Long Commutes or Neighborhood Perceptions: Why Do Employers Avoid Applicants from High-Poverty Neighborhoods?

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Abstract

Why do employers discriminate against job applicants who reside in poor, distant neighborhoods? Previous research indicates that employers call back applicants from these neighborhoods at lower rates, but the motivation for employer discrimination based on residential neighborhood remains unclear. Employers could be responding to long commuting distances, which could lead to higher employee absence/tardiness rates or fatigue on the job. On the other hand, employers may perceive workers from particular neighborhoods to be lower quality workers, on average, and thus discriminate based on neighborhood characteristics such as poverty or racial composition rather than distance to the job. The distinction between discrimination based on commuting distance versus neighborhood characteristics matters for public policy. Some policy responses, such as public transit improvements, may be appropriate if employers respond to distance itself but not if they respond to fixed neighborhood attributes.

However, no experimental studies have measured the extent to which distance vs. neighborhood affluence motivate discrimination based on residential location. The present study addresses this gap using a job application audit experiment. I experimentally vary residential addresses of fictional applicants to real jobs in Washington, DC. Distance to job and neighborhood characteristics will be controlled experimentally via the address listed on the job application, allowing me to measure separately how employers respond to applicants from distant neighborhoods versus poor/black/less-educated neighborhoods.

This study was piloted during summer 2013 and has been demonstrated to be feasible. In the present grant application, I aim to obtain support for expanding the sample to the size necessary for a complete, publishable academic study.

Research Aims and Policy Significance

A large body of evidence argues that the geography of employment matters for poverty in the United States. Most recently, new data on intergenerational income mobility across U.S. cities (Chetty, et. al. 2013) indicates that measures of black isolation and geographic segregation of poverty within a city strongly negatively correlate with intergenerational income mobility. In cities where the poor are concentrated together in neighborhoods with few jobs, the children of poor families are less likely to move up the income distribution. Consequently, public policy on urban labor markets must consider the geography of employment and whether it can be accessed by those living in isolated neighborhoods with concentrated poverty. In the present study, I use a job application field experiment to address one aspect of this issue, employer discrimination based on residential address. I address this question via the following research questions:

1. Do applicants with addresses in poor, distant neighborhoods receive fewer callbacks from employers than those with addresses near the job location?
2. If so, do employers discriminate based on distance from the job or based on other observable neighborhood characteristics (e.g. poverty)?

Addressing these research questions will provide guidance on public policy responses to address inequity in employment across neighborhoods within a city. If employers discriminate on commuting distance, this likely indicates an employer concern that job applicants from distant neighborhoods face unreliable transportation that will make them more likely to be absent or late (Gobillon, et. al., 2007). An appropriate public policy response could be to improve public transit or provide subsidies for firms to locate close to a city center. Meanwhile, interventions that move poor households to more affluent but nearby neighborhoods would be ineffective. On the other hand if employers discriminate against individuals from distant, high-poverty neighborhoods because they associate poverty with low quality workers (whether due to prejudice or statistical discrimination), transportation improvements will do little to alleviate the problem. Meanwhile, housing policy that encourages poor families to move away from concentrated poverty could be effective in preventing employer discrimination. Answering not only *whether* employers discriminate based on an applicant's residential address but *why* this is so matters for choosing which policies will facilitate equitable urban labor markets.

Literature Review

Both economists and sociologists have argued that de-facto racial segregation in housing could negatively affect employment prospects for the poor. Living in a neighborhood with few available jobs nearby could make it more difficult to obtain and maintain employment (Kain, 1968; Wilson, 1997). A large literature based on observational data largely confirms this "spatial mismatch" effect exists.[1] However, empirical confirmation of spatial mismatch has been mixed in experimental studies. Most prominently, the large scale Moving to Opportunity (MTO) project tested whether providing vouchers to families living in public housing to rent in lower poverty neighborhoods would improve employment prospects. While the moves generated quality of life benefits, employment prospects did not improve significantly (Kling, et. al. 2007; Ludwig, et. al. 2012). MTO's (non) result contrasts sharply with strong evidence of spatial mismatch in previous observational studies, generating a major puzzle in the literature. Some favor downplaying the existence of spatial mismatch effects based on MTO, arguing that results from an experiment should be preferred over those using observational data. Such experiments have a strong claim to validity as random assignment of housing vouchers ensures that the only difference between those receiving vouchers and those not receiving vouchers is the voucher

