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Employment Impact of Inner-city Development Projects: The Case of Underground Atlanta

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Summary. This paper makes use of a unique data set to explore the issue of whether inner-city residents are more likely to be hired by a new inner-city development than non-residents. A selection model with partial observability is specified and estimated. This partial observability model allows us to control for self-selection at the application stage and to obtain unconditional estimates at the hiring stage. We determine, holding individual and neighbourhood characteristics constant, that while inner-city residents are less likely to be considered 'hireable', their greater propensity to apply for jobs at this development means that they were at least as likely as non-residents to both apply *and* be hired. We also tentatively conclude that distance between an applicant's residence and the location of the development does not appear to have been an issue in the application decision.

1. Background and Introduction

John Kasarda (1985) details two recent funda- mental transformations older cities have ex- perienced that lie at the heart of the inner-city employment dilemma. The first change is *functional*; inner cities have changed from centres of production and transport to centres of administration and information exchange. One result of this change is the decentralis- ation of blue-collar jobs. Wilson (1987) has argued that this decentralisation of jobs is one of the factors explaining the rise in the urban underclass.[1] The second change is one of *demographics*; inner cities have lost predom- inantly middle-income whites while increas- ing lower-income minority groups. Decline in aggregate personal income and expansion of the economically disadvantaged within the inner city results (see Wheeler (1990) for an account of the impact of these transitions on the living standards in the inner city).

Both of these transformations are apparent in the relatively new city of Atlanta (new compared with New York, Chicago or Philadelphia, for example). Between 1970 and 1990, the number of blacks residing in the city of Atlanta increased by 4 per cent and the number of whites declined by 49 per cent (Bureau of the Census). In addition, the total unemployment rate in 1995 in the city of Atlanta was 7.3 per cent, whereas the unem-

ployment rate for the Atlanta MSA was 4.3 per cent (Bureau of Labor Statistics).

One of the proposed policies for addressing the persistent non-employment of lower-skilled minorities within the inner city is to encourage development within the city. In this paper, we consider the effect of a specific inner-city development on the employment of city residents.

One of the premises on which such a policy is advanced is Kain's (1968) spatial mismatch hypothesis.[2] Kain argued that job decentralisation and residential segregation combine to reduce the employment of inner-city minorities. Central to Kain's argument is that the likelihood of being employed at a given employment site is a decreasing function of distance between one's residence and the job site. While much of the early literature relating the employment of low-skilled, inner-city residents to commuting distance yields mixed conclusions, more recent evidence indicates that access is important (see recent reviews of the literature by Holzer 1991; Ihlanfeldt 1992; and Kain 1992).

The spatial mismatch research suggests two general types of policy: make it easier for inner-city residents to get to or learn about suburban job sites (easier and cheaper public transport, subsidised transport, increased job information or residential relocation), or bring jobs to inner-city residents (promote development projects within the inner city).[3] With regard to the first type of policy, research has found that relocating low-income households to the suburbs has resulted in improved labour market performance (Rosenbaum and Popkin, 1991). Research as to the benefits of improved reverse commuting abilities of public transit, however, is inconclusive.[4] Research on the second type of policy has largely focused on whether employers can be induced to locate in the central city, especially in low-income areas such as enterprise zones. Research concerned with the residential location of those employed by firms in enterprise zones has largely amounted to simple comparisons of the residence of the workers hired (for a literature review, see Ladd, 1994).

In this paper, we provide a more rigorous analysis of the employment of inner-city residents by a major inner-city development. In addition to controlling for selected human capital characteristics, we also control for access and for neighbourhood effects of concentrated poverty.[5]

This paper explores these issues with a unique data set, namely the application and hiring data associated with the recent development of Underground Atlanta. With these data, we address three related issues. The first issue is whether a large inner-city development that creates low- and semi-skilled jobs can materially improve the employment of inner-city residents.[6] The second issue concerns the role of job access. We can determine whether distance (i.e. access) between residence and Underground Atlanta is a factor in determining who is employed. The third issue is the effect that neighbourhood characteristics might have on the decision to apply. The ability to distinguish between applying and being hired offers an advantage over much of the previous research.

While this research focuses on the impact of Underground Atlanta, the results of the analysis are of general interest and applicability. We are able to say more about the employability issue than previous research, allowing us to address whether creating jobs in the inner city is a viable strategy for improving the employment situation of inner-city residents. The results of the research also give additional insights into the question of the effect of job access and of the concentration of poverty on the employment of low-skilled, inner-city residents.

2. Underground Atlanta: A Natural Experiment

When Atlanta built viaducts over the railroad tracks on the south side of downtown, shops closed their street-level stores and moved upstairs, on top of the viaducts. Underground Atlanta is a retail and entertainment complex that contains 165 establishments built under

and above this historic maze of viaducts. The development of Underground Atlanta combined the efforts and resources of the City of Atlanta with those of private business. The development was completed in 1989.[7] Underground Atlanta is located across from the intersection of the two MARTA rail lines. About 51 per cent of the businesses are minority owned.

