land

Article

Does Job Accessibility Matter in the Suburbs? Black Suburbia, Job Accessibility, and Employment Outcomes

Hyunjoo Eom

Department of Urban and Environmental Engineering, Ulsan National Institute of Science and Technology, Ulsan 44919, Korea; hjeom@unist.ac.kr

Abstract: The spatial mismatch hypothesis of John Kain proposes that geographic separation between residential locations and jobs creates a spatial barrier in accessing job opportunities, which has a negative impact on labor market outcomes. A key hypothesis is that Black populations have limited accessibility to suburban job opportunities due to residential segregation in the city, resulting in lower employment and earnings. However, the spatial structure of the U.S. metropolitan area has changed since then, with increased polycentric employment growth and Black suburbanization. This challenges Kain's original hypothesis that residential segregation in the city creates a spatial barrier in accessing jobs. The spatial pattern of mismatch has changed and demonstrates a mismatch between Black suburbs and suburban jobs. Then, what role does job accessibility play in the change in the spatial pattern of mismatch? Does job accessibility continue to matter in the suburbs? Or, are there other more important neighborhood characteristics affecting labor market outcomes? The findings demonstrate that job accessibility remains closely associated with Black labor market outcomes. In Chicago, job accessibility has higher marginal effects on Black employment, especially in predominantly Black neighborhoods. However, in Atlanta, where a majority of the Black population lives in the suburbs, having a higher percentage of Black residents in the neighborhood negates the effects of job accessibility. Instead, the share of Black residents becomes a more significant factor in employment. The findings demonstrate that the effect of job accessibility varies by the spatial pattern of mismatch. Job accessibility becomes less important in highly segregated suburbs, but the share of Black residents matters more in labor market outcomes. In metropolitan areas with the traditional mismatch pattern, job accessibility is significantly associated with employment and earnings, especially in neighborhoods where the majority of the Black population remains segregated in the city.

Keywords: spatial mismatch; job accessibility; black suburbs

check for updates

Citation: Eom, H. Does Job Accessibility Matter in the Suburbs? Black Suburbia, Job Accessibility, and Employment Outcomes. *Land* **2022**, *11*, 1952. https://doi.org/10.3390/land11111952

Academic Editor: Chao Ye

Received: 30 September 2022
Accepted: 28 October 2022
Published: 1 November 2022

1. Introduction

The spatial mismatch hypothesis of John Kain [1] highlights the residential segregation in the inner city and the suburban job opportunities to have created geographic barriers to finding employment. Kain posited that the lack of reliable transportation systems reduced access to jobs in the suburbs, contributing to the high unemployment rate among the Black population. In 1984, Black male adult unemployment rates were nearly three times higher than White male adult unemployment rates (15.7 percent and 5.5 percent, respectively) [2]. This has sparked discussions on whether the racial disparities in employment can be explained by the spatial mismatch, or is a matter of other issues such as the "racial mismatch" [3–5] or "skills mismatch" [6,7]. These scholars argue that the racial gaps in the employment outcome are more likely to be caused by racial discrimination in the labor market and a mismatch between low-skilled workers and high-skilled jobs than the differences in access to jobs. Other factors, such as automobile access—"modal mismatch" [8,9] and "social capital" [10]—have also been proposed. However, many empirical studies have consistently shown that geographic access to employment opportunities is associated with racial disparities in labor market outcomes and the geographic location of Black employment [11–13].

Since the spatial mismatch hypothesis was proposed, the spatial structure of the U.S. metropolitan area has changed significantly. This includes the suburbanization of the Black population during the 1970s and 1980s, polycentric employment growth, and the revitalization and recentralization of inner cities through gentrification [14–17]. These changes in urban structure—especially the movement of the Black population to the suburbs and the relocation of jobs back into the inner city—may have changed the role of job accessibility on labor market outcomes. The association between job accessibility and labor market outcomes may be more robust in metropolitan areas with traditional mismatch patterns than in metropolitan areas with a suburban-to-suburban pattern of mismatch, which suggests that the effect of job accessibility may be different by metropolitan characteristics. Although the impact of decentralization of jobs has been well investigated in literature by measuring accessibility to suburban jobs, studies on the changing geography of segregation and its impact on the role of job accessibility and finding employment have not been widely studied. Thus, this research aims to examine whether the relationship between job accessibility and labor market outcome has changed in the city and the suburbs and how the relationship varies in metropolitan areas with different spatial segregation patterns.

