Racial Diversity and Macroeconomic Productivity across US States and Cities*

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Abstract

Racial diversity in the United States continues to rise. Past analyses have argued that diversity can have both positive and negative consequences. The overall macroeconomic effects of diversity within the US require further examination. This paper exploits variation across US regions from 1980-2000 to determine whether racial heterogeneity creates gains or losses for states and cities. Fixed effects analysis indicates that diversity enhances the productivity of cities. Evidence at the state-level is more ambiguous, as significant results only appear in random effects specifications.

Key Words: Racial Diversity, Macroeconomic Productivity

JEL Classification Codes: O40, R11, J24, O51

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1 Introduction

Racial diversity within the United States has risen dramatically over the past several decades. In 1980, Whites represented 84% of national employment. Twenty year later, the figure declined to just 74%. The US Census Bureau expects that Whites will cease to represent a majority racial group shortly after 2050.[1] Still, some regions remain far more diverse than others. No majority group resided in California or New Mexico in 2000, but minorities composed less than 5% of the populations of Maine, Vermont, and New Hampshire. That same year, Whites made up 80-90% of employees within the major metropolitan areas of Saint Louis, Minneapolis, and Boston, while they constituted only a 44% minority in Los Angeles and San Antonio.[2]

Economists, psychologists, and sociologists have discovered many implications of increased racial diversity. International macroeconomists began to consider the consequences of diversity in the mid 1990s, largely focusing upon the ill effects of institutional inefficiency, instability, corruption, ethnic conflict, lack of trust, and civil war.[3] Other social scientists, however, have argued that people from varied groups may be unique factors of production that could complement each other so that diversity facilitates productivity gains. These opposing effects, in addition to current demographic trends, warrant further examination of the overall relationship between diversity and macroeconomic performance in the United States. This paper employs a decennial panel dataset covering 1980, 1990, and 2000 to assess the aggregate economic effects of diversity on US states and cities.

Section 2 begins with a detailed review of previous research. Importantly, this section discusses the channels through which diversity could affect productivity, though the subsequent empirical analysis does not attempt to assess the validity of these channels. Section 3 defines racial diversity and its measurement. Sections 4 and 5 perform the empirical analysis. The former focuses on state performance. US state-level analysis is the most obvious counterpart to diversity research from the international economics literature. Unfortunately, however, evidence across states for the gains or losses from diversity is limited. Random effects estimation implies that a one standard deviation increase in diversity can lead to an approximate 5.9% rise in gross state output per worker, but fixed effects analysis fails to uncover any causal effects. Section 5 conducts city-level analysis as an alternative. This has the advantage of increasing the number of observations available. Moreover, this methodology may be more appropriate if cities are the centers of economic activity in the US. The limitation, however, is that output per worker measures are not available for cities, so the analysis instead uses wages as a proxy for productivity. Evidence at the city-level is more conclusive than for states. Fixed effects specifications find that diversity generates wage gains — a one standard deviation increase in diversity causes average wages to rise roughly 6.0% after controlling for several other explanatory variables. Robustness checks suggest that these wage increases cannot be fully explained by labor supply effects, and are instead due, at least in part, to productivity gains.

2 Literature

Estimates of the economic effects of diversity vary widely across analyses. Much of this variation might occur because there are several mechanisms through which diversity can affect productivity.

Mauro's (1995) analysis of the determinants of quality institutions that enhance economic growth was the first examination of the productivity consequences of diversity. He finds a negative and significant correlation between diversity and institutional efficiency and concludes, "Ethnic conflict may lead to political instability and, in extreme cases, to civil war. The presence of many different ethnolinguistic groups is also significantly associated with worse corruption, as bureaucrats may favor members of their same group."

Easterly and Levine (1997) canonize the view among growth economists that diversity can only be detrimental when they write, "Polarized societies will be both prone to competitive rent-seeking by different groups and have difficulty agreeing on public goods like infrastructure, education, and good policies… Ethnic diversity may increase polarization and thereby impede agreement about the provision of public goods and create positive incentives for growth-reducing policies." Empirically, the authors find that diversity is strongly related to high black market premiums, poor financial development, weak infrastructure, and low levels of education — all of which are important determinants of a country's income level and growth rate. They estimate that "going from complete homogeneity to complete heterogeneity is associated with a fall in growth of 2.3 percentage points...and an income decrease of 3.8 times."

Many social scientists later added support to Easterly and Levine's conclusions. A more recent paper coauthored by Easterly (Alesina et. al. (2003)), for example, uses improved measures of diversity and finds that the relationship between multiculturalism and productivity remains negative and strongly significant — going from complete homogeneity to complete heterogeneity reduces growth by 1.9 percentage points and income levels by 2.4 times. Alesina and La Ferrara (2005) agree that much of these losses are due to poor public goods provision when they write, "sharing a public good implies contacts between people, and contacts across types produce negative utility." Similarly, Collier (2001) finds that diversity reduces public capital's ability to generate GDP growth, while Alesina and Glaeser (2004), Luttmer (2001), and Gilens (1999) each argue that heterogeneous societies oppose wealth redistribution. Thus, diversity seems to generate losses by conflicting with the public sector and common action.

Diversity might impair productivity through other channels as well. Extensive evidence is available in the social capital literature. Knack and Keefer (1997) argue that social conflict and lack of trust are the negative consequences of multiculturalism. They maintain, “In more polarized societies, groups are more willing to impose costs on society.” As evidence, they estimate the effect of diversity on trust and civic cooperation (which positively affect economic performance). Ethnic heterogeneity is a detriment to both.

In sociology, James Coleman (1988) noted that social networks reinforced by ties within ethnic groups can facilitate trade without the added expense of formal institutions.[4] Francis Fukuyama (1999) warns, however, that “many groups achieve internal cohesion at the expense of outsiders, who can be treated with suspicion, hostility, or outright hatred.” Though this conflict story is popular across the social sciences, Putnam (2007) challenges its validity.[5] He argues “Diversity does not produce ‘bad race relations’ or ethnically-defined group hostility... Rather, inhabitants of diverse communities tend to withdraw from collective life, to distrust their neighbors, regardless of the colour of their skin, to withdraw even from close friends, to expect the worst from their community and its leaders, to volunteer less, give less to charity and work on community projects less often...” That is, diversity reduces social capital within racial groups to the detriment of society at large.

Despite the large body of evidence on losses from diversity, many social scientists argue benefits exist as well. For over 45 years, psychologists have recognized that diversity is conducive to creative thought. Donald Campbell (1960) argued that “persons who have been thoroughly exposed to two or more cultures seem to have an advantage in the range of hypotheses they are apt to consider, and through this means, in the frequency of creative innovation.” Simonton (1999) provides more recent concurring evidence.

