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ABSTRACT

We present evidence that benefits from agglomeration concentrate within race. Cross-sectionally, the black-white wage gap increases by 2.5% for every million-person increase in urban population. Within cities, controlling for unobservable productivity through residential-tract-by-demographic indicators, blacks' wages respond less than whites' to surrounding economic activity. Individual wage returns to nearby employment density and human capital rise with the share of same-race workers. Manufacturing firms' productivity rises with nearby activity only when they match nearby firms racially. Weaker cross-race interpersonal interactions are a plausible mechanism, as blacks in all-white workplaces report less closeness to whites than do even whites in all-nonwhite workplaces.

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I. Introduction

Two well-documented characteristics of American cities are agglomeration economies—cities exhibit higher productivity (Ciccone and Hall 1996; Henderson 2003) and wages (Glaeser and Maré 2001) than do less-urbanized areas—and high levels of racial inequality, with African-Americans facing significant segregation in many aspects of daily life and on average earning substantially less than do whites (Neal and Johnson 1996; Lang and Manove 2011; Black et al. 2006). An entirely unexplored question in the literature is whether one component of racial pay disparities is that blacks and whites derive different benefits from agglomeration, and if so whether social distance between blacks and whites is a cause of the difference.

Consistent with this possibility, we find that the racial wage gap rises with city size. Figure 1 shows that the gap between blacks and whites rises from a base of 12% of wages by 0.3 percentage points (or 2.5%) for each million additional people in a metro area. A simple regression over metropolitan areas indicates that a one-standard-deviation increase in total employment is associated with an increase in the black-white wage gap of 0.66 percentage points, and a one-standard-deviation increase in employment density (workers per square kilometer) is associated with a 1.38 percentage point increase in the black-white wage gap.[1] Looking within metropolitan areas, we find very similar effects. A one standard deviation increase in workplace employment density increases the wage gap by 1.9 percentage points in a wage regression with standard census controls, which is 27 percent of the unexplained black white wage gap in our preferred specification.

In this paper, we use the restricted version of 2000 Census data to demonstrate that African-Americans receive smaller wage benefits from employment density and human capital concentration than do whites. Our findings are robust to including highly flexible controls

[1] Similar regression results arise when the sample is restricted to metropolitan areas with populations over 2 million.

intended to capture both observed and unobserved individual attributes and to allowing for very heterogeneous returns to workplace characteristics. Further, wage and firm total factor productivity analyses show that a major driver of this relationship is African-Americans having fewer same-race peers in the workplace from whom to enjoy productivity spillovers. We observe similar patterns for wage returns to the share of college educated workers in the workplace, which we interpret as reflecting human capital externalities. Finally, we provide evidence that social distance between blacks and whites—that is, lower levels of between-race than within-race social interaction conditional on physical proximity—persists regardless of the racial mix of the workplace. Taken together, these findings are consistent with interpersonal interactions as a transmission mechanism for agglomeration economies, and with blacks being disadvantaged in capturing the benefits of agglomeration by having a lower intensity of interactions in majority-white workplaces.

Studies of both the black-white wage gap and the urban wage premium raise unobserved productivity attributes as a fundamental concern. Neal and Johnson (1996) and Lang and Manove (2011) use AFQT score as an measure of individual ability and find that inclusion of AFQT substantially erodes the estimated black-white gap. Glaeser and Maré (2001), Wheeler (2001), Yankow (2006), and Combes et al. (2008) find that the estimated wage premium associated with city size decreases substantially after the inclusion of a worker fixed effect.

Following Fu and Ross (2013), we address this concern by using residential location fixed effects to compare similar individuals who reside in the same location, but work in different locations, exploiting the fact that households systematically sort into residential locations where they are similar to the other residents. Fu and Ross demonstrate that residence fixed effects provide an effective control for unobserved ability, and find no evidence of bias in agglomeration estimates from worker sorting over employment density.[2]

Further, we find that after controlling for workers' residential location there is effectively no correlation between their race and the employment density in their workplace; moreover, it reduces unexplained racial differences in wages by 53%. This reduction is comparable to the 48% reduction in the black-white wage gap found by Lang and Manove (2011) from the inclusion of the AFQT score. Moreover, additional geographic and demographic expansions of the vector of fixed effects do little to further erode racial wage differences—suggesting that, as found earlier, the residential fixed effects control adequately capture unobserved skill differences between blacks and whites.

We estimate our wage models with residential location fixed effects for a sample of prime age, fully employed males residing in metropolitan areas with more than one million residents. We control non-parametrically for observables such as age, education, and other demographics and allow for the wage return to agglomeration to vary across observable demographics, industry, occupation, and metropolitan area. We find that a one-standard-deviation increase in employment density leads to a 1.8 percentage point increase in the black-white wage gap, very similar in magnitude to the 1.9 percentage point estimate mentioned above.

Next, we explore whether these differences in returns might be explained by race-specific information networks (Hellerstein et al. 2011; Ionnides and Loury 2004). Consistent with this hypothesis, we find that higher own-race representation in a work location increases the returns

[2] Specifically, they find that the inclusion of census tract fixed effects has very little influence on the estimated return to employment density across a wide variety of wage models, including models that omit all individual demographic attributes. Consistent with this conclusion they show that the within-metropolitan-area correlation between observable ability and agglomeration is very low. Further, they demonstrate that neither the wage return to density nor to share college is likely to be driven by unobserved ability, because observationally equivalent workers in different work locations are earning similar wages net of commuting costs and so earning similar real wages. See Albouy and Lue (2014) on the role of real and nominal wages within metropolitan areas.

to employment density. These results are consistent with blacks receiving lower average returns to agglomeration because on average they have fewer same-race peers from whom to enjoy spillovers and so gain less productivity. Given our estimates, the black-white difference in exposure to workers of the same race explains 65% of the standardized effect of race on the return to agglomeration.

To test whether this difference in returns reflects a difference in productivity (rather than in, say, bargaining power), we estimate total factor productivity (TFP) models for manufacturing establishments[3] in the same metropolitan areas as our worker sample. Following Moretti (2004b), we identify a sample of workers in each establishment based on that establishment's zip code-three digit industry cell, and we confirm that firm TFP increases in locations that have high concentrations of employment. Consistent with our hypothesis, we find that the productivity returns to agglomeration fall substantially when the race of the firm's workers does not closely match the racial composition of the surrounding location. This mismatch between the racial makeup of the firm employing the typical black worker and the racial makeup of surrounding firms explains up to 2.1 percentage points, or about 32 percent, of our black-white wage gap.[4]

While the previous evidence on human capital spillovers is mixed,[5] we also examine racial differences in the return to concentrations of college-educated workers, and results are very

[3] TFP models can only be estimated for manufacturing, because establishment data for other industries do not contain estimates of either materials costs or capital stock.

[4] Our model takes advantage of the evidence, discussed above, that no appreciable workplace sorting by worker race over employment density exists within metropolitan areas after controlling for worker unobservables via residential location. This fact gives our approach an advantage relative to cross-metropolitan TFP estimates, which may be biased by worker sorting across metros on unobservables.

[5] Moretti (2004a) finds evidence of higher wages in cities with greater concentrations of college-educated workers, and Moretti (2004b) finds evidence of higher firm total factor productivity in cities with a large share of college graduates using a production function that allows for substitution between high and low skill labor. In contrast, Acemoglu and Angrist (2001) find no evidence of human capital externalities across states, and Ciccone and Peri (2006) find no evidence of human capital externalities in cross-metropolitan wage differences after controlling for changes in the mix of low and high skill workers in production. Fu and Ross (2013) also find mixed evidence. They find that returns to human capital externalities are attenuated significantly by the inclusion of residential fixed effects. However, they also demonstrate that the remaining estimated effects of human capital externalities are not

similar to those for employment density. A one-standard-deviation change in the share of area workers who are college graduates is associated with a 1.3-percentage-point higher black-white wage gap. Looking at college graduates by race, we find these differences are substantially explained by the fact that blacks have lower exposure to same-race college-educated workers. Similarly, we find that a firm's returns from exposure to college educated workers increase when nearby workers are of the same race as the majority of its own workers. The results of this set of analyses generally support our hypothesis that differences in the return to agglomeration by race result from a within-race concentration of productivity spillovers, although for reasons discussed below we interpret the human capital spillover results with caution.

The share of same-race peers at work should not matter for density or human capital spillovers if workers are equally likely to enjoy spillovers from any peer, regardless of race. However, by examining self-report data from the General Social Survey we demonstrate that African-Americans feel much greater social distance from whites than from blacks,[6] and that there is no significant reduction in this gap for African-Americans who work in majority-white firms. Even working in an all-white firm does not increase African-Americans' average self-reported relative closeness to whites. We view this evidence as further support for same-race interpersonal networks as a plausible mechanism by which African-Americans receive smaller returns to agglomeration than do whites.

The rest of the paper proceeds as follows. Section II briefly reviews the literatures on workplace spillovers and the role of social networks in labor markets. Section III describes our

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associated with observationally equivalent workers in different work locations earning different real wages (net of commuting costs).

[6] Defined as the difference between an individual's reported "closeness to blacks" and that individual's reported "closeness to whites" on a 9-point ordinal scale.

wage model. Section IV describes the individual data, and section V presents results. Section VI concludes.

II. Literature review

Given the strong evidence that a major source of agglomeration economies is spillovers across individuals,[7] it stands to reason that peer and social interaction effects that arise in dense areas might increase individual and firm productivity. For example, Nanda and Sorenson (2010) find evidence of peer effects on self-employment that suggests knowledge- or experience-sharing between workers. Peers may also affect one another's productivity through establishing norms about absenteeism or work effort (DePaola 2010; Bandiera, Barankay and Rasul 2005; Falk and Ichino 2006; Mas and Moretti 2009).[8]

These putative mechanisms, however, depend essentially on actual social interactions between peers. To the extent that individuals are more likely to associate with peers of the same race, race-specific social networks could explain why in most industries (where whites make up the majority of workers) knowledge spillovers may accrue more to whites than to nonwhites.

