

Do Low-Wage Employers Discriminate Against Applicants with Long Commutes? Evidence from a Correspondence Experiment

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Abstract

I use a correspondence study of the low-wage labor market in Washington, DC to test whether employers discriminate against applicants who live further from the job location. Fictional résumés randomly assigned to have addresses far from the job location receive 14% fewer callbacks than those with addresses in nearby but similarly affluent neighborhoods. Living 5-6 miles away from the job results in a penalty equal to that received by applicants with stereotypically black names. On the other hand, holding commute distance constant, I find no statistical evidence that employers respond to a neighborhood's affluence.

JEL Codes: J7; R2; J6

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1. Introduction

Does residential location affect success in low-wage labor markets? The urban poor tend to be concentrated in a small number of neighborhoods (Kneebone, 2014). A large literature argues that living in poor neighborhoods hampers labor market success. People moved to the suburbs by the Gautreaux program in Chicago were employed at higher rates than those moving within the city (Rosenbaum, 1995). However, adults provided housing vouchers for low poverty neighborhoods in the Moving to Opportunity (MTO) experiment do not become more economically self-sufficient (Kling et. al. 2007; Ludwig, et. al. 2012).² Many researchers interpret the MTO results as evidence that residential location does not drive labor market success. Alternative interpretations exist for why MTO did not stimulate employment (Quigley et. al., 2008; Galiani, et. al. 2015; Aliprantis, forthcoming; Chyn, 2016). One alternative focuses on the importance of physical distance. Proponents of the “spatial mismatch hypothesis” (Kain, 1968; Wilson, 1997) argue that distance between poor neighborhoods and jobs limits employment opportunities. This spatial interpretation posits that physical distance drives neighborhood effects, and policies addressing concentrated poverty need to prioritize proximity to employment rather than more affluent neighbors.

I conduct a correspondence experiment in the low-wage labor market in Washington, DC testing whether employers respond differently to distant versus nearby applicants. A research team sends 2,260 fictional résumés to actual job vacancies that require only high school education. Employers call back résumés listing residential addresses in distant, poor neighborhoods less frequently than those listing addresses in nearby affluent neighborhoods. I then test whether employers respond to distance independent of other attributes of the address, including neighborhood affluence. I match addresses to have different commute lengths but similar levels of

² Recent evidence indicates a stronger role for neighborhood effects among young children in MTO (Chetty, et. al. 2015) and more broadly (Chetty and Hendren, 2015). However, this new evidence has left untouched the debate on whether neighborhood location matters for adult employment.

affluence (education, income, and racial composition) and send applications with matched addresses to the same job. Addresses far from the job location receive 14 percent fewer callbacks than addresses in nearby but similarly affluent neighborhoods. Distance effects are robust to including address fixed effects, which control for any unmatched characteristics. Alternatively, I estimate how callback rates relate to straight line commute distance, instrumenting this continuous measure with randomly assigned address types. Callback rates fall by 1.1 percentage points for every mile an applicant moves away from the job, holding neighborhood affluence constant. Using the same experiment, I can also measure whether employers respond to neighborhood affluence. While I typically find a slight positive relationship between employer responses and neighborhood affluence, these effects are small and statistically insignificant. Employers respond to distance.

The distance effects I measure are statistically and economically significant. Both the simple comparison of means and the instrumental variables model yield statistically significant main effects at the 5% level. To interpret the distance effect, I compare it to the standard discount in callback rates for stereotypically black names (Bertrand and Mullainathan, 2004), which I replicate. Applicants living 5-6 miles further from the job face approximately the same discount as applicants with stereotypically black names. Alternatively, even within the compact city limits of Washington, the average non-white person lives 1.1 miles further from jobs than the average white person. Differences in housing locations would thus increase the gap in callback rates between black and white applicants by 24% beyond the direct response to different names. Employers respond to distance in a manner that is empirically relevant.

This study provides empirical support for one mechanism of neighborhood effects: employer discrimination by commute distance. Ludwig, et. al. (2011) argue for “mechanism experiments” that test the behavioral mechanisms linking policies and outcomes. Knowledge on mechanisms matters because the case for a policy typically hinges on a particular theory. In the present context,

subsidizing moves to low poverty but nearby neighborhoods may help if employers redline high poverty areas. However, I find that employers respond to distance rather than affluence. In this case, only housing policies that move residents across larger distances will affect employer decisions. The distinction between neighborhood composition mechanisms and spatial mechanisms remains important regardless of why employers care about distance. Low-wage employers may discriminate against applicants who live far away because distance matters intrinsically; long commutes by bus may lower workers' productivity and reliability (Zenou, 2002; Van Ommeren and Gutierrez, 2011). Distance may also provide a negative statistical signal (Phelps, 1972) if only low quality workers bother searching for or accepting jobs far from home. These two motivations have different efficiency implications. But in both cases, moving applicants to closer, not richer, neighborhoods will improve their employment prospects. Since poor minority applicants tend to live farther from jobs, policies with a spatial focus will affect employment disparities.

The fact that employers focus on commute distance rather than affluence can help explain disparate results from the small but growing experimental literature measuring employer discrimination by residential location. Bertrand and Mullainathan (2004) find that employer response rates correlate with the neighborhood affluence of addresses randomly assigned to fictional résumés in Boston and Chicago. Bonnet et. al. (2015) demonstrate similar results for housing applications in Paris while Tunstall, et. al. (2013) find that addresses from poor neighborhoods in the UK receive similar callback rates from employers as addresses in “bland” neighborhoods.³ Differences between these existing studies can be explained by how they treat commute distance. Tunstall, et. al. (2013) send applications matched to have similar commute

³ Duguet, et. al. (2010) also find no effect of the listed town of residence for fictional applicants to French accounting positions; however, their focus on a skilled labor market makes direct comparison difficult.

distances, while Bertrand and Mullainathan (2004) do not control for distance⁴ and thus measure a combination of distance and affluence effects. For comparison, I estimate the combined response of employers to addresses in the present experiment. I measure an overall address effect of the same magnitude as Bertrand and Mullainathan (2004), and commute distance accounts for two-thirds of employers' overall response to addresses.

In the remainder of the paper, section 2 details theories of spatial mismatch incorporating employer discrimination as well as the context of the experiment. Section 3 describes the design of the experiment, and section 4 presents the results. Section 5 concludes.

2. Background

2.1. Spatial Mismatch and Employer Discrimination

Appropriate public policy depends on whether residential segregation contributes to black-white income disparities and, if so, what theoretical mechanisms connect residential location to labor market outcomes. A large theoretical literature identifies several potential mechanisms of spatial mismatch effects (Gobillon, et. al. 2007). Labor market frictions on the worker side including poor information on job vacancies, a lack of connections for referrals, and commuting costs during job search or employment can connect living far from jobs to labor market disparities (Coulson, et. al. 2001; Zenou, 2009). A large empirical literature tests for spatial labor market frictions and spatial mismatch effects using observational data (Zax and Kain, 1996; Holzer and Reaser, 2000; Hellerstein, et. al. 2008; Aslund, et. al. 2010; Manning and Petrongolo, 2013; Marinescu and Rathelot, 2013; Sanchis-Guarner, 2014; Andersson, et. al., 2014; Mulalic, et. al., 2014; Miller, 2015). A few experimental studies test whether worker-side interventions, such as transportation subsidies, can alleviate such spatial mismatch effects (Phillips, 2014; Franklin, 2014).

⁴ Given that their study focuses on racial discrimination this is not a flaw in their study, only an issue for interpretation in the present context.

Discrimination by employers according to residential location can also lead to spatial mismatch effects. The standard monocentric spatial equilibrium model of urban housing implies sorting by income level with wealthier residents with greater appetite for cheap land living far from the center city (Fujita, 1991). Zenou and Boccard (2000) show that a spatial equilibrium model in which black residents have higher commute costs than white residents can lead to housing segregated instead by race with black residents living in the central city. In these models, if employers do not care about the residential locations of their workers, such segregation may not exacerbate racial gaps in employment and wages; however, if employers prefer workers from the more affluent or whiter parts of the city, then housing segregation will contribute to racial gaps in labor market outcomes.

Employers may discriminate against workers from poor, minority neighborhoods because of the neighborhood's affluence. Zenou and Boccard (2000) model employer discrimination as a simple spatial rule with employers who exogenously refuse to hire workers from poor or black parts of town. Such a rule could be motivated by various underlying goals. As in Becker (1971), employers may have prejudice, refusing to associate with workers from predominantly poor or black neighborhoods, or employers may statistically discriminate, using the characteristics of a person's neighborhood to infer the worker's attributes (Phelps, 1972). Employers may even respond to differences in the variance of such unobservables (Heckman and Siegelman, 1993; Heckman, 1998; Neumark, 2012).

On the other hand, employers may care about a worker's residential location because it communicates commute distance. Zenou (2002) shows that if longer commutes diminish a worker's productivity via fatigue and unreliability, employers will discriminate based on residential location and housing segregation will exacerbate racial gaps in labor market outcomes. Van Ommeren and Gutierrez (2011) provide an empirical basis for this theory, showing that worker

absences rise when employers move further from an employee's residence. Employers could also statistically discriminate according to commute distance if workers self-select into applying to jobs far or near from home. While employers may use information regarding the affluence of a worker's neighborhood to discriminate in standard taste-based or statistical manners, they may also discriminate in a more fundamentally spatial manner by focusing on commute distance.

The proper public policy response to residential segregation depends on whether employers care about a neighborhood's geographic accessibility or other attributes, like affluence. If employers care about commute distance because long commutes hurt productivity (Zenou, 2002), public transit investment will be effective in combating employer discrimination. However, an MTO-type housing voucher that helps workers move to lower poverty but nearby neighborhoods will not address this concern. If employers care instead about the affluence of a worker's neighborhood, housing vouchers encouraging integration will narrow labor market disparities. Even if employers statistically discriminate, it matters what information they extract from a residential location. Suppose high-quality workers are not willing to pay high transportation costs to apply for distant jobs because they can easily find work near home, and employers thus avoid distant applicants. A public transit investment will still reduce this type of discrimination, and thus racial labor market disparities, by diluting self-selection into job applications according to commute distance. If employers instead use a neighborhood's fixed attributes like racial composition, median income, or education levels to determine who to hire, public transit investments will likely not affect employer discrimination (unless this somehow breaks racial sorting in the housing market). Thus, the effects of public policies depend on whether employers discriminate according to commute distance or other neighborhood attributes.

Existing experiments provide little evidence on whether employers respond to a worker's commute distance when hiring. Some sources (e.g. Wilson, 1997) provide descriptive evidence that

employers prefer workers from nearby neighborhoods, and a large non-experimental literature documents spatial mismatch effects. More precisely quantifying the extent to which employers respond to commute distance faces some empirical challenges, though. Workers applying to jobs far from home differ from those applying to jobs near to home. A small but growing literature uses correspondence experiments⁵ with carefully controlled fictional applicants to address this concern. Bertrand and Mullainathan (2004) send matched fictional résumés to real jobs and find that employers less frequently call back applicants who list addresses in neighborhoods with lower income neighborhoods. However, employers may be responding to either neighborhood affluence or commute distance, which tends to be correlated with affluence. Tunstall et. al. (2013) selects addresses in neighborhoods with different affluence but similar commute distance and finds no difference in callback rates. While this suggests that employers do not respond to affluence, no similar evidence has confirmed whether commute distance can explain why employers appear to respond to a worker's residential location in other studies. In the present study, I undertake a correspondence experiment in Washington, DC that isolates whether employers discriminate according to the applicant's commute distance.