Richard Florida's (2002) sociological account of the "Creative Class" workers in the economy has been a particularly strong advocate for diversity. He summarizes his work succinctly when he writes, "Essentially my theory says that regional economic growth is driven by the location choices of creative people — the holders of creative capital — who prefer places that are diverse, tolerant, and open to new ideas." He later elaborates, "Diversity increases the odds that a place will attract different types of creative people with different skill sets and ideas. Places with diverse mixes of creative people are more likely to generate new combinations. Furthermore, diversity and concentration work together to speed the flow of knowledge. Greater and more diverse concentrations of creative capital in turn lead to higher rates of innovation, high-technology business formation, job generation, and economic growth."

Interestingly, diverse groups do tend to behave differently than homogenous ones do. Cox, Lobel, and McLeod (1991) performed two-party Prisoner's Dilemma experiments by offering extra-credit payoffs to students. They gave subjects a payoff schedule such that 1) The greatest social benefits occurred if both parties played cooperatively; 2) The greatest social losses occurred if both parties played competitively; 3) The greatest individual gain arises from playing competitively if the opponent plays cooperatively; 4) But the greatest individual loss comes from playing cooperatively if the opponent plays competitively. The researchers performed this experiment both on individual students and teams. They then told the subjects that a fictional opponent had chosen to cooperate. The response to this information was highly varied, with the choice to cooperate being highest among diverse teams, and lowest among all White teams.[6]

Whether differences in group behavior observed by Cox, Lobel, and McLeod (1991) translate into real economic gains or losses remains unclear. However, case-study research by O'Reilly, Williams, and Barsade (1998) found a positive relationship between racial diversity and both creativity and the implementation of new ideas within a "major clothing manufacturer and retailer with a national reputation for its successful management of diversity." Page (2007), Hong and Page (2004), and Hamilton, Nickerson, and Owan (2003) also argue that heterogeneous teams outperform homogenous ones, though they focus more on diverse abilities rather than diverse racial demography.

Could these economic gains lead to aggregate gains as well? Ottaviano and Peri (2005 and 2006) assess the effects of immigrant diversity on the performance of US cities and find that it augments productivity and wages paid to native-born workers. In an analysis of US industries, Sparber (2007) finds that racial diversity generates productivity gains for many sectors of the economy, though some continue to exhibit sizeable losses.

Though cross-country analyses frequently uncover net losses from diversity, those results may be inadequate in describing the US experience. International accounts suffer from massive variation in attitudes toward diversity across countries — cultural sentiments, ethnic strife, racial tolerance, and legal institutions are much more consistent across US states and cities than they are internationally. Furthermore, measurement of diversity across countries is highly suspect.[7] The wide range in empirical results across literatures, the questionable applicability of international evidence to the US experience, and current demographic trends all demand further analysis of the overall effects of diversity on the economic performance of US states and cities.

3 Defining Diversity

While diversity can take many forms, recent demographic trends in the United States suggest that studies on ethnicity and race are especially relevant. Both academic literature and popular nomenclature often treat "ethnicity" and "race" as synonyms. However, the National Research

Council (2004) advocates classifying a person's race according to disparate geographic locales from which he or she descended. That is, a simple racial taxonomy would include categories such as European (White), African (Black), Asian, Native American, and so on. Ethnicity, on the other hand, typically involves sorting people into categories related to cultural, linguistic, or national identities.[8]

Although past studies have typically analyzed ethnic diversity, I prefer to assess the role of race for a number of reasons. First, race is easily identifiable whereas it is imaginable that many individuals are unable to correctly identify their own ethnic background. Second, it is not clear how coarsely one should sort ethnic groups. Third, state and national political policies (such as affirmative action laws aimed at increasing participation of underrepresented minority groups) are often designed to promote racial — not ethnic — diversity.

I assume the US is composed of four large races — Asians, Blacks, Hispanics, and Whites — with a fifth category for those of other backgrounds.[9] Ideal measures of diversity describe the relative size and variety of racial backgrounds in an area. The racial fractionalization (RF) index achieves this goal, and is the most widely employed measure of diversity in the economics literature. RF ranges from zero to one and represents the probability that two people, drawn at random, will be of different racial groups.

The Integrated Public Use Microdata Series (IPUMS) Census data from Ruggles et. al. (2004) facilitates calculation of RF indices for US states and cities in 1980, 1990, and 2000. More specifically, Equation (1) computes the racial fractionalization of employees working in region "s" and year "t." I calculate diversity indices for the 48 contiguous states and 103 metropolitan regions that IPUMS identifies in each decade considered.[10] Table 1 displays summary statistics for the racial fractionalization indices. Average diversity rose over the twenty year period, and is consistently higher for cities than for states.

$$RF_{s,t} = 1 - \sum_{r=1}^{R} \left(Employment\ Share_{r,s,t} \right)^2$$

$$\text{or, } RF_{s,t} = 1 - \sum_{r=1}^{R} \left(\frac{Emp_{r,s,t}}{Tot_{s,t}} \right)^2 \tag{1}$$

where $Emp_{r,s,t}$ = Number of employees of race r working in region s and year t.

r = {Asians, Blacks, Hispanics, Whites, Others}

and $Tot_{s,t}$ = Total employment in region s and year t.

Table 1: Racial Fractionalization Summary

While international investigations assume ethnicity (or race) is exogenous, one should not make the same assumption when analyzing the effects of diversity within a country. Free labor mobility ensures that productive states and cities will attract members of every race. Non-White immigrants, choosing their first place of residence within the US, will disproportionately choose to live in areas that offer the best economic opportunities. Thus, while ordinary least squares regressions will uncover association between diversity and productivity, they will not identify the direction of causation.

I adopt the "shift-share" methodology to create instruments.[11] For the state-level analysis, I begin by recording the number of employees by race for each state in 1970.[12] I also estimate the national growth rate of each racial group from 1970 to 1980, 1970 to 1990, and 1970 to 2000. Next, I predict the racial composition of each state's employed labor force in subsequent decades by multiplying these national growth rates by the observed 1970 demography. These predictions facilitate calculation of new RF indices, which serve as instruments for observed values. I calculate city-level measures analogously.

For these predicted diversity indices to be valid instruments, they must be exogenous to changes in income across state lines. This requires both that national growth rates are unrelated to each racial group's economic performance in 1970, and that prior economic experience cannot have influenced the demographic composition of states in 1970. This second assumption requires examination. Consider the US map in Figure 1. States with racial fractionalization indices greater than 0.35 (i.e., states in which there is more than a 35% chance that two employees, drawn at random, will be of different races) are shaded black. Those with RF indices between 0.30 and 0.35 are gray. A simple regression of racial fractionalization on indicator variables for Southern Border States (accounting for Hispanic Immigration to the Southwest) and former states of the Confederacy (accounting for long-term demographic implications of slavery) reveals that the two variables explained nearly 60% of a state's employment demography in 1970 (Table 2), suggesting that history and geography have shaped the demography of states. Productivity and income had little to do with their racial composition in 1970.

