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Race-Specific Agglomeration Economies: Social Distance and the Black-White Wage Gap

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Abstract

We demonstrate a striking but previously unnoticed relationship between city size and the black-white wage gap, with the gap increasing by 2.5% for every million-person increase in urban population. We then look within cities and document that wages of blacks rise less with agglomeration in the workplace location, measured as employment density per square kilometer, than do white wages. This pattern holds even though our method allows for non-parametric controls for the effects of age, education, and other demographics on wages, for unobserved worker skill as proxied by residential location, and for the return to agglomeration to vary across those demographics, industry, occupation and metropolitan areas. We find that an individual's wage return to employment density rises with the share of workers in their work location *who are of their own race*. We observe similar patterns for human capital externalities as measured by share workers with a college education. We also find parallel results for firm productivity by employment density and share college-educated using firm racial composition in a sample of manufacturing firms. These findings are consistent with the possibility that blacks, and black-majority firms, receive lower returns to agglomeration because such returns operate within race, and blacks have fewer same-race peers and fewer highly-educated same-race peers at work from whom to enjoy spillovers than do whites. Data on self-reported social networks in the General Social Survey provide further evidence consistent with this mechanism, showing that blacks feel less close to whites than do whites, even when they work exclusively with whites. We conclude that social distance between blacks and whites preventing shared benefits from agglomeration is a significant contributor to overall black-white wage disparities.

JEL Codes: J15, J24, J31, R23, R32

Key Words: Black White Wage Gap, Agglomeration Economies, Human Capital Externalities, Information Networks, Total Factor Productivity

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, even when conditioning on a variety of measures of productivity (Neal and Johnson 1996; Lang and Manove 2006; Black, Haviland, Sanders and Taylor 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.

A previous undocumented characteristic of American cities that is consistent with this possibility is 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. [1] A one-standard-deviation increase in total employment increases the black-white wage gap by 0.66 percentage points, and a one-standard-deviation increase in employment density (workers per square mile) increases the black-white wage gap by 1.38 percentage points. Looking within metropolitan areas, we find very similar effects. A one standard deviation increase in workplace employment density (defined as workers per square kilometer in the PUMA[2] of work) increases the wage gap by 1.9 percentage points in

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[1] Put another way, the average racial wage gap in metropolitan statistical areas (MSAs) of around one million people, such as Tulsa, OK, is 20% smaller than the gap in the nation's largest metro areas of Chicago, Los Angeles, and New York City.

[2] Workplace is based on the Public Use Microdata Area (PUMA), defined to report residential location in the Public Use Microdata Sample (PUMS) of the 2000 Decennial Census, and is constructed to contain a population of 100,000 residents. We calculate workplace PUMA variables based on the population of workers reporting their work location at the census tract level, which is then matched to 2000 PUMA definitions. The PUMS also reports individual workplace using an alternative "workplace PUMA," but these definitions vary dramatically across metropolitan

a wage regression with standard census controls. The combination of 1) this new evidence on the relationship between city size, workplace employment density and skill composition, and the racial wage gap, 2) recent research emphasizing the importance of workplace networks (both intra- and inter-firm) in generating wage returns to employment density and human capital concentration, and 3) recent empirical work demonstrating that work networks are race-specific, suggests that the possibility of differential returns to agglomeration by race is worthy of more thorough investigation.

In this paper, we demonstrate that African-Americans receive smaller wage benefits from employment density and human capital concentration than do whites, even when including highly flexible controls intended to capture both observed and unobserved individual attributes and when allowing for very heterogenous returns to workplace characteristics. Further, we provide evidence that one major driver of this relationship is that African-Americans have fewer same-race peers in the workplace from whom to enjoy productivity spillovers. We observe very similar patterns for wage returns to share 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 social interaction conditional on physical proximity—persists regardless of the racial mix of the workplace.

Studies of both the black-white wage gap and of agglomeration and the urban wage premium raise unobserved productivity attributes as a fundamental concern. Neal and Johnson (1996) and Lang and Manove (2006) 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

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area. Fu and Ross (2010) confirm that agglomeration estimates are robust to alternative workplace definitions including workplace PUMA, PUMA, and zip code area.

wage premium associated with city size decreases substantially after the inclusion of a worker fixed effect. Our paper addresses this concern by following an approach developed by Fu and Ross (In Press). They use 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. They demonstrate that residence fixed effects provide an effective control for unobserved ability, and find no evidence of bias in agglomeration estimates from workers sorting into high density locations based on ability.[3] Further, in our sample, we find that controlling for residential location fixed effects eliminates any correlation between employment density or share college and indicators for whether an individual is white or black and reduces unexplained racial differences in wages by 53%, which is comparable to the 48% reduction in the black-white wage gap found by Lang and Manove (2006) from the inclusion of the AFQT score, suggesting that the method adequately captures unobserved skill differences between blacks and whites.