An important consideration when examining the causal relationship between job accessibility and labor market outcomes is the endogeneity problem since residential locations are endogenous to an individual's labor market outcomes [18]. Individuals may self-select into their preferred residential areas, leading to overestimation or underestimation of the effects of job accessibility. Previous studies attempted to address the endogeneity issue by focusing on the youth employment outcomes to control for the potential endogeneity problem of residential location choices [4,11,19], quasi-randomized experiments such as Moving to Opportunity (MTO) program participants and the Temporary Assistance for Needy Families (TANF) [20–22]. More recently, studies have used advanced econometric models using spatial modeling and instrumental variables to account for unobserved confounders correlated with changes in job accessibility [13,23,24]. Although using instruments and a fixed-effects model can control for endogeneity issues, the use of neighborhood-level and establishment-level data fails to control for personal characteristics that influence the labor market outcomes of individual workers. As such, there is no consensus regarding measures to control for endogeneity issues, which may have led to inconsistent findings on the effect of job accessibility on labor market outcomes [25]. Due to the difficulty with addressing the endogeneity problem, only the relationship between local job accessibility and labor market outcomes is inferred in this research rather than determining the causal effect of neighborhood job accessibility. Nonetheless, this research takes advantage of the individual-level microdata that allows control for individual and household characteristics unobserved in neighborhood-level data.

2. Literature Review

In his early seminal work, Kain [1] characterized the spatial mismatch hypothesis into three components: locations of Black residence affect the geographical distribution of Black employment, residential segregation of Black populations affects access to nearby employment opportunities, and decentralization of jobs limits access to jobs. In other words, the spatial mismatch hypothesis focuses on access to job opportunities as the primary mechanism of spatial mismatch. The geographic separation between residential segregation and urban economic structure affects labor market outcomes [26]. In the following decades, since the spatial mismatch hypothesis was proposed, empirical studies focused on examining the effect of job accessibility on labor market outcomes, including employment, wages, and commuting times and distances [4,11,27,28]. These early studies focused on whether Black populations are disadvantaged from having lower access to job opportunities and whether improving accessibility to jobs can increase the likelihood of employment. Empirical evidence from the early years was somewhat mixed due to differences in job accessibility measures and modeling approaches. Still, studies since the 1990s show more consistent findings that support the significant role of job accessibility on labor market outcomes [29–31].

In response to increasing Black suburbanization and changing geographic structure of segregation in the 1980s, Kain [32] and Galster [14] contemplated whether the movement of Black populations into suburbs could offset the geographic separation between the Black population and jobs and how the combined effects of job accessibility and neighborhood level of segregation would affect labor market outcomes. Gobillon and Selod [33] found that neighborhood segregation has an adverse impact on labor market outcomes due to the low quality of social networks in segregated neighborhoods. Zenou [34] and Cutler [35] emphasized that living in a segregated neighborhood aggravates the effect of low job accessibility in finding employment and securing wages among the Black population, as the segregation limits the exchange of job information as well as poor social capital. Zenou [34] further emphasizes that neighborhood segregation intensifies the adverse effects of having low job accessibility through limited social interaction and closed information transmission. In addition, Hu [36] examined the effects of job accessibility may have declined over time due to decreased significance of physical separation via improved transportation systems and increased auto ownership. She also tested whether the changing spatial structure of employment towards polycentric development contributes to the effect of job accessibility on employment and commute times at the census tract level. She found that the share of Black populations is negatively associated with employment rate (worker-to-population ratio) and decreased commute travel time. However, the study findings did not show any evidence that the effects of job accessibility have changed between 1990 and 2007–2011. Despite growing evidence of changing geography of residential segregation and economic structure in U.S. metropolitan areas, there is missing literature on the differing effect of job accessibility and residential segregation on labor market outcomes by the spatial patterns of mismatch.

3. Research Methodology

3.1. Study Background and Study Area

There is extensive literature on the effects of job accessibility on Black employment outcomes in the Midwest and West, but studies in the southern metropolitan areas are relatively scarce. Three metropolitan areas—Chicago, Atlanta, and Dallas—are selected to represent metropolitan areas with different spatial patterns of segregation and mismatch. In Atlanta, around 87.3 percent of working-age Black populations reside in the suburbs, indicating a demographic inversion. In the suburbs of Atlanta and Dallas, where both the Black population and jobs are concentrated in the suburb—Suburbs do not provide as many advantages in terms of access to employment and level of segregation. However, Chicago represents the metropolitan area with a traditional pattern of spatial mismatch wherein Black populations continue to live in the segregated inner city. At the same time, many of the jobs have been suburbanized in the Northwestern suburbs. Thus, the magnitude of job accessibility and residential segregation may differ in these metropolitan areas rather than being equal.

