix for all diversity indexes.

Regression 3 of Table 1 reports that the estimated coefficient for composite index *CDI* which is measured as the geometric mean of the three diversity indices. Mathematically,

$$CDI = \sqrt[3]{Language \times Race \times Culture} \qquad (3)$$

For an arithmetic mean of different diversity indices, an increase in one index can be compensated by a decrease in another index. This is not the case with a geometric mean which is used by statistical agencies when calculating a consumer price index. The geometric mean overcomes input substation bias when applied as an index, such as the Fisher Index, which is the geometric mean of the Laspeyres and Paasche indexes.

Regression 3, Table 1 reports that the estimated coefficient for *CDI* is positive and is statistically significant at 1 percent level of significance. The interaction variable between *CDI* and *LBC* is negative and has a p-value of 0.186. Thus, our results indicate that average wages are higher the more socially diverse are US cities. This is consistent with much of the findings in the literature on the economic benefits of diversity within cities. Although the interaction variable is not statistically significant at the conventional level, the evidence is supportive of the hypothesis that the economic benefits of social diversity may be diminished in US cities overall the greater are the *LBC*.

In terms of the control variables, Regressions 3 results shows that *Education* and experience variables (*Age* and *AgeSq*) have the hypothesized signs and are statistically significant at normal levels of statistical significance. Demographic controls that include the share of the female population, share of African Americans and the share that are Hispanic, have the hypothesized negative sign for their estimated coefficients. Only the share of female population is not statistically significant under any specification. The time dummies are statistically significant at the 1 per cent level of statistical significance under all specifications.

4.2. Endogeneity and Instrumental Variables Estimation

We observe that more prosperous American metropolitan cities like New York, Chicago or Houston are likely to comprise a higher share of its population that is foreign-born than cities such as Omaha, Des Moines or Salt Lake City. Part of the explanation for a higher foreign-born population share in cities located in coastal states such as California, New York or Florida is geographic location, that is, proximity to foreign boundaries and port of entrance for international migration. It is also possible that foreign-born workers are attracted to more productive states, and thereby to cities like New York City, Los Angeles or San Francisco primarily because of better economic opportunities. This is not only true for America, but for most of the major cities in settler countries like Canada, Australia, New Zealand and United Kingdom. If this premise is correct, it violates the assumption of exogeneity of fractionalization measures underlying the OLS estimation and requires Instrumental Variable Estimation (IVE) to account for endogeneity. In other words, given this premise, a diverse population contributes to a city's productivity, but more productive cities also attract people from diverse backgrounds.

To test the hypothesis of endogeneity of diversity indices, we conduct two tests. First, we use a reduced form equation for each of these diversity measures: *Language*, *Race* and *Culture*. Each of the predicted residuals θ_n $(n=1,2,3)$ in the structural equation (1) is added to obtain:

$$\ln\left(\overline{w}_{c,t}\right) = \chi_c + \beta_t + \underline{\delta}_c\left(\underline{c}_{c,t}\right) + \underline{\alpha}_d\left(\underline{d}_{c,t}\right) + e_{c,t} + \theta_1 + \theta_2 + \theta_3 \tag{4}$$

We estimated equation (4) to test the null hypothesis that the set of predicted residuals has no effect on ln(*wage*), that is, $\theta_1=\theta_2=\theta_3=0$. The F-statistic is 2.91 with a p-value of 0.034. Hence, we reject the null hypothesis and conclude that at least one of the fractionalization indices is endogenous.

Second, we undertook the Davidson–Mackinnon test for exogeneity of explanatory variables of each of the regressions in Table 1. The test statistic is 3.085 (with p-value of 0.0268), 2.907 (with p-value of 0.034) and 4.653 (with a p-value of 0.031) for regression 1, regression 2 and regression 3, respectively. Results from the Davidson–Mackinnon test indicate that IVE is the preferred estimation method.