In this paper, we document that wages of blacks rise less with employment density than do white wages for a sample of prime age, fully employed males residing in metropolitan areas with more than one million residents. Even after controlling non-parametrically for the effects of observables such as age, education, and other demographics, as well as of unobservables through residential location, and after allowing for the 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 1.7 percentage point increase in the black-white wage

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[3] 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 also demonstrate that neither the wage return to density or 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 Lou (2011) for similar logic on the difference between real and nominal wages within metropolitan areas.

gap, very similar in magnitude to the 1.9 percentage point estimated effect mentioned above. Further, we demonstrate that there is no within-metropolitan correlation between employment density and worker race.

Next, we explore whether these differences in returns might be explained by race-specific information networks (Hellerstein et al. 2009; Ionnides and Loury 2004). Consistent with this hypothesis, we find that higher own-race representation in a work location increases the returns 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 estimated racial difference in the return to agglomeration.

To test whether this difference in returns reflects a difference in worker productivity (rather than in, say, bargaining power), we estimate total factor productivity (TFP) models for manufacturing establishments[4] covering the same metropolitan areas as our worker sample. Following Moretti (2004), we identify a sample of workers in each establishment based on zip code-three digit industry cells, and we confirm that firm TFP increases in locations that have high concentrations of employment.[5] 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. In fact, we calculate that racial differences in average firm productivity that arise because black workers are employed at firms that have a worse demographic match with the surrounding location can explain up to 0.6 percentage points of the black-white wage gap.

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[4] TFP models can only be estimated in manufacturing establishment data because establishment data for other industries do not contain estimates of either materials costs or capital stock.
[5] Our results are for within-MSA variation, whereas Moretti examines MSA-level variation.

While higher productivity in large cities and dense employment locations is a relatively accepted feature of urban economies, the existence of economies associated with human capital externalities is much more controversial. Moretti (2004a) finds evidence of higher wages in cities with greater concentrations of college-educated workers even after controlling for worker fixed effects. In contrast, Acemoglu and Angrist (2001) find no evidence of human capital externalities across states using quarter of birth as an instrument, and Ciccone and Peri (2006) find no evidence of human capital externalities in cross-metropolitan wage differences after taking into account the effect of the change in the mix of low and high skill workers in production. On the other hand, Moretti (2004b) finds evidence of higher firm productivity in cities with a large share of college graduates even after controlling for both the mix of low and high skill labor and firm fixed effects.[6]

For completeness, we also examine racial differences in the return to the concentration of college-educated workers, and results are very similar to those for employment density, with blacks receiving a lower wage return than whites to their work location's share of college-educated workers. These differences are substantially explained because blacks have lower exposure to same-race college-educated workers and because they tend to work in firms in locations where few of the college-educated workers are of the same race as the majority of their own workers. While there is no correlation between share college and worker race after conditioning on residential location, these results still must be interpreted with some caution

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[6] Fu and Ross (In press) also find mixed evidence. They find that returns to human capital externalities are attenuated significantly by the inclusion of residential fixed effects raising the possibility that remaining effects might be driven by unobservables that were not captured by residential location. However, they also demonstrate that the remaining estimated effects of human capital externalities are unlikely to be driven by unobserved ability because observationally equivalent workers in work locations with different shares of college-educated workers are earning similar wages net of commuting costs.

because the estimated effects for return to share college, unlike our estimates for return to employment density, fall substantially as additional controls are added.[7]

The share of same-race peers at work should not matter for spillovers if workers are equally likely to enjoy spillovers from any peer, regardless of racial (mis)match. However, self-report data from the General Social Survey demonstrate that African-Americans feel much greater social distance from whites than from blacks[8], 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 information 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 reviews the literatures on agglomeration economies and on the causes of wage disparities as motivation for our hypothesis that racial wage gaps are partially driven by weaker same-race workplace networks through which to gain from agglomeration. Section III describes our wage model. Section IV describes the individual data, and section V presents results. Section VI discusses and concludes.