2.2. Spatial Mismatch in Washington, DC

Neighborhood poverty correlates strongly with geographic access to jobs in Washington, DC. Figure 1 displays the poverty rate for different zip codes across the city. The red line displays the outline of the city itself with the Virginia suburbs beyond the Potomac River to the south and Maryland suburbs to the north and east. Poverty rates display a strong tendency to increase as one travels south and east, as evidenced by the darker shades for those zip codes. The three zip codes

⁵ This well-established method has been used to study labor market discrimination by many different factors including but not limited to race (Bertrand and Mullainathan, 2004; Arceo-Gomez and Campos-Vazquez, 2014), immigrant status (Oreopoulos, 2011), unemployment duration (Eriksson and Rooth, 2014; Kroft, et. al. 2013), and age (Lahey, 2006).

just inside the southeast boundary of the city coincide with the part of the city beyond the Anacostia River and exhibit the city's highest poverty rates.

Concentrated poverty leads to a mismatch between where low wage workers live and work. Figure 2 displays heat maps of US Census data on where workers earning less than \$1,250 per month live and work. People employed in low-wage jobs live disproportionately in the far southeast side of the city, while low-wage jobs concentrate tightly in center of the city. Notably, few firms locate jobs east of the Anacostia River. Thus, these areas remain both high poverty and distant from job vacancies. Figure 3 summarizes this relationship for all census tracts in the city. The fraction of residents with at least a bachelor's degree exhibits a strong negative relationship with distance to jobs in my experimental sample. On average, being one mile further from the average job is associated with 13 percentage points fewer people with college degrees. Similar results obtain for tract median incomes or fraction white.

Washington shares this disconnect between where disadvantaged people live and where low-wage jobs locate with many other US cities. Washington only ranks 33rd out of the 94 most populous Metropolitan Statistical Areas (MSAs) in the US for black spatial mismatch, measured by an index of the dissimilarity between where black residents live and where jobs are located (Stoll, 2005). Washington is also not unusual in the extent of its job sprawl, ranking 37th out of the largest 94 MSAs in the proportion of jobs located more than 5 miles from the center city (Stoll, 2005). In some sense Washington actually provides a challenging test for detecting spatial effects in a labor market. I focus on the area within city limits which is compact and well-served by public transit relative to other US cities; if employers respond to commute distance in DC, then they likely would in other cities with greater sprawl and poor public transportation. Thus, Washington provides a useful context. It exhibits a typical disconnect between where low-wage workers live and where they work which parallels many other US cities.

3. Experimental Design

I use a correspondence experiment in the pattern of Bertrand and Mullainathan (2004) to study employer discrimination by residential location. From May 2014 through August 2014, I led a research team sending fictional résumés to actual jobs. I independently and randomly assign different characteristics listed on the fictional résumés. Since the experiment can control and randomly assign all information observed by the employer, any correlation of employers' responses with résumé characteristics can be attributed to employer discrimination based on that attribute. I measure employer responses using e-mail and voicemail accounts according to the information listed on the job applications. I record whether employers positively respond to the application; the vast majority of positive responses are requests to setup interview times, requests for specific information about the applicant, or general requests to call back. Henceforth, I will refer to this outcome equivalently as a "callback" or a "response." I do not include negative responses (e.g. rejection e-mails) or automated messages in this measure. I can then interpret differences in callback rates as employer discrimination.

3.1. Treatment

I carefully select the address listed at the top of the résumé to separately vary the applicant's commute distance and neighborhood affluence. Distance and affluence tend to be correlated with each other such that employer discrimination based on one cannot be disentangled, in general, from discrimination based on the other. I isolate distance and affluence effects by selecting addresses with similar affluence but different commute distance and also addresses with similar commute distance but different affluence. Formally, the experiment implements a 2x2 research design. Given a job location, I select one address each from four categories: near and poor (NP), near and affluent (NA), far and poor (FP), or far and affluent (FA), and I randomly assign the addresses to four job applications. Comparing employer responses for the two far types to the two near types

measures the effect of distance holding affluence constant. I likewise measure the effect of affluence holding distance constant.

3.1.1. Measuring Commute Distance and Affluence

Implementing this experimental design first requires defining measures of commute distance and affluence. I measure commute distance simply as the great circle (i.e. “straight line”) distance in miles between the address listed on the job application and the employer’s location. I choose straight line distance rather than commute time for computational ease. The distinction between straight line distance and commute time can be important in many contexts. However, for designing this experiment, the choice does not greatly affect the results. The two distance measures are strongly correlated in my data ($\rho = 0.62$), and employers may not be able to parse the difference between the two quickly. In any case, I demonstrate below that the results are robust to measuring distance ex-post using public transit travel time.

I measure affluence as an index of fixed attributes of the neighborhood, weighting particular attributes based on employer preferences. The challenge is to summarize all fixed (i.e. not dependent on the location of the employer) neighborhood attributes such as poverty, racial composition and educational attainment into an index describing employers’ perception of the neighborhood. I thus weight neighborhood attributes using employers’ responses to those attributes in a prior experiment. Using data from Bertrand and Mullainathan (2004), I can estimate the following probit regression:

$$\Pr[C_i = 1] = \Phi(\beta_0 + \beta_1 Inc_i + \beta_2 FracWhite_i + \beta_3 FracCol_i)$$

C_i is a indicator of whether applicant i received a callback; Inc_i is the log median income of the census tract of the address listed on i ’s résumé; $FracWhite_i$ is the fraction of census tract residents who are white; $FracCol_i$ is the fraction of the census tract with at least a bachelor’s degree; $\Phi(\cdot)$ is the normal distribution. Appendix Table A.1. presents the results of estimating this equation with

data from Bertrand and Mullainathan (2004). The three variables are jointly significant (F-test p-value of 0.005). The coefficients from this estimation provide relative weights for the affluence index based on employer preferences in a prior experiment.

To measure affluence in the present experiment, I apply the coefficients estimated above to 2011 5-Year ACS data for Washington, DC. I calculate expected callback rates for DC census tracts as:

$$\text{Index of Affluence} = \Phi(\hat{\beta}_0 + \hat{\beta}_1 \text{Inc}_i + \hat{\beta}_2 \text{FracWhite}_i + \hat{\beta}_3 \text{FracCol}_i)$$

where the $\hat{\beta}$ coefficients result from the Bertrand and Mullainathan (2004) data but the covariates represent neighborhood characteristics of DC census tracts in 2011. These fitted values are my measure of affluence, which combines census tract income, racial composition, and educational attainment into one measure with different attributes weighted depending on the observed importance placed on these characteristics by employers in the Bertrand and Mullainathan (2004) sample. More generally, the index is a propensity score that can then be used to match census tracts according to how their characteristics are viewed by employers. Addresses with the same propensity score should be treated similarly by employers if neighborhood income, racial composition, and educational attainment fully characterize the information contained in an address.

Any index of affluence will be imperfect. This particular index measures the relative weight employers place on various characteristics using data from Boston and Chicago. Data limitations prevent inclusion of other relevant variables, including distance to the job. However, the index is relatively robust. I can construct similar indices running univariate probit models that consider each of the three attributes separately. As shown in Appendix Table 2, the main index I use is positively correlated with indices created from each of the three components. For race and income, this correlation is above 0.9. It correlates less strongly but still positively with college attainment.

Overall, this index provides a reasonable measure of affluence, and as shown below, I will use address fixed effects to control for potential errors in measuring affluence.

3.1.2. Selecting Addresses to Separate Affluence from Commute Distance

Given a particular job location, an algorithm selects 4 addresses that separately vary affluence and commute distance. I choose “Near, Affluent” and “Near, Poor” addresses from a grid so that are the same distance from the job. Comparing callback rates for NA and NP addresses allows me to measure the effect of neighborhood affluence separately from commuting distance. I can similarly measure affluence effects by comparing “Far, Affluent” and “Far, Poor” addresses, and greater statistical precision can be obtained by combining NA and FA types to compare to NP and FP types. I can also measure the effect of commute distance holding affluence constant. I match NP and FP addresses to be of similar affluence; likewise for NA and FA. Distance effects can then be measured by comparing callback rates for types FP and FA to types NP and NA. Finally, given a full 2x2 design, I can test for interactions between distance and affluence. The remainder of this section describes in detail an algorithm to select these four types of addresses.

First, I construct an 18x18 equally spaced grid of locations with borders formed by the points of the Washington, DC diamond. I then eliminate addresses outside of Washington, in parks, in bodies of water, and in census tracts dominated by universities (at least 30% college students) or military bases (at least 30% in armed forces). Each remaining point on this grid is paired with an address on the nearest “main street” (defined as streets shown as white or yellow on Google Maps at a particular zoom). I use main streets because a public survey (see below) indicates that respondents can more accurately identify characteristics of addresses on such main streets. This alternative performed better than solely manipulating the quadrant of the address or using addresses whose locations are communicated by the alphanumeric system of streets in DC. The background cloud of blue markers in Figure 4 shows the addresses that result from molding a grid to main

streets in this manner. These addresses provide the pool of potential addresses for fictional applicants.

Then, for a given job location, I carefully select four addresses that separately vary affluence and commute distance. Figure 4 shows my overall strategy graphically. Consider a job located at the dot in the center of the figure. Given the location of the job vacancy, I first define a “Near, Poor” address. The NP address must be below the 10th percentile of the affluence index among all addresses on the grid and be no more than 1 mile further from the job than the closest such address. From all addresses meeting these requirements, I choose one at random. In practice, this typically results in an address just southeast of the job, as shown by the “Near, Poor” box in Figure 4.

Next, I select “Near, Affluent” and “Far, Poor” addresses to match the relevant characteristic of the “Near, Poor” address. An NA address will have similar commute distance as the NP address but be in a more affluent neighborhood. In Figure 4, a circle centered on the job location shows a set of addresses equidistant to the job. Thus, a NA address will be on the same circle as the NP address but in a more affluent neighborhood, likely further northwest. Formally, I require that the NA address be the same distance from the job as NP (± 0.15 miles) and select one address at random from those above median affluence.⁶ I choose the “Far, Poor” address to match the affluence of the NP address but have a longer commute distance. In Figure 4, the box selecting the FP address is on a distance circle further from the job but still in the high poverty Southeast section of the city. Formally, I choose an FP address at random from among those that have the same affluence as the NP address (± 0.01 ; or 0.3 s.d.) and are at least two miles further away from the job than the NP address.

Choosing the “Far, Affluent” address involves a tradeoff. FA addresses should match the affluence of the NA address and the commute distance of the FP address. In Figure 4, I would like

⁶ If there is no such address, I choose the most affluent address with sufficiently similar commute distance.

an address on the same circle as the FP address but with similar affluence to the NA address.

However, these two goals may be inconsistent in an actual city. In practice, I balance these two concerns by choosing the FA address that minimizes the following:

$$\left(\frac{Dist_{FA} - \mu_{dist}}{\sigma_{dist}} - \frac{Dist_{FP} - \mu_{dist}}{\sigma_{dist}} \right)^2 + \left(\frac{Affluence_{FA} - \mu_{aff}}{\sigma_{aff}} - \frac{Affluence_{NA} - \mu_{aff}}{\sigma_{aff}} \right)^2$$

where μ 's are means, σ 's are standard deviations, *Dist* is distance to job, and *Affluence* is the affluence index. In words, I translate measurements of the affluence index and distance into z-scores, calculate the squared difference of the FA type z-score from the one it should match (FP for distance; NA for affluence), and then add the two squared differences together. In the ideal, this calculation would result in zero, indicating that the FA matches the affluence of the NA and the distance of the FP exactly. I will consider the extent to which I achieve this ideal below.