We contend that the treatment of immigrants is likely to be the same or similar for all the cities in a particular state, Further, the diversity of population in a city is likely to be correlated to the diversity of other cities in the same state, but the average wage of a city is not likely to be affected by the social diversity of other cities. Thus, we employ a set of instrumental variables in which the instrumental variable for a diversity fractionalization measure of a city is the average of the fractionalization indexes in the other cities of the same state wherever there are at least two cities in a state. For example, *Language_State* is the instrumental variable for *Language* defined as linguistic fractionalization index, where the value of *Language_State* for a given city is the average of the linguistic fractionalization indexes in the other cities of the same state. These instrumental variables are expected to be correlated with endogenous explanatory variables, but should be uncorrelated with unobserved factors that affect the average wage equation.

Regression 1 of Table 2, reports the results of IVE when three potential endogenous variables, *Language*, *Race* and *Culture* are included. Both *Language* and *Race* retain their estimated positive coefficient and each is statistically significant at the 10 percent and 5 per cent level, respectively. Our results for linguistic diversity support previous findings using state-level data (Ratna et al. 2009) and the findings by Ottaviano and Peri (2005) using city-level data for 1970–1990. The value of the estimated coefficient on *Language* (Regression 1, Table 2) indicates that more linguistically diverse cities will have *higher* average income. Our results are economically significant because they suggest that a completely linguistically heterogeneous city, controlling for all

Table 2 Instrumental Variable Estimation

Variable	*Regression 1*	*Regression 2*	*Regression 3*
Language	0.769*	0.873**	
	(0.421)	(0.427)	
Race	0.520**		
	(0.228)		
Race 1		0.915**	
		(0.365)	
Culture	−0.293	−0.747	
	(1.192)	(1.223)	
CDI			1.910***
			(0.626)
LBC × *Language*	−2.734*	−2.035	
	(1.68)	(1.473)	
LBC × *Race*	−0.099	−0.136	
	(0.511)	(.3028)	
LBC × *Culture*	2.757	2.942	
	(3.334)	(3.219)	
LBC × *CDI*			−2.348**
			(1.021)
Education	0.756***	0.736***	0.678***
	(0.126)	(0.124)	(0.123)
Hispan	−0.611***	−0.481**	−0.741***
	(0.191)	(0.212)	(0.222)
Black	−1.164***	−1.603***	−0.967***
	(0.276)	(0.402)	(0.181)
Female	−0.279	−0.165	−0.308
	(0.332)	(0.327)	(0.316)
Age	0.241***	0.229***	0.205***
	(0.058)	(0.059)	(0.053)
AgeSq	−0.003***	−0.003***	−0.003***
	(0.001)	(0.001)	(0.001)
Time dummies			
Y1990	0.496***	0.496***	0.499***
	(0.022)	(0.022)	(0.021)
Y2000	0.944***	0.943***	0.934***
	(0.028)	(0.028)	(0.027)
Y2010	1.080***	1.086***	1.063***
	(0.046)	(0.045)	(0.040)
Constant	4.625***	4.752***	5.310***
	(1.076)	(1.081)	(0.945)
First stage estimation			
Language_State	0.461***		
	(0.061)		
Race_State	0.593***		
	(0.047)		
Race 1_State		0.472***	
		(0.045)	
Culture_State	0.121***		
	(0.041)		
*CDI*_State			0.203***
			(0.034)
N	904	904	904
R^2	0.878	0.893	0.891
Under identification LM test	LM = 23.677	LM = 22.851	LM = 33.856
	(p = 0.000)	(p = 0.000)	(p = 0.000)

***, ** and * indicate significance level of 1, 5 and 10 per cent respectively.
Note: Coefficients reported in first stage estimation are coefficients of the instruments in reduced forms of the corresponding instrumented variables.

other factors, would have an average income that is 77 percent higher than the average income of a completely linguistically homogenous city.

Importantly, the estimated coefficient of interaction variable between linguistic diversity and *LBC* (Regression 1, Table 2) has a negative sign and is statistically significant at the 10 per cent level. This implies that the positive economic impact of linguistic diversity is reduced when there are linguistic barriers. To evaluate the total economic effect of linguistic diversity, we evaluate the interaction term at the mean value of *LBC*, which is 0.174. At the mean value of *LBC* the economic effect of linguistic diversity is 0.292 [=0.769–2.734 * 0.174].[6] This result indicate that the higher is the percentage of foreign-born population with a lower level of English fluency, the positive economic payoff associated with skill sets and knowledge of people from different linguistic backgrounds is diminished.