II.   Literature review

Racially segregated networks and labor market outcomes

A large and diverse literature documents the disadvantages and adverse outcomes experienced by African-Americans in segregated neighborhoods and metropolitan areas.

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[7] Our simple within-metropolitan-area estimates imply a 5.0 percentage point standardized effect of share college on the black-white wage gap, but the estimated effect falls to only 1.3 percentage points in our preferred specification.
[8] 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.

African-Americans experience much higher levels of residential segregation and centralization than other minority groups (Massey and Denton 1993), and adverse changes in U.S. central cities over the last several decades may have disproportionately affected African-Americans. Wilson (1987) argues that African-Americans' outcomes are negatively affected by their concentration in increasingly poor and distressed central city neighborhoods. Kain (1968) suggests that the increasingly poor job access of African-Americans in central cities may have adverse effects, and recent work by Hellerstein et al. (2008) finds that employment depends heavily on physical access to locations where members of one's own race are employed.[9] Edin et al. (2003) and Damm (2006) find that the placement of refugees into ethnic enclaves in Sweden and Denmark, respectively, affects labor market outcomes.

Beyond the potential social influences of location, labor market outcomes are directly influenced by relationships between workers, and these relationships are mostly segregated by race. Bayer et al. (2008) illustrate the importance of referrals within homophilic networks in obtaining employment; they find that similar individuals who reside on the same block are more likely to work together and that the similarity of a worker to others residing nearby drives both employment and wages. Hellerstein et al. (2009) find that employees at the same firm are more likely to come from the same neighborhood than are employees who work at different firms in the same location, and, notably, that this effect primarily operates within racial and ethnic groups. Dustman et al. (2009) find that minority workers in Germany are much more likely to work in locations where other minorities work.[10]

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[9] The literature associated with the spatial mismatch hypothesis is huge. See Ihlanfeldt and Sjoquist (1998) and Kain (1992) for detailed surveys.

[10] Ioannides and Loury (2004) provide a detailed review of the extensive literature on labor market referrals and networks documenting several important stylized facts. Also see Granovetter (1995).

Networks and agglomeration economies

Given the strong evidence that a major source of agglomeration economies is spillovers across individuals,[11] it stands to reason that peer and social interaction effects that arise in dense areas increase individual and firm productivity. For example, Nanda and Sorenson (2008) find evidence of peer effects on self-employment that suggests knowledge- or experience-sharing between workers. In addition, if peers share knowledge not only about how to be productive on the job, but also about job opportunities, match quality may be greater in denser areas. Peers may affect one another's productivity through establishing norms about absenteeism or work effort (Bokenblom and Ekblod 2007; Ichino and Maggi 2000; Lindbeck et al. 2007; DePaola 2008; Bandiera, Barankay and Rasul 2005; Falk and Ichino (2006); Mas and Moretti 2006).[12] These putative mechanisms, however, depend essentially on actual social interactions between peers. To the extent that, even within the same industry, individuals are more likely to associate with peers of the same race, race-specific knowledge and job-finding networks (Hellerstein et al. 2009) could explain why in most industries (where whites make up the bulk of workers), knowledge spillovers may accrue more to whites than to nonwhites.

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[11] The most direct evidence of workers' productivity being influenced by surrounding firms, workers, and/or economic activity arises from papers exploring reasons for the well-documented fact that wages are higher in large labor markets with high concentrations of employment and human capital. 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 (2006) and Fu and Ross (2010) find evidence that wage benefits from local-area employment density and human capital concentration arise *within* metropolitan areas. Rosenthal and Strange document a fairly rapid decay of these spillovers across space, again consistent with agglomeration resulting from social interactions, as opposed to deriving from shared infrastructure or externalities associated with a broader labor market. At the firm level, Rosenthal and Strange (2003) find that the likelihood of firm births is increased by the geographic proximity of other firms in the same industry, especially within the first mile, suggesting a substantial role for 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, even after controlling for the education level of the firm's workforce. See Audretsch and Feldman (2004), Duranton and Puga (2004), Moretti (2004) and Rosenthal and Strange (2004) for detailed surveys of the literature on agglomeration economies and production externalities within cities.

[12] See Ross (In Press) for a recent review of the general literature on neighborhood and peer effects.