As part of the planning for development of Underground Atlanta, the Atlanta Private Industry Council created a free-of-charge job placement service, First Source, whose goal was primarily to find competent employees for the establishments and secondarily to fill as many of the new jobs as possible with city of Atlanta residents, particularly those from known pockets of the unemployed. In order to accomplish the first goal, First Source provided initial screening and referral of potential job candidates taking into account the stated needs and requests of each of the establishments. The referral service was used by 94 per cent of the establishments in Underground Atlanta (use of the service was not mandatory). First Source took steps towards the secondary goal by visiting and distributing application forms to various known pockets of unemployed poor throughout Atlanta. In addition, First Source engaged in informal training of the unemployed in matters of interviewing technique and presentability. The efforts of job training and placement continue today through the First Source Job Program, which is part of the City of Atlanta Citizens Employment and Training office.

Through the Private Industry Council, we obtained all of the job application forms processed by First Source; a total of 2603. We also know the identity of the 326 individuals who were eventually hired through the efforts of the placement service. The completed job application forms provide a rich source of information with which to examine various issues regarding employment of inner-city residents: the impact of inner-city development projects; the success of targeting inner-city unemployed for jobs created by the development; and the role of distance and neighbourhood characteristics in the application process.

Information from the job applications includes residence location (from which we calculated the census tract centroid distance from Underground Atlanta), education, age, race, gender, number of children, marital status, and previous employment information (types of previous jobs and reasons for termination). The data from the job application forms are supplemented with data from the census tract in which each applicant resides, allowing us to identify potential neighbourhood influences. Table 1 provides the means and standard deviations of the individual characteristics of the job applicants (Appendix 1 defines the variables used in the analysis). On average, the 2603 applicants are young, black, live in the city of Atlanta and are fairly attached to the labour market, given that only a small percentage have no labour market experience. The large number who quit their previous job, however, suggests that this group of applicants may be fairly unstable workers, an observation consistent with the behaviour of lower-skilled workers. Table 1 also shows that there are no significant differences in the means of the individual characteristics between city of Atlanta residents and non-residents.

The address on the application form was used to assign census tract characteristics to that applicant. Applicants that live in the city of Atlanta come from census tracts with higher rates of poverty, lower labour force participation, less education and, of course, shorter distance to Underground Atlanta.

Table 2 contains weighted means of the census tract characteristics for the entire applicant pool, those who were hired, and population means for the entire Atlanta metropolitan area for these variables. There is not much difference in census tract characteristics for those who were hired and the whole applicant pool. Applicants, however, came from census tracts closest to Underground Atlanta and neighbourhoods more heavily black, poverty stricken, and less educated than the average for the entire metropolitan area.

Table 1. Means of individual and census tract (neighbourhood) characteristics of applicants for jobs at Underground Atlanta, 1989 (non-missing observations)

Variables	Full sample	Hired = 1	Atlanta resident	Atlanta non-resident
Individual characteristics				
Age	27.75	26.97	28.84	26.89
	(8.83)	(0.08)	(9.06)	(7.70)
High school graduate = 1	0.88	0.87	0.84	0.91
	(0.33)	(0.33)	(0.36)	(0.29)
Some college = 1	0.38	0.40	0.32	0.42
	(0.49)	(0.49)	(0.47)	(0.49)
College degree = 1	0.06	0.07	0.05	0.06
	(0.23)	(0.25)	(0.22)	(0.23)
In school when applied = 1	0.17	0.23	0.14	0.19
	(0.37)	(0.42)	(0.35)	(0.39)
No labour market experience = 1	0.03	0.01	0.03	0.02
	(0.16)	(0.10)	(0.17)	(0.15)
Female = 1	0.51	0.57	0.48	0.53
	(0.50)	(0.50)	(0.50)	(0.50)
Married = 1	0.14	0.10	0.13	0.14
	(0.34)	(0.30)	(0.34)	(0.35)
Number of children less than six years	0.31	0.29	0.33	0.30
	(0.62)	(0.62)	(0.65)	(0.60)
Black = 1	0.91	0.90	0.92	0.90
	(0.29)	(0.31)	(0.27)	(0.30)
Quit most recent job = 1	0.40	0.49	0.41	0.39
(most common reason: job dissatisfaction)	(0.49)	(0.50)	(0.49)	(0.49)
Fired from most recent job = 1	0.03	0.03	0.03	0.03
	(0.17)	(0.16)	(0.16)	(0.17)
Laid-off most recent job = 1	0.22	0.25	0.22	0.22
	(0.42)	(0.43)	(0.42)	(0.42)
Target applicant = 1	0.44	0.40	1.00	0.00
(city of Atlanta resident)	(0.50)	(0.49)		
Hired = 1	0.13	1.00	0.11	0.14
	(0.33)		(0.32)	(0.34)
Census tract characteristics				
Percentage below poverty level	0.27	0.24	0.34	0.21
	(0.18)	(0.18)	(0.18)	(0.17)
Labour force participation rate	0.78	0.79	0.74	0.80
	(0.11)	(0.10)	(0.11)	(0.10)
Percentage of residents with HS degree	0.66	0.67	0.58	0.73
	(0.17)	(0.17)	(0.16)	(0.14)
Distance to underground (in miles)	6.21	6.58	3.10	8.65
	(4.31)	(4.38)	(1.56)	(4.20)
Number of observations	2603	326	1145	1458

Note: Standard deviations are in parentheses.

