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Agglomeration Economies and Race Specific Spillovers

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Abstract. Racial social isolation within workplaces may reduce firm productivity. We provide descriptive evidence that African-Americans feel socially isolated from whites. To test whether isolation affects productivity, we estimate models of Total Factor Productivity for manufacturing firms allowing the returns to concentrated economic activity and human capital to vary by the match between each establishment's racial and ethnic composition and the composition of local area employment. Higher own-race representation increases the productivity return from employment density and concentrations of college educated workers. Looming demographic changes suggest that this drag on economic productivity may increase over time.

Key Words: Agglomeration Economies; Firm Productivity; Human Capital Externalities; Information Networks; Racial and Ethnic Isolation

JEL Codes: J15, J24, L11, R12, R23, R32

Disclaimer: The majority of the analyses presented in this paper were conducted using restricted data at a Census Research Data Center. Opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. Results have been reviewed to ensure that no confidential information is disclosed.

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Agglomeration Economies and Race Specific Spillovers

1. Introduction

Many studies document the role of knowledge spillovers as a key factor in explaining firm productivity in cities. Moretti (2004) finds that knowledge spillovers in U.S. cities increase the productivity of manufacturing plants. Glaeser and Mare (2001) and De la Roca and Puga. (2017) find that learning plays an important role in explaining the urban wage premium. 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. 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. Similarly, Audretsch and Feldman (1996) and Feldman and Audretsch (1999) demonstrate that the composition of surrounding industry affects the rate of new ideas as captured by product innovation.[1]

Racial and ethnic isolation and racially segregated networks among workers appear to be important drivers of differences in labor market outcomes, especially for African-Americans. Hellerstein et al. (2008) find that an African-American's own employment depends not on nearby overall employment density, but rather on whether nearby employers employ other African-Americans. Hellerstein et al. (2011) find that workers are more likely to be at a firm that contains other workers residing in the same neighborhood, but document that these network effects are substantially stronger for African-Americans and Hispanics if those workers are the same

[1] See Combes and Gobillon (2015) for a recent review.

race/ethnicity.[2] Ananat, Fu and Ross (2018) demonstrate that the wage premium arising from working in a location with high overall employment density is substantially smaller for African-Americans, unless the surrounding employment is comprised predominantly of African-American workers. Even when Blacks are in spatial proximity with other races, research has shown they remain socially isolated from non-Blacks. For example, Davis et al. (2019) document racial segregation in visits to restaurants and find that most of this segregation is due to social barriers and, moreover, is strongest in isolating African-American diners and restaurants. Similarly, many studies document racial isolation within schools (Fletcher et al. 2020; Moody 2001), particularly for Black students (Echinique and Fryer, 2005).

Given the patterns observed in U.S. society, racial and ethnic social isolation within workplaces may have a significant impact on firm productivity, a possibility we investigate in this study. First, we utilize the General Social Survey (GSS) to provide descriptive evidence that African-Americans do in fact feel socially isolated from whites, including when working at majority white firms.[3] Second, we test whether this social isolation of African-American workers affects firm productivity. In this test, we estimate models of Total Factor Productivity (TFP) for manufacturing firms in which we allow the returns to concentrated economic activity and human capital to vary by the match between each establishment's racial and ethnic composition and the

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[2] Bayer et al. (2008) document labor market network effects based on residential proximity of similar workers. Ioannides and Loury (2004) and Ross (2011) review the referral literature.

[3] While perhaps intuitive, this pattern has not to our knowledge been shown in previous work. Unfortunately, the GSS does not collect similar information for Asians, Hispanics, or other race/ethnic groups.

racial and ethnic composition of employment in the surrounding area. We find that higher own-race representation in a local work area for a manufacturing establishment's workers increases the productivity return arising from both employment density and the concentration of workers with a college education.

Specifically, following Moretti (2004) and Hellerstein et al. (1999), we identify a sample of workers in each establishment from the 2000 Census Long Form data based on that establishment's zip code and three-digit NAICS (industry) code, and then estimate the education and racial composition of the establishment's workers.[4] We then estimate a standard translog production function with measures of the establishment's various capital and labor inputs along with controls for the density and education of workers in this establishment's nearby peers (defined as other firms with the same one-digit industry code in the surrounding U.S. Census Public Use Microdata Area, or PUMA). We then calculate the average exposure of the establishment's workers to outside workers of their own race/ethnicity in this PUMA and allow the establishment's productivity returns to employment density and returns to the share of workers in the PUMA who are college-educated to vary with this same-race exposure. Our baseline estimates suggest that the return to employment density falls to zero and the return to nearby share of workers with a college degree is cut in half for establishments whose workers have no exposure to same-race workers in the PUMA.