In this paper, we test whether racial disparities exist in the return to workplace externalities, examining two types of externalities. The first, captured by the density of industry-specific employment in the part of an MSA in which an individual works (the "workplace PUMA"), focuses on general spillovers associated with the total amount of a given type of economic activity in an area, or industry-specific agglomeration economies. The second, captured by the share of workers in an individual's workplace 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. Finally, in order to help explain why racial disparities exist in the return to agglomeration, we show that social distance between blacks and whites is not reduced by workplace proximity. Arguably due to this lack of social contact, we also find that firm-level productivity is not increased by the presence of other firms when there is racial mismatch with the employees of those firms.

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:

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

where Z_{js} is a measure of workplace externalities in an individual's work location, captured by either employment density or share college-educated, X_{ijs} is a vector of individual level demographic indicators, W_{ijs} 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. Equation (1) can be estimated for the entire sample or for specific subsamples, and for consistency this equation (1) implicitly requires the assumption that workers do not sort into locations with high or low Z_{js} based on unobservable attributes α_{is}.

Second, our main analysis collapses the individual data to 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 we allow agglomeration effects to vary in magnitude by both X_{is} and W_{is} via γ_{sx} and ω_{is}, respectively.

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

where

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

δ_{xt} is the demographic cell-residential location fixed effect,[13] 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 remains after conditioning on δ_{xt}, where δ_{xt} is included in the model in order to weaken the correlation between the error and the terms involving Z_{js}. 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 choices are likely to be relatively similar on unobservables. Equations (2) and (3) can be estimated using a single stage linear model.

Standard errors estimates via equation (1) suffer from the bias identified by Mouton (1986) because individuals who selected into the same work location j share the same value of Z_{js}, and so standard errors are clustered at the work location j. The standard errors in equation (2) may suffer from the bias identified by Bertrand, Duflo, and Mullainathan (2004) for clustered

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[13] Note that the demographic cell-residential location fixed effects capture both the coefficients on X_{is} from equation (1) and the MSA fixed effects δ_s.

data with fixed effects, which in our case can be addressed by clustering standard errors at the residential location t. The Moulton (1986) bias is almost certainly far less severe in the model described by equations (2) and (3) because estimates are based on the within-group deviation of Z_{js}, which will only take the same value for individuals who belong to the same demographic cell and choose the same residential location and work locations. Further, all individuals who share a common mean-differenced value of Z_{js} reside in the same location, and so any correlation of this sort is also handled by the clustered standard errors. Nonetheless, 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 captured by θ are only identified by variation across the groups defined by demographic cell x and metropolitan area s.[14]

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.[15] 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.

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[14] See appendix for details.
[15] This sample is comparable to the sample drawn from the Public Use Microdata Sample (PUMS) of the 2000 Census by Rosenthal and Strange (2006) except that we explicitly restrict ourselves to considering residents of mid-sized and large metropolitan areas.

Table 1 reports individual, employment location PUMA, [16] and metropolitan area characteristics by race [17] (white, African-American, Hispanic, or Asian) of the worker. Our 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 using workers per square mile 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. 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.

Table 2 reports the results of a basic agglomeration economies model 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 strongly predict higher wages for that individual, consistent

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[16] As described in footnote 2, 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 workplace PUMA.

[17] 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").

with the existence of agglomeration economies and human capital spillovers.[18] A one-standard-deviation increase in density (i.e. an increase in one's own industry and PUMA of 2100 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 increases of 6.6 percentage points.

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 an indicator for racial identity. Table 3 column 1 presents the correlation for an indicator for whether the individual is white and column 2 presents the correlation for an indicator for whether an individual is black. The first panel shows the unconditional correlations between these variables. The correlation 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. While small, these correlations raise some concerns about sorting over our variables of interest. Conditioning on metropolitan fixed effects lowers the correlation of employment density substantially to -0.003 and 0.003 for the black and white indicators, respectively, but has less effect on the correlations with share college, leaving them at 0.035 and -0.022, respectively. However, the inclusion of tract fixed effects substantially reduces the correlation with share college to -0.001 for blacks and 0.007 for whites. These correlations are consistent with the findings of Fu and Ross (2013) that there is little sorting across workplace based on employment density, but that estimates on share college are likely to

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[18] 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. Earlier models estimated using overall 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.

be substantially more sensitive to controls for unobserved ability. We therefore interpret our results for share college with some caution.

