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Do employers avoid hiring workers from poor neighborhoods? Experimental evidence from the real labor market*

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Abstract

We investigate whether employers avoid hiring workers who live in neighborhoods with low socio-economic status and/or with long commuting times. In a large-scale field experiment in the Swedish labor market, we sent more than 4,000 fictitious résumés, with randomly assigned information about the applicants' residential locations, to firms with advertised vacancies. Our findings show that commuting time has a negative effect on the likelihood of being contacted by an employer, while the socio-economic status of a neighborhood does not appear to be important. These results offer guidance for policymakers who are responsible for reversing segregation patterns.

Keywords: Correspondence study; employer discrimination; neighborhood signaling effects; spatial mismatch

JEL classification: *J*23; *J*71; *R*23

1. Introduction

Most major cities are socio-economically segregated, and these inequalities have tended to worsen over time (Tammaru et al., 2016). Disadvantaged populations often live in suburban areas characterized by low levels of employment, low incomes, and high crime rates. These areas are often located far away from job opportunities. It is fundamental to understand the factors that explain the observed socio-economic segregation – not least for policymakers who have ambitions to reverse this trend.

The existing research has recognized that labor supply factors play an important role in socio-economic segregation (Ellen and Turner, 1997;

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Durlauf, 2004; Galster, 2012). Several studies have highlighted the importance of education and social capital being accessible through neighborhood peers and role models within the neighborhood (Wilson, 1987; Borjas, 1995). It has been shown that exposure to a culture in which joblessness, dropping out of school, and committing crimes are accepted could affect both human capital accumulation and views and expectations related to labor force participation and crime (Katz et al., 2001; Clampet-Lundquist and Massey, 2008; Brattbakk and Wessel, 2013; Galster et al., 2015; Chetty et al., 2016). Long distances to areas where jobs are located could also increase segregation by lowering job search intensity either because of the higher transportation costs or because of the search costs that might arise if information about job openings is less accessible.

However, much less is known about the importance of labor demand factors for socio-economic segregation. Theoretically, two distinct factors on the demand side can explain why employers might be reluctant to hire workers living in economically deprived areas. First, prior to hiring, it is often difficult to assess the human capital and productivity of job applicants; hence, employers might use easily observable characteristics, such as applicants' residential locations, as a sorting criterion. This is especially likely to occur in cases where employers associate a neighborhood with characteristics they perceive as negative, such as low levels of employment, low incomes, high fractions of ethnic minorities, and high crime rates. The result could be statistical discrimination (Phelps, 1972), where workers living in deprived areas are not hired by employers. There could also be redlining, where firms or public authorities do not want to participate in activities with residents of certain neighborhoods, for example, where ethnic minorities live (Hillier, 2003; Small and Pager, 2020).[1] Second, employers could be reluctant to hire workers who live far away from the workplace. A long commuting time could result in expectations that workers will arrive late, or tired, to work, continue their job search after being hired, or have low productivity because of having few other options.[2] Such concerns could also result in statistical discrimination.

In this study, we empirically examine possible neighborhood effects by investigating whether employers act on socio-economic factors associated with certain neighborhoods, that is, neighborhood signaling effects (Zenou and Boccard, 2000), or if they do not want to hire workers with long commuting

[1] The term redlining was coined by sociologist John McKnight in the 1960s and typically refers to the practice of denying (financial) services to residents based on their neighborhood's racial or ethnic composition.

[2] There is some empirical evidence that workers with long commuting distances are less productive (e.g., van Ommeren and Gutiérrez-i-Puigarnau, 2011).

times, that is, spatial mismatch (Zenou, 2002; Gobillon et al., 2007). Although empirically challenging, it is essential to investigate the relative importance of these two explanations because doing so will determine what the appropriate policy intervention is to reverse socio-economic segregation.

We conducted a large-scale field experiment, in the form of a correspondence study, in the Swedish capital, Stockholm. We sent more than 4,000 fictitious résumés, with randomly assigned information about the applicants' residential locations, to firms with advertised vacancies. Correspondence studies are an established method of investigating different forms of discrimination and other employer behavior in hiring situations (Bertrand and Mullainathan, 2004; Carlsson and Rooth, 2007; Eriksson and Rooth, 2014). We randomly assigned workers' residential locations in the résumés and measured the causal effect of residential location on the callback rate (the fraction of positive responses, such as job interviews). We are able to separate the effects of negative socio-economic factors and long commuting times as we use a large number of residential locations with different characteristics and commuting times located across Region Stockholm.

Our findings show that commuting time has a statistically significant negative effect on the callback rate, while socio-economic neighborhood characteristics do not seem to affect employers' hiring decisions. Our main results suggest that an additional 30 minutes of commuting time decreases the callback rate by 2.5 percentage points (−0.025; 95 percent confidence interval (CI) [−0.040, −0.010]), which corresponds to a 6 percent reduction relative to the average callback rate. The point estimate of the socio-economic index in the same regression is 0.005 (95 percent CI [−0.012, 0.022]).

The ground-breaking study in the experimental literature on the demand-side effects of workers' residential locations is Phillips (2020). He conducts a correspondence study in the US capital Washington DC and finds, similar to us, that commuting time has a negative impact on the callback rate to job interviews, while a measure of the affluence of the residential area at the census tract level has no effect. Interestingly, using a similar design to Phillips (2020), Diaz and Salas (2020) find the same result for the Columbian capital, Bogotá. Other experimental studies that have investigated neighborhood effects on callback rates include Tunstall et al. (2014), Bunel et al. (2016), Carlsson et al. (2018), and L'Horty et al. (2019). Each of these studies focuses on neighborhood type, which is randomly assigned to job applications, while commuting distance is not experimentally manipulated. Tunstall et al. (2014) and Bunel et al. (2016) hold commuting distance constant by design, using applicant addresses at a similar distance from the city center. Carlsson et al. (2018) and L'Horty et al. (2019) use non-random variation in commuting distance obtained from the location of employers in their experiments, which provides suggestive evidence of the importance of commuting distance.