3. Empirical Methodology

The data suffer from a problem of partial observability—that is, we are able to observe only those individuals who have applied for jobs at Underground Atlanta. If there are unobservables that influence both the probability of applying for a job and the probability of being hired, then ignoring an individual's decision to apply will result in biased parameter estimates on the determinants of being hired. Borrowing the illus-

Table 2. Weighted means of census tract characteristics for whole (non-missing) applicant pool, for applicants that were hired, and for the Atlanta Metropolitan Area

Census tract characteristics	All applicants	Hires only	Atlanta Metropolitan Area
Distance in miles from Underground	6.21	6.58	18.21
Percentage white	20	20	72
Percentage female	54	54	51
Percentage below poverty level	27	24	10
Percentage receiving welfare	18	16	6
Percentage female headed household	17	16	7
Percent with high school degree	66	67	80
Labour force participation rate	78	79	83

Note: Means for the Atlanta Metropolitan Area represent weighted means of census tract information for those census tracts represented by the applicant pool.

tration in Bloom *et al.* (1983), say there are two groups of potential applicants, and that those in group 1 (non-inner-city residents) have more of some unobserved characteristics (for example, motivation) that make them more likely to apply for jobs at Underground Atlanta. Consequently, individuals in group 2 (inner-city residents) will be less likely to apply than those in group 1 with identical observed characteristics. Therefore, those in group 2 who actually apply will have above-average amounts of those unobserved characteristics. Now, if those unobserved characteristics also enter (for example, positively) into the potential employer's hiring decision, the probability that an applicant is considered hireable will be positively associated with membership in group 2, even though such group membership does not explicitly enter the employer's decision function. Thus, the coefficients in the hiring equation are biased unless the application decision is accounted for. The *empirical* importance of controlling for the application decision will be seen in the presentation of the results. Note also, that if the employer does have a discriminatory ranking function such that group 2 membership increases the likelihood of rejection (not being hired), this will lead researchers to underestimate the degree of discrimination if the application decision is ignored since the group 2 applicant pool is 'above average' relative to the entire group 2,

merely by the nature of having decided to apply.

To overcome this problem of partial observability, we use an econometric model suggested by Bloom *et al.* (1983).[8] In the absence of such a model, an analysis of the application process would not allow the use of the individual-level data; we would have to use census-tract-level data. The implication of partial observability for employment analysis is that merely estimating the probability of an applicant being hired would yield results conditional on that person having applied for a job in the first place. The inability to generalise the results from estimating this conditional probability is particularly acute here since certain applicants were actually sought out by the job placement service. While the conditional probability results would be of interest to some extent (and are also reported), we are particularly interested in obtaining unconditional results; in order to determine whether Underground Atlanta affected employment of inner-city residents, we would like to know whether inner-city residents end up being favoured by the combined application and hiring process.

Following Bloom *et al.* (1983, p. 100), consider the population for which

$$A_i^* = Z_i \, \gamma + \eta_i \qquad (1)$$

$$H_i^* = Y_i \, \delta + v_i \qquad (2)$$

where, a person applies for a job at Underground Atlanta if $A_i^* > 0$, and not otherwise; a person is considered 'hireable' (i.e. capable of eliciting a positive hiring decision) if $H_i^* > 0$, and not otherwise; and Z and Y are vectors of covariates with associated parameters γ and δ. Assume, as is standard, that $(\eta, v) \sim F(0, \Sigma)$ where $F(.)$ is the bivariate normal distribution function with a variance/covariance matrix given by:

$$\Sigma = \begin{bmatrix} 1 & \sigma_{\eta v} \\ \sigma_{v\eta} & 1 \end{bmatrix}.$$

These parameters would be estimated via standard maximum likelihood bivariate probit techniques if individuals for whom $A_i^* \leq 0$ were observed. Since we do not have data on these individuals, we have a truncated sample. By merely specifying the distribution of (the unobserved) H_i^*, over the subset for whom $A_i^* > 0$, we can estimate a conditional univariate probit. But this does not allow for self-selection at the application stage. Consequently, H_i^* is defined over the whole population and the model is analysed from the truncated sample. Defining H_i^* over the population allows us to make inferences about whether someone drawn from the population at random would be hired (i.e. would be considered hireable), regardless of any decision they may have made about applying.

Obviously, since we do not observe non-applicants, equation (1) can not be estimated by itself. However, in the words of Manski (1995, p. 83),

> Sampling from one response stratum obviously reveals nothing about the magnitude of response probabilities[,] ... but inference becomes possible if auxiliary distributional information is available.