In the end, this algorithm selects 4 addresses for job applications to a given job. Far and near address types are matched to have similar affluence levels. Comparing employer responses for near versus far addresses then measures whether employers care about commute distance separate from affluence; similarly, comparing affluent and poor address types measures affluence effects separate from distance.

3.1.3. Characteristics of Addresses Used in the Experiment

I apply this algorithm to a sample of 565 low-wage jobs in Washington, DC. Figure 5 shows heat maps for the locations of addresses in all four treatments in response to job locations shown in Figure 6. With job locations concentrated in the center of the city Near, Poor addresses cluster in two high poverty neighborhoods just northeast and just south of the center of the city. Some Near, Affluent addresses cluster in an affluent neighborhood just east of the center of the city while others are spread throughout the Northwest quadrant of the city. The algorithm locates Far, Poor addresses almost entirely in far Southeast DC across the Anacostia River. Far, Affluent

addresses concentrate in the far Northwest part of the city with a small cluster in an affluent, predominantly black neighborhood in far Southeast.

The first panel of Table 1 quantifies how the four types of addresses differ. The columns show average characteristics for all four address types. For instance, fictional applicants from NA addresses live on average 3.0 miles from the jobs to which they apply. NP addresses are also 3.0 miles away while FA and FP addresses are further away at 5.3 miles and 5.8 miles. The final two columns measure the differences between treatment types, for instance measuring distance effects by comparing FA and FP addresses to NA and NP addresses. The remaining rows display similar results for variables related to neighborhood affluence. The results indicate that the chosen addresses do generate significant variation in both distance and affluence that matches their assigned treatments. Far addresses are 2.6 miles further away from jobs than near addresses, and poor addresses are in neighborhoods with \$74,000 lower median income, 50 percentage points fewer college graduates, and 40 percentage points fewer whites.

The gap in distance between near and far addresses is meaningful. Using data from Germany, Van Ommeren and Gutierrez (2011) estimate that reducing average commutes from 9 miles to zero would cut absence rates by 15-20%. Extrapolating to the present experiment, employers could reasonably expect near addresses to have absence rates 5-6% lower than far addresses. Also, low-wage job applicants in Washington tend to travel by bus rather than train (Phillips, 2014). Commutes by bus tend to be slow and unpredictable, making an additional 2-3 miles important. Consider rush hour commutes to downtown from the most common address in the FP and NP groups.⁷ The NP address is 2.7 miles away by straight line, which takes 32 minutes riding a bus. The FP address is 6.1 miles away with a 77 minute commute. The latter trip also

⁷ I calculate commutes to 1600 K St. NW arriving by 9:00 AM on Thursday, October 20, 2016 using the WMATA Trip Planner.

requires transferring bus lines, which reduces predictability. A service sector employer seeking punctuality and reliability might wish to cut half an hour off an employee's commute.

The gap in commutes between near and far applicants is also reasonable. In one sample of significantly disadvantaged, low wage job applicants in Washington, DC (Phillips, 2014) commute distance for job applications has a mean of 5.3 miles and a standard deviation of 4.2 miles. Accepted job offers have a mean commute of 5.6 miles with a standard deviation of 3.9 miles. Similarly, representative data from the US Census's 2011 matched employer-employee Longitudinal Employer-Household Dynamics dataset indicate that 22% of workers living in DC southeast of the Anacostia River commute more than 10 miles to work.⁸ Finally, I can compute average travel distance to the jobs in this study for the overall white and non-white populations in Washington, DC. I take ACS data on population by census tract and assume that all individuals live at the tract centroid. I compute the average distances to the jobs in my experimental sample for white and non-white residents in the ACS sample. Non-white (mostly black) individuals in DC would travel on average 3.8 miles to the jobs in this study while the average white individual would need to travel only 2.7 miles. Thus, the experimental manipulation of commute distance is about twice the black-white job access gap in DC. Overall, the "near" addresses can be thought of as being similar to the average white person's commute. The "far" addresses in this study can be thought of as a longer than typical commute for an average minority person or a typical commute for a disadvantaged, low-wage, minority worker. Thus, the experimental variation in commute distance meaningfully captures the difference in job access for those living in areas of concentrated poverty.

The experiment manipulates affluence a bit more strongly but still within a reasonable range. The \$74,000 increase in median income represents a move from the 17th percentile of census

⁸ Figures obtained using the Census's "On the Map" tool to isolate the area east of the Anacostia River.

tract median income to the 85th percentile. A 50 percentage point increase in college completion moves from the 20th percentile of census tracts to the 71st percentile. A 40 percentage point increase in the fraction of white residents moves a census tract from the 30th percentile to the 64th percentile. Thus, comparisons between the “poor” and “affluent” addresses in this study should be interpreted as the effect of a large move along the empirical distribution of neighborhood affluence.

I designed and research assistants conducted a small-scale public survey in Washington, DC to confirm that such variation in actual attributes of addresses leads to perceived differences. A sample of 52 individuals were each presented with 2 addresses in Washington, DC and prompted to respond to a series of questions regarding their characteristics. Respondents demonstrated knowledge of both location and affluence subject to some noise. Travel time (p-value = 0.02), neighborhood median income (0.23), fraction college educated (0.03), and fraction white (0.01) all correlate positively with actual values.⁹ Combined with the documented variation in actual commuting distance and neighborhood affluence, these survey results allow us to reasonably conclude that the experiment shifts perceptions of hiring managers observing résumés.

Panel A of Table 1 demonstrates one challenge inherent in the process of selecting addresses: the addresses are not perfectly matched. For instance, addresses that I classify as poor versus near should be the same distance from jobs. In fact, poor addresses are 0.2 miles further away on average. Similarly, far and near addresses should have similar affluence. While this is true for median income, far addresses tend to be in less educated and less white neighborhoods. These remaining differences inherently occur because the available variation in these variables at actual addresses does not always allow for a perfect match to be made (see above). The matching process does, though, significantly reduce the correlation between commuting distance and neighborhood affluence. I will test the robustness of distance effects to imperfect matching with

⁹More detailed results available upon request.

two distinct strategies. An instrumental variables framework that allows each treatment type to affect both affluence and distance can correct for imperfect matching. Adding applicant address fixed effects removes the influence of any fixed attributes, including affluence. Both of these alternative strategies will indicate that imperfect matching does not drive distance effects.¹⁰

3.2. Selecting Employers

A detailed experimental protocol defines the process by which research assistants apply to jobs. The overarching goal of the process is twofold. First, when possible I keep the process similar to previous correspondence studies of the labor market. Second, I tailor the process to studying the labor market for low-wage work by applying to jobs with low skill and education requirements. I apply to jobs requiring no more than high school education. I include eight different job low-wage job categories: administrative assistant (17%), cook (20%), fast food (13%), janitor (2%), building maintenance (6%), retail (14%), server (26%), and valet driver (2%). Each day, I randomly distribute a randomly ordered list of categories to each research assistant. Each research assistant identifies the most recent advertisement in their first assigned category on a popular website for posting job vacancies. Jobs must be located within the District of Columbia (not the suburbs), must request an e-mailed résumé or online application (not in-person application), must have an identifiable location, must not require more than high school education, and must not have been the subject of an application within the previous two weeks.¹¹ If no new appropriate jobs have been posted in the job category, the research assistant moves onto their next category. Each research assistant continues through their list until meeting a daily quota of 2-4 new jobs. Altogether, this leads to a sample which is similar to other studies (e.g. Bertrand and Mullainathan, 2004) in that I focus on entry-level jobs but different from some studies to the extent that I filter out

¹⁰ Distance results are also robust to limiting the sample to jobs for which near and far addresses match racial composition more closely. Results not included but available upon request.

¹¹ Eliminating the small number of repeat employers from the sample does not change the main results.

jobs with higher education requirements. Thus, I tailor the sample to fit an urban poverty research question by requiring limited formal education.

Panel B of Table 1 shows characteristics of the job location's census tract. These employer location variables are perfectly balanced by construction because the experiment sends each address type to each job vacancy. Jobs tend to be in high-income, well-educated, and white neighborhoods near downtown. Figure 6 shows a heat map of these employer locations, which can be compared to representative Census data on low-wage work locations in Figure 2.B. The geographic distribution of jobs used in the experiment matches the overall tendency of low-wage work in Washington, DC to be located in the center of the city.

3.3. Designing Fictional Job Applications

For a given job, the research assistant generates fictional job applications in a manner similar to previous studies (e.g. Bertrand and Mullainathan 2004; Lahey 2008; Oreopoulos, 2011). The research assistant sends four separate applications to the job with at least one hour¹² between applications. The four fictional applications include one of each address type (NP, FP, FA, NA) with specific addresses chosen according to the computerized algorithm described above and the sending order of the applications sorted randomly. Research assistants insert the four addresses into four different base résumé templates (e.g. font type, organization) drawn from online databases of job applicants and a local employment agency in DC. Occasionally, errors by research assistants in entering the inputs of the address selection algorithm result in incorrect address assignment. However, since address selection was completed correctly for 98% of applications, I will measure intent-to-treat effects using the intended address type.

¹² I do not find any evidence that applications are too close together, raising suspicion about later applicants. I find no evidence that that measured treatment effects are different for earlier versus later applicants.

I also randomly and independently assign applicant names, phone numbers, e-mail addresses, prior employment information, and education information to the four templates. Listed applicant names fall in three categories: white, black, or ambiguous. In each category there are male and female names. Each job vacancy receives applications evenly split between male and female. Each vacancy receives one name from all three racial categories with the fourth randomly selected from white or black. I use the same first names Bertrand and Mullainathan (2004) use to indicate stereotypically white or black first names. Ambiguous first names were drawn using data on baby names in New York City (NYC Open Data, 2009) and chosen to be common (at least 1,000 babies per year) and have as close to equal distribution as possible between black and white. White last names come from Bertrand and Mullainathan (2004) as do most black last names. Since they use fewer black last names, I supplement their last names with names from Social Security name data with the highest black-white ratio for names held by at least 160,000 people. Similarly, ambiguous last names are chosen from those held by at least 160,000 people with a black-white ratio near 1 to 2.¹³ Finally, I randomly assign first names to last names within the same ethnic group. E-mail addresses then correspond to the name on the résumé, and phone numbers are matched to a voicemail box with a generic message recorded by a person of the appropriate sex. I use eight phone numbers, one for each address type-sex combination. This ensures that all callbacks will be matched to the appropriate address type.

¹³ The distinctively black last names used here and in other studies have roughly a 1 to 1 ratio. Altogether the names are: Black male: Tremayne Jones, Leroy Thomas, Rasheed Jackson, Jamal Coleman, Kareem Robinson, Darnell Washington, Hakim Harris, Jermaine James, and Tyrone Williams. Black female: Aisha Washington, Ebony Jackson, Keisha Robinson, Kenya James, Lakisha Harris, Latonya Thomas, Latoya Williams, Tamika Jones, and Tanisha Coleman. White male: Geoffrey Kelly, Jay Sullivan, Neil Baker, Todd O'Brien, Brett McCarthy, Brendan Murphy, Matthew Ryan, Brad Walsh, and Greg Murray. White female: Allison Sullivan, Anne Walsh, Carrie Ryan, Emily Murray, Jill Murphy, Laurie McCarthy, Kristen Kelly, Meredith O'Brien, and Sarah Baker. Ambiguous male: Tyler Richardson, Jason Brooks, Eric Scott, Antonio Sanders, Raymond Bell, Brian Mitchell, Richard Ford, Joel Butler, Kyle Davis. Ambiguous female: Alyssa Richardson, Ashley Brooks, Danielle Scott, Amanda Sanders, Morgan Bell, Brianna Mitchell, Erin Ford, Christina Butler, and Paige Davis.