We build on the merits of the study by Phillips (2020) but take advantage of Sweden's long tradition of keeping very detailed individual-level administrative registers, which are available to researchers. These data include exact geographical coordinates for all individuals and firms, and thus do not limit our analysis to a certain level of aggregation. This is different from studies conducted in the US, for which data aggregated at the census tract level are often the only viable option. In analyses using census tract data, an implicit assumption is that the tract constitutes an appropriately large unit for socio-economic variables. However, if this is not the case, then the data could conceal important variation (Lee et al., 2008). Another contribution of our paper in relation to Phillips (2020) is that we conduct our experiment in a European context, which is warranted because major European cities look different compared with their US counterparts, in terms of their construction and spatial socio-economic and segregation patterns. We also use a different method to randomize the applicants' residential locations.

The rest of the paper is organized as follows. In Section 2, we present an overview of relevant geographic and socio-economic characteristics of the Swedish capital, Stockholm. In Section 3, we describe our experimental approach. In Section 4, we present and discuss the results. Finally, we conclude in Section 5.

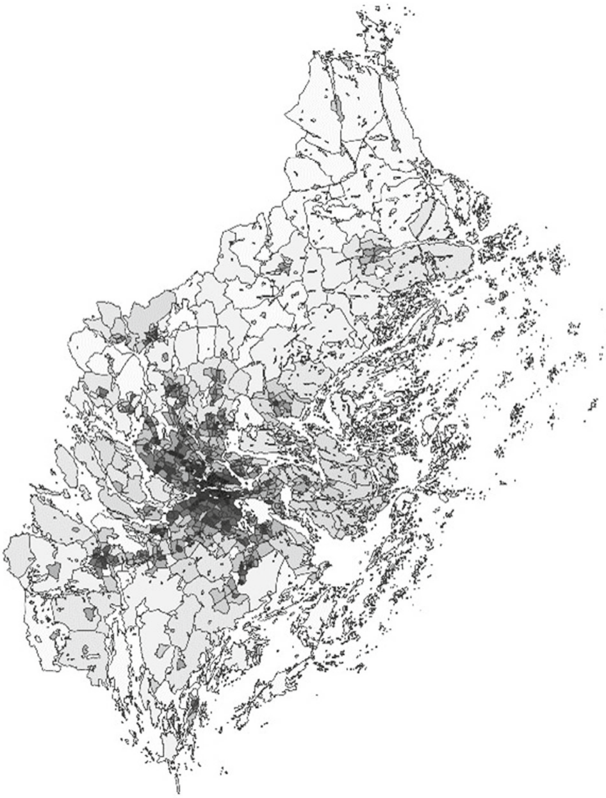
2. Geographic and socio-economic characteristics of Region Stockholm

Region Stockholm has approximately 2.4 million inhabitants, accounting for approximately 20 percent of the Swedish population.[3] The region is divided into 26 municipalities, of which the Stockholm municipality is the largest with approximately one million inhabitants. The Stockholm municipality consists of the city center and a number of suburbs. The remaining municipalities can be characterized as suburban or small-city areas. Figure A1 in the Online Appendix shows a map of Region Stockholm.

Stockholm is similar to many major European cities in its composition. To illustrate this, we constructed a number of maps from individual-level data obtained from Statistics Sweden that include geographical coordinates. Figure 1 shows that population density is highest in the city center and in some of the suburbs. Figure 2 shows that people who are more affluent tend to live in the city center or in some suburbs, while poor people tend to live in a number of specific suburbs often located outside the city center. The figure shows the index of socio-economic status that was calculated and used in the empirical

[3]The figures are for 2019; see Statistics Sweden (https://www.statistikdatabasen.scb.se/pxweb/en/ssd/).

Figure 1. Population density of Region Stockholm

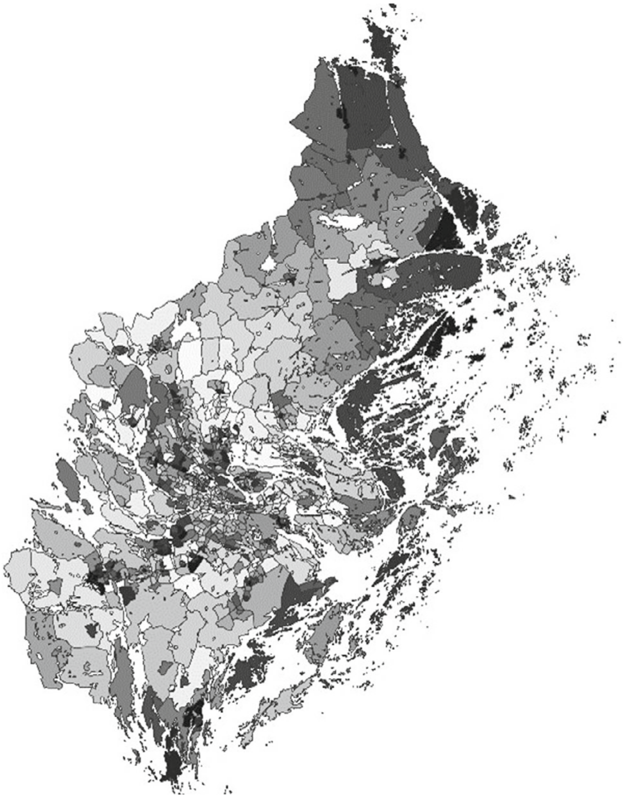


Notes: Darker areas have more dense populations. White and black areas are located in percentiles 1–5 and 96–100, respectively, in the population density distribution.

analysis (see details below). A similar pattern emerges when we instead consider each of the three components of our socio-economic index separately (employment rate, fraction with college education, and fraction born outside Europe; see Figures A2–A4 in the Online Appendix). In Stockholm, ethnic minorities (often refugee migrants from countries in the Middle East and North Africa) tend to live in neighborhoods with low socio-economic status. Hence, ethnic and socio-economic segregation often coincide.

As in most other major European cities, the majority of jobs in Stockholm are located in the city center. This applies especially to high- and medium-skilled jobs but also, to a large extent, to low-skilled jobs. The distribution of jobs across Region Stockholm is shown in Figure 3. Again, we use microdata, now at the firm level, including the geographical coordinates of the firms, to construct the map.