In other words, if we add sufficient structure to the model, we can identify it. For our problem, knowing (assuming) the distribution of η and using the information provided through the covariance $\sigma_{v\eta}$, we are able to identify equation (1)—i.e. the individual's application decision.[9]

We specify a likelihood function that best describes the hiring pattern observed given that we only observe those who applied. The likelihood function (equation (3)) consists of two pieces. The first piece describes the contribution of those who were hired, which is the joint probability of applying and being hired conditional on having applied. The second piece is the contribution of those not hired, which is the joint probability of applying and not being hired conditional on having applied. So, the likelihood function describes all possible outcomes and yields parameter estimates that are most likely to have generated the data, accounting for the fact that we are observing a truncated sample; these are the unconditional parameter estimates for the hiring equation (see Bloom *et al.* 1983, pp. 100–101).

$$L(H_i^* | A_i^* > 0, Z_i, Y_i, \rho)$$

$$= \prod_{H_i^* > 0} \frac{\Pr(H_i^* > 0 \& A_i^* > 0)}{\Pr(A_i^* > 0)}$$

$$\times \prod_{H_i^* \leq 0} \frac{\Pr(H_i^* \leq 0 \& A_i^* > 0)}{\Pr(A_i^* > 0)} \qquad (3)$$

In equation (3), $\Pr(.)$ refers to the probability of the event occurring and ρ is the correlation between η and v.[10] Note that if $\rho = 0$, equation (1) cannot be identified and the estimation of equation (2) reduces to univariate probit, whose results are interpretable only in the context of having applied for a job at Underground Atlanta.

Defining $H_i = 1$ if $H_i^* > 0$ ($H_i = 0$ otherwise) and $A_i = 1$ if $A_i^* > 0$ ($A_i = 0$ otherwise), the following log-likelihood function is maximised to obtain estimates of γ, δ and ρ:

$$\ln L_i = H_i \times \ln \left[\frac{F(Z_i\gamma, Y_i\delta, \rho)}{\Phi(Z_i\gamma)} \right] + (1 - H_i)$$

$$\times \ln \left[\frac{\Phi(Z_i\gamma) - F(Z_i\gamma, Y_i\delta, \rho)}{\Phi(Z_i\gamma)} \right] \qquad (4)$$

where, again, $F(.)$ is the joint normal distribution function, and $\Phi(.)$ is the standard normal univariate distribution function. (See Appendix 2 for estimation details.)

4. Results

Table 3 contains maximum likelihood parameter estimates for the model detailed in equations (1) and (2) as well as the conditional univariate probit results.[11] It is notoriously difficult to obtain estimates for the partial observability model.[12] While we experienced similar difficulty, the presence of census tract variables seems to have allowed us better to identify the first-stage selection of applying for a job at Underground Atlanta.

4.1 Probability of Applying

Three different categories of variable are included in our equation: individual-level variables including whether the individual lives in the city of Atlanta; census-tract-level variables to reflect Wilson's concentration of poverty hypothesis; and, distance from residence to Underground Atlanta to incorporate the potential effect of access on the probability of applying. (See Appendix 1 for the definition of all the variables.) Consider first the probability-of-applying equation (column 3). The coefficient on DIST, distance to Underground Atlanta, is negative but insignificant. We tried several different specifications; DIST was frequently negative, but never significant. The coefficient on RESID (being a resident of the city of Atlanta) is positive and marginally significant. We assume that this slightly higher probability of inner-city residents applying has something to do with the efforts of First Source; however, we have no way of testing this explicitly. We also tried in place of RESID whether the individual lived in the area targeted by First Source; the results were the same.[13]

There are several possible explanations for the insignificance of DIST. First, RESID or PCTPOOR may be picking up the effect of DIST. Eliminating RESID and/or PCTPOOR from the equation, however, had no effect on the DIST coefficient. Regardless of the specification, DIST was never statistically significant.[14] Secondly, it is possible that the result is driven by the decision of applicants

to relocate their residence if they are successful in being hired. However, this is unlikely in the case of Underground Atlanta since it is downtown where there is an absence of housing. Furthermore, many of these jobs are part-time and have high turnover rates. Thirdly, it may be that distance is not a factor in this situation. There are at least three reasons why access is found to be significant in spatial mismatch studies: increased cost and difficulty in commuting to the job site; increased difficulty in acquiring information about and searching for job openings; greater social distance.[15] As noted above, Underground Atlanta is well served by MARTA's rail system. This may mean that commuting distance or time is not a significant factor. Similarly, First Source actively solicited applications from city residents, thereby increasing information regarding job openings and reducing the cost of search. In addition, it seems unlikely that social distance would be a factor given the location of Underground Atlanta and the number of minority businesses in Underground Atlanta. Given these factors, one conclusion that can be drawn is that if access is a factor in general, it is possible to overcome it with appropriate actions or circumstances. Fourthly, we cannot rule out that access simply does not matter and that the other studies that find that it does are wrong.