[4] While Moretti (2004) and Hellerstein et al. (1999) match establishments based on metropolitan area, we match based on zip code and similar to Rosenthal and Strange (2003, 2008), Fu and Ross (2013) and Ananat et al. (2018) examine variation within metropolitan areas.

Our model and robustness checks attempt to address many of the common concerns in empirical work on agglomeration and human capital externalities. Ciccone and Peri (2006) note that the educational composition of workers in a given location can affect local wages due to input complementarities and substitutability, rather than production spillovers. A significant advantage of our use of TFP models is explicitly allowing for substitution between inputs. Another concern is that workers may sort into high-density work locations based on their unobserved productivity (Glaeser and Maré 2001; Combes et al. 2008). We add a control for worker ability based on estimating fixed effects for residential location at the census tract level in a wage equation. We then use the average of these fixed effects over the residential location of workers at an establishment as a proxy for unobserved worker productivity, based on the premise that workers sort over residential locations based on permanent income (Bayer and Ross 2006; Fu and Ross 2013). Our results are also robust to allowing the effects of employment density and share college within PUMA's to be heterogeneous varying across one-digit NAICS industry categories, as well as to allowing for innate differences in place specific productivity by including establishment PUMA fixed effects. Moreover, we also find that the same-race exposure effects on the return to share college, possible human capital externalities, are concentrated in industries with higher levels of patent activity and R&D spending, which suggests that racial isolation within firms may also influence firm operation and innovation.[5]

[5] This is consistent with several previous studies that document the role of peers and social interactions within companies. For example, Nanda and Sorenson (2010) find evidence of peer effects on self-employment that suggests knowledge- or experience-sharing between workers.

2. Are Black workers socially isolated from whites, even when they work in predominantly white firms?

First, we examine whether self-reported patterns of individual associations within and across race/ethnicity are consistent with the hypothesis that social ties are disproportionately within-race and that those whose workplaces include few or no same-race peers are unable to overcome this pattern. While it is well-established that most social interactions are within-race, it remains possible that this pattern is primarily driven by segregation and those workers who lack colleagues of the same race do develop strong cross-race relationships, in which case social distance would be an unlikely explanation for the TFP results that we present below. To test whether Blacks in majority-white workplaces nonetheless report greater social distance from whites than from Blacks, and vice versa, i.e. that race is a barrier to social interactions in the workplace, we draw on data from the U.S. General Social Survey. This survey 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 the survey did not ask comparable questions on closeness and workplace composition concerning Hispanics, Asian-Americans, or other race or ethnicity workers. Our sample includes employed Blacks and whites who responded to the surveys in which the relevant questions were asked.

Other work suggests that peers may affect productivity through establishing productivity-enhancing norms (De Paola 2010; Bandiera et al. 2005; Mas and Moretti 2009).

Survey respondents' workplaces are on average 68% white, and the racial distributions of firms employing Blacks and whites are heavily overlapping: the average white employee worked in a 72% white workplace and the average Black employee worked in a 50% white workplace, with standard deviations of around 37% for both groups. Thus, there is plenty of variation within which to test the relationship between feelings of closeness across race and workplace racial composition, for both Blacks and whites.

Our main focus is on a pair of personal attitude questions about how close the respondent is to whites and how close the respondent is to Blacks reported on a Likert scale running from 1 to 9 where 1 is not close at all and 9 is very close.[6] Columns 1 and 2 of Table 1 Panel 1 show the mean levels of closeness to Blacks and whites respectively. Not surprisingly, both Black and white workers report being closer to their own race than to the other race: Blacks report being 1.4 points on a 9-point scale closer to Blacks than do whites, while whites report being 1.3 points closer to whites than do Blacks (row 1 columns 1 and 2, respectively). Column 3 shows the estimates for difference between a worker's closeness to whites and closeness to Blacks, which we view as a likely proxy for the racial composition of meaningful social interactions and treat as our main

[6] 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. The exception is attitude toward interracial marriage, which was discontinued as a question in 2002. The regression samples include all employed whites and black who responded to the specific racial attitude question. If an independent variable is missing, that variable is set to zero, and an indicator that the variable is missing is set to one.

metric. Blacks on average report feeling 1.7 points closer to Blacks than to whites, while whites report feeling 1.6 points closer to whites than to Blacks, an illustration of the high levels of social distance between races in American society. Columns 4 and 5 of Table 1 report two additional race related attitudinal survey measures: whether the government provides too much assistance to Blacks and support for interracial marriage. Whites are more likely to agree with the first statement on government assistance, and less likely to support interracial marriage.