[1] Hellerstein, Neumark, and McInerney, 2008; Raphael and Stoll, 2000; Holzer, Quigley, and Raphael, 2003; Holzer, Ihlanfeldt, and Sjoquist, 1994; Raphael and Rice, 2002; Zax and Kain, 1996

itself (rather than pre-existing differences). Observational studies face greater difficulty in establishing this level of credibility. Others argue that the details of the housing policy used in MTO could lead to null results even in the presence of spatial mismatch (Quigley and Raphael, 2008). Also, some experimental evidence has detected spatial mismatch effects that can be alleviated by public transit subsidies (Phillips, 2013). This debate necessitates further experimental work on the existence of, mechanisms of, and policy responses to spatial mismatch.

Research Design

Main Experimental Design

Discrimination in the labor market can be difficult to measure separately from other correlated factors. Audit studies of discrimination overcome this problem by creating fictional applicant profiles and experimentally varying the characteristic of interest. Bertrand and Mullainathan (2004) apply to jobs using resumés with randomly assigned, racially identifiable names, and Pager (2003) sends testers to apply for jobs, randomly assigning whether they report a criminal history or not. Random assignment of the characteristic of interest allows researchers to separate actual discrimination from, for example, correlation of race with other relevant facts.

The present study will follow the correspondence method popularized by Bertrand and Mullainathan (2004). The research team will complete online job applications for real jobs in Washington, DC. Rather than focusing on race, I focus on the address listed on the job application. The outcome of interest is whether employers call back to arrange an interview, and employer discrimination will be measured as whether callback rates respond to the address listed. While they focus on discrimination based on the applicant's name, Bertrand and Mullainathan (2004) also vary applicant addresses at random and find evidence that employers call back applicants from poor/black/low-education neighborhoods at lower rates. However, they do not investigate what motivates such discrimination. The present study builds on this existing research, investigating *why* employers discriminate by residential address. I use a 2x2 design, carefully varying the fictional applicant's address to alter distance to job and an index of neighborhood affluence separately. The measures used for quantifying distance and neighborhood affluence are discussed in technical appendix A.1. This 2x2 design leads to four main types of listed addresses: Near, Underprivileged (NU); Far, Underprivileged (FU); Near, Affluent (NA); and Far, Affluent (FA). The method for turning measures of distance and affluence into specific addresses for the 2x2 design is described in technical appendix A.2.

Figure 1 depicts the experimental design with a job located in downtown DC (middle of the map). DC provides a useful context in which to conduct this experiment for two reasons. First, most jobs are located downtown near the "dividing line" of poverty in the city, making it possible to assign all four types of addresses to a given job. Second, DC's system of street addresses makes it easy for employers to associate an address with a neighborhood and thus distance to the job and affluence.[2] Addresses are set so that NA and NU are the same distance from the job, and comparing callback rates for such addresses allows me to measure the effect of neighborhood affluence separately from commuting distance. The same holds for types FA and FU, and greater statistical precision can be had by pooling NA and FA types and comparing to NU and FU types. Likewise, distance effects can be measured by comparing callback rates for types NU and FU, which are both addresses in poor neighborhoods to the East but differ in their distance to the job site;[3] likewise for types NA and FA. The 2x2 design allows me to measure interaction effects as well, testing whether employers screen for distance more stringently for

[2] All addresses list the quadrant of the city (NW, NE, SE, SW). Most streets are numbered/alphabetical at 0.1 mile intervals. For instance, 2400 16th St NW is about 1.6 miles west and 2.4 miles north of the Capitol building. Addresses will be pre-tested to select ones for which their actual attributes are in fact salient to DC residents.