I design prior employment information to fit the low-wage jobs that are the subject of this study but also to indicate highly qualified applicants who should receive non-negligible callback rates. For each job category, the research team designed four separate work history profiles which are randomly assigned to the four different applications. Following the previous literature, we drew actual work histories from an online job applicant database (Indeed.com) from cities other than Washington, DC. Work histories were selected to include positive features such as experience relevant to the job category, promotion within the same organization, and increasing level of responsibility. We modified these work histories if necessary to reflect actual employers in Washington, DC and sometimes shortened job responsibility descriptions to fit our four templates. Work dates were chosen at random. First, the end date of the most recent job was determined by randomly drawing an ongoing unemployment duration of zero to six months from a uniform distribution. Then, the applicant shows continuous employment over three separate jobs. The length of each job was set to be at least 6 months and then randomly drawn from the empirical distribution of job lengths from the sample of low-wage job seekers in Phillips (2014).

I set education information to fit the low wage labor market. In particular, all résumés list only high school graduation. I list high schools that signal high quality by selecting four local parochial and public magnet schools and randomly assigning these to each application independent of all other characteristics. I also list a GPA selected from a random uniform distribution from 3 to 4 when the template requires it. The date of graduation communicates information about age, and I select it at random to match the distribution of ages in Phillips (2014). If the graduation date and work history conflict such that the person would be working as a child, I truncate the work history at age 16.

This process for setting names, contact information, work history, and education history encapsulates all information displayed on the fictional résumés. Beyond this information, jobs

requesting an e-mailed résumé also require a cover letter. We compose four standard cover letters based on publicly available templates and randomly assign these to job applications. Some job vacancies require more extensive online applications asking further information. To meet this need, each work history profile also includes wage information (based on estimates from glassdoor.com) and reasons for leaving each job. Each fictional applicant is also assigned three references from the experiment names not used for other applicants to the job. These applications often require either an IQ/skills test or personality questionnaire which is completed by the research assistants in a manner communicating a high quality applicant (i.e. to the best of their ability). For any other question idiosyncratic to the specific job application, the research assistant composes four different answers and randomly assigns them to the different applications.

Altogether, the research team sent 2,260 fictional applications to 565 job vacancies.¹⁴ Panel C of Table 1 present summary statistics of the various résumé characteristics as well as their balance across address treatment types. The typical fictional applicant has graduated from high school, is 41 years old, has been unemployed for 3 months, and has 8 years of listed work experience. The sample is evenly split between male and female; 25% have ambiguous names with the remainder split evenly between black and white names.

As expected, most applicant characteristics show differences that are small both economically and statistically. Having a white name, age, work experience, and sex are all statistically balanced. By chance, résumés with the “far” treatment are 6 percentage points more likely to have black names and have work gaps that are 5 days longer. These differences are statistically significant though economically small and ultimately not of major concern. One might be concerned that this imbalance could lead to lower callback rates for far addresses, leading to an

¹⁴ This value was chosen based on ex-ante power calculations. The sample size was chosen to detect a 0.036 change in callback rates for either the “poor” or “far” treatments (i.e. for main effects) or a 0.05 change in callback rates for interactions with 80% power at the 5% level.

overestimate of the effect of discrimination by commuting distance. However, controlling for these characteristics does not change the main results significantly (see results below). Additionally, it appears that randomly high values of these “negative” characteristics are counterbalanced by other factors. I measure overall quality of all the applicant characteristics on the résumé by regressing a callback dummy on the listed applicant characteristics and a set of 32 dummies for the interaction of the 4 different job experience profiles with the 8 different job types. This model and results are shown in Appendix Table 3. The fitted values of this regression measure the overall quality of non-address-related characteristics on the résumé. The final row of panel C displays balance on this measure of overall résumé quality. All four types of addresses have predicted callback rates between 18.3% and 19.2% based on observable characteristics, and the difference between near and far addresses is statistically insignificant. Randomization of résumé characteristics has ensured that résumés in different treatment categories are on average of similar quality, except for the listed address.

3.4. Regression Framework

I will test for the effects of commute distance and neighborhood affluence using a regression framework. A simple regression yields differences in callback rates:

$$Y_{aij} = \beta_0 + \beta_1 Far_{aij} + \beta_2 Poor_{aij} + \epsilon_{aij} \quad (1)$$

Y_{aij} is a dummy for whether applicant i with address a applying to job j receives a positive callback; Far_{aij} is a dummy for the Far Poor and Far Affluent treatments; $Poor_{aij}$ is a dummy for the Near Poor and Far Poor treatments, and ϵ_{aij} is an error term. Estimates of β_1 and β_2 thus measure the gap in callback rates for far versus near and poor versus affluent neighborhoods, respectively.

For interpretive reasons, consider continuous measures of treatment:

$$Y_{aij} = \beta_0 + \beta_1 Distance_{aj} + \beta_2 Affluence_a + \epsilon_{aij} \quad (2)$$

$Distance_{aj}$ is the great circle distance between address a and job j while $Affluence_a$ can either be the affluence index or any of its components: log median income, fraction white, or fraction college educated. These continuous treatments are only randomly selected in part. For example, commute distance depends on both the randomly assigned treatment types and how the employer location and city boundaries limit maximum distance. Thus, I estimate equation (2) by instrumental variables, using the randomly assigned Far_{aij} and $Poor_{aij}$ as instruments for continuous measures of treatment.

As discussed above, matching on observable variables with real addresses leads to inherent imperfections in balance across treatment types. I address this concern in two ways. First, the instrumental variables setup in equation (2) tests whether my results conflate distance effects with imbalanced neighborhood attributes in the affluence index. In this IV setup, I allow both far and poor treatment dummies to instrument for both commute distance and neighborhood affluence. Thus, the estimates in (2) will, subject to a linearity assumption, parse the extent to which measured treatment effects are robust to accounting for imperfect matching. Second, I revise my main specification to include fixed effects for the 226 different addresses used in the study.

$$Y_{aij} = \beta_0 + \beta_1 Far_{aij} + \beta_2 Poor_{aij} + \phi_a + \psi_j + \epsilon_{aij} \quad (3)$$

This specification includes address fixed effects, ϕ_a . These fixed effects absorb any fixed characteristics of the applicant's address, whether observed but included imperfectly in my matching algorithm (e.g. racial composition) or unobserved and thus unmatched (e.g. employer perceptions of a neighborhood's average work ethic). This specification identifies treatment effects using applicant addresses that are assigned different treatment status depending on the employer location. For instance, an applicant address near downtown can be "near" for downtown jobs and "far" for jobs near city limits. Equation (3) thus identifies the effects of distance using variation generated by the interaction of applicant and job location. Addresses are rarely assigned both to be

“poor” and “rich” for different jobs, making the estimate of β_2 much noisier. I also include job vacancy fixed effects ψ_j in this specification to avoid confounding distance with fixed employer attributes. These two alternative identification strategies, one which leverages the experimental design via instrumental variables and one which uses quasi-experimental variation in commute distance, complement my main specification and ensure that imperfections in the matching process do not drive my results.

4. Results

4.1. Main Results

Panel D of Table 1 presents the simplest version of the experimental results. As predicted, near affluent addresses have the highest callback rate at 0.207, and near poor addresses have the lowest callback rate of 0.170. This gap of 3.7 percentage points confirms the finding of Bertrand and Mullainathan (2004) that employers discriminate by residential location. In the present study, I aim to test whether neighborhood affluence and commute distance measurably contribute to this discrimination. Near poor addresses receive only a slightly lower callback rate of 0.195 compared to the 0.207 rate of near affluent addresses, indicating a 1.2 percentage point decrease in callback rates for an applicant living in a neighborhood with a similar commute time but lower affluence level. The difference between far affluent and far poor addresses is smaller. Overall, these two differences average to a statistically insignificant 1.0 percentage point decrease in callback rates for poor neighborhoods relative to affluent neighborhood, holding commute distance constant. Discrimination against applicants listing distant addresses appears roughly three times larger. Applicants from far affluent addresses are called back at a rate 3.0 percentage points lower than those with near affluent addresses, and applicants from far poor neighborhoods receive 2.5 percentage points fewer callbacks than applicants from near poor addresses. This averages to a 2.7 percentage point decrease in callback rates which is statistically significant (p-value = 0.03).

Employers respond to commute distance while evidence for responsiveness to neighborhood affluence is less clear.

Table 2 tests the robustness of these differences more carefully using linear regression. Column (1) repeats the simple comparison of callback rates in a regression framework. I pool the treatments into overall near-far and rich-poor comparisons using dummies indicating far addresses (FP or FA) and poor addresses (NP or FP). The results indicate that having an address distant from the job and having an address in a less affluent neighborhood both yield lower callback rates. However, only commute distance is statistically significant at the 5% level. Low-wage employers may avoid those who apply from far away if distance leads the employer to question why the applicant could not get a job near home. This type of distance effect should be stronger for applicants from far, affluent neighborhoods with abundant jobs. Column (2) of Table 2 tests for interactions between affluence and distance and shows no evidence that the two treatments interact significantly; hence, I focus on the pooled results which have greater statistical power. Column (3) includes job fixed effects while column (4) also adds applicant controls (racial name dummies, female name dummy, years of listed work experience, age, length of work gap, and job category-work history profile dummies). Since neighborhood affluence and distance to the job are randomly assigned, adding controls does not change the main story significantly. The coefficient on distance changes very little and the p-value drops slightly to 0.06. The effect of having an address in a poor neighborhood remains negative but statistically insignificant throughout. Thus, the data provide strong statistical evidence that employers discriminate by distance; evidence for discrimination by neighborhood affluence remains weaker.

For comparison, I also display the coefficient on a dummy for having a stereotypically black name. The coefficient of -0.060 indicates that individuals with black names receive 6.0 percentage points fewer callbacks than those with ambiguous or white names. Since there is no difference

between white and ambiguous name callback rates, this can also be interpreted as the standard white/black difference. An applicant living 2.6 miles further from the job receives 2.4 percentage points fewer callbacks, 40% of the penalty received by stereotypically black names.

4.2. Continuous Measures of Distance and Affluence

To draw a more direct comparison with the previous literature and to provide a robustness check against imperfect matching of treatment types, I can replace the 2x2 design and treatment dummies with an instrumental variables approach using continuous measures of distance and affluence. Figure 7 demonstrates that callback rates correlate with distance to the job. Callback rates show a generally monotonically decreasing trend for distances out to about 7 miles, only showing an uptick for the furthest 5% of addresses. Local linear-smoothed callback rates fall from about 0.24 at 1 mile from the job to about 0.16 at 5 miles away. This drop approximately matches the 6.0 percentage point callback penalty incurred by having a stereotypically black name.

Table 3 examines these continuous measures of treatment within the instrumental variables framework as in equation (2). I use the treatment categories to instrument for continuous measures of distance and affluence because some variation in the continuous measure of distance depends on the job location. The first two columns of Table 3 show the first stages of the IV setup. As expected from Table 1, the instruments are strong with the far indicator (t-stat of 48.2) providing a stronger instrument for distance, though the poor neighborhood indicator still matters (t-stat 4.6). The poor dummy correlates with distance because of previously documented imperfect matching of distance across affluent and poor types. Similarly, the second column shows that the poor dummy provides the stronger instrument for affluence though the far dummy also matters. Allowing both treatment dummies to be instruments for both distance and affluence provides an additional check that imperfect matching does not drive the results. The IV estimation will measure the extent to

which the “far” group has both longer commutes and less affluent neighborhoods; it then accounts for this fact in estimating how commute distance relates to employer responses.