As a diagnostic check, we performed tests for the validity of the instruments. In the first-stage estimation results reported in Table 2, each instrument is statistically significant in the reduced form equation of the corresponding diversity fractionalization. We observe that there is a significant correlation between each of the fractionalization measures and its instrument which are 0.593, 0.461 and 0.121 for *Race*, *Language* and *Culture*, respectively. Table 2 provides the results of underidentification test for all specifications. For each regression, the test rejects the null hypothesis that the respective model is not identified and indicates that the set of instruments is relevant to the endogenous explanatory variables.

4.3. The Paradox of Diversity

The estimated coefficients for Regression 2, Table 2 report the estimated coefficients of IVE for Regression 2, Table 1. *Language* and *Race*1 retain their positive signs and are statistically significant at 5 percent level. The interaction variable between *LBC* and *Language*, as in Regression 1, Table 2, is negative with a *p*-value of 0.167. Similar to results in Regression 1 of Table 2, the estimated coefficient for the share of African Americans and the estimated coefficient for the share of Hispanics are both statistically significant and negative.

Regression 3 of Table 2 reports IVE results when we use *CDI* as a measure for diversity as in Regression 3, Table 1. The coefficient of this composite index and its interaction variable with *LBC* have their expected positive and negative signs and are statistically significant, at the 1 percent and 5 percent level, respectively. As for the estimated coefficients in OLS (Regression 3, Table 1), and also in IVE (Regression 1 and 2, Table 2), all of the estimated coefficients for the control variables, except the share of the population that is female, are statistically significant.

In summary, IVE indicates that the effects of social diversity on average wages of working age population in US cities is statistically significant and positive, whether diversity is defined as a linguistic, racial or composite index. As in OLS estimates in Table 1, the estimated coefficient for cultural diversity is not statistically significant in IVE. Importantly, our results provide empirical support for a diversity paradox. Namely, the estimated coefficient for the interaction variable between diversity index and linguistic barrier variable *LBC* is both negative and statistically significant. In other words, the higher is the percentage of foreign-born population without English fluency the smaller is the positive impact of social diversity. Thus, while diversity in US cities is associated with a higher average wage, the economic benefits of such diversity appear to diminish the greater are the *LBC*, as measured by English fluency.

4.4. Policy Implications

Employing both OLS and IV estimation we provide empirical support for the notion that social diversity does, indeed, provide a statistically and economically significant benefit at a

6. Preliminary regressions indicate that for the mean value of percentage of foreign born population who does not speak English 'Very Well', the total economic effect of diversity is −0.281.

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city level, as measured by average wage of the working age population. Further, and for the first time at city level (to our knowledge), we show that the positive economic benefits of social diversity are moderated by linguistic barriers, as measured by proficiency in English. Our results provide a nuanced perspective about the economics of diversity. In other words, while diversity has positive economic benefits because it allows for mutually beneficial exchanges across people with different knowledge sets and experiences, these exchanges appear to be moderated by *LBC*. We call this finding a 'paradox of diversity'.

A Paradox of Diversity offers several possible policy insights. First, immigration from diverse countries, currently supported by the Diversity Immigrant Visa Lottery Program, to the United States appears to offer positive economic benefits to the cities where they choose to locate. Second, there may be an economic justification to subsidize English-language education for migrants from non-English speaking backgrounds as is performed in a number of countries. For instance, in 1992 Canada introduced the Language Instruction for Newcomers to Canada (LINC) program for immigrants and refugees. Under this Canadian program, after the initial assessment of newcomers' proficiency in English or French, they receive free language training. In an evaluation report (Canada, Citizenship and Immigration 2004) of this program, the evidence indicates that in addition to language skills, Language Instruction for Newcomers to Canada has been successful in terms of gaining knowledge of Canada and Canadian services and integration in a culturally diverse environment.

In Finland, a personalized integration plan is drawn up for individual immigrants and refugees as part of 1999 act of 'The Finnish Integration Policy'. This plan includes Finnish or Swedish language training for the newcomers along with many other integration measures like adult skill training and the provision of services to meet the special needs of immigrant children and special needs groups. Targeted to evaluate the impacts on immigrants from Russia, Turkey, Thailand and China, a 2010 study (Seppelin 2010) reports that language skills in Finnish/Swedish contributed to better integration of all migrant groups, except for Chinese migrants, into Finnish society. Third, physical transportation infrastructure, urban planning and public transport provides help with social cohesion as well as potentially helping overcome the paradox of diversity.