[3] This comparison assumes that the index described in the technical appendix includes all neighborhood attributes relevant to employer discrimination. However, census tract fixed effects can be added to control for other attributes.

those from low-income neighborhoods. I assign at random with equal probability only one of these four address types to be the address listed in the applicant's profile.[4] As shown in Table 1, this process results in a valid 2x2 with appropriate experimental control and variation for both distance and affluence. Finally, the job application experimental will allow me to test for important heterogeneous effects including whether spatial discrimination varies by race of the applicant, race of the applicant's references, customer interaction required by the job, and the amount of information included in the application (e.g. presence of a skills test).

Design Modifications and Feasibility

Though I follow the correspondence audit experiment method of Bertrand and Mullainathan (2004) closely, I make two main changes. First, as noted above I carefully select addresses to place focus on the mechanism for why discrimination by residential address occurs rather than just whether it does. Second, I modify some aspects of how jobs are selected and resumés are constructed to tailor this method to the low-wage labor market. See technical appendix A.3 for more details. Most importantly, I piloted this research design during Summer 2013 including the major design modifications with a small sample of 60 job applications. This demonstrated that the experiment is feasible. The pilot netted a callback rate of 10% which is comparable to other resumé studies. Receiving a high contact rate from employers is important for statistical power and demonstrates that the experiment is feasible. Power calculations based on the pilot and other previous research indicates I will need a sample of 2,260 applications. At forty minutes per job application this requires 1,520 hours of research assistant time in the budget below. Table 1 provides the details of this calculation. Together, these pilot results indicate the feasibility of conducting the experiment and scaling it up to a full sample.

[4] It would also be possible to apply to the same job four times with four different profiles reflecting the four different addresses. In the pilot, only one application was sent to each job to minimize the burden on the employer.

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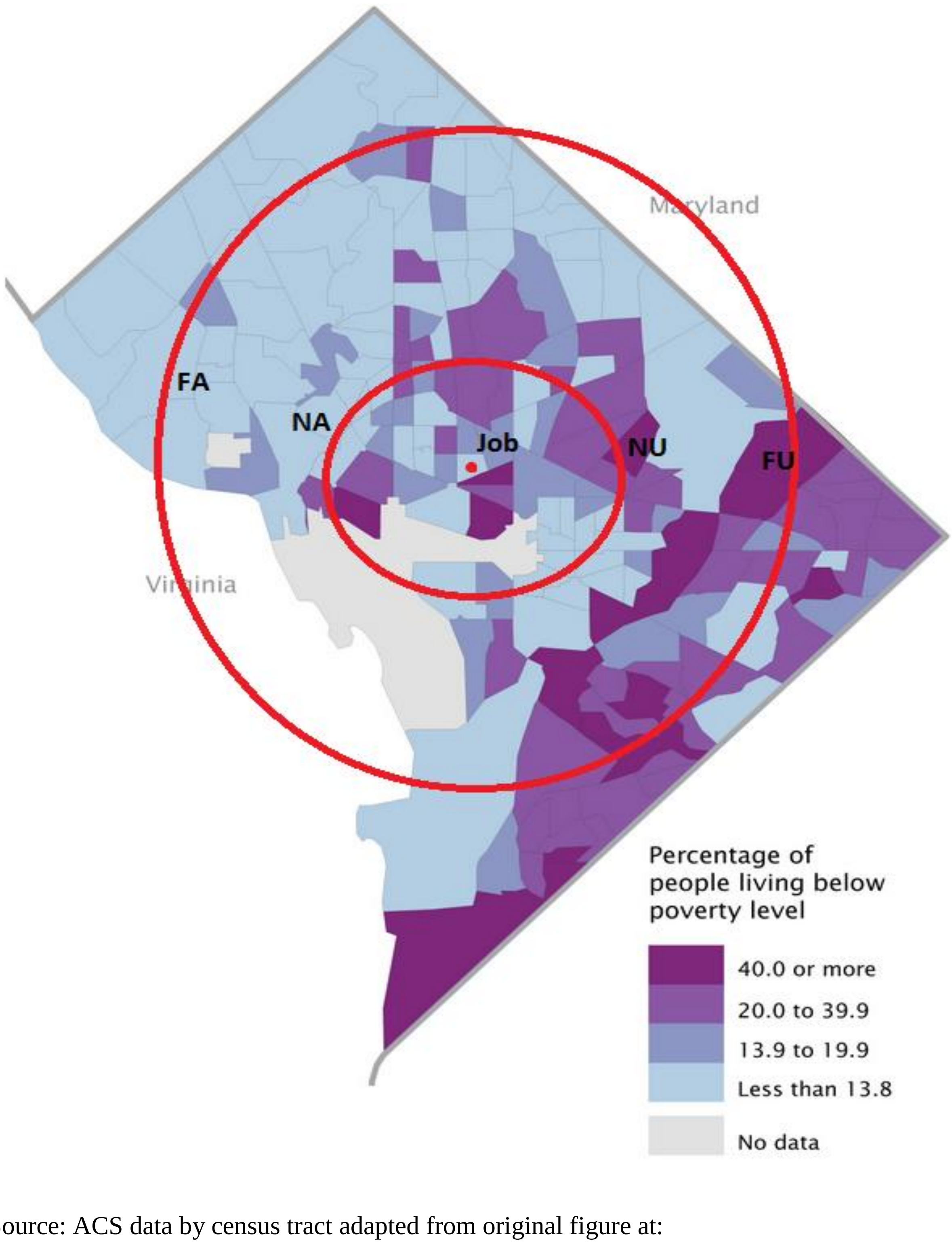
Figure 1: Experimental Design