Figure 2. Socio-economic index for Region Stockholm

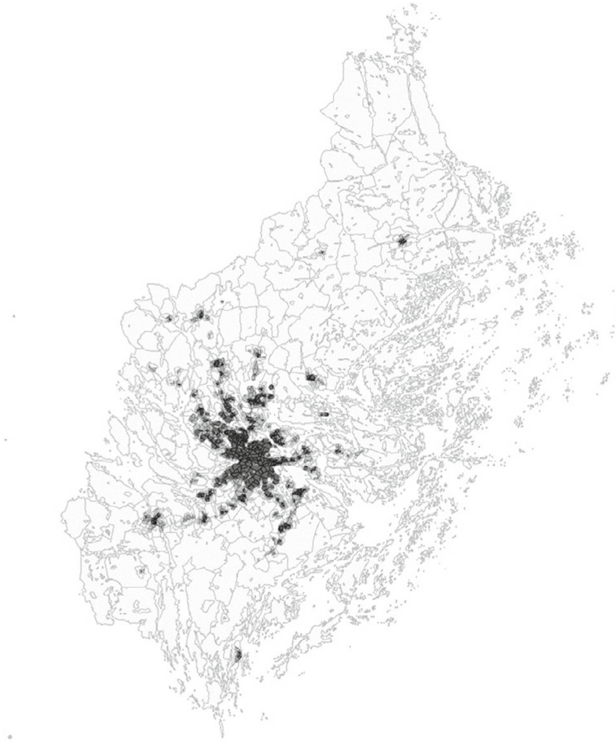


Notes: Darker areas have lower values on the socio-economic index (i.e., are more deprived). White and black areas are located in percentiles 96–100 and 1–5, respectively, in the distribution of the socio-economic index.

Another similarity between Stockholm and other major cities is that neighborhoods with low socio-economic status tend to be located farther away from the city center. Figure A5 in the Online Appendix shows that there is a negative correlation between the socio-economic index that we use and the distance to the city center. Table A4 in the Online Appendix shows that long commuting time is associated with many negative neighborhood socio-economic characteristics.

Highly relevant for our experimental design is that Region Stockholm has a rather extensive public transportation system with commuter trains, subways, and buses. In 2019, the fraction of the population aged 16–84 who traveled to work by public transport was 44 percent, by car 33 percent, by bicycle 11 percent, by walking 12 percent, and by other means 1 percent. The average commuting time to work was 35 minutes, although there was

Figure 3. Location of jobs in Region Stockholm



Notes: Darker areas mean that the density of workplaces is higher. Density refers to the number of workplaces within a small circle (with a radius of approximately 700 m) weighted by the number of employees at the workplace.

substantial variation; commuting times of 60 minutes or more were not uncommon for those living in the outer municipalities of Region Stockholm (Region Stockholm, 2020).

Compared with most other capital cities (e.g., Washington DC), Region Stockholm has fewer inhabitants, more limited income differences (in 2019, the Gini coefficient was 0.36 according to Statistics Sweden), and more extensive public transportation to economically disadvantaged neighborhoods.

3. Method

A job applicant's residential location is largely a choice variable and, thus, unlikely to be an exogenous factor. This makes it challenging to identify the effect of residential location on labor market outcomes using administrative or survey data. To address this identification issue, we conducted a field experiment in the form of a correspondence study. In our case, fictitious résumés containing randomly assigned information about a job applicant's place of residence were sent to employers. We use employers' callbacks (i.e., invitations to job interviews and other positive responses) as our measured outcome. We include advertised vacancies for a selection of the most common low-, medium-, and high-skilled occupations.

3.1. Residential addresses

To obtain representative results, we wanted to use a large number of residential addresses located across Region Stockholm to create substantial variation in neighborhood characteristics and commuting times. To achieve this, we used a method in which we randomly selected a geographical point within Region Stockholm for each résumé. Then, we assigned the nearest residential address associated with this point. In theory, the optimal design would be to include an infinite number of possible geographical points; however, this approach was not feasible for practical reasons because, for each geographical point, we had to identify a postal address, which was a resource-consuming process (see below). Instead, we limited the number of possible geographical points and associated postal addresses by using the midpoints of officially defined neighborhoods (labeled SAMS; see below). This process resulted in 887 coordinates that were evenly distributed across Region Stockholm. An advantage of this approach was that it was practically manageable, but still approximated the described principle.

For each geographical point, we identified an associated postal address. It was important that our choice of postal addresses should not identify real persons living at a particular address. To achieve this, we first used the street view function of Google Maps to determine the type of housing at a given location. If the location contained apartment buildings or a mix of apartment buildings and single- or two-family houses, then we chose an address for an apartment building. Hence, no individual persons could be identified as many people live in each apartment building. If the location contained only single- or two-family houses, then we chose a non-existent street number so as not to identify any real person. We then used Google Maps to verify that the chosen residential location was located no more than a ten-minute walk from public transportation, which was important for our calculation of commuting times (see below). In the end, this approach provided us with a residential address for each of the 887 geographical points. Figure 4 shows the locations of the residential locations used in the experiment.

Our method for selecting residential addresses differs from those of previous studies. Phillips (2020) uses the location of a firm as a starting point when selecting residential addresses. He uses four categories of addresses – near-affluent, near-poor, far-affluent, and far-poor – which are

Figure 4. Location of the residential addresses in the experiment

Notes: For each résumé in the experiment, there is one dot on the map that shows the location of the residential address used in the résumé.

based on the distance to the firm and characteristics of the census tract in which an address is located. Diaz and Salas (2020) use a similar strategy as that used by Phillips. In contrast, our approach produces a continuum of different residential addresses of the dimensions near versus far and rich versus poor, and hence does not reduce these dimensions to two discrete categories.

An important question is what associations employers make when they see a residential address in a résumé. The addresses we use (which have the typical format for addresses in Sweden) consist of a street name with a street number, a postal code, and a city name (which often is the municipality name). We find it likely that employers will have an idea of the approximate location of most of the residential addresses used in the experiment. In cases where employers have no idea of the location of an address, they can easily find this information using, for example, Google Maps. If the residential address does not contain useful information, then we expect to find no effect of either the socio-economic status of the neighborhood or commuting time. However, this result would still have a meaningful interpretation, as it would tell us that the residential address of job applicants, the socio-economic characteristics of the neighborhood in which they live, and their commuting time are irrelevant factors for employers.