The signs on the coefficients in the application equation for other individual characteristics are as expected and generally significant. Turning to the census tract variables, we do not find great support for Wilson's (1987) concentrated poverty hypothesis. The coefficient on PCTPOOR (percentage in poverty) is negative and significant, which is consistent with Wilson's hypothesis. But the coefficients on the other census tract variables either have signs that are counter-expected from the concentrated poverty hypothesis, or are not significant. For example, individuals from census tracts with high labour force participation (LFPR) are less likely to apply, meaning that applicants from low labour force participation areas are more likely to apply. Likewise, PCTHS (per-

Table 3. Maximum likelihood estimates for the single-equation probit and two-equation partial observability model: full sample

Dependent variable	Univariate probit model	Two-equation partial observability model	
	Probability of being hired	Probability of applying	Probability of being hired
Intercept	− 1.271***	8.208*	− 0.359
	(0.203)	(4.931)	(0.335)
Individual characteristics			
AGE	0.00005	0.265**	− 0.014**
	(0.004)	(0.098)	(0.006)
FEMALE	0.110*	4.219**	− 0.202*
	(0.065)	(1.386)	(0.112)
BLACK	− 0.097	0.496	− 0.204^
	(0.109)	(0.731)	(0.128)
MARRIED	− 0.163^	—	− 0.149^
	(0.104)		(0.103)
HS	0.002	—	− 0.020
	(0.104)		(0.108)
SOMECOLL	− 0.069	—	− 0.071
	(0.080)		(0.084)
COLL	0.187	—	0.168
	(0.146)		(0.152)
QUIT	0.299***	—	0.300***
	(0.075)		(0.078)
LAYOFF	0.269**	—	0.264**
	(0.087)		(0.090)
NOEXP	− 0.463*	—	− 0.449*
	(0.271)		(0.272)
SCHOOL	0.207**	2.228**	0.030
	(0.096)	(0.988)	(0.122)
CHILDRN	—	− 1.433**	—
		(0.531)	
RESID	− 0.093^	1.026^	− 0.195**
	(0.066)	(0.665)	(0.079)
Census tract variables			
PCTPOOR	—	− 10.435**	—
		(4.076)	
LFPR	—	− 8.889**	—
		(3.965)	
PCTHS	—	− 8.802**	—
		(3.566)	
DIST	—	− 0.010	—
		(0.080)	
ρ	—	− 0.417**	
Log-likelihood	− 961.38	− 941.80	
N = 2603			

Notes: Standard errors are in parentheses.
Two-tailed significance levels: * = 90 per cent; ** = 95 per cent; *** = 99 per cent.
^ = significant at least at the 90 per cent level with a one-tailed test.
Definitions of variable names are found in Appendix 1.

centage of census tract with a high school degree) is negative, meaning that individuals from areas with lower educational levels were more likely to apply. The results for *LFPR* and *PCTHS* may be a consequence of the types of job available at Underground Atlanta and/or because First Source sought out applicants from poor areas which are likely to have higher rates of non-participation and lower educational levels.

4.2 Probability of Being Judged Hireable

We now turn to the results for 'hireability' (column 4). These results give the determinants of the unobserved variable H_i^* in equation (2), which itself determines whether an application submitted by such a person would be successful. Note that this equation is not conditional on the person actually submitting an application, but rather determines whether the person meets the standards being used by employers in making their hiring decisions. The coefficients on *AGE, FEMALE, BLACK*, and *MARRIED* are negative and significant, suggesting a preferential hiring for young, white, single males; in other words, young, white, single males are more likely to be judged as hireable.

For comparison, we estimated the probability of being hired conditional on having applied; the results from estimating this univariate probit are presented in column 2 of Table 3. It is of interest to note that the *AGE* and *BLACK* coefficients from the conditional, univariate probit estimation are insignificant and that *AGE* and *FEMALE* are positive. From column 3 (the partial observability model), we see that older black females are more likely to apply. When the higher probability of applying is taken into account in the partial observability model, the results in column 2 do not hold. These results illustrate the importance of controlling for selection at the application stage. For example, if one were to form conclusions about how successful females are at being hired at Underground Atlanta, the conditional model says that females are more likely to be hired than males (a significant coefficient of + 0.110). How-

ever, once one controls for the greater likelihood that females apply for the jobs, the unbiased answer is that women are significantly less likely to be judged hireable at Underground Atlanta, controlling for other factors in our analysis (a significant coefficient of − 0.202).

Returning to the results in column 4, the positive coefficients on *QUIT* and *LAYOFF* imply that quitting or being laid off results in less of a stigma than being fired from one's last job. Lack of labour market experience (*NOEXP*) also reduces one's chances of being hired.

Being an Atlanta resident reduces the probability of being judged hireable. This result is consistent with findings from other studies that being from the inner city stigmatises the individual (see, for example, Kirschenman and Neckerman, 1991), although the source of this stigma is not discernible with these data. This indication of a prejudice against hiring inner-city residents is also supportive of Wolman et al. (1994) who find that inner-city successes may be more elusive than otherwise hoped.[16] It is also possible that there may be other employability characteristics specific to city of Atlanta residents that are missing from the estimation.