For a variety of reasons, individuals appear much more likely to associate with peers of the same race. Within the large literature documenting the adverse outcomes experienced by African-Americans (cf. Wilson 1987), researchers have identified their exceptional isolation in

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[7] For example, Glaeser and Maré (2001) find that workers who migrate away from large metropolitan areas retain their earnings gains, suggesting that these permanent gains arise because workers gain skills from working in dense urban areas. Rosenthal and Strange (2008) using wages and Rosenthal and Strange (2003) examining firm births document a fairly rapid decay of spillovers across space, consistent with agglomeration resulting from social interactions. Ellison, Glaeser and Kerr (2010) find evidence that spillovers between firms explain a significant portion of the co-agglomeration of industries using metrics for the extent that firms share workers and ideas. Audretsch and Feldman (1996) and Feldman and Audretsch (1999) demonstrate that the composition of surrounding industry affects the rate of product innovation. Finally, Moretti (2004) finds that firms are more productive and more innovative when located in cities that have more educated workers. See Combes and Gobillon (In Press) for a recent review.

[8] See Ross (2011) for a recent review of the general literature on peer effects.

segregated neighborhoods and metropolitan areas (cf. Massey and Denton 1993, Kain 1968) as a significant cause of these disadvantages (Cutler and Glaeser 1997, Ananat 2011).

A growing body of recent work seeks to interpret findings on the effects of residential segregation and spatial isolation on earnings by illustrating that demographic match with those who are employed at a work location affect individuals' employment opportunities. Bayer et al. (2008) find that similar individuals who reside on the same block are more likely to work together than dissimilar neighbors, and that the similarity of a worker to others residing nearby drives both employment and wages. Hellerstein et al. (2008) find that the benefit to an individual of nearby job locations depends heavily on whether members of one's own race, not merely otherwise similar workers of different races, are employed there.[9] This previous research evidence on segregation in social and employment networks, and its relationship to workplace outcomes, lends support to our hypothesis that racial disparities exist in the return to workplace externalities.

In this paper, we examine two potential types of externalities. The first, captured by the density of industry-specific employment in the sub-area of an MSA, i.e. Public Use Microdata Area (PUMA), in which an individual works, focuses on general spillovers associated with industry-specific agglomeration economies. The second, captured by the share of workers in an individual's industry and PUMA who are college graduates, focuses on skill-based human capital spillovers. We also test whether own-race share of employment in the area where an individual works moderates the racial disparity in return to agglomeration. We conduct a similar test examining firm total factor productivity. Finally, in order to help understand why racial

[9] Ioannides and Loury (2004) and Ross (2011) provide detailed reviews of the extensive literature on labor market referrals and networks.

disparities exist in the return to agglomeration, we test whether social distance between blacks and whites is affected by workplace proximity.

III. Model Specifications for the Wage Models

First, to establish a baseline measure of agglomeration economies, we estimate the following equation for the log wages (y_{ijs}) of individual *i* in work location *j* and metropolitan area *s*:

$$y_{ijs} = Z_{js}\gamma + X_{is}\beta + W_{is}\rho + \delta_s + \alpha_{is} + \varepsilon_{ijs} \tag{1}$$

where Z_{js} is a measure of workplace externalities in an individual's work location, either employment density or share college-educated, X_{is} is a vector of demographic indicators, W_{is} is a vector of industry and occupation indicators, δ_s captures metropolitan area fixed effects, α_{is} represents individual unobservables, and ε_{ijs} represents an idiosyncratic error term. Standard errors are clustered at the workplace to address correlation across industries within each workplace.

Our main analysis organizes the individual's in the sample into observationally equivalent groups, indexed by *{xt}* to indicate individuals who belong to the same demographic cell *x* and reside in the same residential location *t*, and $X_{is}\beta$ is replaced by a demographic cell-residential location fixed effect (δ_{xt}).[10] We also allow agglomeration effects to vary in magnitude by both X_{is} and W_{is} via γ_{sx} and ω_{is}, respectively.

$$y_{ijsxt} = Z_{js}(\gamma_{sx} + \omega_{is}) + W_{is}\rho + \delta_{xt} + \tilde{\alpha}_{isxt} + \varepsilon_{ijsxt} \tag{2}$$

where

$$\gamma_{sx} = X_{sx}\theta + \varphi_s \text{ and } \omega_{is} = W_{is}\pi \tag{3}$$

X_{sx} is subscripted by *x* instead of *i* to capture the fact that *X* does not vary within group, φ_s represents the metropolitan specific return to Z_{js}, and $\tilde{\alpha}_{isxt}$ is the individual unobservable that

[10] Note the demographic cell-residential location fixed effects also captures the MSA fixed effects.

remains after conditioning on δ_{xt}. Following Fu and Ross (2013), the logic behind this specification is that observationally equivalent individuals who observe the same residential opportunities within a metropolitan area and then make the same residential choices are likely to be relatively similar on unobservables, and so we can reasonably assume that workers do not sort into locations with high or low Z_{js} based on unobservable attributes $\tilde{\alpha}_{is}$ (a testable assumption). Equations (2) and (3) are estimated using a single stage linear model with standard errors clustered at the residential location t.[11]

IV. Data for the Wage Models

The main models in this paper are estimated using the confidential data from the Long Form of the 2000 U.S. Decennial Census. The sample provides detailed geographic information on individual residential and work location. A subsample of prime-age (30-59 years of age), full time (usual hours worked per week 35 or greater), male workers is drawn for the 49 Consolidated Metropolitan and Metropolitan Statistical Areas that have one million or more residents.[12] These restrictions lead to a sample of 2,343,092 workers, including 1,705,058 whites, 226,173 blacks, 264,880 Hispanics, and 135,577 Asians.

Table 1 reports individual, employment location PUMA, [13] and metropolitan area characteristics by race (white, African-American, Hispanic, or Asian) of the worker.[14] Our

[11] The clustering of standard errors on residential location addresses the bias identified by Bertrand, Duflo, and Mullainathan (2004) for clustered data with fixed effects. The Moulton (1986) bias associated with standard errors on variables that do not vary within a cluster is almost certainly far less severe in the model described by equations (2) and (3) because the within-group deviation of Z_{js} only take the same value for individuals who belong to the same demographic cell and choose the same residential location. As a robustness test for our standard errors, we examine an alternative model based on Donald and Lang (2007) that explicitly recognizes that the demographic differences in the return to agglomeration are only identified by variation across the groups defined by demographic cell *x* and metropolitan area *s*. See appendix for details.

[12] This sample is comparable to the sample drawn from the Public Use Microdata Sample (PUMS) of the 2000 Census by Rosenthal and Strange (2008) except that we explicitly restrict ourselves to considering residents of mid-sized and large metropolitan areas**.**

[13] We use the more homogenously defined residential PUMA, which is used to report residential location in the PUMS, to classify employment location, rather than measuring location using the census definitions for workplace PUMA.

dependent variable is the logarithm of the wage, which is based on an individual's labor earnings last year divided by the product of the number of weeks worked and the average hours per week worked last year. Our demographic controls include categorical variables by age, education, family structure, and immigration status. These controls are also used to create the observationally equivalent cells described above. At the employment PUMA, we measure employment density in units of 1000 workers per square kilometer and potential human capital spillovers by calculating the share of workers with at least four years of college education based on all full-time workers reporting this employment location. [15] The variables capturing the share of workers in each category who are the same race as the individual are also constructed using all full-time workers.[16]

For illustrative purposes, Table 2 reports the results of a traditional wage model with agglomeration controls for the entire sample. The regression controls for a variety of individual characteristics (age, race, education, family structure, and nativity), metropolitan, industry and occupation fixed effects, as well as for education levels in the worker's industry and occupation at the MSA level, with standard errors clustered at the level of the employment location PUMA. As expected, both within-industry employment density and within-industry share of workers with a college degree in an individual's PUMA of employment are strongly associated with

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[14] Throughout the paper we use the term "race" interchangeably with "race and ethnicity" to capture distinctions between non-Hispanic whites ("whites"), non-Hispanic blacks ("blacks" or "African-Americans"), non-Hispanic Asian-Americans ("Asians"), and Hispanics of any race ("Hispanics").

[15] The average area of PUMAs in our sample of 183 square miles is comparable to the geographic scope of within metropolitan-spillovers identified in the literature. Rosenthal and Strange (2008) examine wage effects of the number of full time workers within rings between 0 and 5 miles of a location (78 square miles) and find effects that are 4 to 10 times larger than the effects found between 5 and 25 miles. Fu (2007) finds that attenuation is fairly flat within 6 miles for human capital externalities and flat within 3 miles for employment density. Also, Fu and Ross (2013) find qualitatively similar, but somewhat larger, agglomeration estimates for PUMAs compared to the smaller zip code areas of 7 square miles on average in the same sample.

[16] The controls shown in Table 1 include human capital measures by metropolitan area and industry and occupation. These controls are similar in spirit to controls used by Glaeser and Maré (2001) for occupation education levels nationally in their across metropolitan study.

higher wages for that individual.[17] A one-standard-deviation increase in density (i.e. an increase in one's own industry and PUMA of 2,100 workers per square kilometer) is associated with increases in wages of 2.6 percentage points. A one-standard deviation increase in share college-educated (i.e. a 17-point increase in share college-educated in one's own PUMA-industry) is associated with an increase in wages of 6.6 percentage points. These estimates are highly consistent with existing research on returns to agglomeration.[18]

In order to provide additional insight into our identification strategy, we examine the correlation between our work location attributes, employment density and share college, with indicators for racial identity. Table 3 presents the correlations with indicators of whether the individual is white and whether the individual is black. The unconditional correlation in panel 1 between employment density and white is -0.018 and between share college and white is 0.053. The correlations for the black indicator are substantially smaller, at 0.008 and -0.007, respectively. Conditioning on metropolitan fixed effects lowers the correlation of employment density substantially to 0.000 and 0.003 for the white and black indicators, respectively, but has less effect on the correlations with share college, leaving them at 0.063 and -0.012, respectively. With tract fixed effects, the black indicator correlation remains around 0.003 for employment density, and while the white indicator correlation jumps up with tract fixed effects, including indicators for race-neutral tract-by-demographic cells reduces the correlation back to very low levels. The inclusion of tract fixed effects substantially reduces the correlation with share college to 0.022 for the white indicator, but no controls reduce the correlations for share college

[17] The within-industry and overall values of employment density and share college are highly correlated, and horse race models with the same controls as those used in Table 2 suggest that the within-industry variables better fit the data. Like the models presented here, models estimated using overall PUMA values of employment density and share college instead of own industry value also find racial differences in the wage returns to density and share college, as well as a substantial role for share own race in workplace in terms of explaining these differences.