Figure 1: Racial Diversity of Employment in 1970. States with racial fractionalization indices above 0.35 are shaded black. Those between 0.30 and 0.35 are shaded gray.

Table 2: Exogeneity of Diversity, 1970 Employment

4 Empirical Analysis — Productivity of States

International studies regress GDP per capita on fractionalization to ascertain the effects of diversity. I adopt an analogous methodology for state-level regressions and employ the natural log of Gross State Product (GSP) per worker as the dependent variable.[13] Figure 2 suggests a strong and positive association between racial fractionalization and productivity in 2000. I use a decennial panel dataset covering the 48 contiguous US states from 1980 to 2000 to explore this relationship further. Equation (2) represents the general regression specification, which includes only a few explanatory variables due to the limited number of observations available.[14] Regressions will cluster states to control for time correlation in standard error calculations, and reported results provide cluster-robust standard errors unless noted otherwise.

Figure 2: Racial Fractionalization and State Productivity in 2000

$$
\begin{gathered}
\ln\left(y_{s,t}\right) = \alpha + \beta \cdot Div_{s,t} + \gamma \cdot Ed_{s,t} + \sum_{t=1990}^{2000}\left(\delta_t \cdot Decade_{s,t}\right) + \varepsilon_{s,t} \\
\text{where } s = 48 \text{ contiguous states, } t = 3 \text{ decades.} \\
y = \text{Gross state product per worker.} \\
Div = \text{Racial diversity (fractionalization) of employment.} \\
Ed = \text{Average years of schooling among employees.} \\
Decade = \text{Decade indicator variables for 1990 and 2000.} \\
\varepsilon = \text{Error term.}
\end{gathered}
\tag{2}
$$

I begin with simple ordinary least squares estimation of Equation (2), which controls only for average educational attainment and decade fixed effects.[15] The results, displayed in Column 1 of Table 3, augment the evidence for the merits of diversity suggested by Figure 2. After controlling for educational differences, diversity retains a strong and positive relationship with productivity. Immediate interpretation of the magnitude of the diversity coefficient (0.522) can be difficult. Instead, multiply the coefficient by a one standard deviation increase in diversity (0.148, approximately a move from Massachusetts to North Carolina, or from New Jersey to California). Such a diversity shock would correlate with a 7.7% rise in output per worker.

If unobserved, time-invariant, variables that are correlated with the explanatory variables in the regression exist, then the estimates of the coefficients in Column 1 will be biased. The regression in Column 2 employs a fixed effects specification to control for this possibility. This alternative nearly doubles the magnitude of the association between diversity and productivity.

Table 3: Racial Diversity of State Employment and its Effect on Productivity

To get a better sense of the causal effects of diversity, I return to the OLS framework of Column 1, but conduct a two-stage least squares regression with the exogenous instruments described in Section 3. The first-stage results indicate that the instrument is a strong predictor of observed diversity, with a partial correlation coefficient of 0.960. By employing this instrumental variables methodology, the magnitude of the diversity coefficient declines to 0.433, but we now have more evidence that diversity causes productivity to rise. A one standard deviation shock to diversity would lead to a 6.4% rise in GSP per worker, assuming that the model is not omitting other variables correlated with diversity that affect productivity.

The two-stage least squares regression in Column 4 relaxes this assumption by reintroducing fixed effects. Unfortunately, the model delivers null results. Neither diversity nor years of schooling are significant, though point estimates of previous regressions remain within the 95% confidence interval of the results. Coefficients are largely identified by cross-state variation, and state fixed effects might inhibit the ability of regressions to uncover meaningful results. Moreover, this specification destroys 48 degrees of freedom (one third of the observations), which reduces precision of the estimates. One compromise is to replace state fixed effects with regional indicator variables, as defined by the Bureau of Economic Analysis.[16] An instrumental variable regression with BEA regional fixed effects (Column 5) restores the significance of diversity and education.

As a final alternative, I assume that unobserved variables are not correlated with the regressors. Under this assumption, random effects analysis becomes appropriate and fixed effects are unnecessary. Column 6 adopts a random effects specification. The results add further evidence that diversity might cause productivity to rise, as its coefficient is again positive and significant. Importantly, a robust Hausman test fails to reject the null hypothesis that a random effects model is sufficient.[17] A one standard deviation increase in racial heterogeneity causes gross state output per worker to rise 5.9%.

5 Empirical Analysis — Productivity of Cities

The results of the previous section are unsatisfactory. Fixed effects specifications are unable to uncover any significant coefficients, though a Hausman test did uphold the validity of random effects analysis. Since education, a clear determinant of productivity, is insignificant in state-level two-stage least squares regressions with fixed effects, further control variables are likely be insignificant as well.

Limitations of state-level regressions may be due to the small number of observations available for the empirics. City-level analysis can alleviate this constraint. Furthermore, cities might also be more appropriate units of analysis if diversity generates gains from creativity and idea-exchange as Florida (2002), Simonton (1999), O'Reilly, Williams, and Barsade (1998), and others suggest, since cities are likely to be focal points of such activity.[18] Unfortunately, however, gross output per worker measures are only available since 2001 — a time series that is too short to isolate the long-run productivity effects of interest in this paper. Instead, I must adopt a productivity proxy.

Macroeconomists frequently assume that the aggregate labor demand curve reflects the marginal productivity of labor, which is proportional to average labor productivity. If diversity does not affect labor supply, but does cause wages to rise, then diversity must have increased productivity as well. Suppose, for the moment, that this labor supply assumption is true.[19] Then IPUMS Census data on yearly wages can serve as a substitute for unobserved output per worker figures. Figure 3 suggests that a slight positive relationship exists between the diversity of a city's workforce and average wages paid in 2000. The following sections assess whether this relationship holds in the presence of further control variables.

Figure 3: Racial Fractionalization and City Productivity in 2000

5.1 Wage Effects

Rather than perform random effects regressions as in the state-level analysis, the specifications in Table 4 use metropolitan fixed effects to control for time-invariant omitted variables and help ascertain how diversity might affect wages. Each column reports two-stage least squares results, with instruments developed according to the shift-share methodology described by Equation (1), to better understand the direction of causality.

Fixed effects analysis now finds evidence that diversity might generate productivity gains for cities, whereas it failed to uncover any statistical significance at the state-level. Column 1 examines the role of diversity controlling for education only. The diversity coefficient is positive and significant, and it suggests that a one standard deviation increase in racial diversity (0.157, roughly the difference caused by moving from Chicago to Los Angeles, or from Seattle to Austin) would lead to an 18% rise in wages in the absence of further control variables.

The large magnitude of this coefficient suggests that further controls are necessary. First, many papers on metropolitan productivity emphasize the key role of population density in fostering creativity and generating urbanization externalities and productivity spillovers.[20] Column 2 accounts for employment density and potential urbanization spillovers by including a term measuring hundreds of employees per square mile. The coefficient on density (0.058) is positive and significant — an increase in 100 employees per square mile is associated with a 5.8% increase in wages. More interestingly, the magnitude of the diversity coefficient reduces by about a third.