3.2. Socio-economic status and commuting time

3.2.1. The neighborhood's socio-economic status. We use individual-level microdata obtained from Statistics Sweden for the same year (i.e., 2017) as the experiment was conducted to calculate different measures of socio-economic status for the neighborhoods. These data are unique in that they include exact geographical coordinates for all individuals. Hence, we are able to try different neighborhood sizes around the residential addresses in the experiment, and to be flexible in how we define a neighborhood.

We calculate our baseline measure of socio-economic status at the small-area market statistics (SAMS) level. SAMS are defined by Statistics Sweden and constructed based on the population and housing characteristics of an area; they are designed to divide a municipality into small homogeneous areas. Region Stockholm consists of approximately 900 SAMS. Unlike US census tracts, SAMS are not constructed for administrative purposes and are typically smaller.

When defining neighborhoods, we aimed to use a level of aggregation that approximates the size of the area around the residential address in the résumé that an average employer associates with the address. It is a neighborhood's socio-economic characteristics at this level of aggregation that might trigger employers' beliefs about the neighborhood and could lead to statistical discrimination against job applicants living there. The fact that SAMS are constructed to be homogeneous makes it likely that SAMS areas are a level of aggregation that employers can associate with a residential address in a résumé.

However, the exact size of the area that employers associate with a residential address is unknown to us. Therefore, we use the individual-level microdata to also construct other neighborhoods around each of our residential addresses, which are defined by circles with radii of 500 m and 100 m.[4]

To characterize a neighborhood's socio-economic status, we use three individual-level indicators: *Employed* (0 = not employed, 1 = employed), *College education* (0 = no college education, 1 = at least some college education), and *Born outside Europe* (0 = not born outside Europe, 1 = born outside Europe). A low employment rate is often associated with economic

[4]We also repeated the analyses using other (larger) circles and obtained similar results.

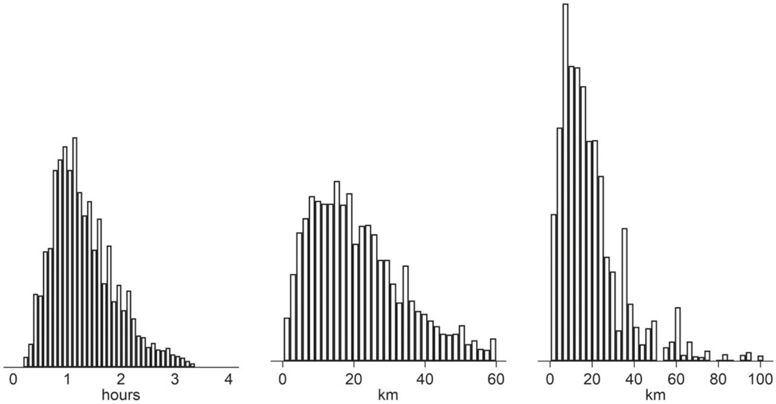
and social problems; hence, it is an appropriate measure of the socio-economic status of a neighborhood. The share holding a college education is a common measure of socio-economic status, and it is typically strongly associated with income. We use the variable born outside Europe because most immigrants to Sweden in recent decades have been refugees or family migrants born in conflict-ridden countries outside Europe (e.g., Afghanistan, Iraq, and Syria). These individuals often struggle to integrate into the labor market; hence, their population share is a reasonable measure of the socio-economic status of a neighborhood. In Sweden, socio-economic and ethnic segregation often coincide, and there is a tendency of native Swedes to leave areas where many immigrants settle. We calculate the share of these indicators for each of the three levels of aggregation from information about the geographical points where our applicants reside and the boundaries of the neighborhoods.

To combine the three measures into one overall measure of socio-economic status, we use a principal component analysis at the neighborhood level using all neighborhoods in Region Stockholm. The result is a socio-economic index with mean of zero and standard deviation of one (its unit of measurement is a principal component score). A higher value means a higher socio-economic status. An advantage of this method is that it does not rely on an arbitrarily chosen weighting scheme, which reduces the degree of subjectivity in the analysis. However, we also conduct the empirical analysis with each of the three socio-economic characteristics included separately in the regressions. Table A1 in the Online Appendix shows summary statistics for the socio-economic index and Figure A6 illustrates its distribution.

Although the three variables that we use in our measure of the socio-economic status of a neighborhood are all motivated by both economic theory and previous empirical studies, there are other variables that could potentially be included, such as income, unemployment, and crime. However, most of these factors are strongly correlated with the measures that we use. As a robustness check, we use several additional variables, including two measures of the crime rate of the neighborhood (see below).

3.2.2. Commuting time. To measure commuting time, we construct three measures based on the job applicant's place of residence and the location of the workplace for the vacancy. As our baseline measure, we calculate the commuting time to the workplace using the travel planning tool available on the website of Stockholm Public Transport (SL), in which a "from" and a "to" address can be entered, and the most convenient travel route (by commuter train, subway, and/or bus) is then suggested. As explained above, public transportation is the most commonly used mode to travel to

Figure 5. Distribution of the measures of commuting distance



Notes: From left to right, the charts show commuting time to firm (public transportation), air distance to firm, and air distance to city center.

work in Region Stockholm, which explains why we use this measure as our baseline.

However, not all workers travel to work by public transportation; therefore, we consider alternative measures as a robustness check. One such measure is the air distance (in kilometers) from the place of residence to the workplace in the vacancy, which we calculate using information from Statistics Sweden's business register on the geographical coordinates of the firms in our sample. This measure should be relevant to workers who travel to work by car or bicycle. In addition, we consider a measure of the air distance (in kilometers) from the applicant's place of residence to the city center. An advantage of this measure is that it is unrelated to the location of the workplace. This might be important as the location of a workplace is not a randomly assigned factor in the experiment, which could introduce problems with omitted variables at the firm level.

Figure 5 shows the distribution of the different measures of commuting time for the job applicants included in the experiment. There is rather considerable variation in these measures. The average commuting time using public transportation is 75 minutes, which is longer than the average commuting time to work, but not unrealistic for people living in many municipalities within Region Stockholm (see above).[5]

[5]It can be argued that in a study of the effects of commuting time it is reasonable to focus on applicants with substantial commuting times, while applicants with very short commuting times are less interesting to consider.