Using the IV framework, I find that continuous measures of treatment provide similar results to the simple analysis of treatment categories above. As shown in Column (3), a 1-mile increase in distance to the job decreases callback rates by 1.1 percentage points. This difference is statistically significant at the 5% level. Distance still matters allowing for an IV framework in which all treatment types may affect both distance and affluence. The affluence measure again shows no statistically significant relationship with callback rates. These results hold constant across different specifications. Columns (4) and (5) add job fixed effects and a vector of applicant controls, respectively. These control variables do not change the main results. A model using continuous measures of treatment confirms that callback rates fall as applicants live further from the job location.

Table 4 verifies that the IV results are robust to alternative measures of distance and affluence. The first column replicates the results of a simple IV model with no controls; callback rates diminish by 1.1 percentage points per mile, and affluence demonstrates a positive but statistically insignificant relationship with employers’ responses. Column (2) shows that these results change little using log median income instead of the affluence index.¹⁵ Column (3) shows that the results remain very similar if I use all 4 treatment types as instruments rather than just the far and poor dummy variables. Column (4) demonstrates that distance effects extend out several miles. A quadratic term in distance is not statistically significant, but even taking its positive sign and magnitude at face value indicates that callback rates decrease out to 5 miles from the job. Column (5) shows that measuring distance as public transit commute times rather than linear distance does not change the results greatly. I can measure public transit travel time between job

¹⁵ Results are also similar for fraction white and fraction college-educated.

and home locations using the Washington Metropolitan Transit Authority's "Trip Planner."¹⁶ Ten minutes of additional commute time lowers callback rates by 3 percentage points. Great circle and commute time measures of distance provide similar results because the two are highly correlated in this context; as column (6) shows, attempting to include both in the regression leads to statistical imprecision.

4.3. Interpreting the Magnitude of Distance Effects

The continuous measure of distance provides a natural way gauge the magnitude of the estimated effects. Commute distances for far and near types differ on average by 2.6 miles. Inserting this difference into the IV model implies a gap in callback rates of 0.029 ($2.6 \times 0.011 = .029$) between far and near types, which matches the results from Table 2. Alternatively, a person assigned an address 5.5 miles away will face a similar impediment to their job application as someone assigned a stereotypically black name ($5.5 \times 1.1 = 6.0$). Even modest racial gaps in job access in Washington, DC could contribute noticeably to racial differences in the labor market, not just at the lower tail but even at the mean. As documented above, the average non-white person in Washington, DC lives 1.1 miles further from the jobs in this study than the average white person does. According to the model in column (3) of Table 3, the average non-white person would thus receive about 1.2 percentage point fewer callbacks than the average white person if only residential location mattered. This gap represents 24% of the direct effect of having a stereotypically black name. Given the large distance effects that I measure, even small differences in geographic access to employment can lead to meaningful racial gaps in treatment by employers.

The continuous measures also provide a means of directly comparing the relative magnitude of distance and affluence effects. Consider someone who moves to a more affluent but also more distant neighborhood. Since the variables have different scales, I use the model in column (3) of

¹⁶ All travel times are measured at 8:30 AM on Friday, January 9, 2015.

Table 3 to test whether a one standard deviation increase in both distance (4.26 miles) and affluence (0.036) affects callback rates. It is worth noting that I compute these standard deviations within the boundaries of Washington, DC, and a move to the suburbs would likely involve similar changes in affluence but a much larger change in distance to jobs. Changing this combination of attributes would decrease callback rates by 0.04, though this is only statistically significant at the 10% level. This comparison suggests that distance matters not only in an absolute sense but also relative to affluence.

Results with continuous measures can also be used to test whether the distance effect I measure is large enough to account for the previously documented relationship between callback rates and neighborhood income. For instance, Bertrand and Mullainathan (2004) examine how callback rates respond to neighborhood characteristics, but because their focus is on racial discrimination, they do not measure commute distance. They omit distance, estimating regressions of the following form:

$$Y_{aij} = \alpha_0 + \alpha_1 \text{Log Median Income}_a + u_{aij}$$

They estimate α_1 at 0.018, indicating that doubling median income drops callback rates by 1.8 percentage points. However, if the true model includes distance, then estimates of α_1 will include both distance and affluence effects. I cannot replicate their approach exactly because I have chosen addresses to remove the correlation between distance and income; however, I can find the estimate of α_1 implied by my results using the standard omitted variable bias formula:

$$\hat{\alpha}_1 = \frac{\partial Y}{\partial \text{Log Med. Inc.}} + \frac{\partial Y}{\partial \text{Distance}} * \frac{\partial \text{Distance}}{\partial \text{Log Med. Inc.}} = 0.006 + (-0.011) * (-1.08) = 0.018$$

I draw the first two values from column (2) of Table 4. I compute the distance-income gradient using a simple regression across all census tracts in DC as in Figure 3 and find that doubling neighborhood income is associated with being 1.08 miles closer to the jobs in my sample.

Replicating Bertrand and Mullainathan's specification during my sample period with representative addresses would thus yield an estimate of 0.018 of the coefficient on log median income of which 0.012 results from commute distance. The overall effect matches exactly their results from an earlier time period in Boston and Chicago. Thus, the distance and affluence effects I measure can explain the previously documented relationship between callback rates and neighborhood income, and commute distance contributes roughly 2/3 of this effect.

4.4. Controlling for Fixed Address-Specific Attributes

I can use applicant address fixed effects to test the robustness of my results to imperfect matching of neighborhood attributes. The experimental design could overestimate distance effects due to imperfect matching on neighborhood education, race, and income or because I cannot match on unobservable neighborhood characteristics. This problem will confront any experimental design attempting to isolate distance effects given the available variation from actual addresses and the multi-dimensionality of affluence. However, the design of the experiment allows me to tackle both of these issues convincingly using applicant address fixed effects. An address fixed effect will absorb any remaining differences in neighborhood income, education, and racial composition due to imperfect matching. More importantly, address fixed effects control for differences in unobserved aspects of affluence across different addresses. This specification relies on applicant addresses that are assigned as "far" for some résumés and "near" for other résumés. Variation in the employer location drives these "switches." This sub-sample covers 987 out of 2,260 applications with locations similar to the full sample. Using only variation in commute distance within the same listed address, I can measure a pure distance effect separate from all fixed attributes of the address.

Table 5 displays results exploiting within-address variation in commute distance. Column (1) replicates column (4) of Table 2 for comparison. Column (2) displays the results for the regression including address fixed affects. These results allay concerns that distance discrimination

has been conflated with imperfect matching, due to either observed or unobserved variables. The measured gap between far and near addresses actually increases in magnitude to 7.4 percentage points. Even with a much larger standard error, it remains statistically significant at the 5% level. Given the large standard error resulting from using address fixed effects, I conservatively reference the specifications without address fixed effects as the main results. However, the results including address fixed effects indicate that my main results do not overestimate discrimination by commute distance.

Caution should be exercised in over-interpreting the relatively noisy results using address fixed effects; however, the point estimate do increase dramatically when including address fixed effects. This increase could occur because fixed effects control for fixed, unobservable, positive features of distant addresses or because the fixed effects estimation focuses attention on a sub-sample of employers who respond more sensitively to distance. Column (3) shows estimates from a specification without address fixed effects but limiting the sample to only those addresses with some within-address variation in the far versus near treatment. These addresses tend to be toward the Northwest quadrant of the city as addresses in the Southeast and Southwest quadrants tend to be consistently classified as far and near, respectively. Simply limiting the sample to the addresses exploited by a fixed effects specification without actually including the fixed effects also increases the distance effect dramatically to 5.8 percentage points. It appears that, rather than controlling for time invariant unobservables, a specification with address fixed effects measures larger distance effects mostly because it puts greater weight on residential locations where employers respond more sensitively to distance.

The results for affluence in the address fixed effects specifications prove somewhat less helpful. While assignment to far versus near types can vary with the location of the job leading to substantial within address variation in treatment assignment, very few addresses are assigned as

poor sometimes and affluent other times.¹⁷ In column (2) of Table 5, exploiting the limited within address variation in the affluent vs. poor treatment generates a large *positive* estimate of being from a poor neighborhood but also an extremely large standard error. More useful results can be obtained by an intermediate step between no address controls and address fixed effects.

Washington, DC addresses are divided into four quadrants (defined by location relative to the US Capitol Building) with differing reputations regarding neighborhood affluence. In column (4), I remove the address fixed effects and instead control for quadrant fixed effects, testing how controlling for neighborhood attributes at the level of the quadrant affects the results.

Discrimination by neighborhood affluence disappears in this specification. The effect of being assigned a poor address is positive but now with a small standard error. This more precise zero suggests that any discrimination by neighborhood affluence that does exist is very broad according to large regions of the city. On the other hand, discrimination by distance remains negative and statistically significant. Employers do appear to discriminate against job applicants from distant neighborhoods even conditional on quadrant of the city. These results with quadrant dummies provide additional evidence that employers discriminate according to commute distance, per se, rather than simply redlining large, distant areas of the city.

4.5. Different Outcome Measures

My interpretation of the main results is consistent with different employer response measures. Table 6 shows these results. In the paper thus far, I have used as my preferred outcome an indicator of receiving either a positive or neutral response from the employer. I replicate the

¹⁷ Though unlikely, it is possible for an address to be classified sometimes as poor and sometimes as affluent. For example, consider an address in near southeast DC which has below median affluence. This address will most commonly be classified as near and poor for downtown job locations. On rare occasions, the job location will be in far southeast DC where there may not be any nearby addresses with above median affluence. So, the address may be classified as the most affluent nearby address. However, only 16 addresses representing 18 percent of applications are assigned to both poor and affluent at least once. Only in one case do I assign more than two applications as poor and more than two applications as affluent from the same address.

main results in Column (1), demonstrating a statistically significant 2.7 percentage point gap between near and far applicants using my preferred outcome measure. Though 70% of the responses in my preferred measure include explicit requests to setup an interview, the other 30% are more neutral responses that do not state the reason for calling or simply request more information. Column (2) tests my main specification using only specific interview requests as the outcome and obtains nearly identical results. My decision to include more neutral responses does not drive the results. Any correspondence experiment also necessarily separates out clearly negative responses rejecting the applicant. However, these responses also convey information that can be exploited. Column (3) demonstrates that listing an address far from the job not only decreases positive responses but also increases clear rejections by 0.9 percentage points. Because of this fact, commuting distance does not exhibit a statistically significant relationship with the probability of receiving any response. Commuting distance affects the pattern of positive and negative responses in a manner consistent with my interpretation of the main results.

5. Conclusion

In this study, I demonstrate that employers discriminate against job applicants who list more distant residential addresses. When presented with otherwise similar fictional résumés, hiring managers for real low-wage job vacancies call back applicants living further away 14 percent less often. This effect is large. Living 5-6 miles further away decreases callback rates by the same discount experienced by applicants with ‘black names’ relative to those with ‘white names.’ Because commuting distance and neighborhood poverty are correlated, discrimination by distance can account for two-thirds of the previously documented penalty in callback rates for addresses in poor neighborhoods. On the other hand, the results provide limited support for the notion that the listed address’s neighborhood affluence directly affects employer behavior.

These results provide support for one potential mechanism behind the spatial mismatch hypothesis, the idea that living far from employment opportunities directly diminishes labor market prospects of the urban poor. While I cannot observe actual employment or wage offers, a drawback of all résumé studies, standard random search models predict that a lower arrival rate of contacts with employers should result in lower employment rates and wages in equilibrium (McCall, 1970). In a labor market with frictions, evidence of employer discrimination provides a causal mechanism running between living in a neighborhood far from jobs and poor labor market outcomes. While a large non-experimental literature has examined spatial mismatch, very few experiments have directly tested such mechanisms of spatial mismatch. The present study confirms that a mechanism on the employer side can contribute to spatial mismatch effects.