Next, in Table 4, we examine the racial and ethnic differences in wages over a variety of models with alternative sets of fixed effects. The column 1 estimates are from the same metropolitan area fixed effect model as 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 (2006) 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 of 0.094 in the tract fixed effect model to 0.066 in the cell by tract fixed effect model.

V. Results

Table 5 re-estimates the models from Table 2 separately by race and ethnicity, and reveals that whites receive higher than average returns to both employment density and share college, while nonwhites receive much lower than average returns. African-Americans, in particular, get returns only 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, we turn in Table 6 to 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 interacted with worker demographics, industry, occupation and metropolitan area in order to control for differential returns to agglomeration that might be correlated with observable factors. . The estimates presented in the top panel of Table 6 represent the interactions of employment density and share college with education, family structure and immigration status. As discussed above, standard errors are clustered at the census tract level.

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 in most cases to greatly affect the relationship between wages and employment density. Age and, especially, education increase the wage benefit from the share college-educated in one's workplace and industry, as might be expected. 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 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, as shown in Table 2, 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 wage gap, and the differences estimated in Table 6 are consistent with a 1.7 percentage point increase.

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, race is not the dominant demographic factor for explaining differences in the wage return to share college. The effect of education on returns is substantially larger than the effect of race, and the effect of experience/age differences is similar in magnitude to the observed race coefficients. Further, this estimated effect is substantially smaller than the 5.0 percentage point increase in the wage gap implied by a one-standard deviation increase in share college in Table 5; unlike with employment density, our controls substantially erode the black-white gap in return to share college.[19] Therefore, again, the results for share college should be interpreted with more caution than the employment density results.

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 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 fully interacted model, but no significant difference in return to density, and marginally significantly lower

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[19] 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.

return than whites to density in the two-stage model shown in the appendix, but no significant difference in return to share college.[20]

The racial return gap and the racial composition of the workforce

Table 7 tests whether the pattern of racial disparities in the returns to agglomeration is consistent with agglomeration economies arising from race-specific networks. Under such circumstances, nonwhites may be disadvantaged because they lack same-race peers in the area where they work. To examine this hypothesis, we control for own-race share in order to test whether it moderates racial differences in the return to agglomeration. For employment density, the return to and racial difference in return to overall employment density are interacted with own-race share of employment in the PUMA. For share college, the return to share college educated and racial differences in return are interacted with own-race share of college educated workers in the PUMA. 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.[21]

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 members of one's own race in one's PUMA (.0537) on the return to density is much larger than the average return to density from Table 2 (.0118). The effect of having only

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[20] The appendix contains estimated standard errors using a three-stage estimation approach based on Donald and Lang (2007). This approach yields quite similar standard error estimates as clustering at the census tract level. In addition, the appendix presents a series of robustness tests showing the estimated racial differences across the same set of alternative fixed effect structures considered in Table 4.

[21] The estimates presented 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.

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 (.389), is still appreciable.[22]

Moreover, black-white differences in own-race share of the workforce can explain a significant portion of the black-white difference in the return to employment density and in the return to share college-educated. From Table 4, the effect of a one standard deviation change in employment density on racial differences in wages is 1.7 percentage points, while the estimates from Table 6 and the observed racial differences in exposure to own race of 0.211 are associated with a standardized effect of 1.1 percentage points, or 65% of the estimated racial difference. Racial differences in exposure to college educated workers of the same race are 0.101, implying a standardized effect of 1.6 percentage points, which is actually larger than the 1.3 percentage point effect of share college on the black-white wage gap from Table 4. These findings complement earlier work by Hellerstein et al. (2009) arguing that employment networks operate along racial lines, and suggest that not only finding a job, but also benefiting from returns to agglomeration on the job, depend on own-race share in the workplace.[23]

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

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[22] We also investigated estimating models where the effect of own race is allowed to vary by the individual's race. The estimated racial differences in the effect of own race on the returns to density and share college were very noisy and entirely uninformative.