Density alone may be insufficient in controlling for city characteristics. For example, two cities may be identical in density, but one could be growing and attracting people of different races, while the other is decaying. If so, then diversity will be positively correlated with the strength of a city, and its coefficient in Columns 1 and 2 will exhibit a positive bias. To better account for a city's health and the heterogeneous macroeconomic shocks that correlate with both wages and diversity, Column 3 includes the metropolitan area unemployment rate as a proxy for city-specific economic performance. Its coefficient is insignificant (though it exhibits a surprising positive correlation with wages in later regressions), and does not alter the results for diversity.

Table 4: Racial Diversity and its Effect on Metropolitan Wages, a Proxy for Productivity

Column 4 controls for public sector employment, since wages in this sector might not be determined by market forces as the use of wages as a proxy for productivity assumes. Inclusion of this variable does little to alter the marginal effect of diversity. The results suggest that a one standard deviation increase in diversity still facilitates an 11% rise in wages.

Some analysts argue that higher wages associated with diversity may simply reflect cost of living differences across metropolitan areas that the employment density variable fails to capture, and that regressions should control for this accordingly. Ottaviano and Peri (2005 and 2006), however, argue that unadjusted wages are indeed the appropriate proxy for productivity, that cost of living differences establish the equilibrium number of workers in each city, and that wage regressions should not include cost of living proxies among the explanatory variables. Though I am more sympathetic to Ottaviano and Peri's arguments, Columns 5 and 6 include the average home rental price per dwelling room as a proxy for a city's cost of living for completeness.[21] This causes the effects of diversity to drop substantially, even losing statistical significance in Column 5.

One might suspect that an increase in diversity would lead to lower average wages paid to workers since minorities do tend to earn lower wages than White workers earn. The final specification in Table 4 accounts for this fact by including both racial fractionalization (as a measure of diversity) and the Non-White share of employment (to control for lower wages paid to minorities). This restores the positive and significant relationship between diversity and wages. If the model's assumptions are correct, a one standard deviation increase in diversity causes average wages to rise roughly 6.0%.[22]

5.2 Wages and Employment

If diversity does not affect labor supply, then the wage regression results of the previous subsection imply that diversity causes city productivity to rise. If this assumption is untenable, however, then macroeconomic wage regressions are insufficient in identifying the productivity effects of diversity. Glaeser, Scheinkman, and Shleifer (1995), for example, argue that cross-city regressions should employ population size (or growth) as a proxy for productivity since labor mobility implies that individuals will move to high-income areas. Moreover, economists since Becker (1971) have recognized the possible existence of a compensating differential paid to White workers. That is, diversity could alter labor supply if Whites are less willing to work with minorities. If true, then no instrument would be capable of identifying whether an increase in wages associated with diversity reflects productivity gains or reduced labor supply. To robustly determine whether diversity augments productivity, I now pursue a comparative statics exercise and consider simultaneous estimation of wages and employment.[23]

Changes in equilibrium wages and employment together demonstrate the net effect of supply and demand shifts. If diversity causes either employment or wages to rise, without causing the other to fall, then diversity generated productivity gains. Conversely, if diversity causes wages or employment to fall without causing the other to rise, diversity reduces productivity. Ambiguous productivity implications occur only when diversity has opposite effects on wages and employment.

The three-stage least squares specification in Equation (3), with instrumental variables described in Section 3, can help ascertain the direction of diversity's effect on productivity. The wage equation replicates previous wage regressions that argued for the existence of positive gains from diversity. The innovation lies in the employment equation, which relates a city's employment to the same diversity and control variables of the wage equation. Importantly, the dependent variable controls for size effects caused by employment growth at the national level by dividing the size of each city's employment by the total size of the US workforce.[24] Diversity is likely to increase productivity if the sign on fractionalization in either the wage or employment regression is positive, and the sign in the other is non-negative. Conversely, if the sign in one regression is negative and the other is non-positive, diversity likely causes productivity to decrease.

$$
\begin{aligned}
\ln(w_{c,t}) &= \alpha_w + \beta_w \cdot Div_{c,t} + \sum_{k=1}^{K} \gamma_{w,k} \cdot Control_{k,c,t} + \sum_{t=1990}^{2000} (\delta_{w,t} \cdot Dec_{c,t}) + \varepsilon_{c,t} \\
Emp_{c,t} &= \alpha_l + \beta_l \cdot Div_{c,t} + \sum_{k=1}^{K} \gamma_{l,k} \cdot Control_{k,c,t} + \sum_{t=1990}^{2000} (\delta_{l,t} \cdot Dec_{c,t}) + \varepsilon_{c,t}
\end{aligned}
\qquad (3)
$$

$$
\begin{gathered}
\text{where } c = 103 \text{ metropolitan areas, } t = 3 \text{ decades.} \\
w = \text{Average yearly wage earnings of employees.} \\
Emp = \text{Employment share of total US employment.} \\
Div = \text{Racial diversity (fractionalization) of employment.} \\
Control = \text{Control variables 1 through } K. \\
Decade = \text{Decade indicator variables for 1990 and 2000.} \\
\varepsilon = \text{Error term.}
\end{gathered}
$$

The first set of regressions in Table 5 control for the share of Non-White employment, educational attainment, employment density, unemployment, the size of the public sector, and the cost of living. One limitation of this specification, however, is that it includes a measure of employment on both the left and right hand side of the specification. Column 2 compensates by dropping the density term. Column 3 also drops the cost of living variable, given that the appropriateness of its inclusion is questionable. In all three specifications, the results suggest that diversity causes average wages to rise. Furthermore, employment is insensitive to changes in diversity. Thus, it appears that diversity-generated wage gains are at least partly the consequence of productivity increases, not just changes in labor supply.

Table 5: Racial Diversity and its Effect on Wages and Employment

6 Conclusions

Racial diversity has risen dramatically in the United States during recent decades and will continue to do so in the near future. International studies often find that diversity reduces macroeconomic growth and productivity. However, other analyses suggest that diversity may be capable of augmenting productivity. This paper analyzed the role of racial heterogeneity within the US.

State-level regressions deliver mixed results. Fixed effects analysis fails to uncover any causal connection between diversity and gross state output per worker. A robust Hausman test supports a parsimonious random effects specification, however, which argues that a one standard deviation increase in diversity raises productivity by roughly 5.9%.

Unlike for states, fixed effects analysis at the city-level is informative. A one standard deviation diversity shock causes wages to rise by about 6.0% in regressions controlling for many other wage determinants. Furthermore, three-stage least squares regressions demonstrate that changes in labor supply cannot explain the entirety of this increase. Wage gains appear to be due, at least in part, to productivity shifts.