These high levels of average social distance, however, would mean little for race-specific spillovers at work if they merely reflected low average levels of interaction between races due to segregation across work locations, and disappear for workers with high levels of cross-race exposure in the workplace. If that were the case, we would see that a worker's relative closeness to a group would increase with the representation of that group in their workplace, so that, for example, a Black worker in an all-white firm would report on average the same closeness to whites as would a white worker in an all-white firm. Therefore, we estimate models to explain these variables that include an indicator for own race, a measure of the percent white in workplace, and an interaction of the two; the model also includes the indicators for survey year.[7]

Table 1 Panel 2 and Figure 1 report results. As percent white in the workplace increases, whites become substantially less close to blacks (column 1) and minimally more close to whites (column 2). The interaction of black with percent white in workplace implies that closeness of blacks to blacks decreases modestly at most, but closeness to whites does increase with percent white. Turning to column 3, the net effect on relative closeness is that both groups increase their closeness

[7] 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.

to whites relative to closeness to blacks as percent white increases, but the point estimate on the interaction between black and percent white implies that the effect for whites is more than 50% larger than the effect for blacks. While the interaction estimate is somewhat noisy, the negative sign implies that increasing percent white in the workplace does not mitigate the large gap between whites and blacks in terms of their relative closeness to whites.

Figure 1 graphs the estimated relationship between firm racial composition and closeness to whites relative to Blacks separately for whites and for Blacks. We observe a large gap of over two Likert scale points in an all-black workplace where lower relative closeness to whites might be an advantage, but this large gap persists and may even grow as the percent white in the work place increases. As a result, white workers may have a significant advantage in communication opportunities within workplaces that contain primarily white workers. Finally, the estimates in columns 4 and 5 in the second panel of Table 1 imply that unlike closeness to whites and blacks, increases in the share whites of workplaces has no impact on more general racial attitudes like support for government programs that are utilized heavily by Blacks and support for interracial marriage.

3. Do Racially-Segregated Networks Affect Productivity?

Next, we test whether the apparent racial segregation of workplace networks affects firm productivity by modeling Total Factor Productivity (TFP) as a function of firm demographics and local area demographics. Our TFP models are estimated using a combination of confidential datasets based on the Long Form of the 2000 U.S. Decennial Census and the Longitudinal Business Database (LBD). The confidential long-form sample provides detailed geographic information on individual residential and work location down to the census block level, and the LBD identifies the zip code of every establishment. We restrict ourselves to manufacturing establishments that participate in the 2002 Annual Survey of Manufacturers, and merge in data on estimated firm capital stock (Foster, Grim, and Haltiwanger 2016).[8] For each establishment, we observe revenue, materials cost, number of employees, estimated capital stock of structures, and estimated capital stock of equipment in 2002. We further restrict our sample to the 49 Consolidated Metropolitan and Metropolitan Statistical Areas with populations over 1 million so that each metropolitan area is divided into a minimum of 10 PUMA's.

Starting with our sample of establishments in large metropolitan areas, we link information from the census long form. First, we assign establishments into zip code by three-digit industry NAICS code cells to represent a "firm". We then use the place of work at the zip code level and industry of employment in the decennial census data to calculate the fraction of workers in each cell who have a four-year or more college education, as well as the fraction of workers who are non-Hispanic white, non-Hispanic African-American, Non-Hispanic Asian or Pacific Islander, and Hispanic for each "firm". Then, we merge establishments into residential PUMAs and use the long form decennial census data to calculate employment density and share of employees with four-year college degrees based on manufacturing workers in each PUMA, as well as fraction manufacturing workers who are non-Hispanic white, non-Hispanic African American, non-Hispanic Asian or Pacific Islander, and Hispanic in each PUMA.[9]

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[8] We thank Cheryl Grim at the US Census Bureau for both providing this data and providing advice in terms of its application.

[9] We first match each plant in the 2002 Census of Manufacturing firms with a plant in the Standard Statistical Establishment List (SSEL) data by plant ID. The SSEL data have assigned a PUMA ID to each plant through the census tract-PUMA linkage.