Source: ACS data by census tract adapted from original figure at: http://www.theatlanticcities.com/jobs-and-economy/2011/12/map-day-uneven-spread-urban-poverty/721/

Table 1

Average Distance to Job in Miles (Pilot Data)

	Affluent	Underprivileged
Near	2.3	2.3
Far	5.4	5.6

Average Affluence Index (Pilot Data)

	Affluent	Underprivileged
Near	7.1	2.9
Far	7.0	2.9

Table 2

	Parameter	Rationale
Level of test (two-sided)	0.05	Standard
Power	0.8	Standard
Response rate	0.1	From pilot
Variance of outcome	0.09	Function of response rate
Minimum detectable effect	0.05	Estimated from Bertrand and Mullainathan (2004). They find that doubling zip code median income cuts the callback rate by 0.018. In the DC sample, median income will increase by a factor of five. So, the expected effect is 0.09. To be cautious, I aim to detect an effect of 0.05.
Sample size per arm:	565	
Total sample size:	2,260	
Time required per observation	40 min.	
Total time required	1,520 hr.	

Note: sample sizes are calculated to ensure sufficient power for interaction effects as well as main effects.

Technical Appendix

A.1. Measuring Distance and Affluence

The 2x2 research design described above requires measuring both commuting distance from an applicant's address to a job location and measuring an index of affluence for any address. I measure distance using straight line distance in miles. This can be easily measured by geo-coding the address of the job vacancy and the address listed on the job application. Measuring distances by public transit, though potentially more valid, is not feasible due to the need to measure millions of distances (see below) when selecting addresses. However, ex-post I will be able to measure and control for the distance by public transit for those addresses used in the study.