The macroeconomic methodology in this paper explored whether cross-sectional evidence within the United States suggests that diversity generates net economic gains or losses. It did not evaluate the channels through which diversity affects productivity. These important issues are probably better served by alternative methodologies, including those employing experimental, behavioral, and less aggregated data. Further research in these areas will provide valuable added insight into the economic consequences of diversity.

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A Appendix

A.1 Metropolitan Regions in City-Level Regressions

The city-level regressions in Section 5 include only the metropolitan areas for which racial composition data is available in 1970, 1980, 1990, and 2000. IPUMS provides this data for the 103 metropolitan areas in Table 6.

Table 6: Metropolitan Areas Considered in City-Level Analysis

A.2 Alternative State-Level Regressions

The regression specification in Equation (2) is missing a clear determinant of labor productivity — capital per worker. Many growth economists resist introducing capital stock measures directly into labor productivity regressions since capital is highly correlated with omitted variables in the error term. If true, then estimation of the coefficient will have a large upward bias. One solution is to instead follow a growth accounting procedure.

Suppose Equation (4) describes how output per worker (y) is determined by physical and human capital per worker (k and h, respectively) and a total factor productivity term (TFP) complementing these factors of production.

$$y = TFP \cdot k^{\alpha} \cdot h^{1-\alpha} \tag{4}$$

Total factor productivity can only be measured after employing a number of assumptions. Hall and Jones (1999) propose a production function similar to (4). They appeal to economic theory and assume that α equals the percentage of income earned by capital (roughly 1/3). To ascertain values of h, they turn to evidence on the rate of return to education from Mincer (1974) and Psacharopoulos (1994) that suggests h=exp(0.94+0.068·(t-8)), where t measures the average number of years of schooling. By substituting this expression into (4), taking the natural logarithm of both sides, and rearranging, the level of TFP in an economy then equals the identity in Equation (5).

$$\ln(TFP) = \ln(y) - \left(\frac{1}{3}\right)\cdot \ln(k) - \left(\frac{2}{3}\right)\cdot \left(0.94 + 0.068\cdot (t-8)\right) \tag{5}$$

Suppose diversity affects labor productivity (y) through total factor productivity (TFP). To test this possibility, I first construct TFP estimates for states by using BEA gross state output data, education data from IPUMS, capital stock figures developed according to the methodology created by Garofalo and Yamarik (2002), and the identity in Equation (5). Then I perform two-stage least squares regressions, with instruments described in Section 3, according to the specification in Equation (6). The regression methodology is analogous to that in Section 4.

$$\begin{gathered} \ln\left(TFP_{s,t}\right) = \alpha + \beta \cdot Div_{s,t} + \sum_{t=1990}^{2000}\left(\delta_t \cdot Decade_{s,t}\right) + \varepsilon_{s,t} \\ \text{where } s = 48 \text{ contiguous states}, t = 3 \text{ decades.} \\ TFP = \text{Total factor productivity.} \\ Div = \text{Racial diversity (fractionalization) of employment.} \\ Decade = \text{Decade indicator variables for 1990 and 2000.} \\ \varepsilon = \text{Error term.} \end{gathered} \tag{6}$$

Qualitatively, the TFP results in Table 7 are quite similar to the labor productivity regressions in Table 3, though differences do exist. Most interestingly, the magnitudes of the diversity estimates are smaller. The random effects specification in Column 6 suggests that a one standard deviation increase in diversity (0.148) leads to a 2.5% rise in total factor productivity. Disappointingly, however, the Hausman test now resoundingly rejects the validity of this specification, and instead requires fixed effects specifications. State fixed effects regressions (Columns 2 and 4) fail to uncover an association between diversity and productivity, though a BEA regional fixed effects regression (Column 5) does argue for a positive relationship.

Table 7: Racial Diversity of State Employment and its Effect on Total Factor Productivity

A.3 Region-Specific Effects of Diversity

Diversity may possibly affect some regions more than others. One obvious scenario worth exploring is whether diversity has a different effect within Southern Border States and former states of the Confederacy, given the high rates of diversity in those states due to geographical and historical factors. Columns 1, 2, and 3 of Table 8 test this possibility by altering the specifications in Columns 1, 4, and 5 of Table 4, respectively. The final column assesses whether the West Coast's proximity to Asia might also lead to a differential effect of diversity. Despite the intuitive argument that differential effects might exist, evidence suggests that the effects are quite similar across regions.

Table 8: Racial Diversity and its Effect on Metropolitan Wages within Regions.

Tables and Figures

Table 1: Racial Fractionalization Summary Statistics

	1980	1990	2000	Whole Sample
State Average	0.207	0.244	0.308	0.253
Standard Deviation	0.133	0.144	0.153	0.148
City Average	0.256	0.299	0.365	0.307
Standard Deviation	0.139	0.153	0.159	0.157

Table 2: Exogeneity of Diversity, 1970 Employment

Dependent Variable: Racial Fractionalization of States in 1970

	Coefficient	Std Error
Confederacy	0.174	(0.027)***
Border State	0.219	(0.044)***
Constant	0.119	(0.015)***
Observations	48	
R-Squared	0.59	

Unit of observation: states.
US Confederacy and Border States are indicator variables for states that were part of the Confederacy or share a border with Mexico, respectively.
*** Coefficient significant at 1%.
** Coefficient significant at 5%.
* Coefficient significant at 10%.

Table 3: Racial Diversity of State Employment and its Effect on Productivity

Dependent Variable:
ln(GSP per Worker)

	1	2	3	4	5	6
Fixed Effects	None	State (48)	None	State (48)	Region (8)	Random Effects
IV	No	No	Yes	Yes	Yes	Yes
Diversity	0.522	0.921	0.433	-0.987	0.469	0.401
	(0.098)***	(0.418)**	(0.098)***	(1.375)	(0.110)***	(0.099)***
Years of Schooling	0.250	0.216	0.243	0.091	0.184	0.221
	(0.045)***	(0.072)***	(0.045)***	(0.104)	(0.043)***	(0.038)***
Constant	7.642	7.922	7.760	10.449	8.536	3.636
	(0.568)***	(1.015)***	(0.559)***	(1.821)***	(0.551)***	(0.212)***
Predicted Diversity - First Stage			0.960	0.374	1.006	0.928
			(0.026)***	(0.104)***	(0.030)***	(0.034)***
Observations	144	144	144	144	144	144
R-Squared	0.67	0.93	0.66	0.89	0.74	0.78
Hausman F						1.66
Hausman P						0.20

Panel covers 48 contiguous US states in 1980, 1990, and 2000.
Diversity measured as racial fractionalization (RF) of employed labor force.
Cluster-robust standard errors in parenthesis.
*** Coefficient significant at 1%.
** Coefficient significant at 5%.
* Coefficient significant at 10%.
Decade indicator variables suppressed.