3.2.3. The relative importance of a neighborhood's socio-economic status and commuting time. Randomly assigning residential addresses to résumés solves the problem of selection of job applicants into certain neighborhoods, which is a prerequisite for investigating the mechanisms behind why the residential address of a job applicant might matter. A residential location is associated with both a particular socio-economic status and a distance from the job applicant's residential location to the recruiting firm. To be able to investigate the relative importance of these effects, we enter the two variables simultaneously into a regression:

$$Callback_{ijk} = \alpha + \beta_1 \times (\textit{Socio-economic status})_{ijk} + \beta_2 \times (\textit{Commuting time})_{ijk} + \varepsilon_{ijk}. \quad (1)$$

The dependent variable is the $Callback_{ijk}$ indicator, which equals one if applicant i living in neighborhood j receives a positive response[6] from firm k, and otherwise equals zero. The explanatory variables are socio-economic status and commuting time.[7] The parameters of interest, β_1 and β_2, are estimated with the linear probability model; however, we show that the results are similar when using the probit model.

Both of our explanatory variables are measured on a continuous scale, which means that we can make statements about the effect on the callback rate from, for example, moving to a neighborhood one standard deviation lower in the distribution of socio-economic status or with a 30-minute longer commuting time. The fact that both our explanatory variables exhibit substantial variation should also increase the external validity of the results.

3.3. Résumés and occupations

To create realistic résumés, we studied a large number of real résumés available from a database at the Swedish Public Employment Service. We then created résumés that consisted of two parts, namely, a cover letter and a curriculum vitae (CV; Figures A7 and A8 in the Online Appendix provide an example). Each cover letter starts with a short summary that includes the applicant's name, a description of his or her work experience, and some information about

[6]We define a positive response as an invitation to a job interview or another positive response. The latter includes all responses from employers that eventually could lead to a job interview. Examples are responses that asked for further information by email or asked the applicant to call the employer by phone. We define a non-positive response as no response at all or a negative response. A negative response is a response that (most likely) will not lead to a job interview (e.g., a response that the job has been filled by another applicant).

[7]The correlation between socio-economic status and commuting time in our main sample is −0.05 ($p = 0.003$).

his or her personal interests. The CVs include each applicant's residential location, name, date of birth, work experience, education, contact details, and other information to make the CVs appear realistic.

Randomly assigning a residential location to each résumé is the key manipulation in the experiment; this information is shown at the top of each CV.

We included both female and male names for applicants, and we use the most common names listed in the Statistics Sweden name register. All names are Swedish-sounding names. We did not include immigrant-sounding names to keep the number of dimensions of the experiment low, and to avoid issues with ethnic discrimination. We used three female and three male names, and randomly assigned a name to each résumé to prevent any systematic correlations with residential locations.[8]

As we wanted to focus on prime-aged workers, we chose the lower age limit of 27 to ensure that all applicants were old enough to have both completed their education and obtained some work experience. We chose an upper age limit of 50 to avoid retirement issues. Age was randomly drawn from a uniform distribution.

We aimed to include a sufficient number of common occupations to obtain a fairly representative account of the Swedish labor market, and we wanted to include low-, medium-, and high-skilled occupations. There are two main limitations related to our selection of occupations. First, jobs in the public sector (e.g., healthcare workers and teachers) are difficult to include as most employers in the public sector in Sweden use web-based recruitment systems, in which applicants must state their social security number. Second, many occupations requiring a college education are typically either not advertised in web-based vacancy databases or they require more elaborate résumés tailored to a specific advertisement. In the end, we included eight occupations. Three occupations can be classified as high-skilled: accountants, business sales representatives, and computer professionals. The first and third of these typically require a college education, while the second typically requires at least an academic high school education. The remaining five can be classified as medium- or low-skilled: chefs, construction workers, machine operators, mechanics, and truck drivers. These occupations typically require a vocational high school education. All of these occupations are among the most common occupations not only in Sweden but also in most other countries. All applicants were given an education that was relevant for the occupation and a few years of work experience in the occupation in which we applied.

[8]The male names are Lars Andersson, Peter Nilsson, and Anders Eriksson. The female names are Anna Johansson, Eva Karlsson, and Lena Larsson. These are clear Swedish-sounding names.

To enable employers to contact job applicants, an email address and a mobile telephone number (with voicemail) were included in the applications, which were registered at a large Internet provider and phone company, respectively. Each of the names used in the experiment had a separate email address and telephone number.

A typical Swedish résumé also contains some personal information that is not necessarily directly related to the advertised vacancy. To make our applications appear complete and realistic, we included information about each applicant's number of children, parental leave, and leisure activities. We randomly assigned these characteristics to the résumés to avoid creating any systematic relationship with residential location.

There is an efficiency argument for sending several résumés to each employer because a given number of observations can then be collected using fewer resources. However, the risk of making employers suspicious also increases when more résumés are sent to the same employer. We thus had to trade-off these two factors and decided that it was reasonable to send two or three résumés to each employer. This design required the construction of three types of résumé templates that differed in terms of structure, layout, typeface, and general phrases to prevent employers from becoming suspicious. We randomly assigned a template to each résumé; hence, template type is independent of residential location.

If the randomization of the residential addresses in the résumés has worked as intended, then the socio-economic index or commuting time should not be correlated with the other applicant characteristics, which is confirmed in Table A2 in the Online Appendix.

3.4. Conducting the experiment

For the eight chosen occupations, we randomly sampled firms that posted an advertisement on the website of the Swedish Public Employment Service, which is the most important vacancy website in Sweden. Between October 2017 and November 2018, we sent 4,207 résumés to 1,683 employers who had an advertisement posted on this website. For each advertisement, we recorded the address of the workplace in order to calculate the commuting measures.[9] Then two or three résumés were randomly selected and sent in random order

[9]When registering vacancies, employers are instructed to enter the address of the workplace where the job is located. Although the instruction is clear, we cannot rule out the possibility that some employers with more than one workplace enter another address (e.g., the address of the main office). Around 85 percent of the résumés in the main sample were sent to employers with one workplace (based on the 3,436 of the 3,605 résumés for which we have data on the number of workplaces). The results remain unchanged if we restrict our sample to these résumés.