To explore further the hireability of Atlanta residents, we ran separate regressions for city of Atlanta residents and nonresidents. These results are reported in Table 4.[17] For the probability of applying equations, the results for the two groups are quite similar; while the magnitudes of some of the coefficients differ, the coefficients have the same sign, except for *LFPR*, and similar levels of significance. The noticeable difference occurs in the probability of being hired equations. While the coefficients have the same signs for the two samples, all except the intercept are significant for the non-residents, but none is significant for residents. This suggests that there are other factors that determine hireability for city residents. This conclusion is consistent with the observation from Table 3 that city of Atlanta residents are less likely to be judged hireable than non-residents.

Table 4. Maximum likelihood estimates for the two-equation partial observability model: target and non-target applicants

Dependent variable	Atlanta residents (target applicants)		Atlanta non-residents (non-target applicants)	
	Probability of applying	Probability of being hired	Probability of applying	Probability of being hired
Intercept	12.228^	− 1.016	− 5.353^	0.075
	(9.241)	(0.248)	(3.320)	(0.273)
Individual characteristics				
AGE	0.304**	− 0.005	0.177**	− 0.032***
	(0.141)	(0.006)	(0.054)	(0.008)
FEMALE	4.338*	− 0.149	3.051***	− 0.431***
	(3.204)	(0.118)	(0.707)	(0.054)
QUIT	—	0.141	—	0.412***
		(0.123)		(0.102)
LAYOFF	—	0.175	—	0.333**
		(0.140)		(0.113)
NOEXP	—	− 0.256	—	− 0.589^
		(0.364)		(0.403)
SCHOOL	3.307^	—	0.849*	—
	(2.351)		(0.458)	
CHILDRN	− 1.252**	—	− 0.993***	—
	(0.590)		(0.222)	
Census tract variables				
PCTPOOR	− 11.038*	—	− 1.162	—
	(5.705)		(2.292)	
PCTHS	− 12.970**	—	− 7.061**	—
	(4.792)		(2.232)	
LFPR	− 9.122^	—	6.416**	—
	(6.971)		(2.552)	
DIST	0.132	—	0.047	—
	(0.460)		(0.044)	
ρ	− 0.614***		− 0.511***	
		(0.106)		(0.104)
Log-likelihood	− 392.40		− 544.52	
N	1145		1458	

Notes: Standard errors are in parentheses.

Two-tailed significance levels: * = 90 per cent; ** = 95 per cent; *** = 99per cent.

^ = significant at least at the 90 per cent level with a one-tailed test.

Definitions of variable names are found in Appendix 1.

Because of the difficulty in getting this type of model to converge, the likelihood functions were maximised via an iterative procedure. After convergence is achieved for a subset of regressors, that subset is held constant while the likelihood function is maximised for the remaining regressors. This is repeated until regressors do not change much from one iteration to another. For the target applicants (Atlanta residents), the log-likelihood value corresponds to a model where the correlation coefficient (ρ) is held constant. For the non-target applicants (Atlanta non-residents), the log-likelihood value corresponds to a model where *FEMALE* is held constant.

4.3 Joint Probability of Applying and Being Hired

We calculate the partial derivatives of the probability of applying, the probability of being judged hireable, and the joint probabil-

ity of applying *and* being hired with respect to changes in each of the independent variables. To do this, we differentiated the univariate and joint distribution functions respectively, and calculated the values at the full sample means (see Table 5; see Appen-

Table 5. Partial derivatives of the marginal and joint probabilities of applying and of being hired: full sample

Independent variables (X)	$\dfrac{\partial P(\text{Apply} = 1)}{\partial X}$	$\dfrac{\partial P(\text{Hired} = 1)}{\partial X}$	$\dfrac{\partial P(\text{Apply} = 1, \text{Hired} = 1)}{\partial x}$
Intercept	0.715	− 0.087	0.383
Individual characteristics			
AGE	0.023	− 0.003	0.012
FEMALE	0.367	− 0.049	0.194
BLACK	0.043	− 0.049	− 0.011
MARRIED	—	− 0.036	− 0.028
HS	—	− 0.005	− 0.004
SOMECOLL	—	− 0.017	− 0.013
COLL	—	0.040	0.032
QUIT	—	0.072	0.056
LAYOFF	—	0.064	0.050
NOEXP	—	− 0.108	− 0.084
SCHOOL	0.194	0.007	0.128
CHILDRN	− 0.125	—	− 0.079
RESID	0.089	− 0.047	0.020
Census tract variables			
PCTPOOR	− 0.909	—	− 0.573
LFPR	− 0.774	—	− 0.488
PCTHS	− 0.766	—	− 0.483
DIST	− 0.001	—	− 0.001

Notes: The mean joint probability of applying and being hired, $f(\overline{Z}'\hat{\gamma}, \overline{Y}'\hat{\delta}, \hat{\rho})$ from equation (4), is 0.1181. While standard errors for these partial derivatives could be calculated through standard (but time-consuming) bootstrapping techniques, the significance of the estimated coefficient for each variable usually yields a good idea as to whether the partial derivative is significantly different from zero.

dix 2 for the analytical expressions of these partial derivatives). In general, the partial derivatives are small. The effect of distance on the univariate probability of applying, besides not being significant, implies that even a one standard deviation reduction in distance (4.31 miles) would increase the probability of applying by only 0.4 percentage points.[18] While being black increases the probability of applying, the negative effect of being black on the perception of hireability results in a negative impact of being black on the joint probability of applying *and* being hired. The larger partial derivatives for the neighbourhood variables reflect the units in which those variables are measured; a standard deviation change in any of the those variables also results in a small change in the probabilities.