[18] For example, our estimate of the return to worker density in the industry-PUMA cell implies that a doubling of density at the mean is associated with a 0.6 percent increase in wages, which is comparable to Rosenthal and Strange's (2008) estimate of 1 percent for a doubling of density within a 25-square mile radius.

much below 0.02. These correlations are consistent with the findings of Fu and Ross (2013) that there is little sorting on unobservables across workplace based on employment density, but that estimates on share college are likely to be substantially more sensitive to controls for unobserved ability.

Next, in Table 4, we examine the racial and ethnic differences in wages over a variety of models with alternative sets of fixed effects. We find that the race coefficient in our preferred model is consistent with existing black-white wage gap estimates that control for observed ability, and that this residual is unaffected by a variety of expanded vectors of fixed effects. The column 1 estimates are repeated from the same metropolitan area fixed effect model reported in Table 2. The inclusion of tract fixed effects in column 2 reduces the black-white difference in wages from over 14 percentage points with just metropolitan area fixed effects to just below 7 percentage points, which is in line with Lang and Manove's (2011) estimates of the black-white wage gap after controlling for ability using the AFQT test. The black-white difference in wages remains between 6 and 7 percentage points across a variety of controls including block group, demographic cell by tract, industry by tract, and occupation by tract fixed effects. Note, however, that the inclusion of demographic cell by tract fixed effects erodes the Hispanic/non-Hispanic differences in wages, decreasing the difference to 0.066, compared to 0.094 in the tract fixed effect model. This may explain the higher correlation for the white indicator in the tract fixed effect model in Table 3, since whites are being compared to both blacks and Hispanics.

V. Results

We begin by showing the within-metropolitan area conditional correlations between wages and our production externality variables, and then turn to a richer model that is intended to address potential sources of bias in the correlation between race and the returns to agglomeration and human capital externalities. Table 5 presents re-estimates of the models from Table 2 separately by the race and ethnicity subsamples. African-Americans get returns about one-third as large as the white returns, 0.0047 versus 0.0138 for employment density and 0.145 versus 0.439 for share college. While other groups have smaller differences overall, Hispanics get half as much return as whites from share college and Asians get half as much return as whites from employment density.

Having established the basic pattern of racial differences in returns, Table 6 presents estimates of the complete model described in equations (2) and (3), where demographic cell by census tract fixed effects are included to control for unobserved ability differences, and where the agglomeration variables are also interacted with worker demographics, industry, occupation and metropolitan area in order to control for heterogeneous returns to agglomeration. The estimates presented in the left column of Table 6 represent the interactions of employment density with race, ethnicity, education, family structure and immigration status, and the right column presents the estimates on the interactions of share college. As discussed above, standard errors are clustered at the census tract level.[19]

Table 6 column 1 reveals that the return to employment density differs little by age, education (with the exception of graduate level education), or immigration status. While these are significant drivers of wages themselves (see Table 2), they do not appear to greatly affect the relationship between wages and employment density. By contrast, blacks receive a substantially lower return to employment density than do workers of other races. The estimated difference between whites and blacks in the gain from agglomeration is greater than the difference in gain

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[19] Appendix Table A1 presents the race and ethnicity interaction estimates for the two stage model based on Donald and Lang (2007). The standard errors are very close to the standard errors in Table 5, and the point estimates are quite similar (nearly identical for the black interaction with employment density). Our two stage model is described in the appendix.

among those with a degree beyond a master's degree relative to those with only a high school diploma. In comparison, this same education difference for wages is more than three times the racial gap for wages. Further, the inclusion of cell by tract fixed effects and the large number of interactions with employment density do little to erode the observed racial differences. In Table 5, the racial differences in the return to employment density imply that a one standard deviation increase in agglomeration is associated with a 1.9 percentage point increase in the black-white wage gap, and the differences estimated in Table 6 are consistent with a 1.8 percentage point increase.[20]

We also find a substantial relationship between share college and the black-white wage gap, as shown in Table 6 column 2. A one standard deviation increase in share college is associated with a 1.3 percentage point increase in the black-white wage gap. However, unlike with employment density, education and age are just as important as race for explaining differences in the wage return to share college. Further, our controls substantially erode the black-white gap in return to share college from 5.0 percentage points in Table 5 to 1.3 percentage points.[21] Therefore, the results for share college should be interpreted with more caution than the employment density results.[22]

Significantly, Hispanics do not experience lower wage premiums than whites from density or share college-educated in the workplace in our full model specification. In other words, it appears that Hispanics get the same returns from agglomeration and human capital externalities as do whites after controlling for heterogeneity in the return to these spillovers and for

[20] The standard deviation of employment density is 2.142. We also re-estimate our fully interactive model with the different vectors of fixed effects, and our findings for the interaction between black and employment density are robust across all specifications (see Table A2).

[21] The black-white gaps for tract and tract by demographic cell fixed effect models estimated separately by race are 2.8 and 3.4 percentage points, respectively. Therefore, the fixed effects explain between 43 and 59 percent of the reduction and the heterogeneous returns to share college explain the rest of the reduction.

[22] On the other hand, the second panel of Table A2 shows that the black-white differences in the returns to share college are robust in magnitude to the alternative fixed effect vectors.

unobservables that are identified by residential sorting. For Asian-Americans, results are less consistent, with significantly higher returns to share college than whites in the full model, but no significant difference in return to density.[23] The persistence of effects for blacks, but not Hispanics or Asians, is consistent with the literature on racial segregation that typically finds that a large unexplained residual in segregation exists for blacks, but that segregation of Hispanics and Asians is explained almost entirely by observables (Bayer, McMillan and Rueben 2004).

The racial return gap and the racial composition of the workforce

Next, we test whether the pattern of racial disparities in the returns to agglomeration is consistent with agglomeration economies arising from race-specific networks. Under such circumstances, minorities may be disadvantaged because they lack same-race peers in the area where they work. To examine this hypothesis, in the left-hand column of Table 7 we interact employment density with the share of all workers in the PUMA who have the same racial or ethnic classification as the worker himself. In the right-hand column, we interact the share of workers who are college educated with the share of college-educated workers who are of the worker's race.

Not surprisingly, the effect of each of these interactions is positive and highly significant, consistent with own-race workplace networks as a conduit for receiving returns to agglomeration.[24] In fact, the magnitudes of the coefficients on these controls suggest that exposure to others of the same race is a very important conduit for receiving returns to agglomeration. The effect of having only workers of one's own race in one's PUMA (0.0537) on the return to density is much larger than the average return to density from Table 2 (0.0118). The

[23]In the two-stage model shown in the appendix, Asian-Americans have marginally significantly lower returns than whites to density and no significant difference in return to share college.

[24] Table A2 presents the interaction estimates for all demographic variables. The estimates presented here are from specifications that include level controls for the two own-race variables. All results are robust to whether these level controls are included or excluded from wage models.

effect of having only members of one's race make up the college-educated workforce in one's PUMA is 0.160, which, while smaller than the average return to share college-educated (0.389), is still appreciable.

Moreover, black-white differences in own-race share of the workforce can explain a significant portion of the black-white wage gap. For the entire sample, the average difference in whites' versus blacks' exposure to same race-employment density is 0.211. Multiplying by the estimated coefficient on the own-race interaction with density implies that racial differences in own-race exposure to employment density can explain 1.1 percentage points of the black-white wage gap. From Table 6, the effect of a one-standard-deviation change in employment density on the black-white difference in wages is 1.8 percentage points, and so differences in own race explain 61% of the standardized racial differences in return to employment density. The racial difference in exposure to college educated workers scaled by share same race is 0.101, implying an effect of 1.6 percentage points, which is actually larger than the 1.3 percentage point standardized effect of share college on the black-white wage gap from Table 6. These findings complement earlier work by Hellerstein et al. (2011) arguing that employment networks operate along racial lines; our results suggest that not only finding a job but also *benefiting from returns to agglomeration on the job depends on own-race share in the workplace.*

Our finding that blacks' lower exposure to own-race workers explains 61% of the standardized black-white difference in returns to agglomeration might appear at odds with the positive coefficient on the black interaction with employment density in the second panel, which would seem to imply that, after controlling for own race, returns to agglomeration are larger for blacks. However, the estimated coefficient on black in Table 7 is conditional on holding own-race share in workplace fixed, while the effect of being black rather than white in a given work location is actually the black coefficient plus the product of [(the own-race share coefficient) X (the difference between the share of black workers and white workers)]. We have verified that for the vast majority of work locations the effective net coefficient on the black interaction is negative.

Finally, we conduct a series of robustness tests and present those results in Table 8, with the results from Table 7 repeated in column 1. First, we focus on the share workers who are same-race based on a simplified black/non-black classification.[25] Next, we demonstrate that our findings are robust to allowing the returns to employment density and share college to be quadratic. The fourth column incorporates controls for the racial composition of the PUMA, i.e. the percent of workers who are black, Hispanic or Asian. The fifth column adds additional controls for the linear variables, such as age and years of education, that were divided into bins to create the observationally equivalent cells. Finally, we drop family structure from the demographic cells because these variables may be most at risk of being determined simultaneously with the wage. The estimated racial differences in returns to both employment density and share college, as well as the estimated effects of own-race share in workplace on returns to these variables, are quite stable across these alternative specifications.