Effective policy depends on whether a spatial mechanism drives neighborhoods effects. For instance, the Moving to Opportunity (MTO) project prominently found that providing housing vouchers to public housing residents did not improve their labor market outcomes (Kling, et. al., 2007; Ludwig, et. al. 2012). However, while MTO participants moved to neighborhoods with lower poverty rates, Quigley, et. al. (2008) note that the voucher recipients tended to move to neighborhoods with similarly poor access to jobs. If neighborhood effects operate through a spatial mechanism, then housing vouchers that facilitate moves to less poor but equally distant neighborhoods will not improve labor market outcomes. Housing interventions moving residents close to jobs would be more effective. Perhaps more feasibly, better public transit could shorten the effective distance between areas of concentrated poverty and jobs. If low-wage employers respond to an applicant's commute distance, the relative location of workers and jobs matters for anti-poverty policy.

References

- Aliprantis, D. (forthcoming) “Assessing the Evidence on Neighborhood Effects from Moving to Opportunity.” *Empirical Economics*.
- Aliprantis, D. and F. Richter (2012) “Evidence of Neighborhood Effects from MTO: LATEs of Neighborhood Quality.” *Federal Reserve Bank of Cleveland Working Paper*, No. 12-08.
- Andersson, F., J.C. Haltiwanger, M.J. Kutzbach, H.O. Pollakowski, and D.H. Weinberg (2014) “Job Displacement and the Duration of Joblessness: The Role of Spatial Mismatch.” *NBER Working Paper No. 20066*.
- Arceo-Gomez, E. O., and R.M. Campos-Vazquez (2014) ‘Race and Marriage in the Labor Market: A Discrimination Correspondence Study in a Developing Country.’ *The American Economic Review: Papers and Proceedings*, 104(5).
- Åslund, O., Östh, J., & Zenou, Y. (2010). How important is access to jobs? Old question—improved answer. *Journal of Economic Geography*, 10(3), 389-422.
- Becker, G. S. (1971). The Economics of Discrimination. *University of Chicago Press*.
- Bertrand, M. and S. Mullainathan (2004) ‘Are Emily and Greg More Employable Than Lakisha and Jamal.’ *American Economic Review*, 94(4).
- Bonnet, F., E. Lalé, M. Safi, and E. Wasmer (2015). Better residential than ethnic discrimination! Reconciling audit and interview findings in the Parisian housing market. *Urban Studies*.
- Chetty, R. and N. Hendren (2015) “The Impacts of Neighborhoods on Intergenerational Mobility: Childhood Exposures Effects and County-Level Estimates.” Unpublished Working Paper.
- Chetty, R., N. Hendren, and L. Katz (2015) “The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Project.” Unpublished Working Paper.
- Chyn, E. (2016) “Moved to Opportunity: The Long-Run Effect of Public Housing Demolition on Labor Market Outcomes for Children.” Unpublished Working Paper.
- Coulson, N. E., Laing, D., & Wang, P. (2001). “Spatial mismatch in search equilibrium.” *Journal of Labor Economics*, 19(4), 949-972.
- Duguet, E., N. Leandri, Y. L’Horty, and P. Petit (2010) “Are Young French Jobseekers of Ethnic Immigrant Origin Discriminated Against? A Controlled Experiment in the Paris Area.” *Annals of Economics and Statistics*, No. 99/100.
- Eriksson, S., & Rooth, D. O. (2014). Do employers use unemployment as a sorting criterion when hiring? Evidence from a field experiment. *The American Economic Review*, 104(3), 1014-1039.
- Franklin, S. (2014) “Location, Search Costs and Youth Unemployment: The Impact of a Randomized Transport Subsidy in Urban Ethiopia.” Unpublished Working Paper.

Fujita, M (1991) *Urban Economic Theory*. Cambridge University Press.

Galiani, S., Murphy, A., & Pantano, J. (2015). Estimating neighborhood choice models: Lessons from a housing assistance experiment. *The American Economic Review*, 105(11), 3385-3415.

Gobillon, L., Selod, H., and Zenou, Y. (2007). The mechanisms of spatial mismatch. *Urban Studies*, 44(12), 2401-2427.

Heckman, J. (1998) "Detecting Discrimination." *Journal of Economic Perspectives*, 12(2).

Heckman, J. and P. Siegelman (1993) "The Urban Institute Audit Studies: Their Methods and Findings." in *Clear and Convincing Evidence: Measurement of Discrimination in America*, ed. Fix and Struyk. Washington, D.C.: The Urban Institute.

Hellerstein, J., D. Neumark, and M. McInerney (2008) 'Spatial Mismatch or Racial Mismatch?' *Journal of Urban Economics*, 64(2)

Holzer, H. J., & Reaser, J. (2000). Black applicants, black employees, and urban labor market policy. *Journal of Urban Economics*, 48(3), 365-387.

Kain, J. (1968) "Housing Segregation, Negro Employment, and Metropolitan Decentralization." *Quarterly Journal of Economics*, 82.

Kling, J., J. Liebman, and L. Katz (2007) "Experimental Analysis of Neighborhood Effects." *Econometrica*, 75.

Kneebone, E. (2014) "The Growth and Spread of Concentrated Poverty, 2000 to 2008-2012." *Brookings Institution Research Brief*.

Kroft, K., Lange, F., and Notowidigdo, M. J. (2013). Duration Dependence and Labor Market Conditions: Evidence from a Field Experiment. *The Quarterly Journal of Economics*, 128(3).

Lahey, J. N. (2008). Age, Women, and Hiring An Experimental Study. *Journal of Human Resources*, 43(1), 30-56.

Lang, K. (2007) *Poverty and Discrimination*. Princeton University Press.

Ludwig, J., J.R. Kling, and S. Mullainathan (2011) "Mechanism Experiments and Policy Evaluations." *Journal of Economic Perspectives*, 25(3): 17-38.

Ludwig, J., et. al. (2012) 'Neighborhood Effects on the Long-Term Well-Being of Low-Income Adults.' *Science*, 337(September 21).

Manning, A., and B. Petrongolo (2013) 'How local are labor markets? Evidence from a spatial job search model.' Working Paper.

Marinescu, I., Rathelot, R. (2013) 'The geography of job search and mismatch unemployment.' Working Paper.

- McCall, J. J. (1970). Economics of information and job search. *The Quarterly Journal of Economics*, 113-126.
- Miller, C. (2015) "When Work Moves: Job Suburbanization and Black Employment." Unpublished Working Paper.
- Mulalic, I., Van Ommeren, J. N. and Pilegaard, N. (2014) "Wages and Commuting: Quasi-natural Experiments' Evidence from Firms that Relocate." *The Economic Journal*, 124.
- Neumark, D. (2012) "Detecting Discrimination in Audit and Correspondence Studies," *Journal of Human Resources*, 47(4).
- NYC Open Data (2009) "Most Popular Baby Names by Sex and Mother's Ethnic Group." <https://nycopendata.socrata.com/> Accessed: 4/24/2014
- Oreopoulos, P. (2011) "Why Do Skilled Immigrants Struggle in the Labor Market? A Field Experiment with Thirteen Thousand Resumes." *American Economic Journal: Economic Policy*, 3(4): 148-71.
- Phelps, E.S. (1972) "The statistical theory of racism and sexism." *The American Economic Review*.
- Phillips, D.C. (2014) "Getting to work: Experimental evidence on job search and transportation costs" *Labour Economics*, 29.
- Quigley, J.M., S. Raphael, L. Sanbonmatsu, and B.A. Weinberg (2008) "Neighborhoods, Economic Self-Sufficiency, and the MTO Program" *Brookings-Wharton Papers on Urban Affairs*.
- Rosenbaum, J. E. (1995). Changing the geography of opportunity by expanding residential choice: Lessons from the Gautreaux program. *Housing Policy Debate*, 6(1), 231-269.
- Sanchis-Guarner, R. (2012) "Driving Up Wages: The Effects of Road Construction in Great Britain." *SERC Discussion Papers*, No. 120.
- Stoll, M. A. (2005). *Job sprawl and the spatial mismatch between blacks and jobs*. Brookings Institution Metropolitan Policy Program.
- Tunstall, R., A. Green, R. Lupton, S. Watmough, and K. Bates (2014) "Does Poor Neighbourhood Reputations Create a Neighbourhood Effect on Employment? The Results of a Field Experiment in the UK." *Urban Studies*, 51(4).
- Van Ommeren, J. N., & Gutiérrez-i-Puigarnau, E. (2011). "Are workers with a long commute less productive? An empirical analysis of absenteeism." *Regional Science and Urban Economics*, 41(1), 1-8.
- Wilson, W.J. (1997) *When Work Disappears: The World of the New Urban Poor*. Vintage Books.

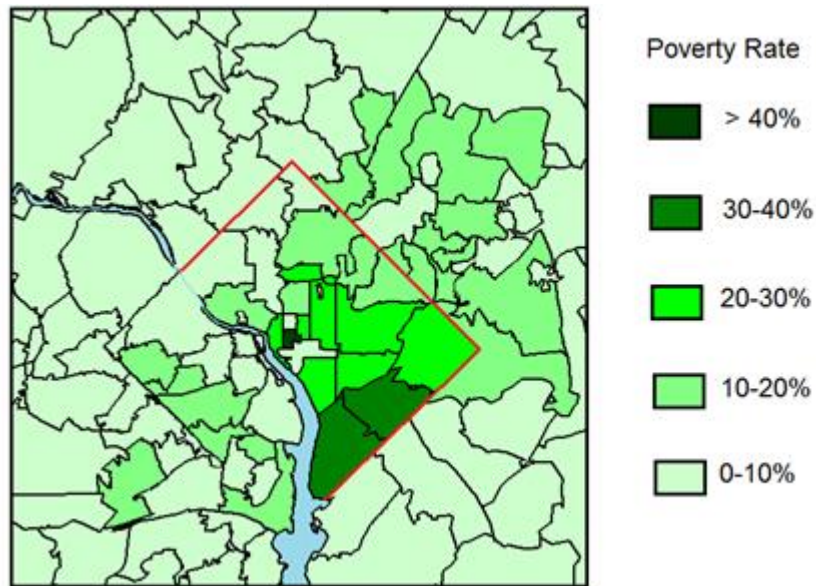
Zax, J. and J. Kain (1996) "Moving to the Suburbs: Do Relocating Companies Leave Their Black Employees Behind?" *Journal of Labor Economics*, 14.

Zenou, Y. and N. Boccard (2000) "Racial discrimination and redlining in cities." *Journal of Urban Economics*, 48.

Zenou, Y. (2002) "How do firms redline workers?" *Journal of Urban Economics*, 52.