While being a city of Atlanta resident increases the probability of jointly applying and being hired by only two percentage points (17 per cent of the mean joint probability), the higher probability of residents applying appears to overcome their lower chance of being judged hireable. This result is consistent with the descriptive statistics reported in Table 2; the sample of people hired at Underground Atlanta contains much higher proportions of people from poor, non-white census tracts than does the Atlanta metropolitan area.

5. Conclusions

Our results suggest that distance, once we control for individual characteristics and sample selection, did not matter in deciding

whether to apply for a job at Underground Atlanta. This result is inconsistent with much of the literature which suggests that, in general, access does matter. However, given the accessibility to Underground Atlanta through MARTA, that First Source made a significant effort to recruit inner-city applicants and that Underground Atlanta is not likely to be viewed as hostile to minority employees, the result suggests that it may be possible to overcome the effect access has on employment of lower-skilled, inner-city minorities.

What about the policy of trying to employ inner-city workers? The results are somewhat encouraging. While being a resident of the city of Atlanta reduced the probability of being judged hireable, city of Atlanta residents were much more likely to apply for the jobs. The net outcome was that city of Atlanta residents were at least as likely as non-residents both to apply *and* to be hired. This provides some encouragement that job location and/or placement efforts on behalf of those deemed less employable may be effective in actually placing them in jobs.

Notes

1. Ihlanfeldt and Sjoquist (1989) also find that decentralisation results in lower net earnings. For a review of the underclass literature, see Sjoquist (1990) and chapters in Lynn and McGeary (1990).
2. Wilson (1987) relies heavily on Kain's argument and Kasarda's (1985) analysis of job suburbanisation in his theory of the underclass.
3. See, for example, Kain and Persky (1969); Harrison (1974) and Downs (1968).
4. While HUD (through its 'Bridges to Work' programme) is experimenting with alternative transport between central cities and suburban job sites, a recent study by Turner (1997) suggests that these efforts will not be successful in landing inner-city residents in suburban jobs.
5. Wilson (1987) has argued that factors associated with concentrated poverty lead residents of such areas to engage in non-productive behaviour. For a review, see Jencks and Mayer (1990).
6. Note that improvement in employment opportunities is only one dimension of overall

economic well-being as defined by Wolman *et al.* (1994: 838).
7. The original Underground Atlanta, started in the 1960s, was closed in the late 1970s.
8. Bloom and Killingsworth (1982, 1985) developed this approach for the case in which the dependent variables are continuous. They show it is a generalisation of Heckman (1979).
9. It should be noted that models that result from sampling from "one response stratum", as described by Manski (1995), can yield parameter estimates that are not considered very reliable (also see Maddala, 1983, p. 267). Consequently, while we will discuss the parameter estimates obtained from the decision-to-apply equation, they should be received with caution. However, although the reliability of the decision-to-apply parameter estimates can be called into question, the presence of the decision-to-apply equation has served its primary purpose of producing unbiased parameter estimates for the hiring equation.
10. See Abowd and Farber (1982) for a version of this likelihood function when the error terms are assumed to be independently distributed.
11. The conditional results are presented to demonstrate the importance of controlling for selection at the application stage and are discussed in greater detail later.
12. For example, see Bloom *et al.* (1983) and Maddala (1983, p. 282). Although we, too, experienced difficulty in achieving convergence, we were able to obtain estimates for a number of specifications, giving us confidence in the stability of the estimates reported.
13. We report the results for *RESID* here because we do not have a lot of confidence in the consistency with which First Source identified an applicant as coming from a target area.
14. This result held even when *DIST* was the *only* neighbourhood characteristic left as a regressor.
15. By social distance, we mean that inner-city minorities may believe that they will not be socially accepted at suburban job sites.
16. Wolman *et al.* (1994) find that,

   the change in the economic well-being of residents of cities that are typified as 'urban success stories' between 1980 and 1990 did not differ from—and in some cases was inferior to—change in the economic well-being of residents of other cities that were (like the 'urban success stories') distressed in 1980.

17. The inherent difficulty in getting estimates for a partial observability model forced us to restrict the number of regressors in the estimations for the two sub-samples.
18. This amounts to about 34 per cent of the mean joint probability.