Using these data, for establishment i located in PUMA j, we estimate models for the logarithm of establishment net revenue (N_{ij}, total revenues minus material costs) as a translog function, given Ciccone and Peri's (2006) concerns about factor substitution. The translog function includes establishment structure capital, equipment capital, college educated employment and non-college educated employment (X_{ij}). We also include linear controls for manufacturing employment density and share college among manufacturing employees at the PUMA level in our TFP models, omitting employment associated with the establishment's three-digit industry (Z_j^{-i}).

$$N_{ij} = F(X_{ij}) + \beta Z_j^{-i} + \varepsilon_{ij} , \tag{4}$$

where F is a quadratic additive function of all elements of X_{ij} including all two-way interactions.

To obtain college and non-college educated employment, we follow Moretti (2004) and Hellerstein et al. (1999) and develop estimates of the share of workers at an establishment with four-year college degrees, using as a proxy the characteristics of workers in the establishment's three-digit industry code by zip code cell in the decennial Census. This share is multiplied by establishment total employment to estimate the number of college-educated workers, and one minus this share is multiplied by employment to estimate the number of non-college educated workers.[10] All models control for three digit industry and MSA fixed effects, and standard errors are clustered at the PUMA level. The summary statistics of all variables are presented in Appendix Table A1.

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

The results of our initial translog model are shown in Column 1 of Table 2.[11] We estimate that the effects on establishment productivity of a one-standard-deviation increase in employment density (1.032) and in share college (0.1060) in a local work area (PUMA) are 0.030 and 0.022 log points, respectively. The share college estimate is comparable in magnitude to Moretti's cross-MSA estimates of between 0.035 and 0.049 for human capital externality spillovers for a one standard deviation increase in share college in an MSA, especially considering that our estimate is reduced substantially by the inclusion of the control for employment density, which was not included in Moretti's model.

We also use the decennial Census data to calculate: 1. the share of the workforce at each establishment i that is white, Black, Hispanic, or Asian-American (α_{rij}) based on the establishment's industry-zip code cell, where r indicates race, and 2. the share of the manufacturing workforce in each PUMA j that is of a given race r omitting the employment associated with the establishment cell (θ_{rj}^{-i}). Using these shares and assuming that we can aggregate individual own race exposure across all employees at an establishment cell, we calculate the average exposure of workers in an establishment to manufacturing workers of the same race in the establishment's PUMA.

$$E_{ij} = \sum_r \alpha_{rij}\theta_{rj}^{-i}.$$

A larger value of this racial exposure index suggests workers of the dominant race/ethnicity in an establishment are more widely exposed to same-race peers in other firms in the same local area. We calculate a similar measure for exposure of workers in an industry-zip code cell to college-educated workers of the same race in this PUMA again omitting college educated workers from

[11] A full set of estimates for the first three columns of Table 2 are shown in Appendix Table A2.

the establishment cell, where share of college educated manufacturing workers of a given race is relative to all college-educated manufacturing employment. We then interact these two variables with the PUMA-manufacturing employment density and the PUMA-manufacturing share college-educated, respectively, to test whether returns to employment density and share college in terms of firm productivity depend upon predicted establishment employees' interaction opportunities with same-race workers in other establishments. We also include direct controls for the estimated racial composition of the workers in each establishment (i.e. industry-zip code cell).

The estimates including these interactions are shown in column 2 of Table 2. We find a strong, statistically significant effect on productivity of the interaction between employment density and workers' average exposure to own-race manufacturing workers in the PUMA. A one standard deviation increase in exposure to own race or ethnicity workers (0.207) implies an increase in the effect of employment density of 0.019, relative to a baseline effect of employment density (column 1) of 0.029. In fact, our estimates suggest that there is no return to employment density for an establishment whose workers have no exposure to same-race workers in the PUMA. In other words, increased density of employment increases an establishment's productivity, but only if the increased density comes from an increase in workers of the same race as that establishment's workers. A zero return to density for non-white firms in predominantly white local work areas is consistent with the GSS results showing significant social isolation of Black workers from whites even in all-white workplaces.

The estimated interaction between firm average exposure to same-race college-educated workers and 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. While noisily estimated, the standardized effect of exposure to own race college educated workers is 0.041, relative to a baseline effect (column 1) of 0.203. The direct effect of share college falls from 0.20 to 0.10 with the inclusion of the interaction term. An establishment with zero exposure to college-educated workers in the PUMA who are the same race as its own workers is estimated to receive one-half the productivity benefit from college-educated workers in the PUMA that the average establishment does, according to the point estimates.