[23] The appendix presents robustness tests that involve additional controls at the PUMA level, which is the same level at which own race is measured. Specifically, the appendix shows that our results are robust to including controls for non-linear returns to density and share college, controls for PUMA-level worker racial and ethnic composition, and to specifying share own race based on a black – non-black classification. We also examine subsamples of industries with high and low returns to employment density and share college based on the estimated coefficients of the interactions between these variables and industry fixed effects. However, in both cases, the subsample of high return industries is small enough that the large number of cell by tract fixed effects yields very noisy and insignificant estimates in the high sample and results very similar to our baseline results in the low sample.

restricted to examining only manufacturing data because information on the cost of materials and on the stock of capital, which is necessary to estimate total factor productivity (TFP), is only available for the manufacturing industry.[24]

Using these data, we can estimate models for firm net revenues (total revenues minus material costs) as a translog[25] function of structure capital, equipment capital, and employment. For employment, we follow Moretti (2004) 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.[26] In cases where we cannot match establishment zip code to decennial Census data, we base our estimates on industry-PUMA cells. 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.

The results of our baseline translog model are shown in Table 8 column 1. We estimate that the effect of a one-standard-deviation increase in the share of workers in a PUMA who are college-educated on firm total factor productivity is 0.020. This estimate is comparable in

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[24]We also explore estimating the wage models for a subsample of manufacturing workers. Again, the estimates are qualitatively very similar to the results in Table 7, but have very large standard errors and are statistically insignificant.

[25] We have also estimated the model using a Cobb-Douglas production function (results available upon request). However, we strongly prefer the translog. Theoretically, 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, a huge increase given the relatively small change in available degrees of freedom. The resulting F-statistic is 8,147, dramatically rejecting the Cobb-Douglas model. Further, 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. This difference between the translog and Cobb-Douglas models in terms of R-squared and precision of estimates does not arise in Moretti's across-metropolitan-area models.

[26] Because our analysis looks within metropolitan areas and we have confidential data for both the decennial Census and the Census of Manufacturers, we are able to estimate the number of college-educated and other workers in each firm based on placing firms into three digit industry code by zip code cells, rather than industry code by metropolitan area cells as done by Moretti (2004).

magnitude to Moretti's cross-MSA estimates that a one-standard-deviation increase in share college-educated increases total factor productivity by between 0.035 and 0.049, especially given that our estimate is reduced substantially by the inclusion of a 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 at other firms in this PUMA-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 in which their firm is located. 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 actual firm productivity depends upon firm employees' within-race interaction opportunities. We also include direct controls for the racial composition of the workers in each firm cell.

The estimates including these variables are shown in column 2. We find a strong, statistically significant effect on productivity of the interaction between firm workers' average exposure to own-race workers in PUMA-industry and employment density. 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. Similarly, there is no increase in productivity from increased exposure to same-race workers when holding industry density of employment constant. In other words, increased density of employment increases a 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 that 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[27] and an indicator for whether we were able to match zip codes between the establishment and decennial Census data or were required to match based on industry-by-PUMA cells. 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 9 presents a series of robustness checks for the final model in Table 8 by adding a series of fixed effects.[28] Column 2 includes indicators for three-digit-industry interacted with density and share college-educated; column 3 includes PUMA fixed effects; and column 4

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[27] In other words, we control for unobserved worker ability using the mean of the residential-tract fixed effect estimate of the employees of the firm. The estimates for mean tract FE/unobserved worker ability are not shown because the variable is included in the translog production as another input and so involves several interactions. However, we also estimated the Cobb-Douglas model with this control and find that, as expected, the mean tract FE variable has a positive and statistically significant effect on firm net revenue with an estimate of 0.145 and a t-statistic of 2.69.

[28] These results are included in the paper rather than with the other robustness checks in the appendix because they have a relatively dramatic effect on the magnitude of the estimates.

includes both. Each of these changes greatly increases the precision of the estimates, as well as the magnitude of the return to share college interacted with same-race college-educated exposure. In terms of magnitude, racial differences in exposure to firms with high values on the own race variables can also explain a substantial fraction of the black-white wage gap. Given these racial differences, one standard deviation increase in exposure to employment density is associated with a 0.3 to 0.7 percentage point increase in the black-white wage gap, while a one standard deviation increase in exposure to share college is associated with between a 0.9 and 2.1 percentage point increase. These changes are very similar in magnitude to the own race effects estimated in the wage models of 1.1 and 1.6 percentage points for employment density and share college.

Finally, Table 10 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. low rate of patent production.[29] Again, precision increases, 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 one might expect. For employment density, effects are similar across R&D but are significantly higher in the high patent than in the low-patent industries. Overall, the estimates in Tables 8 through 10 strongly support the hypothesis that returns to agglomeration are driven by increases in productivity due to workers' interactions with others of the same race.