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Appendix 1. Definitions of Variable Names

Variable name	Variable definition
Individual Characteristics:	
AGE	Age of applicant in years (divided by 100)
FEMALE	Dummy variable that equals one if applicant is female
BLACK	Dummy variable that equals one if applicant is black
MARRIED	Dummy variable that equals one if applicant is married
HS	Dummy variable that equals one if applicant has a high school degree
SOMECOLL	Dummy variable that equals one if applicant has some college education
COLL	Dummy variable that equals one if applicant has a college degree
QUIT	Dummy variable that equals one if applicant quit his or her most recent job
LAYOFF	Dummy variable that equals one if applicant was laid off from his or her most recent job
NOEXP	Dummy variable that equals one if applicant has no labour market experience
SCHOOL	Dummy variable that equals one if applicant is in school at time of application
CHILDRN	The number of children the applicant has less than six years old
RESID	Dummy variable equal to one if applicant is a city of Atlanta resident (city of Atlanta residents were targeted for application for jobs at Underground Atlanta)
Census Tract Variables (all variables refer to the census tract in which the applicant lives)	
PCTPOOR	Number of persons in census tract with incomes below poverty level / total number with incomes above poverty level plus total number with incomes below poverty level). UNIVERSE: Persons for whom poverty status is determined. Percentage of census tract population below poverty line
LFPR	Number of persons aged 16–64 in census tract in the labour force (both employed and unemployed)/total number in the labour force plus total number of persons aged 16–64 in census tract not in the labour force. UNIVERSE: Civilian non-institutional persons 16 years and over
PCTHS	Total number of persons aged 25 and over in census tract with a high school diploma or equivalent / total number of persons aged 25 and over in census tract
DIST	Linear distance in miles from the centroid of the census tract to the centroid of the census tract in which Underground Atlanta is located

Appendix 2. Estimation Details and Partial Derivatives

The likelihood function in equation (4) was maximised using the Berndt-Hall-Hall-Hausman (1974) optimisation method for approximating the Hessian and for calculating the asymptotic covariance matrix of the parameter estimates. The empirical analysis was performed using the TSP software (TSP International, Palo Alto, CA), version 4.2B, on a Power Macintosh 7100/80. The following standard approximation for the bivariate normal cumulative distribution function was used in the maximum likelihood estimation procedure:

$$F(Z_i\gamma, Y_i\delta, \rho) = \Phi(Z_i\gamma)\Phi(Y_i\delta) + \phi(Z_i\gamma)\phi(Y_i\delta)\left\{\rho + \frac{1}{2}\rho^2(Z_i\gamma)(Y_i\delta) + \frac{1}{6}\rho^3[(Z_i\gamma)^2 - 1][(Y_i\delta)^2 - 1]\right\}$$

This is a Taylor expansion around ρ for small ρ.

The following partial derivatives were evaluated at the sample means and the parameter estimates reported in Table 3 to measure the impact on the probability of applying and the probability of being judged hireable, respectively, of a one-unit change in some regressor, X_k:

$$\frac{\partial \Phi(\bar{Z}'\hat{\gamma})}{\partial X_k} = \phi(\bar{Z}'\hat{\gamma})\hat{\gamma}_k$$

$$\frac{\partial \Phi(\bar{Y}'\hat{\delta})}{\partial X_k} = \phi(\bar{Y}'\hat{\delta})\hat{\delta}_k$$

The following partial derivative was evaluated at the sample means and the parameter estimates reported in Table 3 to measure the impact on the joint probability of applying and being hired of a one-unit change in some regressor, X_k:

$$\frac{\partial F(\overline{Z}'\hat{\gamma}, \overline{Y}'\hat{\delta}, \hat{\rho})}{\partial X_k} = \phi(\overline{Z}'\hat{\gamma})\Phi(\overline{Y}'\hat{\delta})\hat{\gamma}_k + \Phi(\overline{Z}'\hat{\gamma})\phi(\overline{Y}'\hat{\delta})\hat{\delta}_k$$

$$- \phi(\overline{Y}'\hat{\delta})\hat{C}(\overline{Z}'\hat{\gamma})\phi(\overline{Z}'\hat{\gamma})\hat{\gamma}_k - \phi(\overline{Z}'\hat{\gamma})\hat{C}(\overline{Y}'\hat{\delta})\phi(\overline{Y}'\hat{\delta})\hat{\delta}_k$$

$$+ \phi(\overline{Z}'\hat{\gamma})\phi(\overline{Y}'\hat{\delta})\left[\frac{1}{2}\hat{\rho}^2(\overline{Z}'\hat{\gamma})\hat{\delta}_k + \frac{1}{2}\hat{\rho}^2(\overline{Y}'\hat{\delta})\hat{\gamma}_k + \frac{1}{3}\hat{\rho}^3(\overline{Z}'\hat{\gamma})^2\hat{\gamma}_k\right.$$

$$\left. + \frac{1}{3}\hat{\rho}^3(\overline{Z}'\hat{\gamma})^2(\overline{Y}'\hat{\delta})\hat{\delta}_k - \frac{1}{3}\hat{\rho}^3(\overline{Z}'\hat{\gamma})\hat{\gamma}_k - \frac{1}{3}\hat{\rho}^3(\overline{Y}'\hat{\delta})\hat{\delta}_k\right],$$

where,

$$\hat{C} = \left\{\hat{\rho} + \frac{1}{2}\hat{\rho}^2(\overline{Z}'\hat{\gamma})(\overline{Y}'\hat{\delta}) + \frac{1}{6}\hat{\rho}^3[(\overline{Z}'\hat{\gamma})^2 - 1][(\overline{Y}'\hat{\delta})^2 - 1]\right\}.$$