Do Racial Networks Affect Productivity?

In order to examine whether racial networks affect productivity (rather than affecting wages through, for example, improved bargaining), we turn to estimating models of firm productivity using establishment data gathered in the 1997 Census of Manufacturers. We are restricted to

[25] The effect sizes for the black-non black model are larger than the estimates from Table 8 column 1. However, we cannot distinguish statistically between the own-race and the black-non black model. The F-statistics from comparing the models in columns 1 and 2 to a composite model are 1.90 and 2.02, respectively, insignificant with type 1 error probabilities of 0.149 and 0.133.

examining only manufacturing data because information on the cost of materials and on the stock of capital is only available for the manufacturing industry.[26]

Using these data, we estimate models for firm net revenue (total revenues minus material costs) as a translog[27] function of the firm's structure capital, equipment capital, and employment, plus linear controls for manufacturing employment density and share college at the PUMA level. To characterize firm employment, we follow Moretti (2004b) and Hellerstein, Neumark, and Troske (1999) and develop estimates of the share of workers at a firm with four-year college degrees based on analysis of three-digit industry code by zip code cells in the decennial Census. This share is combined with firm total employment to estimate the number of college-educated and non-college-educated workers as separate factor inputs.[28] All models control for three digit industry and metropolitan area fixed effects, and standard errors are clustered at the level of the work-location PUMA.

A natural concern in any model of the effect of agglomeration and human capital externalities on TFP is that workers may sort across firms based on unobserved ability. Unlike across-metropolitan areas studies (Glaeser and Maré 2001; Combes et al. 2008), however, the correlations of both observable worker human capital and worker race with employment density across PUMAs are near zero (see Table 3; see also Fu and Ross 2013). Further, we use the census tract fixed effect model of wages from Table A2 to calculate a measure of expected

[26]We have also explored estimating the wage models for a subsample of manufacturing workers. Estimates are qualitatively similar to the results in Table 7, but have very large standard errors.

[27] We strongly prefer the translog to the Cobb-Douglas production function. The translog model allows the marginal product of factor returns to change with the level of factors employed in production, addressing concerns raised by Ciccone and Peri (2006) that models of human capital externalities may confound spillovers with changes in the mix of inputs. Further, the R-squared increases from 0.84 to 0.91 when moving from Cobb-Douglas to translog, and the resulting F-statistic is 8,147, dramatically rejecting the Cobb-Douglas model. Moreover, the translog model yields much more precise estimates of both the return to employment density and the return to share college-educated; the standard errors fall by 30 and 35 percent, respectively.

[28] In cases for which we cannot match to establishment zip code, we base our estimates on industry-PUMA cells.

worker quality for each tract. We then use the residential location of workers within an industry-zip code cell to estimate implied average worker quality as an additional factor input.

The results of our baseline translog model are shown in Table 9 column 1.[29] We estimate that the effects of a one standard deviation increase in employment density and share college in a PUMA are 0.030 and 0.022, respectively. The share college estimate is comparable in magnitude to Moretti's cross-MSA estimates of between 0.035 and 0.049, especially considering that our estimate is reduced substantially by the inclusion of the control for employment density.

For each industry-zip code cell, we also use the decennial Census data to calculate the share of the workforce that is white, black, Hispanic, or Asian-American. Using these shares, we calculate the average exposure of workers in an industry-zip code cell to workers of the same race in other zip codes in this PUMA and in the same industry. We calculate a similar measure for exposure of a firm's workforce to college-educated workers of the same race in the PUMA-industry cell. We then interact these two variables with the PUMA-industry employment density and the PUMA-industry share college-educated, respectively, in order to test whether returns to agglomeration in terms of firm productivity depend upon firm employees' within-race interaction opportunities. We also include direct controls for the racial composition of the workers in each firm (i.e. industry-zip code cell).

The estimates including these variables are shown in column 2. We find a strong, statistically significant effect on productivity of the interaction between employment density and firm workers' average exposure to own-race workers in PUMA-industry. In fact, our estimates suggest that there is no return to employment density for a firm whose workers have no exposure to same-race workers in the PUMA. In other words, increased density of employment increases a

[29] All the estimates for the translog models in Table 9 are shown in Table A4.

firm’s productivity, but *only to the extent that the increased density comes from an increase in the number of workers of the same race as that firm’s workers*.

The estimated interaction between firm average exposure to same-race college-educated workers and returns to share college-educated workers in a PUMA, while not quite statistically significant in column 2 (p-value=.11), is in the expected direction and sizable, with nearly the same magnitude as the estimate in column 1 of the direct effect of share college-educated in the PUMA. The direct estimate on share college falls from 0.20 to 0.09 with the inclusion of the interaction term, and a firm with zero exposure to college-educated workers in the PUMA who are the same race as its own college-educated workers is estimated to receive one-half the productivity benefit from college-educated workers in the PUMA than the average firm does, according to the point estimates.

In column 3 we include controls for the unobserved ability of workers at the firm based on the residential location of those workers.[30] In this model, the effect of the firm’s own race match with its work location on return to density is very stable, and the effect of race match on return to share college increases by 19 percent and becomes statistically significant. Further, the estimated return to share college with zero average exposure is now a mere 12 percent of the original estimate in column 1.

Table 10 presents a series of robustness checks for the final model in Table 9 by adding a series of fixed effects.[31] Column 2 includes indicators for three-digit industry interacted with density and share college-educated; column 3 includes PUMA fixed effects; and column 4

[30] In order to illustrate the average effect of the mean tract FE on firm TFP, we also estimated the Cobb-Douglas model with this control and find that, as expected, the mean tract FE variable has a strong positive effect on firm net revenue with an estimate of 0.145 and a t-statistic of 2.69. This model also includes an indicator for whether we were failed to match the zip code and were required to match based on industry-by-PUMA cells.

[31] These results are included in the paper rather than with the other robustness checks in the appendix because they have notably large effects on the magnitude of the estimates.

includes both. The PUMA fixed effects control non-parametrically for any relationship between firm location and TFP, while the three-digit-industry interactions allow the returns to our two location variables to vary across manufacturing industries. These changes greatly increase the precision of the estimates, as well as the magnitude of the employment density and share college interactions.

In terms of magnitude, racial differences in workers' exposure to firms whose employees' race matches the race of the surrounding workforce can also explain a substantial fraction of the effect of agglomeration on the black-white wage gap. We calculate racial differences in the average exposure to a firm's own-race index for blacks and whites in the sample, which is 0.148 for own-race exposure and 0.166 for own-race exposure among college graduates. Given these racial differences, a one-standard-deviation increase in employment density in the firm sample is associated with a 1.0 to 2.1 percentage point increase in the black-white wage gap, due to higher exposure of blacks to firms with lower productivity gains from employment density. A one-standard-deviation increase in share college in the firm sample is associated with a 0.4 to 0.9 percentage point increase in the black-white wage gap, due to higher exposure of blacks to firms with lower productivity gains from share college.[32] These changes are similar in magnitude to the standardized race effects estimated in the wage models, 1.8 and 1.3 percentage points for employment density and share college, respectively.

Finally, Table 11 shows results for subsamples split by how much they rely on innovation: columns 1 and 2 split by whether the three-digit industry has high vs. low research and development spending; columns 3 and 4 split by whether the three-digit industry has a high vs.

[32] In the firm sample weighted by number of employees, the standard deviation of employment density is 0.735 and of share college is 0.104.

low rate of patent production.[33] If the hypothesized mechanism of information spillovers that are segregated within same-race networks holds, then racial match with surrounding firms should matter more for productivity in industries that rely on innovation. Again, we find that precision increases when we take account of industry type, and effects are much larger for the share college-educated interacted with same-race college-educated exposure in high-R&D and high-patent industries, as hypothesized. For employment density, effects are similar across R&D levels, but are significantly higher in the high-patent than in the low-patent industries. Overall, the estimates in Tables 9 through 11 strongly support the hypothesis that returns to agglomeration are driven by increases in productivity due to workers' interactions with others of the same race.

Social distance by workplace racial composition

Finally, we examine whether self-reported patterns of individual association are consistent with the hypothesis that social ties are disproportionately within-race, even for those whose workplaces include no same-race peers. While it is well-established that most social interactions are within-race, it may be that workers who lack colleagues of the same race develop strong cross-race relationships, which would cast doubt on the proposed mechanism for our findings. To test this possibility, we draw on data from the U.S. General Social Survey, which has been fielded every one or two years since 1972 and contains a standardized set of demographic and attitudinal questions, many of which are asked consistently over time. A substantial number of respondents across a number of waves are surveyed on: racial attitudes; the racial composition of their workplace; and how close they feel to blacks and to whites. We focus on black and white respondents, as questions were not comparable for Hispanics and Asian-Americans. Our sample

[33] We are grateful to Bill Kerr at the Harvard Business School for providing us with these data. For details on the R&D spending data see Kerr and Fu (2008) and for patent data see Kerr (2008).

includes employed blacks and whites who responded to surveys in which the relevant questions were asked.[34] The sample is further truncated specific to each dependent variable by setting the variable to missing when the question was not answered by the respondent.[35]

The first set of models that we estimate examines racial attitudes as a function of the racial composition of the firm. We investigate survey responses to: a political attitudes question about whether enough is being done by the government to address the condition of blacks, a social attitudes question about whether the respondent approves of a law banning interracial marriage, and a pair of personal attitude questions about how close the respondent is to whites and how close the respondent is to blacks. We also construct a measure of the difference in an individual's reported closeness to blacks relative to whites. Our estimation sample is all employed whites and blacks who responded to the specific racial attitude question. The purpose of these models is to test whether more positive attitudes towards blacks are held by whites (and vice versa) when an individual interacts with more whites (non-whites) in the workplace. We estimate a model including an indicator for race, a measure of the percent white in workplace, and an interaction of the two; the model also includes indicators for survey year, for missing response to percent white in workplace, and for the interaction of race with missing response to percent white in workplace.[36]

Table 12 reports results. Estimates in columns 1 and 2 demonstrate that, while African-Americans are more likely to support increased government help for blacks than are whites and

[34] Race, closeness to whites and blacks, and attitude toward government help for blacks was asked in all years of the survey. Workplace racial composition was determined in 1990 and biannually (i.e., in every survey) between 1996 and 2010, so nearly all of the analysis uses survey waves 1990 and 1996 through 2010. The exception is the analysis of attitude toward interracial marriage, which was discontinued as a question in 2002, meaning that analysis of that attitude is restricted to 1990 and 1996 through 2002.