Table 1. Descriptive statistics

	Number of ŕesumés (1)	Share of résumés (2)	Callback rate (3)
Accountants	561	13.3	47.8
Business sales representatives	736	17.5	38.2
Chefs	714	16.9	42.3
Computer professionals	523	12.4	60.4
Construction workers	463	11.0	25.1
Machine operators	267	6.3	49.4
Mechanics	381	9.0	36.8
Truck drivers	569	13.5	42.4
Total	4,214	100	42.6

to the employer with a one-day delay included between each résumé sent. The employers replied by email or by leaving a voicemail message. After we recorded a reply, we declined any invitations to a job interview.

Column 1 of Table 1 shows the number of résumés sent for each of the eight occupations, which ranges from 267 to 736. Column 2 shows the corresponding shares of sent résumés (from 6.3 to 17.5 percent). The last column shows the callback rates for the eight occupations, which vary from 25.1 to 60.4 percent, with an average of 42.6 percent. The variation in the number of résumés and the callback rates likely reflects differences in labor demand between the occupations. Figure 6 shows the locations of the workplaces included in the experiment. From the map, it is clear that even though the vacancies are distributed across the entire region, many of them are located near the city center.

In the empirical analysis, we include as many of these résumés as possible, but there are two limitations. First, for some cases, commuting time cannot be calculated as the public transportation planner did not offer a realistic route to the location of the firm (e.g., because the firm was located far from any public transportation).[10] Second, for some résumés (especially when we use the smaller definitions of neighborhoods) the socio-economic index could not be calculated because there are too few people living in the area (we treat the socio-economic index as missing if there are fewer than five residents in a neighborhood). In the main estimation where we use SAMS, we include 3,605 résumés.

[10]In most of these cases, the transportation planner offered no travel option. In a few cases, the transportation planner offered a travel option that was unrealistically long. In the estimation, we exclude the 1 percent of the sample with the longest commuting times.

Figure 6. Location of the vacancies in the experiment

Notes: For each vacancy we applied for in the experiment, there is one dot on the map that shows the location of the workplace with the job opening.

4. Results

4.1. Main results

In Table 2, we present the results for our three definitions of neighborhoods. Panel A shows the results obtained when we define a neighborhood as the SAMS area in which the applicant resides. The first column only includes commuting time to the workplace as an explanatory variable, and shows that commuting has a negative effect on the callback rate, which is statistically significant at the 1 percent level. In Column 2, we instead include our measure of the socio-economic status of the neighborhood as the only explanatory variable and find no evidence that it has an effect. Finally, when we include both variables in the same regression (Column 3), we find that the negative effect of commuting time remains unchanged, while there is still no evidence that the measure of socio-economic status has an effect. The size of the

Table 2. Probability of a callback: main results

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. SAMS areas, $N = 3{,}605$						
Commuting time (h)	−0.0510***		−0.0505***	−0.0459**		−0.0448**
	(0.0153)		(0.0153)	(0.0183)		(0.0183)
Socio-economic index		0.0068	0.0052		0.0097	0.0078
(score)		(0.0089)	(0.0089)		(0.0100)	(0.0099)
R^2	0.0037	0.0002	0.0038	0.7334	0.7322	0.7335
Panel B. Circle $r = 500$ m, $N = 3{,}582$						
Commuting time (h)	−0.0576***		−0.0568***	−0.0551**		−0.0543***
	(0.0156)		(0.0156)	(0.0188)		(0.0189)
Socio-economic index		0.0096	0.0073		0.0072	0.0044
(score)		(0.0090)	(0.0091)		(0.0097)	(0.0096)
R^2	0.0045	0.0003	0.0047	0.7366	0.7349	0.7367
Panel C. Circle $r = 100$ m, $N = 2{,}911$						
Commuting time (h)	−0.0661***		−0.0666***	−0.0530**		−0.0534**
	(0.0195)		(0.0195)	(0.0265)		(0.0265)
Socio-economic index		−0.0002	−0.0029		−0.0019	−0.0032
(score)		(0.0091)	(0.0090)		(0.0108)	(0.0106)
R^2	0.0048	0.0000	0.0048	0.7761	0.7751	0.7761
Firm fixed effects	No	No	No	Yes	Yes	Yes

Notes: Of the 4,214 résumés in Table 1, we were able to obtain a measure of commuting time using the public transportation planner for 3,635 résumés. In addition, in some cases, an area is so sparsely populated that the socio-economic index cannot be calculated. This occurs more often for the smaller areas (500 m and 100 m), which explains the difference in sample size between the panels. The regressions in Panel A (SAMS), Panel B (500 m), and Panel C (100 m) use the résumés for which both commuting time and the socio-economic index are observed. See also the text in Sections 3.4 and 4.1. The regressions include no covariates other than those listed in the table. Standard errors are clustered by firm. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

commuting time estimate suggests that an additional 30 minutes of commuting time (which is a reasonable example given the average commuting time in Region Stockholm) decreases the callback rate by 2.5 percentage points. Relative to the average callback rate in the experiment, the reduction of the callback rate is 6 percent (0.025/0.426). For applicants living in more remote areas in Region Stockholm, the negative effect could be more substantial; for example, 1.5 hours of commuting time would lead to an 18 percent reduction. In Columns 4–6, we add firm fixed effects to the regressions in Columns 1–3, and the results remain qualitatively unchanged.[11]

[11] Most of the variation in commuting time comes from the experimental manipulation of the applicant's place of residence, and therefore firm fixed effects should not affect the results. However, *a priori*, we cannot entirely rule out the possibility that the variation in commuting time that comes from the non-experimental variation in the location of the firms introduces an

The regressions shown in Panels B and C repeat those in Panel A but with the socio-economic index constructed using a circle with radii of 500 m and 100 m around the applicant's place of residence. In these cases, the sample size is reduced (3,582 in Panel B and 2,911 in Panel C) because smaller areas have fewer residents and we need at least five residents to calculate the socio-economic index. The results are qualitatively the same as those shown in Panel A.[12]

The absence of evidence of an effect of the socio-economic index on the callback rate raises the question of how precisely estimated is the statistically insignificant close to zero coefficient of 0.0052 in Table 3. The 95 percent CI of this estimate goes from −0.012 to 0.022. The estimate shows the effect of moving one standard deviation up in the socio-economic index distribution at the SAMS level. The distribution of the socio-economic index is shown in Figure A6 in the Online Appendix.