A common concern in the agglomeration literature is that workers may sort across firms or locations based on the unobserved attributes of either the firms or the locations. Unlike across-metropolitan areas studies (Glaeser and Maré 2001; Combes et al. 2008), Fu and Ross (2013) and Ananat et al. (2018) document that the within-metropolitan area-across local work area correlations of both observable worker human capital and worker race with employment density are near zero. However, these studies suggest that workers may sort over work locations based on individual human capital levels. Therefore, following Fu and Ross (2013), we use the decennial census data to estimate a wage model for prime-age, full-time male workers in our large metropolitan areas that include controls for census tract fixed effects as a proxy for the unobserved human capital of workers, as well as a standard set of individual demographic variables.[12] For each firm, we calculate average unobserved human capital by averaging the estimated census tract fixed

[12] Prime-age workers are defined as 30-59 years of age, and full time is defined as usual hours worked per week 35 or greater. Wages are calculated as last year's earnings divided by the product of number of weeks worked last year and usual hours per week. Our demographic controls include categorical variables by race and ethnicity, age, education, family structure, and immigration status.

effects from the wage regression over the residential location of the workers matched to each three digit industry by zip code establishment cell.[13] This measure of worker human capital is then included in the translog production function as a fifth input.

In column 3, we present our results after including this new control for the unobserved human capital of workers at the firm.[14] The effect of the within PUMA, own race exposure of an establishment's workers on the return to density is very stable to the inclusion of controls for worker human capital, as expected given the low correlation between employment density and both worker race and education. Therefore, while establishment TFP depends strongly on the unobserved productivity of the establishment's workers, we find no evidence that workers are sorting based on those attributes over employment density. However, the effect of an establishment's worker's own race match on return to share college increases by 19 percent and is statistically significant after the inclusion of this control for worker unobserved productivity, suggesting that, if anything, the omission of worker unobservables biases these estimates downwards. As a result, the estimated return to share college for a establishment with zero same-race exposure is now only 12 percent of the original estimated return to share college in column 1.

[13] The residential fixed effects have substantial explanatory power eroding the return to educational attainment in wage regressions by about 25% (Fu and Ross 2013) and the Black-white wage gap by half (Ananat et al. 2018).

[14] In order to illustrate the effect of the mean tract FE on firm TFP, we also estimated the Cobb-Douglas model with this control and find that the mean tract FE variable has a strong positive effect on TFP with an estimate of 0.145 and a t-statistic of 2.69.

Column 4 of Table 2 presents robustness checks for the final model in Column 3 by adding PUMA fixed effects as well as controls for three-digit industry interacted with PUMA employment density and share college. The PUMA fixed effects control non-parametrically for any general relationship between establishment location and TFP arising from location-specific productivity. The three-digit-industry interactions allow the returns to employment density and share college to vary across different types of manufacturing industries, since establishments in different industries likely differ in their innate productivity attributes. These changes greatly increase both the magnitude and the precision of the estimates on the employment density and share college interactions with own race exposure, doubling the own race effect for the returns to employment density and increasing the own race effect for share college by two and one-half times. The inclusion of the PUMA fixed effects to control for location-specific productivity is entirely responsible for the magnitude increases.

In order to consider normative effects on workers, we also examine the impact of exposure to own-race or own-ethnicity workers on the productivity of firms at which nonwhite workers are employed, essentially racial differences in worker exposure to establishment productivity. White workers' average exposure to their establishment's own race match (over all establishment workers) within its work location is 0.635, while the exposures for African-American, Hispanic and Asian workers are 0.487, 0.407 and 0.406, respectively.[15] Multiplying the smallest estimated coefficient of 0.0913 from column 3 of Table 2 by the employment-weighted mean employment density for the establishment sample of 0.209 implies a lower bound Black-white gap in exposure

[15] The average exposure rates are calculated by estimating the mean exposure index across establishments weighted by the number of estimated workers of each race at each establishment.

to establishment productivity of 0.3 percentage points ((0.635-0.487)*0.0913*0.209), while the larger coefficient from column 4 after controlling for PUMA fixed effects and differential returns by three digit industry implies an upper bound contribution of 0.6 percentage points. Further, the exposure gaps for Hispanics and Asian workers are 80 percent larger than the Black-white gap. Similarly, the white, African-American, Hispanic and Asian worker exposures to their establishment's own-race match for college-educated workers are 0.665, 0.499, 0.376 and 0.419, respectively, implying productivity exposure differences ranging between 0.8 and 3.6 percentage points depending upon the group and model.