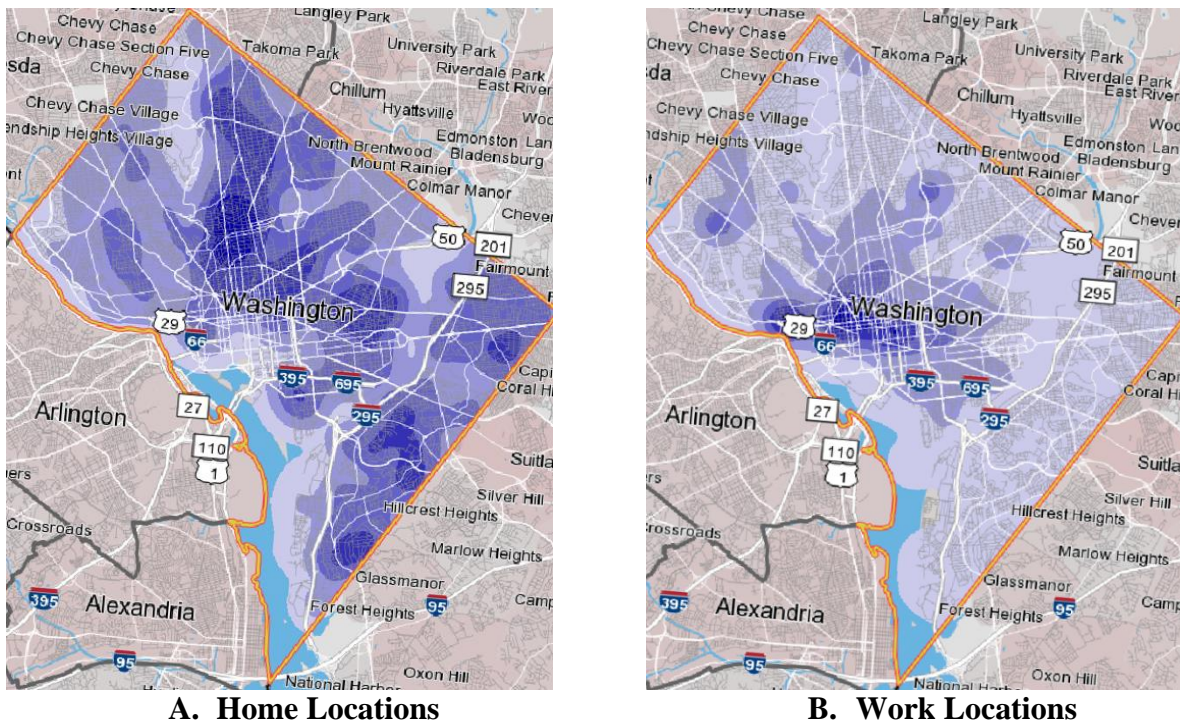
Zenou, Y. (2009) *Urban Labor Economics*. Cambridge University Press.

Figure 1. Poverty Rates across Washington, DC Area Zip Codes



Source: US Census of Population, 2000

Figure 2. Home and Work Locations of Workers Earning \$1,250 or Less per Month



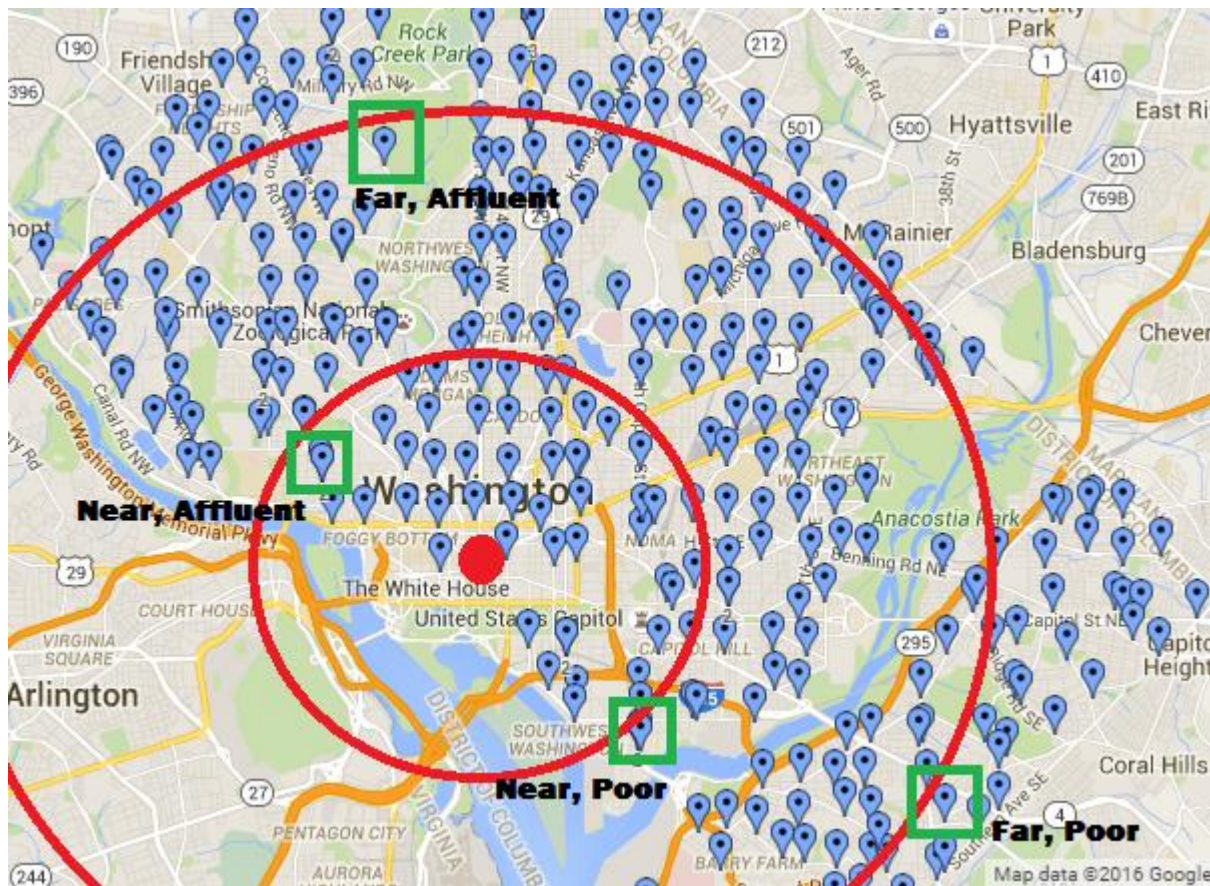
Source: 2014 Longitudinal Employer-Household Dynamics Data. Images created using <http://onthemap.ces.census.gov/>

Figure 3. Job Access and Education Levels in Washington, DC Census Tracts



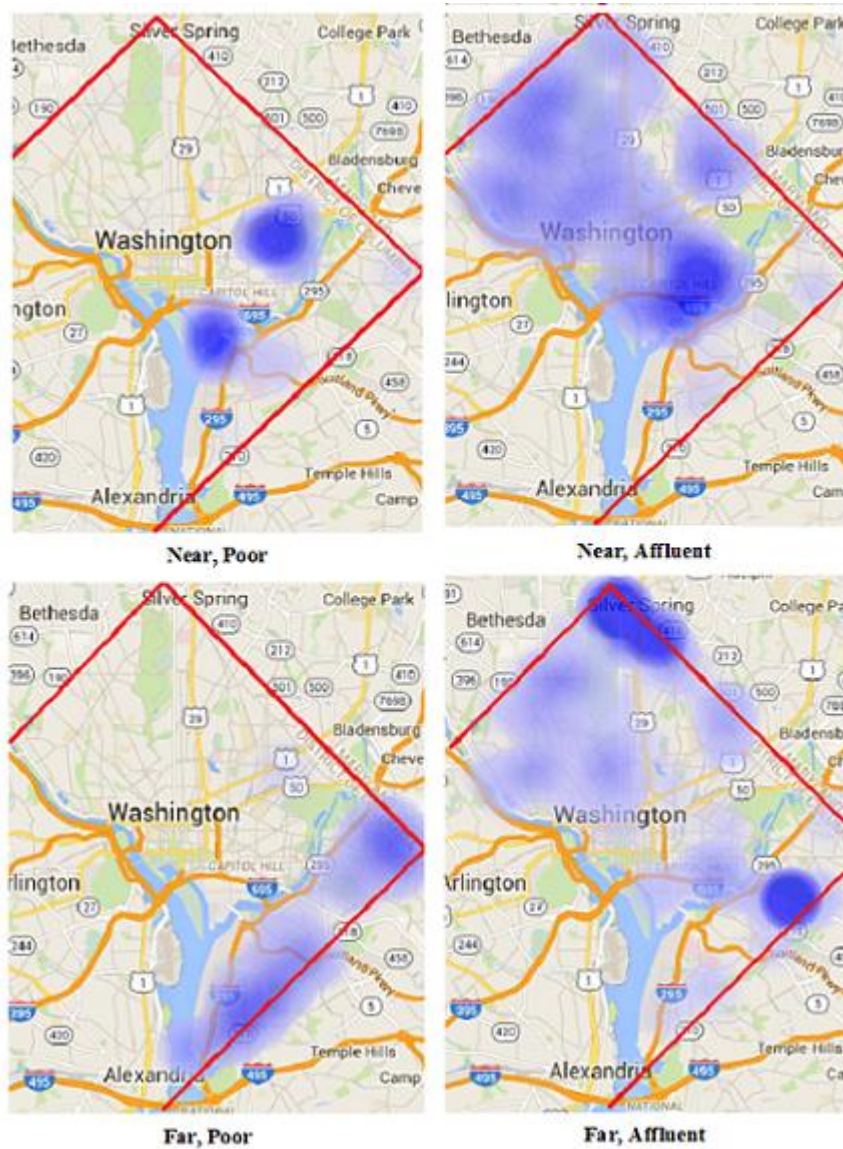
Source: Average distance to jobs is computed as average great circle distance from the tract centroid to the job vacancies used in the correspondence experiment. Fraction of the population with a Bachelor's or More comes from the American Community Survey 2011 5-Year estimates.

Figure 4. Identification Strategy



The large number of markers show the potential addresses that can be chosen for the experimental applicants. Job refers to a particular job location. The boxes near the indications for Near Affluent, Near Poor, Far Poor, and Far Affluent provide examples of addresses in the four treatment categories for this job location.

Figure 5. Locations of Residential Addresses in Experiment, by Treatment Type



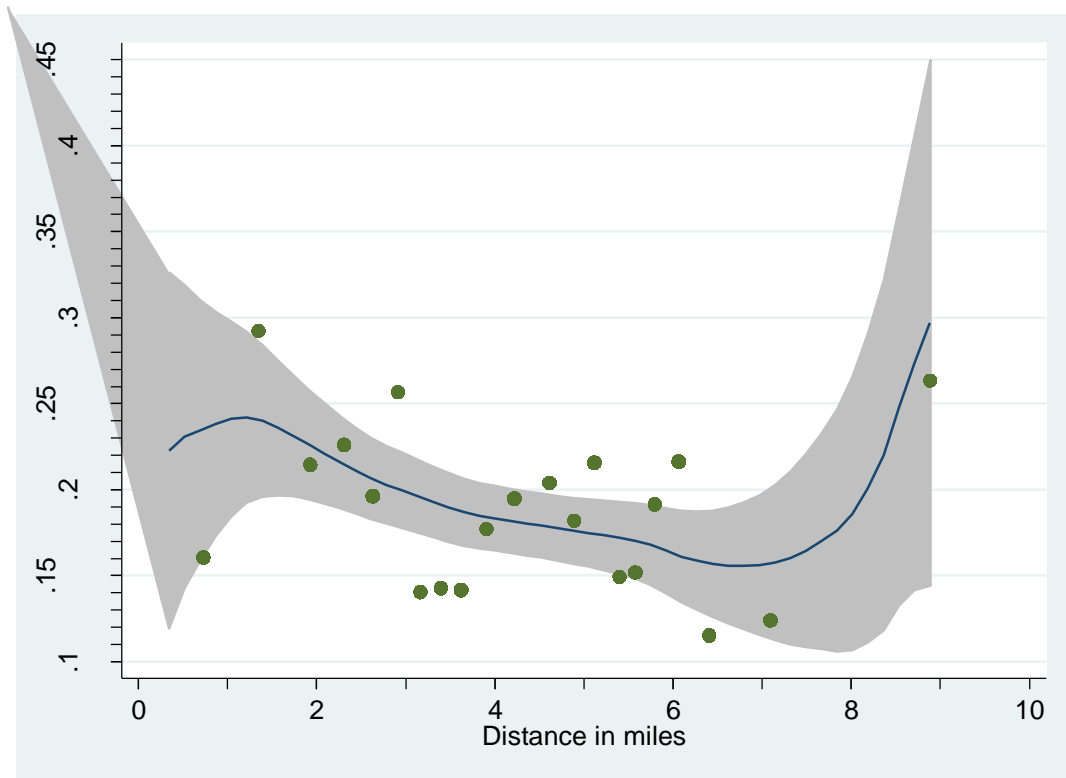
Source: Author's calculations using experimental data. Darker areas indicate greater density.