Overall, the results in Table 2 suggest that spatial mismatch is important when employers decide between job applicants, while neighborhood-signaling effects are not.

The fact that the results shown in the three panels are very similar suggests that it does not matter for our conclusions which level of aggregation we use. This is important as we cannot know for sure how large the area is that an employer associates with the residential address in the résumé. Because it is plausible that employers create stronger associations with homogeneous areas, SAMS (which is an officially defined concept that is constructed with the purpose of defining homogeneous areas) are likely to be a reasonable approximation of the area that employers think about when they see the residential address in the résumé. Therefore, we consider SAMS as the baseline in the remaining analyses.

4.2. Robustness

4.2.1. Alternative measures of commuting. While most workers in Region Stockholm commute using public transportation, some workers use

omitted variable bias. This does not seem to be the case, however, as the results with and without firm fixed effects are very similar. The result for commuting time is also similar if we use only the non-experimental variation in the location of the firms by including address fixed effects (but not firm fixed effects). In this case, the socio-economic index cannot be estimated because it does not vary within an address.

[12]Note that the magnitudes of the estimated coefficients of the socio-economic index are smallest when we use areas with a radius of 100 m. This pattern is consistent with more attenuation bias for such areas. If employers associate the residential address in the résumé with larger areas, the result is measurement error in the explanatory variable when we use the lowest level of aggregation.

Table 3. Alternative measure of commuting, air distance to the firm

	(1)	(2)	(3)	(4)	(5)	(6)
Air distance to firm (km)	−0.0014***		−0.0014***	−0.0016***		−0.0016***
	(0.0005)		(0.0005)	(0.0006)		(0.0006)
Socio-economic index (score)		0.0057	0.0001		0.0069	0.0002
		(0.0093)	(0.0095)		(0.0106)	(0.0107)
R^2	0.0025	0.0001	0.0025	0.7188	0.7172	0.7188
Firm fixed effects	No	No	No	Yes	Yes	Yes

Notes: N = 3,247. Of the 4,214 résumés in Table 1, we were able to calculate the air distance between the location of the residential address in the résumé and the firm for 3,267 résumés. See details in the text. In addition, among the cases where the air distance is observed, the socio-economic index is missing in 20 cases (for the same reason as in Table 2, i.e., because there are fewer than five residents in a neighborhood). The regressions use the résumés for which both the air distance and the socio-economic index are observed. The regressions include no covariates other than those listed in the table. Standard errors are clustered by firm. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

other forms of transportation, which could introduce noise into the measure of commuting time constructed using the travel planner for public transportation. To determine whether our results are sensitive to this, we use two alternative measures of commuting time.

The first is the air distance in kilometers between the applicant's residential address and the workplace. This measure should better reflect commuting times for those who travel to work by car, for example. In this case, the sample size is smaller (N = 3,247), mainly because we do not observe the geographical coordinates of all workplaces and, thus, cannot calculate the air distance.[13] Table 3 shows that our main results remain qualitatively unchanged when we use this measure.

The second measure is the air distance in kilometers between the applicant's residential location and the city center. This measure should largely reflect actual commuting time because most firms are located in the city center. An advantage of this measure is that it is independent of the locations of firms; hence, unobserved omitted variables at the firm level are not a relevant issue (these regressions are without firm fixed effects). In this case, we can include almost all résumés in the experiment (N = 4,184) as we do not need the location of the workplace to calculate the commuting measure. Table 4 shows that, for this measure too, our main results remain qualitatively unchanged.

[13] For some workplaces, this information is missing in Statistics Sweden's business register, or we are unable to identify the workplace identifier using the information in the advertisement. In a few cases, firms have coordinates in the business register that are not in Region Stockholm, although the address in the advertisement is in Region Stockholm. We treat the air distance as missing if the coordinates of the firm are outside Region Stockholm (approximated by a circle with a radius of 60 km).

Table 4. Alternative measure of commuting, air distance to the city center

	(1)	(2)	(3)
Air distance to city center (km)	−0.0013***		−0.0013***
	(0.0005)		(0.0005)
Socio-economic index (score)		0.0080	0.0028
		(0.0082)	(0.0085)
R^2	0.0018	0.0002	0.0018

Notes: $N = 4{,}184$. Of the 4,214 résumés in Table 1, the midpoint of the SAMS had a missing value on the coordinates in Statistics Sweden's register in 30 cases. Thus, we were able to calculate the air distance between the location of the residential address in the résumé and the city center for 4,184 résumés. Cases where the socio-economic index is missing (for the same reason as in Table 2, i.e., because there are fewer than five residents in a neighborhood) are the same as those where the air distance is missing, meaning that this does not reduce the sample further. The regressions include no covariates other than those listed in the table. In particular, the regressions do not include firm fixed effects as this measure of commuting is independent of the locations of firms. Standard errors are clustered by firm. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

4.2.2. Alternative measures of socio-economic status. Our results may depend on which variables are used as proxies for socio-economic status and how they enter the analysis. To investigate whether our results are sensitive to this, we repeated the main analysis using alternative specifications and proxy variables for socio-economic status.

First, we estimated the main model with each of the three measures of socio-economic status included separately instead of our baseline measure. Table 5 shows that none of the three individual factors has a statistically significant effect on the callback rate in any of the regressions, while the estimate of commuting time remains almost unchanged.

Second, we estimated more flexible specifications. In Panel A of Table A3 in the Online Appendix, we include the socio-economic index and its square. In Panel B, we include the three terms used to construct the socio-economic index and their full second-order expansion (i.e., all squares and interactions). The results show that the estimate of commuting time remains almost unchanged, and F-tests show that the terms related to socio-economic status are jointly insignificant.