5. Concluding Remarks

Since at least as far back as Marshall (1920) economists have been concerned with the characteristics of cities and their implications on economic performance. In contrast to empirical and theoretical work at a national level, many of the studies at a city-level stress the economic value of social diversity. Using a comprehensive US city-level data from the United States over four censuses, and to our knowledge for the first time, we test whether social diversity contributes to a higher average wage of US cities and if this positive impact is moderated by *LBC*.

We contend our results help to bridge what appear to be contradictory findings about what are mainly negative economic effects of social diversity at a national and cross-country level with the positive effects of diversity within cities. At a national level, multiple diversity factors that include geographical, linguistic and cultural distance may offset the positive effects of productivity-enhancing knowledge exchange that allows for much greater use of specialized human capital. While our findings are limited to data from US cities, they provide an important economic justification for public policies in support of improved fluency by migrants in the language of discourse within multicultural cities.

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References

Alesina A, Baqir R, Easterly W (1999) Public Goods and Ethnic Divisions. *The Quarterly Journal of Economics* 114(4), 1243–84. DOI: 10.1162/003355399556269.

Alesina A, Devleeschauwer A, Easterly W, Kurlat S, Wacziarg R (2003) Fractionalization. *Journal of Economic Growth* 8 (2), 155–94. DOI: 10.1023/A:1024471506938.

Alesina A, La Ferrara E (2005) Ethnic Diversity and Economic Performance. *Journal of Economic Literature* 43(3), 762–800. DOI: 10.1257/002205105774431243.

Bellini E, Prarolo G, Ottaviano GIP, Pinelli D (2009) Cultural Diversity and Economic Performance: Evidence from European Regions. In FEEM Working Paper No. 63.2009. Milan: Fondazione Eni Enrico Mattei.

Canada, Citizenship and Immigration (2004) Evaluation of the Language Instruction for Newcomers to Canada (LINC (Language Instruction for Newcomers to Canada)) Program. Government of Canada, Last Modified 01/11/2004 Accessed 24 March. <http://www.cic.gc.ca/english/resources/evaluation/linc/2010/exec-summary.asp>.

Cheng S, Li H (2012) New Firm Formation Facing Cultural and Racial Diversity. *Papers in Regional Science* 91(4), 759–74.

Collier P (2000) Ethnicity, Politics and Economic Performance. *Economics and Politics* 12(3), 225–45. DOI: 10.1111/1468-0343.00076.

D'Amuri F, Ottaviano GIP, Peri G (2010) The Labor Market Impact of Immigration in Western Germany in the 1990s. *European Economic Review* 54(4), 550–70. DOI: 10.1016/j.euroecorev.2009.10.002.

Easterly W, Levine R (1997) Africa's Growth Tragedy: Policies and Ethnic Divisions. *The Quarterly Journal of Economics* 112(4), 1203–50. DOI: 10.1162/003355300555466.

Florida R (2002) Bohemia and Economic Geography. *Journal of Economic Geography* 2(1), 55–71. DOI: 10.1093/jeg/2.1.55.

Fu S (2007) Smart Café Cities: Testing Human Capital Externalities in the Boston Metropolitan Area. *Journal of Urban Economics* 61(1), 86–111. DOI: 10.1016/j.jue.2006.06.002.

Glaeser EL, Kallal HD, Scheinkman JA, Shleifer A (1992) Growth in Cities. *Journal of Political Economy* 100(6), 1126–52. DOI: 10.2307/2138829.

Grafton RQ, Knowles S, Owen PD (2004) Total Factor Productivity, Per Capita Income and Social Divergence. *The Economic Record* 80(250), 302–13. DOI: 10.1111/j.1475-4932.2004.00190.x.

Grafton RQ, Kompas T, Owen PD (2007) Bridging the Barriers: Knowledge Connections, Productivity and Capital Accumulation. *Journal of Productivity Analysis* 28(3), 219–31. DOI: 10.1007/s11123-007-0054-6.