[35]Whenever a respondent does not supply an answer for an independent variable used in our analysis, that variable is set to zero, and an indicator that the variable is missing is set to one, for regressions including that independent variable.

[36] We have also estimated this set of regressions with fixed effects for MSA; standard errors increase but neither coefficients nor the pattern of significance changes.

are less likely to oppose interracial marriage, views on these issues do not differ by the racial composition of the firm, among either blacks or whites. This suggests that there is no systematic sorting by racial attitudes into firms with different racial compositions,[37] and no effect of percent white in a firm on individual employees' broader racial attitudes. By contrast, columns 3 through 5 demonstrate that there is a strong relationship between firm percent white and employee reports of closeness to whites and to blacks.

Not surprisingly, blacks overall report being closer to blacks than do whites and report being less close to whites than do whites; the additional "social distance" between blacks and whites, relative to whites with whites, is 1.4 points on a 9-point scale (column 3 row 1). In addition, people in whiter workplaces report being 1.2 points less close to blacks (column 3 row 2) and 0.3 points closer to whites (column 4 row 2). Most relevant to the central question of this paper is the following: while black employees of otherwise all-white firms report being 0.7 (nonsignificant) points closer to whites than do blacks employed in all-nonwhite firms (sum of rows 2 and 3 of column 4), they are still significantly less close to whites than are whites. In fact, blacks in all-white firms are less close to whites than are whites in all-nonwhite firms (sum of all coefficients in column 4). These conditional correlations are suggestive that *African-Americans fail to access white social networks to the extent that whites do, even when the African-American in question works in an all-white firm.*

VI. Discussion

This paper demonstrates that blacks receive lower returns to agglomeration economies in their place of work than do whites, a pattern that may contribute to overall racial income disparities and a host of other social concerns. Racial differences both in the return to

[37] Analysis using the percent black in the respondent's MSA/one-digit-industry produce qualitatively similar, though less precise, results, providing further evidence that our results are not due to race-specific sorting into firms based on attitudes (results available upon request).

employment density and in share college in the workplace are robust to controlling for differences in the returns over demographics, industry, occupation, and metropolitan area, and to controlling for unobserved differences in skill as proxied by residential location. The black-white difference in returns to employment density is substantially larger than the estimate on any other demographic characteristic, including education, and the magnitude of the effect is relatively stable even after including controls that are known to substantially erode the overall black-white wage gap. For returns to share college, while the estimated racial differences decline substantially when controls are added, the general findings are robust across a series of specifications.

Several pieces of evidence suggest that the black disadvantage in compensation is driven by race-specific social networks in the workplace. First, the returns to both density and share college increase as the fraction of workers who share an individual's race increases, and racial differences in own-race share of workers explain a substantial fraction of the role of agglomeration in black-white differences in returns. Second, we estimate a model of firm total factor productivity for a sample of manufacturing establishments to directly test whether the exposure of firm workers to workers of the same race at other nearby firms affects firm productivity. We find strong evidence that the returns to agglomeration rise as the average exposure of workers in a firm to same race peers rises. Finally, we find that the racial differences in the social distance that workers report with respect to whites persists even among blacks who work in all-white firms, suggesting that blacks experience relatively little access to white workplace networks.

As a whole, these findings are consistent with racial differences in social interactions between workers explaining a substantial fraction of the black-white wage gap that is observed in

U.S. urban areas. Our preferred model of the racial wage gap, with demographic cell by tract fixed effects, results in an unexplained black-white difference in wages of 6.9 percentage points. In comparison, given racial differences in exposure to own-race workers, one-standard-deviation changes in employment density and share college are associated with 1.8 and 1.3 percentage point increases in the black-white wage gap. Similarly, given racial differences in workers' exposure to firms whose workers' race matches the dominant racial group of surrounding workers, one-standard-deviation changes in same-race employment density and same-race share college are associated with 2.1 and 0.9 percentage point (given our preferred models) increases in the black-white difference in exposure to firm productivity. These findings suggest that a better understanding of how agglomeration economies operate, in addition to benefiting economic science, can also help explain the reasons that African-Americans' wages continue to lag behind those of whites.

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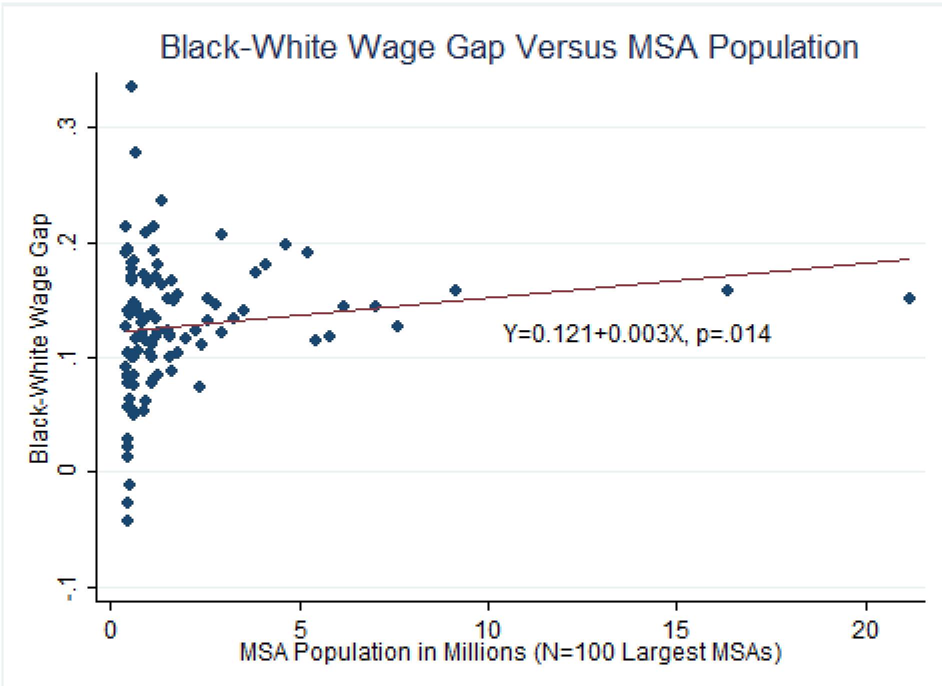
Figure 1.



Black-White Wage Gap Versus MSA Population
Black-White Wage Gap
-.1
0
.1
.2
.3
Y=0.121+0.003X, p=.014
0
5
10
15
20
MSA Population in Millions (N=100 Largest MSAs)

Table 1: Descriptive Statistics

	White	Black	Hispanic	Asian
Sample size	1,705,058	226,173	264,880	135,577
Dependent Variable				
Average hourly wage	28.6959 (45.6694)	19.5287 (31.1947)	17.7986 (32.7494)	26.1993 (40.8411)
Workplace Controls				
Employment density in own one digit industry	0.4606 (2.1408)	0.5348 (2.0841)	0.4436 (1.9072)	0.7810 (2.6242)
Share workers with college degree in industry	0.3549 (0.1703)	0.3456 (0.1687)	0.2959 (0.1580)	0.3926 (0.1726)
Share of workers of own race or ethnicity	0.7403 (0.1414)	0.1949 (0.1282)	0.2138 (0.1523)	0.1152 (0.0882)
Share college educated workers own race/ethnicity	0.3055 (0.0846)	0.0484 (0.0386)	0.0328 (0.0334)	0.0618 (0.0491)
Metropolitan Area Controls				
Percent college educated in MSA and occupation	0.0414 (0.0433)	0.0276 (0.0357)	0.0224 (0.0314)	0.0386 (0.0404)
Percent college educated in MSA and industry	0.0401 (0.0322)	0.0409 (0.0353)	0.0334 (0.0290)	0.0459 (0.0339)
Individual Worker Controls				
Age 30 to 39	0.4111 (0.4920)	0.4499 (0.4975)	0.5462 (0.4979)	0.4738 (0.4993)
Age 40 to 49	0.3663 (0.4818)	0.3605 (0.4801)	0.3103 (0.4626)	0.3455 (0.4755)
Age 50 to 59	0.2225 (0.4160)	0.1896 (0.3920)	0.1435 (0.3505)	0.1807 (0.3848)
Less than high school degree	0.0512 (0.2205)	0.1257 (0.3315)	0.3908 (0.4879)	0.1068 (0.3089)
High school degree	0.2043 (0.4032)	0.2863 (0.4520)	0.2181 (0.4130)	0.1159 (0.3201)
Associates degree	0.3020 (0.4519)	0.3560 (0.4788)	0.2391 (0.4265)	0.2037 (0.4027)
Four year college degree	0.2670 (0.4424)	0.1536 (0.3605)	0.0932 (0.2907)	0.2897 (0.4536)
Master degree	0.1126 (0.3161)	0.0546 (0.2272)	0.0324 (0.1770)	0.1706 (0.3762)
Degree beyond Masters	0.0629 (0.2428)	0.0239 (0.1528)	0.0264 (0.1603)	0.1132 (0.3168)
Single with no children	0.2296 (0.4206)	0.2811 (0.4496)	0.1822 (0.3860)	0.1483 (0.3554)
Married with no children	0.0289 (0.1674)	0.0762 (0.2653)	0.0744 (0.2624)	0.0276 (0.1638)
Single with children	0.3022 (0.4592)	0.2686 (0.4432)	0.2343 (0.4236)	0.2828 (0.4504)
Married with children	0.4393 (0.4963)	0.3741 (0.4839)	0.5091 (0.4999)	0.5413 (0.4983)
Born in the United States	0.9279 (0.2587)	0.8490 (0.3580)	0.3778 (0.4848)	0.1153 (0.3194)
Not born in U.S. resident less than 8 years	0.0149 (0.1212)	0.0272 (0.1626)	0.0966 (0.2954)	0.1807 (0.3848)
Not born in the U.S. resident 8 years or more	0.0572 (0.2322)	0.1238 (0.3294)	0.5256 (0.4993)	0.7040 (0.4565)

Notes: Means and standard deviations are for a sample of 2,343,092 observations containing all male full-time workers aged 30 to 59 who responded to the 2000 Decennial Census long form survey and reside in the metropolitan areas with populations over 1 million residents where full-time work is defined as worked an average of at least 35 hours per week. Standard deviations are shown in parentheses.