If the hypothesis that information spillovers are segregated within same-race networks holds, then racial match with surrounding establishments should matter more for productivity in industries that rely on innovation and high-intensity social interactions. We test this implication in Columns 2 through 5 of Table 3, which show results for subsamples split by how much establishments rely on innovation, i.e. whether the three-digit industry has a high vs. low rate of patent production or has high versus low R&D spending, using the TFP model from column 3 of Table 2 (column 1 repeats the Column 3 results).[16] For both patent activity and R&D spending, share college/human capital externality effects are significantly higher in the high-patent/high R&D spending industries than in the below median industries. Results are less clear for employment density with larger agglomeration effects in low patent industries and similar estimates over R&D spending.

[16] We are grateful to William Kerr at the Harvard Business School for providing this data (Kerr 2008).

4. Discussion

In this paper, we examine the role of race and ethnicity in shaping the productivity spillovers experienced by manufacturing firms operating within large metropolitan areas. First, we use the General Social Survey to document communication barriers between whites and African-Americans, finding that the racial differences in the social distance that Black workers report with respect to whites persists even among Blacks who work in all-white firms. These results suggest that African-Americans experience relatively little access to white workplace networks. Next, we use confidential establishment data to estimate a model of firm total factor productivity for a sample of manufacturing establishments, and we find strong evidence that the productivity returns to local employment density and share college rise as the average exposure of workers in a firm to same-race peers in the local work area or PUMA rises. These spillovers are quite low or even zero for firms whose employees lack same-race peers at surrounding firms. Further, for human capital externalities, same-race exposure matters even more in patent-intensive and R&D spending industries.

These findings are consistent with the idea that limited social interactions between workers across race or ethnicity may have negative impacts on the overall productivity of manufacturing firms and innovation in the manufacturing sector, as well as particularly large negative impacts on majority-nonwhite firms. We cannot distinguish whether these differences in spillovers arise from implicit barriers to interracial social interactions or from working conditions and other institutional barriers to communication. Our approach is unable to answer the question of whether this differential exposure to establishment productivity leads to welfare differences between Blacks and whites, but evidence in Fu and Ross (2013) and Ananat et al (2018) imply that African-American workers experience lower wage returns from exposure to higher levels of agglomeration.

It is also worth noting, however, that the lower firm productivity among firms that have a worse racial and ethnic match with the local employment area may also be harmful to the wages and productivity of whites, as it reduces the effective size of the agglomeration from which they can benefit.[17] It is less harmful to whites than to minorities merely because whites currently make up the majority of most manufacturing employment. Looming demographic changes suggest, therefore, that social distance between races will become more of a drag on productivity for whites, and for the economy overall, going forward, unless proactive steps are taken to reduce racial and ethnic isolation in workplace networks. Our results suggest that this holds in particular for high-innovation industries expected to drive the nation's economic growth. Our findings thus provide additional motivation for policies to improve race relations and increase interracial contact.

[17] It is also possible that white workers benefit from this phenomena if the increased concentration of social interactions with the members of a worker's own race lead to interactions for whites with individuals who on average are more skilled and have more advanced knowledge to share. See Logan and Zhang (2013) and De la Roca, Ellen, and O'Regan (2014) for examples of evidence that whites may benefit from segregation.