Jacobs J (1970) *The Economy of Cities*. Random House, New York.

Jacobs J (1984) *Cities and the Wealth of Nations*. Random House, New York.

Lucas RE Jr (1988) On the Mechanics of Economic Development. *Journal of Monetary Economics* 22(1), 3–42. DOI: 10.1016/0304-3932(88)90168-7.

Manacorda M, Manning A, Wadsworth J (2006) *The Impact of Immigration on the Structure of Male Wages: Theory and Evidence from Britain*. Institute for the Study of Labor (IZA).

Marshall A (1920) *Principles of Economics*, 8th edn. Macmillan, London.

Niebuhr A (2010) Migration and Innovation: Does Cultural Diversity Matter for Regional R&D Activity? *Papers in Regional Science* 89(3), 563–83. DOI: 10.1111/j.1435-5957.2009.00271.x.

Ottaviano GIP, Peri G (2005) Cities and Cultures. *Journal of Urban Economics* 58(2), 304–37. DOI: 10.1016/j.jue.2005.06.004.

Ottaviano GIP, Peri G (2006) The Economic Value of Cultural Diversity: Evidence from US Cities. *Journal of Economic Geography* 6(1), 9–44. DOI: 10.1093/jeg/lbi002.

Polanyi M (1967) *The Tacit Dimension*. Anchor Books, New York.

Ratna NN, Grafton Q, MacDonald IA (2012) Does Multiculturalism Pay? Empirical Evidence from the United States and Canada. *Economic Papers: A journal of applied economics and policy* 31(4), 401–17. DOI: 10.1111/1759-3441.12003.

Ratna NN, Grafton RQ, Kompas T (2009) Is Diversity Bad for Economic Growth? Evidence from State-Level Data in the US. *The Journal of Socio-Economics* 38(6), 859–70. DOI: 10.1016/j.socec.2009.05.006.

Seppelin M (2010) Finnish Integration Policy. Accessed 19 April, <http://ec.europa.eu/social/BlobServlet?docId=8212&langId=en>.

Appendix 1.

Table A1 Variable Definitions

Variable	*Definition*	
Language	Fractionalization index with:	
	i. English	xiii. Persian
	ii. German	xiv. Hindi
	iii. Yiddish	xv. Other Indo-Iranian
	iv. Other Anglo-Saxon and Scandinavian	xvi. Arabic
	(Dutch, Danish, Swedish, Norwegian, Icelandic)	xvii. Chinese
	v. Spanish	xviii. Japanese
	vi. French	xix. Vietnamese
	vii. Italian	xx. Tagalog
	viii. Portuguese	xxi. Korean
	ix. Greek	xxii. Other East Asian
	x. Russian	xxiii. Hebrew
	xi. Other Slavic/Baltic (Polish, Slovak, Serbo-Croatian)	xxiv. Native American
	xii. Armenian	xxv. Other European Language
		xxvi. African Languages
		xxvii. Other languages
Race	Fractionalization index with:	
	i. Non-Hispanic White	iv. Non-Hispanic American Indian/Alaskan
	ii. Non-Hispanic Black	Native
	iii. Non-Hispanic Asian, Native Hawaiian and Pacific	v. Hispanic; and
	Islanders	vi. Some other race
Culture	Fractionalization index with:	
	i. Europe	v. Latin America
	ii. Asia	vi. North America (United States and Canada)
	iii. Africa	
	iv. Oceania	vii. Mexico
Education	Percentage of population with a bachelor degree or higher	
LBC	Percentage of foreign-born population/non-native speakers who do not speak English 'very well' or 'well'	
Language_State	Average of *Language* for other cities of the same state	
Race_*State*	Average of *Race* for other cities of the same state	
Culture_State	Average of *Culture* for other cities of the same state	
*Race*1	Racial diversity index with:	
	i. White	
	ii. Black	
	iii. American Indian/Alaskan Native	
	iv. Asian and Pacific Islander; and	
	v. Some other race	