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

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 includes employed blacks and whites who responded to surveys in which the relevant questions were asked.[30] 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. 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.

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

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[30] 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.

social attitudes question about whether the respondent approves of a law banning interracial marriage, and a pair of personal attitudes 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.[31]

Table 11 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 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,[32] 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

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[31] 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.

[32] 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).

whites, relative to whites with whites, is 1.3 points on a 9-point scale. In addition, people in whiter workplaces report being 1.2 points less close to blacks and 0.3 points closer to whites. 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, they are still significantly less close to whites than are whites—even whites employed in all-nonwhite firms (who are 1.3 points closer to whites than are blacks in all-nonwhite firms). These results are suggestive (although they cannot be conclusive) 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 in the U.S. that are believed to be exacerbated by income inequality. Racial differences both in the return to employment density and in human capital spillovers associated with worker education levels 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 substantially erode the black-white wage gap. While the estimated racial differences in the return to share college decline substantially relative to simple within metropolitan area estimates, our general findings for share college are robust across a series of specifications.

Several pieces of evidence suggest that black undercompensation is driven by race-specific social networks in the workplace. First, the returns to both density and share college-educated 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 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 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 (or of college-educated workers in the firm to same-race college-educated peers) rises. Finally, we find that the social distance blacks report with respect to whites persists even among blacks who work in all-white firms, suggesting that blacks do in fact 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 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 1.1 and 1.6 percentage point increases in the black-white wage gap. Similarly, given racial differences in exposure to firms whose racial composition matches the dominant racial group of surrounding workers, one standard deviation changes in employment density and share college are associated with 0.7 and 2.0 percentage point (given our preferred models) increases in the black-white difference in exposure to firm productivity. We conclude that social distance between blacks and whites preventing

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shared benefits from agglomeration is a significant contributor to overall black-white wage disparities in U.S. metropolitan areas.

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Appendix: Wage Model Robustness Tests

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}.[33] 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

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[33] 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. Additional controls

Finally, we revisit our key model results presented in Table 7 for a series of additional controls at the workplace PUMA level. Table A3 column 1 repeats the black and own race results from Table 7. The second column allows the return to employment density and share college to be non-linear by incorporating the square of these variables into the wage equation. The third column incorporates additional PUMA controls, e.g. the percent of workers in a PUMA who are black, Hispanic or Asian. The fourth column repeats own race analysis in Column 1 except that percent black in workplace is used for black workers and percent non-black is used for all other workers. Both the estimated racial differences in returns to employment density and share college and the estimated effects of own race on return to these variables are relatively stable to these alternative specifications.
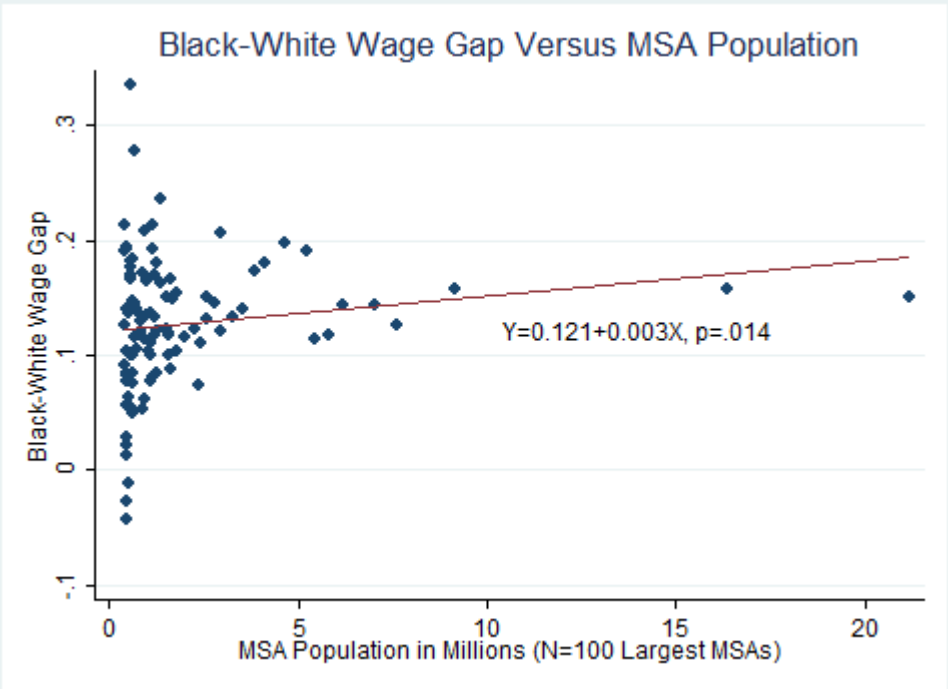
Figure 1.