Third, we have experimented with including additional characteristics, which could potentially reflect socio-economic status. These include measures of crime (the share of people with at least one criminal conviction living in the neighborhood; the average number of criminal convictions of the residents living in the neighborhood), demographic variables (females; married; average age; age less than 25; age over 65; born in Europe; population size), education (high school), economic status (median income; uptake of social assistance), and other variables (voter turnout). Tables A5 and A6 show that none of these additional variables affects the estimate of commuting time or

Table 5. Separate measures of the socio-economic characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Commuting time (h)	−0.0510***	−0.0505***	−0.0569***	−0.0495***	−0.0570***	−0.0459**	−0.0448**	−0.0548***	−0.0468**	−0.0623***
	(0.0153)	(0.0153)	(0.0169)	(0.0159)	(0.0189)	(0.0183)	(0.0183)	(0.0207)	(0.0192)	(0.0237)
Employed (%)		0.0006			0.0002		0.0009			−0.0003
		(0.0010)			(0.0007)		(0.0011)			(0.0008)
College educated (%)			−0.0006		−0.0009			−0.0007		−0.0012
			(0.0007)		(0.0008)			(0.0007)		(0.0008)
Born outside Europe (%)				0.0002	0.0012				−0.0001	0.0015
				(0.0006)	(0.0011)				(0.0007)	(0.0013)
R^2	0.0040	0.0038	0.0040	0.0037	0.0043	0.7334	0.7335	0.7336	0.7334	0.7340
Firm fixed effects	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes

Notes: $N = 3{,}605$. The regressions include separate measures of the socio-economic characteristics instead of the socio-economic index. See also the notes for Table 2. Standard errors are clustered by firm. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

is statistically significant.[14] In particular, there is no evidence that the two measures of crime have an effect.

Finally, we have used a data-driven approach in which lasso regressions are used to select which socio-economic characteristics to include in the model. Table A7 shows the results of this analysis (the details are explained in the notes below the table). Again, the estimate of commuting time is qualitatively unaffected.

4.2.3. Other robustness checks. In Table A8, we conduct a number of additional robustness checks of the baseline results in Panel A of Table 2 using only callbacks to explicit job interviews as the dependent variable (Column 2), including applicant characteristics as covariates (Column 3), using commuting time and socio-economic status above their respective median as explanatory variables instead of our continuous variables (Column 4), using the probit model (Column 5), excluding callbacks from staffing companies (Column 6), including the 1 percent most extreme outliers in terms of commuting time (Column 7), and including occupational fixed effects (Column 8). In all cases, the main results remain qualitatively unchanged.

Finally, we conducted an explorative heterogeneity analysis to investigate whether the results are stronger or weaker in certain subgroups. When considering these results, it should be noted that the subsamples are much smaller, meaning that the precision of the estimates is lower. In Table A9, using interaction terms in the regressions, we compare female and male job applicants, low-/medium- and high-skilled occupations, female and male recruiters (using the gender of the contact person mentioned in the advertisement), and small and large firms (divided around the median). The results show that commuting time has a statistically significant negative effect in all subgroups except one, while the socio-economic index only is (weakly) significant in one case. There is some indication that the negative effect of commuting is greater for male applicants than for female applicants and for high-skilled occupations than for low-/medium-skilled occupations, although the null hypothesis that the commuting coefficients are equal cannot be rejected (see the *p*-values in the table).

[14]We have also run regressions including all 16 measures and we obtain similar results as in Table 2.

5. Conclusions

The present study was designed to analyze the importance of two demand-side explanations – spatial mismatch and socio-economic status – for why people who reside in economically deprived neighborhoods often face worse labor market outcomes than those who live in more affluent neighborhoods. We conducted a large-scale field experiment in the Swedish labor market, where we sent more than 4,000 fictitious résumés to employers with a vacancy and experimentally manipulated the residential locations of the job applicants.

Our findings show that commuting time has a negative effect on the callback rate. Statistical discrimination is likely to explain why employers reject workers with long commuting times. Employers might worry that such workers will be less productive if they are hired, for example, because they might arrive late, or tired, to the workplace, might be more likely to continue their job search if they are hired, and might have few other options. In contrast, we do not find any evidence that the socio-economic status (e.g., employment, education, and ethnic composition) of an applicant's residential neighborhood matters. Hence, neighborhood signaling effects do not appear to be an important explanation of the weak labor market outcomes of people living in economically deprived neighborhoods. Our findings are qualitatively consistent with the results of Phillips (2020) and other previous studies, which also find that commuting has a negative effect, while neighborhood type seems unimportant. However, the magnitude of the negative effect of commuting appears smaller in our experiment. For example, Phillips finds that a worker residing at a location labelled "far" instead of "near" receives 0.027 fewer callbacks, while the comparable effect in our experiment would be 0.0059.[15]

A limitation of correspondence studies is that they measure unequal treatment in employers' responses to written résumés, while there could also be unequal treatment later in the hiring process, for example, at the interview stage (Quillian et al., 2020; Quillian and Midtboen, 2021). Laws (e.g., discrimination acts), other regulations (e.g., affirmative action requirements),

[15]Phillips (2020) uses the air distance to the firm coded as far or near as the main measure of commuting and finds an effect on callbacks of −0.027. To compare results, we could use our estimate of the effect of the air distance to the firm in km on callbacks, which is −0.0014 (i.e., our alternative measure of commuting time reported in Column 3 in Table 3). Because the air distance between far and near in Phillips (2020) is 4.184 km (2.6 miles), the comparable far versus near effect in our study would be $-0.0014 \times 4.184 = -0.0059$. Phillips also considers travel time with public transportation in a robustness analysis and finds that 10 minutes of additional commuting time reduces the callback rate by 3 percentage points, while our estimate in Column 3 in Table 2 implies that an additional 10 minutes of commuting time results in 0.0084 fewer callbacks ($-0.0505 \times (10/60)$).

or company norms could potentially delay some of the sorting of applicants to a later stage in the hiring process. If any of these considerations are important in our setting, then our estimates would not capture the full effect of an applicant's residential address on hiring.

In terms of government policy, the results suggest that it might be more important to ensure that public transportation is available, inexpensive, and time efficient for people living in economically deprived neighborhoods than to undertake measures aimed at improving the reputations of these neighborhoods. Another policy intervention could be to give firms incentives to establish workplaces in close proximity to economically deprived neighborhoods.

It should be emphasized that our study focuses on demand-side effects. In reality, there could also be important supply-side effects. Workers living in economically deprived neighborhoods might invest less in acquiring education and other forms of human capital or search less intensively for jobs, especially if they expect to face employer discrimination. They might also have less access to high-quality education and informal networks. However, even if supply-side effects matter, our results show that it is important not to ignore demand-side effects from the behavior of recruiting firms.

Supporting information

Additional supporting information can be found online in the supporting information section at the end of the article.

Online appendix
Replication files

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