Table A2 Summary Statistics

Variables	*Mean*	*Standard deviation*	*Minimum*	*Maximum*
Language	0.209	0.142	0.025	0.727
Race	0.331	0.161	0.006	0.689
Culture	0.136	0.112	0.008	0.602
LBC	0.174	0.087	0.00	0.433
Education	0.440	0.103	0.158	0.725
Average age	37.438	1.901	29.383	42.539
Female	0.507	0.016	0.356	0.544
Hispanic	0.091	0.136	0	0.917
Black	0.108	0.0967	0	0.492
Ln(wage)	9.705	0.490	8.466	11.059
Wage	18,329.84	8,179.862	4,749.1	63,494.22
CDI	0.202	0.216	0.171	0.668

Table A3 Correlation Matrix for Diversity Indexes

	Race	*Language*	*Race_1*	*Culture*	CDI
Race	1.0000				
Language	0.1346	1.0000			
Race_1	0.7628	0.6055	1.0000		
Culture	0.2140	0.9119	0.6071	1.0000	
CDI	0.3703	0.9414	0.7800	0.9526	1.0000

Table A4 Metropolitan Areas

State	*Metropolitan Area*	
Alabama (AL)	Anniston	Mobile
	Birmingham	Montgomery
	Florence	Tuscaloosa
Alaska (AK)	Anchorage	
Arizona (AZ)	Tucson	Phoenix
Arkansas (AR)	Fayetteville-Springdale	*Memphis (TN/AR/MS)
	Little Rock-North Little Rock	
California (CA)	Bakersfield	San Francisco-Oakland-Vallejo
	Chico	San Jose
	Fresno	Santa Barbara-Santa Maria-Lompoc
	Los Angeles-Long Beach	Santa Cruz
	Modesto	Santa Rosa-Petaluma
	Redding	Stockton
	Riverside-San Bernardino	Ventura-Oxnard-Simi Valley
	Sacramento	Visalia-Tulare-Porterville
	Salinas-Sea Side-Monterey	Yuba City
	San Diego	
Colorado (CO)	Colorado Springs	Greeley
	Denver-Boulder	Pueblo
	Fort Collins-Loveland	
Connecticut (CT)	Bridgeport	New Haven-Meriden
	Danbury	Stamford
	Hartford-Bristol-Middleton-New Britain	Waterbury
Florida (Florida)	Daytona Beach	Ocala

(*Continues*)

Table A4 (Continued)

State	*Metropolitan Area*	
	Fort Myers-Cape Coral	Orlando
	Gainesville	Pensacola
	Jacksonville	Sarasota
	Lakeland-Winterhaven	Tampa-St. Petersburg-Clearwater
	Melbourne-Titusville-Cocoa-Palm Bay	West Palm Beach-Boca Raton-Delray Beach
	Miami-Hialeah	
Georgia (GA)	Atlanta	*Augusta-Aiken (GA-SC)
	Macon-Warner Robins	*Chattanooga (TN/GA)
	Savannah	
Hawaii (HI)	Honolulu	
Illinois (IL)	Bloomington-Normal	Rockford
	Champaign-Urbana-Rantoul	Springfield
	Chicago	*Davenport, IA-Rock Island-Moline
	Decatur	*St. Louis (MO-IL)
	Peoria	
Indiana (IN)	Elkhart-Goshen	South Bend-Mishawaka
	Fort Wayne	Terre Haute
	Indianapolis	*Cincinnati-Hamilton (OH/KY/IN)
	Lafayette-W. Lafayette	*Louisville (KY/IN)
	Muncie	
Iowa (IA)	Cedar Rapids	*Davenport, IA-Rock Island-Moline, IL
	Des Moines	*Omaha (NE/IA)
	Waterloo-Cedar Falls	
Kansas (KS)	Wichita	*Kansas City (MO-KS)
Louisiana (LA)	Alexandria	Monroe
	Baton Rouge	New Orleans
	Lafayette	Shreveport
Maryland (MD)	Baltimore	*Washington (DC/MD/VA)
	Hagerstown	*Wilmington (DE/NJ/MD)
Massachusetts (MA)	Brockton	Worcester
	New Bedford	*Boston (MA-NH)
	Springfield-Holyoke-Chicopee	*Providence-Fall River-Pawtucket (MA/RI)
Michigan (MI)	Ann Arbor	Jackson
	Benton Harbor	Kalamazoo-Portage
	Detroit	Lansing-E. Lansing
	Flint	Saginaw-Bay City-Midland
	Grand Rapids	*Toledo (OH/MI)
Minnesota (MN)	Minneapolis-St. Paul	*Duluth-Superior (MN/WI)
	St. Cloud	
Mississippi (MS)	Biloxi-Gulfport	*Memphis (TN/AR/MS)
	Jackson	
Missouri (MO)	Joplin	*Kansas City (MO-KS)
	Springfield	*St. Louis (MO-IL)
Montana (MT)	Billings	
Nebraska (NE)	Lincoln	*Omaha (NE/IA)
Nevada (NV)	Las Vegas	Reno
New Hampshire (NH)	Manchester	*Boston (MA-NH)
	Nashua	
New Jersey (NJ)	Atlantic City	*New York-Northeastern NJ
	Trenton	*Philadelphia (PA/NJ)
	Vineland-Milville-Bridgetown	*Wilmington (DE/NJ/MD)