Table 2: Baseline Agglomeration Model for Logarithm of the Wage Rate

Independent Variables	Baseline Model
Employment density in own one digit industry (1000s per square KM)	0.0118 (16.23)
Share workers with college degree within own industry	0.3894 (27.87)
African-American worker	-0.1465 (-45.11)
Hispanic worker	-0.1656 (-49.39)
Asian and Pacific Islander worker	-0.1349 (-24.00)
Other race	-0.1516 (-22.61)
Age 40-49	0.1010 (66.72)
Age 50-59	0.1568 (66.91)
Less than high school degree	-0.1456 (-59.85)
Associates degree	0.0851 (54.37)
Four year college degree	0.2711 (113.63)
Master degree	0.3903 (105.64)
Degree beyond Masters	0.5069 (117.4)
Single with children	0.0548 (22.19)
Married with children	0.2110 (94.37)
Married without children	0.1335 (96.46)
Not born in U.S. resident less than 8 years	-0.2533 (-46.21)
Not born in the U.S. resident 8 years or more	-0.0987 (-33.62)
Percent college educated in MSA and occupation	0.7453 (5.37)
Percent college educated in MSA and industry	1.1029 (8.23)
Sample Size	2,343,092
R-squared	0.2873

Notes: Coefficients from a model with industry, occupation and metropolitan fixed effects. Standard errors are clustered on PUMA of employment with T-statistics in parentheses.

Table 3: Correlations between Race and Workplace Attributes

Unconditional Correlations	White Indicator	Black Indicator
Employment density in 1000's per square KM	-0.0179	0.0077
Share workers with college degree	0.0531	-0.0073
Conditional on Metropolitan Fixed Effects		
Employment density in 1000's per square KM	0.0000	0.0036
Share workers with college degree	0.0632	-0.0122
Conditional on Residential Tract Fixed Effects		
Employment density in 1000's per square KM	0.0081	0.0034
Share workers with college degree	0.0220	0.0193
Conditional on Tract by Cell Fixed Effects (omitting race)		
Employment density in 1000's per square KM	-0.0035	0.0036
Share workers with college degree	-0.0215	0.0231
Sample Size	2,343,092	

Notes: Correlations for regression sample with a dummy variable indicating race of worker. Conditional correlations based on deviations from cell means.

Table 4: Race Coefficients with Various Fixed Effects Structures

Variables	Metropolitan Area Fixed Effect	Tract Fixed Effect	Block Group Fixed Effect	Tract-Cell Fixed Effect	Tract-Industry Fixed Effect	Tract-Occupation Fixed Effect
Race Coefficients from Wage Equation						
African-American worker	-0.1465	-0.0696	-0.0623	-0.0694	-0.0710	-0.0662
	(-45.11)	(-38.81)	(-33.55)	(-19.76)	(-33.18)	(-36.68)
Hispanic worker	-0.1657	-0.0939	-0.0859	-0.0660	-0.0909	-0.0881
	(-49.40)	(-53.49)	(-47.70)	(-17.83)	(-43.92)	(-49.81)
Asian and Pacific Islander worker	-0.1349	-0.1041	-0.1010	-0.0963	-0.0986	-0.1038
	(-24.00)	(-43.15)	(-40.81)	(-16.01)	(-35.71)	(-42.56)
R-square	0.2873	0.3307	0.3572	0.6718	0.4467	0.3436

Notes: Coefficients from fixed effect models using the regression sample of 2,343,092 observations. Each column represents estimates from a separate model, and the first column begins with the model from Table 2. Standard errors clustered on PUMA of employment with T-statistics in parentheses.

Table 5: Baseline Agglomeration Model by Race or Ethnicity

White	
Employment density in 1000's per square KM	0.0138 (14.98)
Share workers with college degree	0.4390 (28.69)
R-squared	0.2461
Sample size	1,705,058
African-American	
Employment density in 1000's per square KM	0.0047 (5.80)
Share workers with college degree	0.1453 (6.57)
R-squared	0.2108
Sample size	226,173
Hispanic	
Employment density in 1000's per square KM	0.0097 (9.09)
Share workers with college degree	0.2069 (9.15)
R-squared	0.2536
Sample size	264,880
Asian	
Employment density in 1000's per square KM	0.0076 (6.48)
Share workers with college degree	0.3885 (12.19)
R-squared	0.3316
Sample size	135,577

Notes: Coefficients from a model with metropolitan fixed effects. Each panel presents estimates from a separate subsample. Standard errors clustered on PUMA of employment, and T-statistics in parentheses.

Table 6: Model of the Wage Return to Agglomeration

Fully Interacted Model	Employment Density	Share College Educated
African-American worker	-0.0083***(-2.99)	-0.0776***(-2.92)
Hispanic worker	-0.0021 (-0.58)	0.0157 (0.39)
Asian and Pacific Islander worker	-0.0044 (-1.16)	0.1215**(2.05)
Age 40-49	0.0014 (1.02)	0.0721*** (5.14)
Age 50-59	0.0009 (0.44)	0.1238*** (5.64)
Less than high school degree	-0.0062 (-1.29)	-0.0408 (-1.10)
Associates degree	0.0007 (0.31)	0.1044*** (6.02)
Four year college degree	0.0022 (1.02)	0.1522*** (7.29)
Master degree	0.0050**(2.03)	0.1920*** (6.24)
Degree beyond Masters	0.0043 (1.20)	0.3689*** (6.00)
Single with children	-0.0025 (-0.26)	-0.0380 (-0.63)
Married with children	0.0033* (1.92)	-0.0353** (-2.07)
Married without children	0.0022 (1.02)	-0.0248 (-1.20)
Not born in U.S. resident less than 8 years	-0.0016 (-0.31)	0.0390 (0.46)
Not born in the U.S. resident 8 years or more	-0.0004 (-0.13)	0.0741* (1.81)
R-square	0.7139	
Sample size	2,331,688	

Notes: Coefficient estimates from the interactions of employment density and share college with demoraphic attributes based on a model specification that includes demographic cell by census tract fixed effects and interacts both employment density and share college with demographic attributes, industry, occuption, and metropolitan area. Standard errors are clustered on the census tract of residence, and T-statistics in parentheses.

Table 7: Agglomeration Model with Own Share Controls

Own Share Model	Employment Density	Share College Educated
African-American worker	0.0140* (1.65)	0.0030 (0.06)
Hispanic worker	0.0234**(2.40)	0.0821 (1.36)
Asian and Pacific Islander worker	0.0215**(2.16)	0.1918***(2.69)
Own Share in Workplace	0.0537***(2.74)	
Own Share College Educated		0.1603**(2.26)
R-Square	0.7141	
Sample size	2,331,688	

Notes: Coefficient estimates from the interactions of employment density and share college with race and ethnicity based on a model specification that includes demographic cell by census tract fixed effects and interacts both employment density and share college with demographic attributes, industry, occuption, and metropolitan area. The estimates arise from a model that includes controls for share own race workers and share own race college educated workers in work PUMA. The own share estimates presented are the interactions with employment density and share college. Standard errors are clustered on the census tract of residence, and T-statistics in parentheses.

Table 8: Robustness tests

	Baseline Model	Black-Non Black	Non-Linear Agglomeration	Workplace Racial Composition	Continuous Demographics	Dropping Family Structure
Employment Density						
African-American worker	-0.0083***(-2.99)	NA	-0.0081***(-2.91)	-0.0072***(-2.58)	-0.0083***(-3.00)	-0.0095***(-5.50)
with Own Share Controls						
African-American worker	0.0140* (1.65)	0.0332***(2.83)	0.0078 (0.92)	0.0124 (1.46)	0.0132(1.57)	0.0150***(2.61)
Own Share in Workplace	0.0537***(2.74)	0.0639***(3.53)	0.0385**(1.96)	0.0493**(2.51)	0.0519***(2.66)	0.0581***(4.38)
Share College Educated						
African-American worker	-0.0776***(-2.92)	NA	-0.0787***(-2.95)	-0.0682**(-2.55)	-0.0785***(-2.96)	-0.0797***(-4.63)
with Own Share Controls						
African-American worker	0.0030 (0.06)	0.07831(1.00)	0.0233 (0.44)	0.0310 (0.59)	-0.0003(0.00)	0.0059(0.16)
Own Share College Educated	0.1603**(2.26)	0.2276**(2.31)	0.1929***(2.71)	0.1933***(2.71)	0.1565**(2.20)	0.1625***(3.28)

Notes: Coefficient estimates from the interactions of employment density (panel 1) and share college (panel 2) with demographic attributes based on a model specification that includes tract by cell fixed effects, and interacts both employment density and share college with demographic attributes, industry, occuption, and metropolitan area. The top row of each panel presents the model estimates from the baseline model in Table 6, and the bottom row of each panel presents the own race estimates from the Table 7 model. Each column represents separate models with modified or extended controls. The first column presents the results from Table 6 and 7. Column 2 presents estimates where own race is based on a black-non black classification. The specification for column 3 includes the quadratic terms of employment density and share college including the interaction, column 4 includes controls for percent of black, hispanic, and Asian workers in each PUMA, and column 5 includes linear controls for all continuous demographic variables. Column 6 presents estimates from the baseline model where the cell structure is modified to eliminate any reference to information on family structure. Standard errors are clustered on the census tract of residence, and T-statistics in parentheses.