Black-White Wage Gap Versus MSA Population

Y=0.121+0.003X, p=.014

Black-White Wage Gap

MSA Population in Millions (N=100 Largest MSAs)

Table 1: Descriptives				
	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 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 metropolitan fixed effects and heteroskedasticity-robust standard errors clustered on PUMA of employment. 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	-0.0034	0.0034
Share workers with college degree	0.0346	-0.0222
Conditional on Tract Fixed Effects		
Employment density in 1000's per square KM	0.0002	0.0037
Share workers with college degree	-0.0005	0.0072
Sample Size	2,343,092	

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

Table 4: Race Coefficients with Various Fixed Effects Structures						
Variables	MSA 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: Race and ethnicity coefficients from fixed effect models using the regression sample of 2,343,092 observations and heteroskedasticity-robust standard errors clustered on PUMA of employment. 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 and heteroskedasticity-robust standard errors clustered on PUMA of employment. 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 demographic 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 7: Agglomeration Model with Own Share Controls		
Baseline 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)
R-Square	0.7139	
with Own Share Controls		
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 first panel repeats the estimates from Table 6, and the second panel presents estimates for 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. Heteroskedasticity-robust standard errors are clustered on the census tract of residence, and T-statistics in parentheses.

Table 8 Total Factor Productivity models			
Variables	Translog model	Translog Interaction Model	Translog Interaction with mean tract FE
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 in a translog model of production where inputs are capital equipment, capital structure, college educated labor and non-college educated labor; the last column also includes average unobserved quality based on 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 in metropolitan areas with population 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 9 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 in 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 FE's, respectively. Heteroskedasticity-robust standard errors are clustered on PUMA of employment. T-statistics in parentheses.

Table 10: 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 of firm revenue net of materials cost in 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. Heteroskedasticity-robust standard errors are clustered on PUMA of employment. T-statistics in parentheses.

Table 11: 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***
	(-13.963)	(-2.394)	(6.949)	(-6.184)	(-11.119)
Workplace % white	0.051	-0.042	-1.226***	0.273*	1.52***
	(0.981)	(-1.355)	(-9.015)	(2.150)	(9.325)
Black*workplace % white	0.026	0.025	0.98**	0.438	-0.606
	(0.333)	(0.543)	(3.063)	(1.369)	(-1.582)
N	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; T-statistics from heteroskedasticity-robust standard errors in parentheses.

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 models, and interacts both employment density and share college with demographic attributes, industry, occupation, and metropolitan area. Heteroskedasticity-robust standard errors are clustered on the census tract of residence, and T-statistics in parentheses.

Table A3: Agglomeration and Own Share Models with PUMA Controls				
	Baseline Model	Non-Linear Agglomeration	Workplace Racial Composition	Black-Non Black Shares
Employment Density				
African-American worker	-0.0083***(-2.99)	-0.0081***(-2.91)	-0.0072***(-2.58)	-0.0083***(-2.99)
with Own Share Controls				
African-American worker	0.0140* (1.65)	0.0078 (0.92)	0.0124 (1.46)	0.0332*** (2.83)
Own Share in Workplace	0.0537***(2.74)	0.0385**(1.96)	0.0493**(2.51)	0.0639*** (3.53)
Share College Educated				
African-American worker	-0.0776***(-2.92)	-0.0787***(-2.95)	-0.0682**(-2.55)	-0.0776***(-2.92)
with Own Share Controls				
African-American worker	0.0030 (0.06)	0.0233 (0.44)	0.0310 (0.59)	0.0783 (1.00)
Own Share College Educated	0.1603**(2.26)	0.1929***(2.71)	0.1933***(2.71)	0.2276** (2.31)

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. Column 2 includes the quadratic terms of employment density and share college, column 3 also includes controls for percent of black, hispanic, and Asian workers in each PUMA, and column 4 shows the results where own race is based on percent black and percent non-black. The own share results are for models based the specifications in Table 7 panel 2. Heteroskedasticity-robust standard errors are clustered on the census tract of residence, and T-statistics in parentheses.