To measure affluence, I draw on publicly available data from the American Community Survey (2011 5-Year Estimates) and previous work by Bertrand and Mullainathan (2004). The challenge is to summarize all fixed (i.e. not dependent on the location of the employer, such as distance) neighborhood attributes such as poverty, racial composition and educational attainment into an index describing employer perception of that neighborhood. I use propensity-score matching techniques to this end. Using the Bertrand and Mullainathan (2004) experimental data, 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 resumé; $FracWhite_i$ 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. I estimate this equation with the publicly available

Bertrand and Mullainathan (2004) data. I extrapolate these results to the new setting in Washington, DC and combine the results with the ACS data to calculate expected callback rates for any census tract in DC as:

$$\text{Index of Affluence} = \Phi\left(\hat{\beta}_0 + \hat{\beta}_1 Inc_i + \hat{\beta}_2 FracWhite_i + \hat{\beta}_3 FracCol_i\right)$$

This is my measure of affluence. This process combines census tract income, racial composition, and educational attainment into one measure where different attributes are weighted depending on the observed importance placed on these characteristics by employers in the Bertrand and Mullainathan (2004) data. More technically, the index is the propensity score that can then be used to match census tracts by how their characteristics are viewed by employers.

A.2. Choosing Addresses

To choose specific addresses, I list all addresses in a 70x70 grid over Washington, DC. Given the location of the job vacancy, I first define "Near, Underprivileged" addresses by requiring that they be below the 10^{th} percentile of the affluence index. Then, I select addresses that are no more than 0.5 miles further from the job than the closest such address. From this group of potential addresses, I choose one at random. I require that "Near, Affluent" addresses be the same distance from the job as "Near, Underprivileged" ($\pm$ 0.15 $miles$) and select one address at random from those that have an index above median affluence.[5] For "Far, Underprivileged" addresses I choose an address at random from among those than have the same affluence as the NU address ($\pm$ 0.5; or ¼ s.d.) and are at least two miles (1 s.d.) further away from the job than the NU address. Choosing the "Far, Affluent" address is the most difficult as it

[5] If there is no such address, I choose the most affluent address.

requires matching both the affluence of the NA address and the distance of the FU address. Sometimes these two goals trade off against each other. In practice, I balance these two concerns by choosing the address that minimizes the following:

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

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 the affluence index and distance into z-scores, calculate the squared difference of the FA type z-score from the one it should match (FU for distance; NA for affluence), and then add the two squared differences together. In the ideal, this calculation would result in a zero, indicating that the FA matches the affluence of the NA and the distance of the FU exactly. In practice, I come close to this ideal in the vast majority of cases, as demonstrated in Table 2.

A.3. Modifications of the Standard Resumé Experiment

Bertrand and Mullainathan's (2004) original audit correspondence method must be updated and adapted to appropriately measure spatial mismatch effects. For many aspects, I follow their example: I apply to real jobs using fictional resumes; I use the same applicants names; I follow them in generating fictional job histories by altering publicly available resumés from real applicants in other cities (in my case drawn from online job boards); and I measure success as callback rates to dummy voicemail boxes. However, some minor aspects must be updated. For instance, as in other recent studies (e.g. Oreopoulos, 2011) I will draw job applications from the Internet rather than newspapers. In particular, I draw the jobs from an Internet job board as well as the websites of the Top 200 employers in Washington, DC according to the DC Department of Employment Services. I also use geographically specific information (e.g. high school) that are appropriate to the Washington, DC area. Thus, I follow their existing protocol closely and make only minor, logical updates in most cases.

I make one major intentional change to better tailor the method to studying phenomena affecting low wage employment. The original Bertrand and Mullainathan (2004) study focuses on applying to disproportionately white collar jobs (sales, administrative, etc.) from newspaper ads using fictional applicants who have completed some college. While useful for some topics, including measuring racial discrimination, this sample is less appropriate for studying an issue like spatial mismatch where effects are mainly of concern for low-wage, less-educated job applicants. Thus, I will focus on a more representative group of low-wage job categories (administrative assistant, building maintenance, janitor, cook, fast food crew, server, retail clerk, stock clerk, security guard, and valet attendant). In fitting with this group of jobs, I design applicant profiles that list only high school graduation rather than some college experience. By making these changes, I adapt a proven experimental method to studying low-wage employment.