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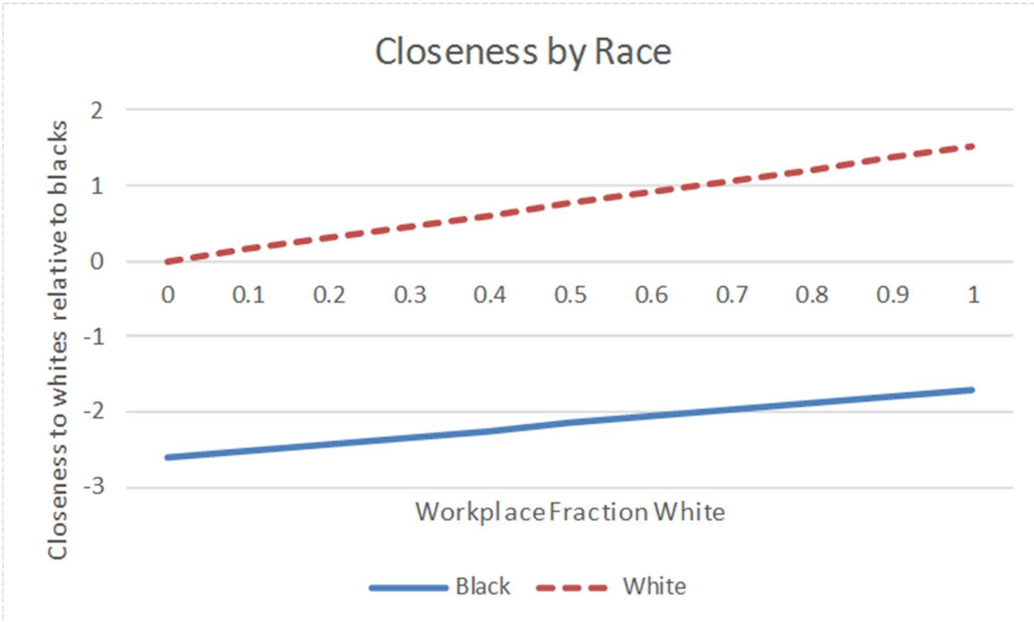

Figure 1: Relative Closeness to Whites over Workplace Fraction White

Notes: The dashed line represents the product of workplace fraction white and the coefficient estimate on workplace fraction white (i.e.,1.52) from a model of the closeness to whites relative to Black closeness (Column 3 of Table 1). The solid line takes the value of the race coefficient at a zero percent white workplace, and then adds the product of the percent white in workplace times the sum of the level and the race interaction coefficients on percent white in workplace: -2.613+workplace fraction white*(1.52-0.606).

Table 1: Relationship between workplace racial composition and responses to survey questions about race

	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)	Attitude toward gov't help for blacks (1=too little, 3=too much)	Opposed to interracial marriage
			Summary Statistics		
Black mean	*7.625*	*5.921*	*-1.711*	*1.242*	*.035*
White mean	*5.439*	*6.997*	*1.555*	*1.991*	*.091*
			Coefficient Estimates		
Black	1.376***	-1.274***	-2.613***	-0.754***	-0.079*
	(0.198)	(0.206)	(0.235)	(0.054)	(0.033)
Workplace % white	-1.226***	0.273*	1.520***	0.051	-0.042
	(0.136)	(0.127)	(0.163)	(0.052)	(0.031)
Black*workplace % white	0.980**	0.438	-0.606	0.026	0.025
	(0.320)	(0.320)	(0.383)	(0.078)	(0.046)
N	6,505	6,469	6,437	6,603	3,964

Notes: Estimates based on Black and non-Hispanic white sample respondents to the General Social Survey (GSS) in relevant years. Each column represents a specific survey variable from the GSS except for the last column, which is based on the difference between the survey responses to the two preceeding questions. The first panel presents sample means, and the second panel presents coefficient estimates where each column contains the results of a single regression. The regression model specification includes indicators for year of survey and for missing report of workplace % white and its interaction with black; heteroskedasticity-robust standard errors in parentheses.

Table 2: Total Factor Productivity Regresions with Controls for Local Work Area

Variables	Translog model	Translog Model with Own Race Exposure Indices	Own Race Translog Model with Mean Tract FE	Industry Interactions and PUMA FE
Employment Density	0.0288*** (16.68)	-0.0012 (-0.10)	-0.0001 (-0.00)	NA
Density*Race Exposure Index		0.0919** (2.57)	0.0913*** (2.94)	0.1851*** (10.45)
Share College	0.2033*** (8.30)	0.096 (1.30)	0.0253 (0.34)	NA
Share College*Race College Exposure Index		0.1779 (1.59)	0.2115* (1.91)	0.4897*** (2.87)
R Squared	0.9086	0.9086	0.9088	0.9106
Sample Size	111695	111695	111538	111538