Table 4: Racial Diversity and its Effect on Metropolitan Wages, a Proxy for Productivity

Dependent Variable:
ln(Average Yearly Wage)

	1	2	3	4	5	6
Diversity	1.156	0.796	0.781	0.699	0.225	0.383
	(0.304)***	(0.291)***	(0.281)***	(0.258)***	(0.194)	(0.150)**
Non-White Employment						-0.006
						(0.004)
Years of Schooling	0.165	0.134	0.139	0.142	0.180	0.136
	(0.045)***	(0.047)***	(0.047)***	(0.049)***	(0.026)***	(0.044)***
Employment Density		0.058	0.057	0.064	0.011	0.023
		(0.024)**	(0.024)**	(0.023)***	(0.025)	(0.024)
Unemployment Rate			0.006	0.009	0.009	0.013
			(0.005)	(0.005)**	(0.004)**	(0.004)***
Public Employment				-0.010	-0.006	-0.005
				(0.004)***	(0.003)**	(0.003)
Average Rent					0.002	0.002
					(0.000)***	(0.000)***
Observations	309	309	309	309	309	309
R-Squared	0.95	0.96	0.96	0.96	0.98	0.98

Panel covers 103 metropolitan areas in 1980, 1990, and 2000.
Two-stage least squares (IV) with fixed effects.
Diversity measured as racial fractionalization (RF) of employed labor force.
Non-White and Public Employment measure the share of a state's employees who are not white and are working for government agencies, respectively.
Employment Density measures hundreds of employees per square mile.
Average Rent measures the average residential rental price per room in a city.
Cluster-robust standard errors in parenthesis.
*** Coefficient significant at 1%.
** Coefficient significant at 5%.
* Coefficient significant at 10%.
Constant and decade indicator variables suppressed.

Table 5: Racial Diversity and its Effect on Wages and Employment

Dependent Variables:
ln(Average Yearly Wage)
Employed Labor Force (Share of US Employed LF)

	1		2		3	
	Wage	Emp	Wage	Emp	Wage	Emp
Diversity	0.383	1.186	0.444	0.241	0.727	0.567
	(0.119)***	(0.747)	(0.114)***	(0.504)	(0.151)***	(0.460)
Non-White Employment	-0.006	-0.057	-0.007	-0.035	0.007	-0.019
	(0.003)**	(0.017)***	(0.003)**	(0.013)***	(0.003)***	(0.008)**
Years of Schooling	0.136	-0.328	0.141	-0.403	0.226	-0.305
	(0.026)***	(0.160)**	(0.024)***	(0.107)***	(0.026)***	(0.080)***
Employment Density	0.023	-0.348				
	(0.011)**	(0.069)***				
Unemployment Rate	0.013	0.050	0.014	0.035	0.005	0.026
	(0.003)***	(0.017)***	(0.003)***	(0.012)***	(0.003)*	(0.010)***
Public Employment	-0.005	-0.007	-0.004	-0.009	-0.014	-0.020
	(0.002)***	(0.010)	(0.002)***	(0.007)	(0.002)***	(0.006)***
Average Rent	0.002	0.009	0.003	0.003		
	(0.000)***	(0.002)***	(0.000)***	(0.001)***		
Constant	7.832	16.739	7.991	14.296	6.986	13.140
	(0.322)***	(2.024)***	(0.337)***	(1.482)***	(0.376)***	(1.146)***
Observations	309	309	309	309	309	309

Panel covers 103 metropolitan areas in 1980, 1990, and 2000.
Three-stage least squares (IV) with fixed effects.
Diversity measured as racial fractionalization (RF) of employed labor force.
Non-White and Public Employment measure the share of a state's employees who are not white and are are working for government agencies, respectively.
Employment Density measures hundreds of employees per square mile.
Average Rent measures the average residential rental price per room in a city.
Standard errors in parenthesis.
*** Coefficient significant at 1%.
** Coefficient significant at 5%.
* Coefficient significant at 10%.
Decade indicator variables suppressed.

Table 6: Metropolitan Areas Considered in City-Level Analysis

Akron, OH
Albany-Schenectady-Troy, NY
Albuquerque, NM
Allentown-Bethlehem-Easton, PA/NJ
Appleton-Oskosh-Neenah, WI
Atlanta, GA
Austin, TX
Bakersfield, CA
Baltimore, MD
Baton Rouge, LA
Beaumont-Port Arthur-Orange,TX
Birmingham, AL
Boston, MA-NH
Buffalo-Niagara Falls, NY
Canton, OH
Charleston-N.Charleston,SC
Charlotte-Gastonia-Rock Hill, NC-SC
Chicago, IL
Cincinnati-Hamilton, OH/KY/IN
Cleveland, OH
Columbia, SC
Columbus, OH
Corpus Christi, TX
Dallas-Fort Worth, TX
Dayton-Springfield, OH
Denver-Boulder, CO
Des Moines, IA
Detroit, MI
El Paso, TX
Erie, PA
Flint, MI
Fort Lauderdale-Hollywood-Pompano Beach, FL
Fort Wayne, IN
Fresno, CA
Grand Rapids, MI
Greensboro-Winston Salem-High Point, NC
Greenville-Spartanburg-Anderson SC
Harrisburg-Lebanon-Carlisle, PA
Hartford-Bristol-Middleton- New Britain, CT
Houston-Brazoria, TX
Indianapolis, IN
Jackson, MS
Jacksonville, FL
Johnstown, PA
Kansas City, MO-KS
Knoxville, TN
Lancaster, PA
Las Vegas, NV
Little Rock-North Little Rock, AR
Los Angeles-Long Beach, CA
Madison, WI
Milwaukee, WI
Minneapolis-St. Paul, MN
Mobile, AL
Nashville, TN
New Haven-Meriden, CT
New Orleans, LA
New York-Northeastern NJ
Norfolk-VA Beach-Newport News, VA
Oklahoma City, OK
Orlando, FL
Peoria, IL
Philadelphia, PA/NJ
Phoenix, AZ
Pittsburgh, PA
Portland, OR-WA
Providence-Fall River-Pawtucket, MA/RI
Reading, PA
Richmond-Petersburg, VA
Riverside-San Bernadino, CA
Rochester, NY
Rockford, IL
Sacramento, CA
Salinas-Sea Side-Monterey, CA
Salt Lake City-Ogden, UT
San Antonio, TX
San Diego, CA
San Francisco-Oakland-Vallejo, CA
San Jose, CA
Santa Barbara-Santa Maria-Lompoc, CA
Scranton-Wilkes-Barre, PA
Seattle-Everett, WA
Shreveport, LA
South Bend-Mishawaka, IN
Spokane, WA
Springfield-Holyoke-Chicopee, MA
St. Louis, MO-IL
Stockton, CA
Syracuse, NY
Tacoma, WA
Tampa-St. Petersburg-Clearwater, FL
Trenton, NJ
Tucson, AZ
Tulsa, OK
Utica-Rome, NY
Ventura-Oxnard-Simi Valley, CA
West Palm Beach-Boca Raton-Delray Beach, FL
Wichita, KS
Worcester, MA
York, PA
Youngstown-Warren, OH-PA