Table 9 Total Factor Productivity models

Variables	Translog model	Translog Interaction Model	Translog Interaction with mean tract FE
Own-Race Exposure Index			
Employment Density	0.0288*** (16.68)	-0.0012 (-0.10)	-0.0001 (-0.00)
Own-Race Exposure Index		-0.065 (-0.70)	-0.0567 (-0.63)
Density*Race Exposure Index		0.0919** (2.57)	0.0913*** (2.94)
Share College	0.2033*** (8.30)	0.096 (1.30)	0.0253 (0.34)
Share College Own Race Exp Index		0.0534 (0.42)	0.0236 (0.20)
Share College*Coll Race Exp Index		0.1779 (1.59)	0.2115* (1.91)
R Squared	0.9086	0.9086	0.9088
Sample Size	111695	111695	111538

Notes: Coefficients estimates of firm revenue net of materials cost on a translog model of production where inputs are capital equipment, capital structure, college educated labor and non-college educated labor plus for the last column average unobserved quality based on the worker residential locations and the tract FE estimates from the wage model in column 2 of Table 4. Model is estimated for respondents of the 1997 Census of Manufacturers for in the metropolitan areas with populations over 1 million residents. The model also includes metropolitan area and three digit industry fixed effects. Heteroskedasticity-robust standard errors are clustered on PUMA of employment. T-statistics in parentheses.

Table 10 Total Factor Productivity models with 3-digit industry FE interactions and/or PUMA FE

Density*Index	0.0913*** (2.94)	0.1922*** (8.81)	0.1190*** (8.11)	0.1851*** (10.45)
Coll share*Coll Index	0.2115* (1.91)	0.2939** (2.52)	0.4377*** (2.72)	0.4897*** (2.87)
FEs for 3-digit-Ind*(Density, Coll share)		X		X
PUMA fixed effects			X	X
R Squared	0.9088	0.9094	0.9102	0.9106
Sample size	111538	111538	111538	111538

Notes: Coefficients estimates of firm revenue net of materials cost on a translog model of production where inputs are capital equipment, capital structure, college educated labor and non-college educated labor, and unobserved quality based on the worker residential locations. Column 1 repeats the estimates from Column 3 of Table 8, and the next columns add the interaction of three digit industry FE's with employment density and share college, PUMA FE's and both sets of controls, respectively. Heteroskedasticity-robust standard errors are clustered on PUMA of employment. T-statistics in parentheses.

Table 11: Total Factor Productivity Models by Level of Research Activity

	R&D activity in 3-digit industry:		Patent activity in 3-digit industry:	
	Above median	Below median	Above median	Below median
Density*Index	0.1609*** (4.10)	0.1611*** (4.10)	0.0952** (2.24)	-0.0873 (-0.59)
Coll share*Coll Index	0.7386*** (2.92)	0.0551 (0.27)	0.7358*** (3.04)	0.2049*** (6.24)
R Squared	0.908	0.9125	0.9049	0.9162
Sample size	61194	50344	65412	46126

Notes: Coefficients estimates by firms with above or below median levels of R&D expenditures or patent activity based on a model where firm revenue net of materials cost on a translog model of production where inputs are capital equipment, capital structure, college educated labor and non-college educated labor, and unobserved quality based on the worker residential locations. All models include industry FE's, the interaction of the industry FE's with employment density and share college, and PUMA FE's. Standard errors are clustered on PUMA of employment, and T-statistics in parentheses.

Table 12: Relationship between workplace racial composition and responses to survey questions about race

	Attitude toward gov't help for blacks (1=too little, 3=too much)	Opposed to interracial marriage	Closeness to blacks (1= not at all close to 9=very close)	Closeness to whites (1= not at all close to 9=very close)	Difference between how close to whites and how close to blacks (-8=much closer to blacks, 8=much closer to whites)
Black	-0.754***	-0.079*	1.376***	-1.274***	-2.613***
	(0.054)	(0.033)	(0.198)	(0.206)	(0.235)
Workplace % white	0.051	-0.042	-1.226***	0.273*	1.52***
	(0.052)	(0.031)	(0.136)	(0.127)	(0.163)
Black*workplace % white	0.026	0.025	0.98**	0.438	-0.606
	(0.078)	(0.046)	(0.320)	(0.320)	(0.383)
Sample Size	6,603	3,964	6,505	6,469	6,437

Notes: Estimates based on Black and non-Hispanic white sample respondents to the General Social Survey in relevant years. Model specification includes indicators for year of survey and for missing report of workplace % white and its interaction with black. Robust standard errors in parentheses.

Appendix for On-line Publication Only

I. Standard errors

As a robustness test for our standard errors, following Donald and Lang (2007), we estimate the coefficients γ_{sx} separately for each demographic cell-metropolitan area group, in recognition of the fact that the demographic differences in the return to agglomeration captured by θ are only identified by variation across the groups defined by demographic cell *x* and metropolitan area *s*. However, given the incidental controls W_{is}, we estimate this model in three stages. First, we estimate

$$y_{ixst} = Z_{ixst}\gamma + W_{is}\rho + Z_{ixst}W_{is}\pi + \delta_{xt} + \tilde{\varepsilon}_{ijsxt} \tag{A1}$$

in order to remove the effect of the incidental controls W_{is} while mitigating bias by estimating parameters using within-demographic-cell residential location group variation. Second, we estimate the demographic cell-MSA group-specific parameters on Z_{ixst} using the following equation:

$$(y_{ixst} - \hat{y}_{ixst}) = (Z_{ixst} - \bar{Z}_{xst})\gamma_{xs} + \tilde{\tilde{\varepsilon}}_{ixst} \tag{A2}$$

Note that it is infeasible to estimate equation (A2) in levels rather than, as written, in deviations, because the inclusion of the incidental controls W_{is} in the demographic cell-MSA group specific models would lead to severe attrition in the resulting sample. Finally, we estimate

$$\hat{\gamma}_{sx} = X_{sx}\theta + \varphi_s + (\hat{\gamma}_{sx} - \gamma_{sx}) + \bar{\lambda}_{xs} \tag{A3}$$

using feasible GLS, as described in Donald and Lang (2007), where $\bar{\lambda}_{xs}$ is the group mean of any individual-specific heterogeneity in the return to agglomeration. This approach is imperfect because estimates of π may be biased by the omission of $Z_{js}X_{sx}\theta$ from the first stage, but this bias is mitigated by use of demographic cell-tract fixed effects, which reduces the correlation between X_{sx} and the incidental controls W_{is}.[38] Nonetheless, we only use the multi-stage approach as a general check on the inference provided by clustered standard errors in the baseline model, and all wage model estimates presented in the body of the paper rely on direct estimation of equations (2) and (3) with standard errors clustered at the census tract level.

Table A1 shows the results of the two-stage estimation, where standard errors are the result of GLS estimation. The standard errors are relatively stable for the two-stage estimates, declining from 0.0028 based on the clustered standard errors presented in Table 6 to 0.0021 for the black-white gap in return to employment density and increasing from 0.027 in table 6 to 0.032 for the black-white gap in return to share college. These findings suggest that clustering at the tract level provides reasonable standard errors for inference, particularly for employment density. While, as discussed above, we have some concerns about bias in estimating the racial gap when using the three-stage approach, the estimated racial differences are quite stable for employment density (0.0081 as compared to 0.0083 in the top panel) and reasonably stable for share college (falling from 0.0776 to a two stage estimate of 0.0528).

II. Alternative fixed effects specifications

Next, we examine the robustness of our racial differences in returns to alternative fixed effect structures. Specifically, Table A2 presents the estimated differential returns to employment density and share college for the same set of fixed effect structures that were considered in Table 4. The estimated black-white differences in the return to employment density and share college are relatively stable, with the employment density estimates ranging between

[38] As discussed above, it is not feasible to skip the first stage and estimate equation (A2) in levels with the incidental controls because the number of incidental variables is large and would lead to substantial selection in our final sample of groups in equation (6). The alternative of estimating equation (5) in levels without the incidental controls suffers from the same bias as the above approach, but the bias is exacerbated because the correlations between X_{sx} and the incidental controls W_{is} is much larger in the levels than in the demographic-cell residential location deviations.

0.0054 and 0.0086 and the share college estimates ranging between 0.0411 and 0.0776. The inclusion of tract fixed effects reduces black-white differences in the return to employment density and share college somewhat, but the use of block group fixed effects has no additional impact on these estimates and the use of tract by demographic cell fixed effects increases these estimates. The use of census tract by industry or occupation fixed effects leads to moderate reductions in the estimated black-white differences. Unlike for blacks, the inclusion of tract by demographic cell fixed effects substantially erodes the estimated differences for Hispanics and Asians. A similar erosion of the Hispanic wage gap was observed in Table 4 with the inclusion of tract by demographic cell fixed effects.

III. Estimates for own race specifications

Table A3 presents the employment density and share college interactions for all demographic variables, not just race and ethnicity as shown in Table 7 Panel 2. The interaction estimates are very similar to those in Table 6 with the employment density interactions primarily small and insignificant with the exception of graduate education and many of the share college educations statistically significant. Most notably, returns to share college increase with education levels and age.

IV. Total factor productivity models

Table A4 presents all estimates from the translog total factor productivity models presented in Table 9 where the left hand side is the log of net firm revenue, total revenue minus materials costs. These models include logarithm of college employment, non-college employment, equipment capital, structure capital, and in the third model the mean residential tract estimated fixed effect over all firm workers. The translog model includes the squares and the interactions of all factor inputs plus linear controls for employment density and share college in the three digit industry by PUMA cell. The second and third models also include controls for share own race workers in the PUMA, share of college educated workers who are of the worker's own race, and the interaction of each variable with either employment density or share college, respectively.