Notes: Coefficients estimates of establishment 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. Each column presents estimates from a single regression. Column 1 presents the baseline estimates with just the controls for density, share college, factor inputs and metropolitan area and three digit industry fixed effects. The next column adds controls for the same race exposure to workers and college educated workers plus the interaction of these variables with employment density and share college, respectively. The third column expands the translog production function to include the average unobserved quality based on the residential locations of workers in the establishment's zip code by 3 digit industry cell and the tract FE estimates from the wage model. The fourth column adds the interaction of employment density and share college with the three digit industry dummies and PUMA fixed effects. College and non-college labor are based on total labor inputs and the fraction of workers in the Census long form data in an establishment's zip code by 3 digit industry cell who have a four year college degree. Employment density and share college are calculated for all manufacturing workers in the census long form sample working in the establishment's PUMA excluding the workers in the establishment's zip code by 3 digit industry cell. The exposure indices are the average exposure of all workers in the establishment's zip code by three digit industry cell to manufacturing workers or college educated manufacturing workers of the same race in the establishment's PUMA (omitting employment in the establishment's zip code). Establishment net revenue is estimated for respondents of the 1997 Census of Manufacturers in metropolitan areas with populations over 1 million residents. Heteroskedasticity-robust standard errors are clustered on PUMA of employment. T-statistics in parentheses.

Table 3: Total Factor Productivity Regresions by Industry Patent Levels

Variables	Own Race Translog Model with Mean Tract FE	Industry Patent Activity Above Median	Industry Patent Activity Below Median	Industry R&D Activity Above Median	Industry R&D Activity Below Median
Density*Race Exposure Index	0.1851*** (10.45)	0.0952** (2.24)	0.2049*** (6.24)	0.1609*** (4.10)	0.1611*** (4.10)
Share College*Race College Exposure Index	0.2115* (1.91)	0.7358*** (3.04)	0.0039 (0.02)	0.7386*** (2.92)	0.0551 (0.27)
R Squared	0.9106	0.9049	0.9162	0.908	0.9125
Sample Size	111538	65412	46126	61194	50344

Notes: Coefficients estimates of establishment 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. Each column presents estimates from a single regression. Column 1 presents the estimates with controls for unobserved worker quality in the translog production function, plus density, share college, factor inputs and metropolitan area and three digit industry fixed effects. The next four columns present estimates for this specification estimated seperately for samples in three digit industries with above and below median levels of patent activity and above and below median levels of R&D activity. College and non-college labor are based on total labor inputs and the fraction of workers in the Census long form data in an establishment's zip code by 3 digit industry cell who have a four year college degree. Employment density and share college are calculated for all manufacturing workers in the census long form sample working in the establishment's PUMA excluding the workers in the establishment's zip code by 3 digit industry cell. The exposure indices are the average exposure of all workers in the establishment's zip code by three digit industry cell to manufacturing workers or college educated manufacturing workers of the same race in the establishment's PUMA (omitting employment in the establishment's zip code). Establishment net revenue is estimated for respondents of the 1997 Census of Manufacturers in metropolitan areas with populations over 1 million residents. Heteroskedasticity-robust standard errors are clustered on PUMA of employment. T-statistics in parentheses.

Table A1: Descriptive Statistics for the Establishment Sample

Variables	Mean	Standard Deviation
Revenue minus Materials Cost	5055.8	176398.3
Non College Employment	57641.8	213107
College Employment	17096.8	133139.6
Equipment Capital ($1,000s)	1762.7	16149.4
Structure Capital ($1,000)	632.6	8725.2
Mean Tract FE	-0.0287	0.0931
Employment Density	0.3065	1.0318
Own-Race Exposure Index	0.5564	0.2073
Share College	0.2598	0.106
Share College Own Race Exp Index	0.574	0.2331
Firm Percent Black	0.0773	0.13
Firm Percent Hispanic	0.1859	0.2302
Firm Percent Asian	0.0836	0.1554
Firm Percent Other Race	0.0055	0.0326
Single Establishment Firm	0.8663	0.3404
Zip Code Missing	0.2284	0.4198
Sample size	111,695	

Notes: The table presents the means and standard deviations of establishment and local work area attributes for the large metropolitan area manufacturing establishment sample.

Table A2: Total Factor Productivity Regresions with Controls for Local Work Area

Variables	Translog model	Translog Model with Own Race Exposure Indices	Own Race Translog Model 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)
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)
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)
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)
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. Each column contains estimates for a single regression, and these regressions are the same as the regressions presented in the first three columns of Table 2. The regression model is estimated for respondents of the 1997 Census of Manufacturers for in the metropolitan areas with populations over 1 million residents. The regression also includes metropolitan area and three digit industry fixed effects. Heteroskedasticity-robust standard errors are clustered on PUMA of employment. T-statistics in parentheses.