Table 7: Racial Diversity of State Employment and its Effect on Total Factor Productivity

Dependent Variable:
ln(Total Factor Productivity)

	1	2	3	4	5	6
Fixed Effects	None	State (48)	None	State (48)	Region (8)	Random Effects
IV	No	No	Yes	Yes	Yes	Yes
Diversity	0.287	0.178	0.207	-0.625	0.286	0.170
	(0.073)***	(0.313)	(0.075)***	(0.722)	(0.071)***	(0.080)**
Constant	6.012	6.120	6.028	6.522	6.077	2.532
	(0.016)***	(0.157)***	(0.017)***	(0.362)***	(0.025)***	(0.008)***
Predicted Diversity - First Stage			0.960	0.374	1.006	0.891
			(0.026)***	(0.104)***	(0.030)***	(0.034)***
Observations	144	144	144	144	144	144
R-Squared	0.55	0.89	0.54	0.87	0.71	0.72
Hausman F						35.54
Hausman P						0.00

Panel covers 48 contiguous US states in 1980, 1990, and 2000.
Diversity measured as racial fractionalization (RF) of employed labor force.
Cluster-robust standard errors in parenthesis.
*** Coefficient significant at 1%.
** Coefficient significant at 5%.
* Coefficient significant at 10%.
Decade indicator variables suppressed.

Table 8: Racial Diversity and its Effect on Metropolitan Wages within Regions

Dependent Variable:
ln(Average Yearly Wage)

	1	2	3	4
Diversity	0.894	0.417	0.312	0.373
	(0.314)***	(0.245)*	(0.191)	(0.197)*
Diversity * Confederate	0.158	-0.014	0.050	0.002
	(0.246)	(0.196)	(0.158)	(0.155)
Diversity * Border	0.438	0.322	0.207	0.249
	(0.215)**	(0.275)	(0.239)	(0.218)
Diversity * West				-0.193
				(0.139)
Non-White Employment		0.003	0.141	-0.007
		(0.006)	(0.048)***	(0.006)
Years of Schooling	0.204	0.193	0.029	0.138
	(0.048)***	(0.051)***	(0.027)	(0.045)***
Employment Density		0.057	-0.007	0.025
		(0.029)**	(0.005)	(0.027)
Unemployment Rate		0.008	0.013	0.012
		(0.007)	(0.006)**	(0.006)**
Public Employment		-0.010	-0.004	-0.004
		(0.004)**	(0.004)	(0.004)
Average Rent			0.002	0.002
			(0.001)***	(0.000)***
Observations	309	309	309	309
R-Squared	0.95	0.97	0.98	0.98

Panel covers 103 metropolitan areas in 1980, 1990, and 2000.
Two-stage least squares (IV) with fixed effects.
Diversity measured as racial fractionalization (RF) of employed labor force.
Non-White and Public Employment measure the share of a state's employees who are not white and are working for government agencies, respectively.
Employment Density measures hundreds of employees per square mile.
Average Rent measures the average residential rental price per room in a city.
Confederate, Border, and West are indicator variables for former members of the Confederacy, states that share a border with Mexico, and West Coast states, respectively.
Cluster-robust standard errors in parenthesis.
*** Coefficient significant at 1%.
** Coefficient significant at 5%.
* Coefficient significant at 10%.
Constant and decade indicator variables suppressed.

Figure 1: Racial Diversity of Employment in 1970. States with racial fractionalization indices above 0.35 are shaded black. Those between 0.30 and 0.35 are shaded gray.