Figure 6. Locations of Jobs in Experiment



Source: Author's calculations using experimental data. Darker areas indicate greater density.

Figure 7. Callback Rates and Commuting Distance



Source: Author's calculations using experimental data. Distance is measured as great circle distance between the employer's listed location and the residential location generated for the fictional applicant. Applicants are grouped into 20 equal ventiles by distance with callback rates within the group displayed. The curve shows a local linear fit with 95% confidence interval in gray.

Table 1. Summary Statistics and Baseline Balance		Near, Affluent	Far, Affluent	Near, Poor	Far, Poor	Poor - Affluent	Far - Near
A. Applicant Address							
Distance to Job (miles)		3.0 (1.3)	5.3 (1.1)	3.0 (1.3)	5.8 (1.3)	0.2 [0.001]	2.6 [0.000]
Tract Median Income (\$)		101,698 (29,066)	106,371 (26,392)	32,429 (19,822)	27,812 (4,832)	-73,914 [0.000]	28 [0.98]
Tract Percent Bachelor's or Higher		70 (16)	62 (18)	20 (18)	11 (5)	-50 [0.000]	-9 [0.000]
Tract Percent White		60 (24)	31 (27)	9 (18)	1 (1)	-40 [0.000]	-19 [0.000]
Tract Affluence Index		0.146 (0.018)	0.142 (0.019)	0.083 (0.021)	0.077 (0.005)	-0.064 [0.000]	-0.005 [0.000]
B. Job Address							
Tract Median Income (\$)		95,672 (34,951)	95,672 (34,951)	95,672 (34,951)	95,672 (34,951)	0 [1.00]	0 [1.00]
Tract Percent Bachelor's or Higher		74 (20)	74 (20)	74 (20)	74 (20)	0 [1.00]	0 [1.00]
Tract Percent White		65 (22)	65 (22)	65 (22)	65 (22)	0 [1.00]	0 [1.00]
C. Other Applicant Characteristics							
White		0.35 (0.48)	0.35 (0.48)	0.40 (0.49)	0.34 (0.48)	0.02 [0.42]	-0.03 [0.20]
Black		0.36 (0.48)	0.42 (0.49)	0.35 (0.48)	0.41 (0.49)	-0.01 [0.65]	0.06 [0.01]
Age		41 (11)	41 (12)	41 (11)	41 (12)	-1 [0.27]	0 [0.56]
Work Gap (days)		88 (52)	91 (53)	89 (55)	95 (52)	2 [0.31]	5 [0.04]
Work Experience (years)		8.1 (5.5)	7.7 (4.7)	8.0 (5.4)	8.2 (5.2)	0.2 [0.32]	0.0 [0.82]
Female		0.49 (0.50)	0.49 (0.50)	0.54 (0.50)	0.48 (0.50)	0.02 [0.31]	-0.03 [0.11]
Overall Quality (Predicted Callback Rate)		0.186 (0.107)	0.183 (0.109)	0.192 (0.105)	0.188 (0.111)	0.005 [0.053]	-0.003 [0.22]
D. Outcome							
Callback Rate		0.207	0.177	0.195	0.170	-0.010 [0.46]	-0.027 [0.03]
Sample Size		565	565	565	565		

The first four columns display means for each characteristic by treatment group. The final two columns measure differences in characteristics by regressing the variable of interest on a dummy variable for a poor address or a dummy variable for a far address, respectively. P-values are reported in brackets. Standard deviations are in parentheses. Standard errors for the final two columns are clustered by job. The overall quality variable predicts a callback dummy using a female name dummy, racial name dummies, age, years of listed work experience, length of work gap, and job profileXjob category dummies.

Table 2. Effect of Address Treatments on Employer Response

Dependent Variable:	Callback Dummy			
	(1)	(2)	(3)	(4)
Far	-0.027** (0.013) [0.03]	-0.030* (0.018) [0.09]	-0.027** (0.013) [0.03]	-0.024* (0.013) [0.06]
Poor	-0.010 (0.013) [0.46]	-0.012 (0.018) [0.50]	-0.010 (0.013) [0.46]	-0.015 (0.013) [0.24]
Far X Poor	--	0.005 (0.024) [0.83]	--	--
Black	--	--	--	-0.060*** (0.016) [0.00]
Job Fixed Effects	N	N	Y	Y
Applicant Controls	N	N	N	Y
Sample size	2,260	2,260	2,260	2,260

Statistical significance at the 1, 5, and 10 percent levels is denoted by ***, **, and * respectively. Applicant controls include a female name dummy, racial name dummies, age, years of listed work experience, length of work gap, and job profileXjob category dummies. Standard errors are clustered at the job vacancy level. Selected p-values are in brackets.

Table 3. Instrumental Variable Estimates for Continuous Measures of Distance and Affluence

Dependent Variable	Distance (1)	Affluence (2)	Callback (3)	Callback (4)	Callback (5)
Far	2.56*** (0.05)	-0.005*** (0.001)	--	--	--
Poor	0.24*** (0.05)	-0.064*** (0.001)	--	--	--
Distance to Job (miles)	--	--	-0.011** (0.005)	-0.011** (0.005)	-0.009* (0.005)
Affluence Index	--	--	0.11 (0.21)	0.11 (0.21)	0.20 (0.20)
Job Fixed Effects	N	N	N	Y	Y
Applicant Controls	N	N	N	N	Y
Address FE	N	N	N	N	N
Instruments	N/A	N/A	Far, Poor	Far, Poor	Far, Poor
Kleibergen-Paap F-Statistic	N/A	N/A	3,742	3,211	3,243
Sample size	2,260	2,260	2,260	2,260	2,260

Statistical significance at the 1, 5, and 10 percent levels is denoted by ***, **, and * respectively. Standard errors are clustered at the job vacancy level. Applicant controls include a female name dummy, racial name dummies, age, years of listed work experience, length of work gap, and job profileXjob category dummies.

Table 4. Robustness of Instrumental Variables Results

Dependent Variable	Callback (1)	Callback (2)	Callback (3)	Callback (4)	Callback (5)	Callback (6)
Distance to Job (miles)	-0.011** (0.005)	-0.011** (0.005)	-0.010** (0.005)	-0.06 (0.12)	--	-0.013 (0.023)
Distance Sq.	--	--	--	0.006 (0.014)	--	--
Affluence Index	0.11 (0.21)	--	0.11 (0.21)	0.19 (0.29)	-0.09 (0.24)	0.09 (0.37)
Log Med. Inc.	--	0.006 (0.01)	--	--	--	--
Public Transit Travel Time (min.)	--	--	--	--	-0.003** (0.001)	0.000 (0.005)
Instruments	Far, Poor	Far, Poor	Far, Poor, Far*Poor	Far, Poor, Far*Poor	Far, Poor, Far*Poor	Far, Poor, Far*Poor
Kleibergen-Paap F- Statistic	3,742	3,978	2,609	29	171	10
Sample size	2,260	2,260	2,260	2,260	2,116	2,116

Statistical significance at the 1, 5, and 10 percent levels is denoted by ***, **, and * respectively.

Standard errors are clustered at the job vacancy level. Sample sizes are lower when using the travel time measure because some addresses cannot be assigned a transit time by WMATA trip planner.

Table 5. Effect of Address Treatments on Employer Response, Applicant Address Controls

Dependent Variable:				
Callback Dummy	(1)	(2)	(3)	(4)
Far	-0.024*	-0.074**	-0.058**	-0.030**
	(0.013)	(0.030)	(0.025)	(0.014)
	[0.06]	[0.02]	[0.02]	[0.03]
Poor	-0.015	0.092	-0.006	0.006
	(0.013)	(0.065)	(0.027)	(0.019)
	[0.24]	[0.16]	[0.84]	[0.74]
Job Fixed Effects	Y	Y	Y	Y
Applicant Controls	Y	Y	Y	Y
Applicant Address				Quadrant
Controls	N	Address FE	N	Dummies
			Far Varies	
			within	
			Address	
Sample	Full	Full	Full	Full
Sample size	2,260	2,260	987	2,260

Statistical significance at the 1, 5, and 10 percent levels is denoted by ***, **, and * respectively. Applicant controls include a female name dummy, racial name dummies, age, years of listed work experience, length of work gap, and job profileXjob category dummies. Standard errors are clustered at the job vacancy level. Selected p-values are in brackets.

Table 6. Different Outcome Measures

Dependent Variable:	Preferred Measure (1)	Interview Only (2)	Rejected Only (3)	Any Response (4)
Far	-0.027** (0.013) [0.03]	-0.027** (0.012) [0.03]	0.009** (0.004) [0.02]	-0.014 (0.013) [0.27]
Poor	-0.010 (0.013) [0.46]	-0.004 (0.011) [0.75]	0.004 (0.003) [0.29]	0.005 (0.013) [0.69]
Applicant Controls	N	N	N	N
Job Fixed Effects	N	N	N	N
Applicant Address Controls	N	N	N	N
Overall response rate	0.19	0.13	0.02	0.21
Sample size	2,260	2,260	2,260	2,260

Statistical significance at the 1, 5, and 10 percent levels is denoted by ***, **, and * respectively. Applicant controls include a female name dummy, racial name dummies, age, years of listed work experience, length of work gap, and job profileXjob category dummies. Standard errors are clustered at the job vacancy level. Selected p-values are in brackets.

Appendix Table 1. Probit Predicting Callback Dummy Using Bertrand and Mullainathan (2004) Data

	(1)
Tract Median Income (\$)	0.17 (0.12)
Tract Percent Bachelor's or Higher	0.25 (0.20)
Tract Percent White	0.01 (0.11)
Sample size	4,784

Probit index coefficients reported. Standard errors in parentheses. Statistical significance at the 1, 5, and 10 percent levels is denoted by ***, **, and * respectively.

Appendix Table 2. Correlation Matrix for Different Affluence Measures

	All Three Factors	Race Only	Income Only	Schooling Only
All Three Factors	1.00			
Race Only	0.92	1.00		
Income Only	0.99	0.89	1.00	
Schooling Only	0.25	0.24	0.24	1.00

Appendix Table 3. Coefficients for Quality Index – Full Sample

	(1)
White	0.009 (0.021)
Black	-0.061*** (0.021)
Female	0.029* (0.016)
Work Experience (Years)	-0.001 (0.002)
Age (Years)	-0.0016** (0.0007)
Work Gap (Days)	-0.0000 (0.0002)
Occupation X Profile Dummies	YES
R^2	0.08
Sample size	2,260

OLS Regression of response dummy on the listed variables. Standard errors in parentheses. Statistical significance at the 1, 5, and 10 percent levels is denoted by ***, **, and * respectively.