Following Moretti, the measures of employment density are calculated omitting the employment of the firm's own three digit industry from the measures of employment density and share college. These exclusions are made to eliminate bias from correlations between firm unobservables and their contribution to the aggregate variables. However, Guryan, Kroft and Notowindingo (2009) point out that such exclusions can bias estimates in the opposite direction, and propose constructing a second variable omitting the same information at a higher level of aggregation as a control function to absorb the bias. While their analysis is in the context of an experiment, they recommend this approach for observational data as well. We include the metropolitan employment excluding the PUMA level employment from the firm's own three digit industry as our control function. The control functions are also interacted with the own race variables in columns 2 and 3 since the aggregation variables are interacted with the own race variables in those models.

The vast majority of estimates on factor inputs are highly significant including the terms involving unobservable ability of firm workers based on residential location. The highly significant quadradic and interaction terms strongly support the use of a translog production function relative to Cobb-Douglas. Most of the squared terms are positive suggesting economies of scale, and the interaction terms are negative consistent with substitutability of these factor inputs. The one exception is the strong complementarity between high and low labor and the measure of average worker quality.

Table A1. Two Stage Model Estimates

Independent Variables	Employment Density	Share College Educated
African-American worker	-0.0081*** (-3.80)	-0.0528* (-1.65)
Hispanic worker	-0.0052 (-1.37)	-0.0291 (-0.65)
Asian and Pacific Islander worker	-0.0063* (-1.74)	-0.0401 (-0.37)
Second Stage R-square	0.2580	0.1067
Second Stage Sample Size	6203	6204

Notes: Estimates from regressions of demographic cell by metropolitan area fixed effects from a wage equation on a vector of demographics and metropolitan area FE's using Feasible GLS. Heteroskedasticity-robust standard errors clustered on the tract of residence. T-statistics in parentheses.

Table A2: Race Coefficients with varying Fixed Effects Structure

Variables	Metropolitan Area Fixed Effect	Tract Fixed Effect	Block Group Fixed Effect	Tract-Cell Fixed Effect	Tract-Industry Fixed Effect	Tract-Occupation Fixed Effect
Race Differences in the Return to Employment Density						
African-American worker	-0.0086	-0.0075	-0.0076	-0.0083	-0.0054	-0.0071
	(-10.07)	(-9.47)	(-9.23)	(-2.99)	(-5.26)	(-8.84)
Hispanic worker	-0.0076	-0.0041	-0.0042	-0.0021	-0.0037	-0.0035
	(-9.90)	(-4.86)	(-4.71)	(-0.58)	(-3.65)	(-4.02)
Asian and Pacific Islander worker	-0.0108	-0.0071	-0.0068	-0.0044	-0.0071	-0.0070
	(-13.81)	(-7.35)	(-6.86)	(-1.16)	(-6.25)	(-7.22)
Race Differences in the Return to Share College-Educated						
African-American worker	-0.0687	-0.0491	-0.0491	-0.0776	-0.0411	-0.0416
	(-5.69)	(-5.76)	(-5.57)	(-2.92)	(-3.51)	(-4.76)
Hispanic worker	0.0440	0.0238	0.0224	0.0157	0.0037	0.0280
	(3.15)	(2.47)	(2.25)	(0.39)	(0.30)	(2.85)
Asian and Pacific Islander worker	0.1952	0.1821	0.1815	0.1215	0.1725	0.1873
	(8.98)	(13.57)	(13.16)	(2.05)	(10.85)	(13.79)
sample size	2,343,092	2,343,092	2,343,092	2,343,092	2,343,092	2,343,092

Notes: Coefficient estimates from the interactions of employment density (panel 1) and share college (panel 2) with demographic attributes based on a model specification that uses various fixed effect structures, includes controls for demographic attributes for all but the tract by cell fixed effects, and interacts both employment density and share college with demographic attributes, industry, occuption, and metropolitan area. Heteroskedasticity-robust standard errors are clustered on the census tract of residence, and T-statistics in parentheses.

Table A3: Model of the Wage Return to Agglomeration with Own Race Controls

Fully Interacted Model	Employment Density	Share College Educated
African-American worker	0.0140* (1.65)	0.0030 (0.06)
Hispanic worker	0.0234**(2.40)	0.0821 (1.36)
Asian and Pacific Islander worker	0.0215**(2.16)	0.1918***(2.69)
Age 40-49	0.0014(0.99)	0.0727***(5.18)
Age 50-59	0.0008(0.40)	0.1254***(5.72)
Less than high school degree	-0.0055(-1.14)	-0.0434(-1.17)
Associates degree	0.0006(0.28)	0.1046***(6.03)
Four year college degree	0.0021(0.97)	0.1547***(7.42)
Master degree	0.0049*(1.99)	0.1946***(6.32)
Degree beyond Masters	0.0044(1.22)	0.3769***(6.14)
Single with children	0.0018(0.84)	-0.0396(-0.66)
Single without children	-0.0029(-0.30)	-0.0270(-1.31)
Married without children	0.0029*(1.67)	-0.0377**(-2.22)
Not born in U.S. resident less than 8 years	-0.0012(-0.23)	0.0513(0.60)
Not born in the U.S. resident 8 years or more	0.0003(0.12)	0.0736*(1.79)
Own Share in Workplace	0.0537***(2.74)	NA
Own Share College Educated	NA	0.1603**(2.26)
R-square	0.7141	
Sample size	2,331,688	

Notes: Coefficient estimates from the interactions of employment density and share college with demoraphic attributes based on a model specification that includes demographic cell by census tract fixed effects and interacts both employment density and share college with demographic attributes, industry, occuption, and metropolitan area. Heteroskedasticity-robust standard errors are clustered on the census tract of residence, and T-statistics in parentheses.

Table A4 Total Factor Productivity models

Variables	Translog model	Translog Interaction Model	Translog Interaction with mean tract FE
Non College Employment	0.3502***(21.07)	0.3515***(21.37)	0.3461***(21.22)
Non College Employment Squared	0.0512***(71.91)	0.0515***(76.59)	0.0523***(80.49)
College Employment	0.0695***(13.57)	0.0679***(13.15)	0.0745***(15.02)
College Employment Squared	0.0169***(35.96)	0.0166***(37.01)	0.0159***(37.17)
Equipment Capital	0.4729***(27.42)	0.4743***(27.55)	0.4842***(29.21)
Equipment Capital Squared	0.0217***(22.11)	0.0218***(22.11)	0.0215***(22.06)
Structure Capital	0.0872***(21.37)	0.0869***(21.27)	0.0872***(21.44)
Structure Capital Squared	0.0022***(6.20)	0.0022***(6.19)	0.0023***(6.35)
Mean Tract FE			-1.0220***(-4.58)
Mean Tract FE Squared			0.2806**(2.09)
Equipment Capital*Non College Employment	-0.0600***(-34.96)	-0.0604***(-36.30)	-0.0607***(-35.94)
Equipment Capital*College Employment	-0.0111***(-14.76)	-0.0109***(-14.45)	-0.0110***(-14.85)
Structure Capital*Non College Employment	-0.0027***(-4.47)	-0.0027***(-4.48)	-0.0027***(-4.46)
Structure Capital*College Employment	-0.0014***(-6.38)	-0.0014***(-6.39)	-0.0014***(-6.16)
Equipment Capital*Structure Capital	-0.0053***(-8.22)	-0.0053***(-8.13)	-0.0054***(-8.22)
Non College Employment*College Employment	-0.0034***(-4.30)	-0.0033***(-4.16)	-0.0031***(-3.95)
Mean Tract FE*Equipment Capital			0.0314(0.92)
Mean Tract FE*Structure Capital			-0.0030(-0.42)
Mean Tract FE*Non College Employment			0.0722***(2.66)
Mean Tract FE*College Employment			0.0389***(5.18)
Employment Density	0.0288*** (16.68)	-0.0012 (-0.10)	-0.0001 (-0.00)
Own-Race Exposure Index		-0.065 (-0.70)	-0.0567 (-0.63)
Density*Race Exposure Index		0.0919** (2.57)	0.0913*** (2.94)
Share College	0.2033*** (8.30)	0.096 (1.30)	0.0253 (0.34)
Share College Own Race Exp Index		0.0534 (0.42)	0.0236 (0.20)
Share College*Coll Race Exp Index		0.1779 (1.59)	0.2115* (1.91)
Firm Percent Black		-0.0377 (0.93)	-0.0311 (0.79)
Firm Percent Hispanic		-0.08473** (2.06)	-0.07597* (1.92)
Firm Percent Asian		-0.07857** (2.04)	-0.06999* (1.89)
Firm Percent Other Race		-0.0981 (1.57)	-0.0914 (1.46)

Variables	Translog model	Translog Interaction Model	Translog Interaction with mean tract FE
Guryan controls for emp den	-0.5166(-0.02)	-3.8784(-0.12)	-4.6216(-0.16)
Guryan controls for college share	-6.2514**(-2.19)	-5.8335**(-1.97)	-5.3116*(-1.82)
Guryan controls for emp den*Race Exposure Index		2.7116*(1.77)	2.1239(1.43)
Guryan controls for college share*Coll Race Exposure Index		-0.3994(-1.62)	-0.3420(-1.50)
R Squared	0.9086	0.9086	0.9088
Sample size	111695	111695	111538

Notes: Coefficients estimates of firm revenue net of materials cost on a translog model of production where inputs are capital equipment, capital structure, college educated labor and non-college educated labor plus for the last column average unobserved quality based on the worker residential locations and the tract FE estimates from the wage model in column 2 of Table 4. Model is estimated for respondents of the 1997 Census of Manufacturers for in the metropolitan areas with populations over 1 million residents. The model also includes metropolitan area and three digit industry fixed effects. Heteroskedasticity-robust standard errors are clustered on PUMA of employment. T-statistics in parentheses.