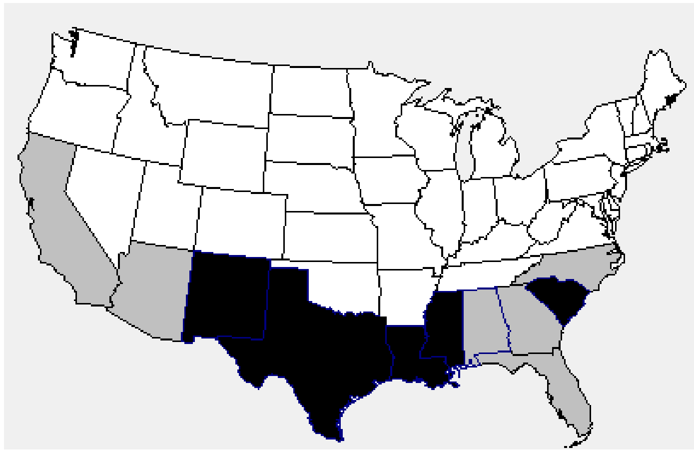


Figure 2: Racial Fractionalization and State Productivity in 2000

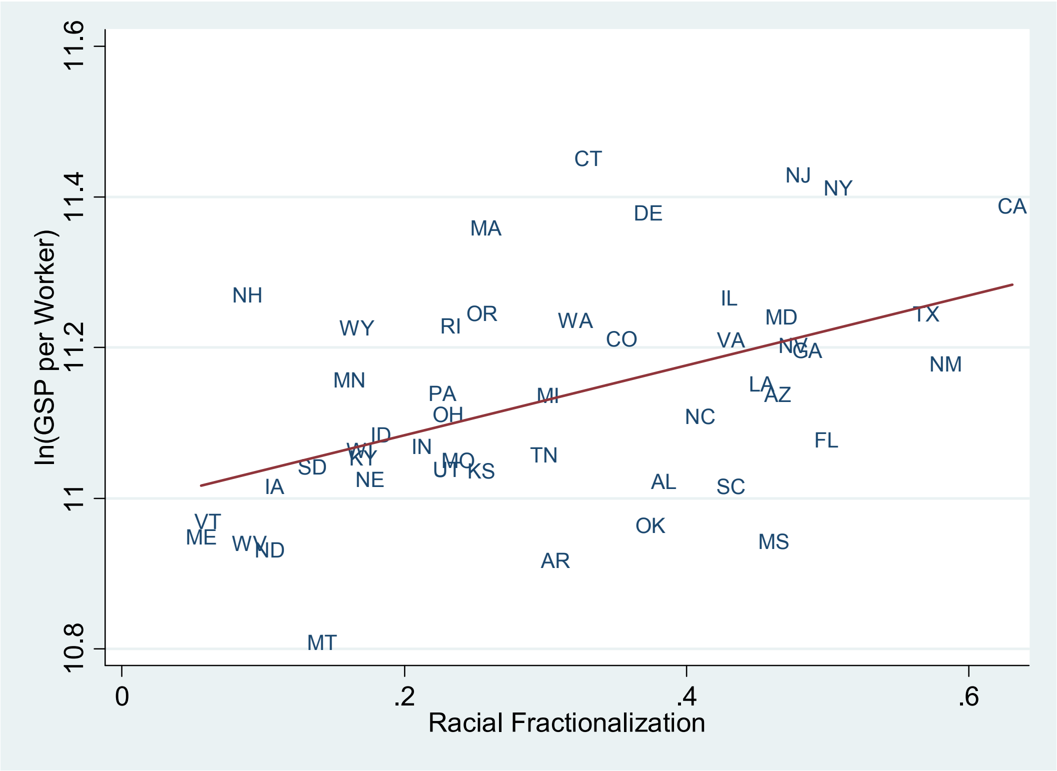
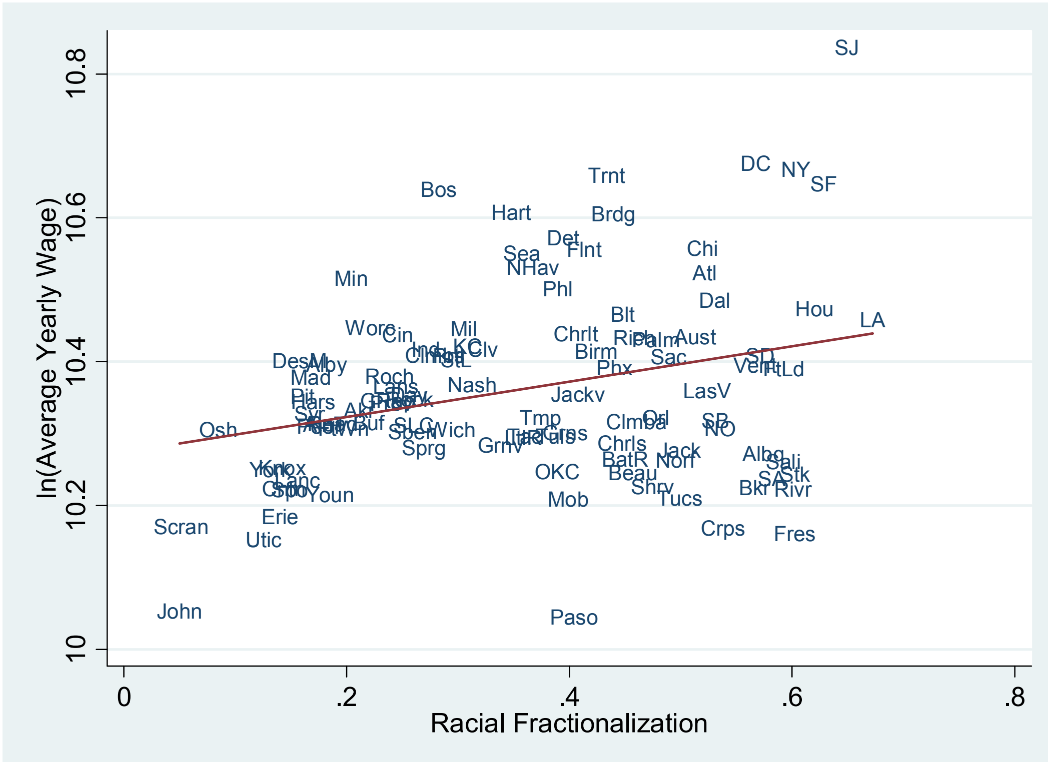


Figure 3: Racial Fractionalization and City Productivity in 2000



Endnotes

[1] See Bergman (2004).

[2] Estimates are based on standard metropolitan areas — not incorporated city limits.

[3] See Mauro (1995) and Knack and Keefer (1997) for the earliest analyses.

[4] Also see Avner Greif's (1993) account of 11th century Maghribi traders.

[5] In addition to previously cited literature, also see Caselli and Coleman (2002), Alesina, Baqir, and Easterly (1999), and Poterba (1997). Putnam (2007) provides a more extensive survey of this literature.

[6] Individual minorities also chose to cooperate more frequently than individual Whites did, but these rates fell between the cooperation rates of White teams and diverse teams.

[7] See Posner (2004) and Fearon (2003) for similar objections.

[8] Hispanics complicate the race and ethnicity dichotomy. According to the US Census, as well as the National Research Council, Hispanics compose an ethnic group. However, Hispanics often see themselves as belonging to a separate race. The National Research Council (2004) writes, "In the 2000 Census, 97 percent of people reporting 'some other race' were of Hispanic origin." Rather than subscribing to a traditionally defined race, "about one-half of Hispanics either marked 'some other race' or marked 'two or more races'" on the Census form. This motivates the National Research Council to argue that "Hispanic" is an ethnicity and not a race in the traditional definition of the term, but that analyses of race in the United States should include Hispanics as a distinct group.

[9] "Hispanics" includes all those who claimed Hispanic origin on the Census form. Therefore, the "White" variable is equivalent to "White, Non-Hispanic" (and similarly for Asians, Blacks, and Others). In 2000, respondents were allowed to select "Two or more races" on the Census

form. I categorize individuals who chose this option as "Others," so long as they did not also mark "Hispanic" on the form.

[10] See Appendix A.1 for a list of the 103 metropolitan regions for which IPUMS provides necessary demographic data in each decade.

[11] Also see Card (2001), Ottaviano and Peri (2006), and Sparber (2007).

[12] Unlike for subsequent decades, the 1970 Census does not record the state (or metropolitan area) of a person's employment. Instead, I assume that an employee worked in the same state (and metropolitan area) in which he or she lived in 1970.

[13] Employment figures come from IPUMS. The US Department of Commerce, Bureau of Economic Analysis (2004) provided real GSP data for each of 1980, 1990, and 2000. As of October 26, 2006, the BEA renamed the GSP series "gross domestic product by state." This revision created a discontinuity in 1997, when data changed from SIC to NAICS industry classifications. The BEA now recommends against appending data before and after this date. However, the data in this paper was obtained before the BEA revisions occurred, and is available upon request.

[14] Appendix A.2 offers an alternative methodology involving growth accounting and total factor productivity regressions.

[15] I estimate the average years of education for the workforce using the IPUMS education recode (EDUCREC) variable.

[16] The BEA identifies eight economic regions: New England, Mid East Coast, Great Lakes, Plains, Southeast, Southwest, Rocky Mountains, and Far West.

[17] The Hausman test maintains the null hypothesis that random effects are sufficient and fixed effects are unnecessary. The test statistic comes from the F-distribution, and the null is

rejected if the corresponding p-value is less than 0.05. The regression in Column 6 of Table 3 delivers a p-value of 0.20, suggesting that the random effects specification is valid.

[18] See Harris and Ioannides (2000), Ciccone and Hall (1996), and Jacobs (1969).

[19] I will relax this assumption later in the analysis.

[20] See Harris and Ioannides (2000), Ciccone and Hall (1996), and Jacobs (1969).

[21] This is the IPUMS variable RENT divided by ROOMS.

[22] Appendix A.3 illustrates that the wage effects identified in this section do not vary across regions of the United States.

[23] Also see Ottaviano and Peri (2006) and Sparber (2007).

[24] As with all other share variables, I record the employment share value in whole-number terms.