(*Continues*)

Table A4 (Continued)

State	*Metropolitan Area*	
	*Allentown-Bethlehem-Easton (PA/NJ)	
New Mexico (NM)	Albuquerque	
New York (Polanyi)	Albany-Schenectady-Troy	Syracuse
	Binghamton	Utica-Rome
	Buffalo-Niagara Falls	*New York-Northeastern NJ
	Rochester	
North Carolina (D'Amuri, Ottaviano, and Peri)	Asheville	Jacksonville
	Fayetteville	Raleigh-Durham
	Greensboro-Winston Salem-High Point	Wilmington
	Hickory-Morgantown	*Charlotte-Gastonia-Rock Hill (NC-SC)
Ohio (OH)	Akron	Lima
	Canton	Mansfield
	Cleveland	*Cincinnati-Hamilton (OH/KY/IN)
	Dayton-Springfield	*Toledo (OH/MI)
	Hamilton-Middleton	*Youngstown-Warren (OH-PA)
Oklahoma (OK)	Oklahoma City	Tulsa
Oregon (OR)	Eugene-Springfield	Salem
	Medford	*Portland (OR-WA)
Pennsylvania (PA)	Altoona	Scranton-Wilkes-Barre
	Erie	Sharon
	Harrisburg-Lebanon-Carlisle	State College
	Johnstown	Williamsport
	Lancaster	*Allentown-Bethlehem-Easton (PA/NJ)
	Pittsburgh	*Philadelphia (PA/NJ)
	Reading	*Youngstown-Warren (OH-PA)
South Carolina (SC)	Charleston-N. Charleston	*Augusta-Aiken (GA-SC)
	Greenville-Spartanburg-Anderson	*Charlotte-Gastonia-Rock Hill (NC-SC)
Tennessee (TN)	Knoxville	*Clarksville-Hopkinsville (TN/KY)
	Nashville	*Johnson City-Kingsport-Bristol (TN/VA)
	*Chattanooga (TN/GA)	*Memphis (TN/AR/MS)
Texas (TX)	Abilene	Kileen-Temple
	Amarillo	Longview-Marshall
	Austin	Lubbock
	Beaumont-Port Arthur-Orange	McAllen-Edinburg-Pharr-Mission
	Brownsville-Harlingen-San Benito	Odessa
	Corpus Christi	San Antonio
	Dallas-Fort Worth	Tyler
	El Paso	Waco
	Galveston-Texas City	Wichita Falls
	Houston-Brazoria	
Utah (UT)	Provo-Orem	Salt Lake City-Ogden
Virginia (VA)	Danville	Roanoke
	Norfolk-VA Beach-Newport News	*Johnson City-Kingsport-Bristol (TN/VA)
	Richmond-Petersburg	*Washington (DC/MD/VA)
Washington (WA)	Bellingham	Spokane
	Bremerton	Tacoma
	Olympia	Yakima
	Richland-Kennewick-Pasco	*Portland (OR-WA)

(*Continues*)

Table A4 (Continued)

State	*Metropolitan Area*	
	Seattle-Everett	
Wisconsin (WI)	Appleton-Oskosh-Neena	Milwaukee
	Eau Claire	Racine
	Green Bay	Sheboygan
	Janesville-Beloit	Wausau
	Kenosha	*Duluth-Superior (MN/WI)
	Madison	

*Cross-border SMAs.