3.2. Data

The primary dataset for the analysis is the 5-year 2015 ACS Public Use Microdata Samples (PUMS), which provide individual-level data on labor force participants, including socioeconomic, household, and geographic characteristics. PUMS data are commonly used to analyze the impact of spatial mismatch on employment status since it provides individual-level data [37–39]. The PUMS data are then merged with 2015 LEHD Origin-Destination Employment Statistics (LODES) workplace area characteristics and American Community Survey (ACS) data for job counts that are aggregated to Public Use Microdata Areas (PUMAs). These areas have around 100,000 population each and use census tracts and counties as building blocks. Since the size of PUMAs is dependent on the population size, PUMAs in large metropolitan areas tend to be smaller in size, which enables PUMAs to be a reasonable size to capture the differences in neighborhood job opportunities [40]. The count of jobs from LEHD LODES is also aggregated to the PUMA level. However, the job information from LEHD is the number of actual workers employed rather than the number of vacancies or job openings. Previous literature established that the number of jobs correlates highly with job creation and job openings [41,42].

Black individuals in their working ages (17–65) in the labor force, not enrolled in school or the military, and not having disabilities were selected for the study. The dependent variables are employment status and earned income. Independent variables for individual and household characteristics include age, Hispanic or Latino origin, education attainment, auto availability in the household, marital status, and presence of own children under age 5. Neighborhood characteristics include a dummy variable for residence in the suburb, percent of Black populations in PUMA, and job accessibility. Three dummy variables are used to represent neighborhood shares of the Black population—Low (share of the Black population is less than 30 percent), moderate (between 30 and 60 percent), and high (over 60 percent). It allows measuring the interaction effect between the neighborhood share of the Black population and job accessibility. Figure 1 illustrates the percentage of the Black population in each of the PUMAs. In Atlanta, southern suburbs are predominantly Black neighborhoods, and the share is highest in the inner suburbs just outside the city boundary. In Chicago, the majority of the Black population resides in the southern inner city and in the suburbs. Figure 1 illustrates the geographical distribution of Black population and the distinct spatial pattern of suburbanization in Atlanta and Dallas.

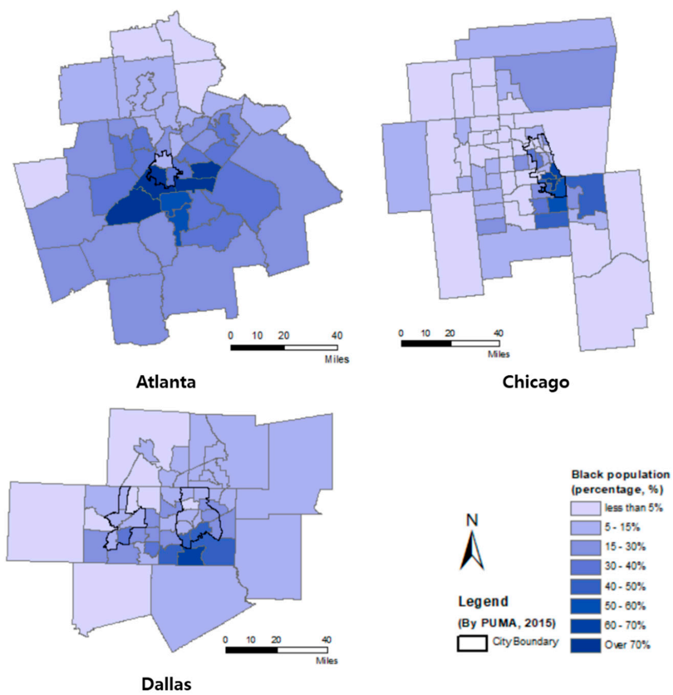

Figure 1. Black population percentage in the PUMA area, 2015.

3.3. Measuring Local Job Accessibility

Job accessibility represents the potential for reaching job opportunities within a certain distance or travel time. The cumulative opportunity measure is the most straightforward approach to measuring geographical accessibility that counts the total number of opportunities that are reachable within a specific time or distance threshold [43]. The gravity-based accessibility measure proposed by Hansen [44] is the most commonly used approach that measures the number of opportunities using a distance decay function that assigns lower weights to jobs that are located further away. Because Hansen's gravity model only considers the supply side of jobs when measuring job accessibility, Shen [41] further modified the gravity model that considers the demand side of the jobs—the competition among job seekers for available jobs. Shen's accessibility measure considers the supply and demand potential most commonly used in the literature [8,13,36]. The model follows:

$$A_i = \sum_j \frac{O_j e^{-\gamma d_{ij}}}{D_j}, \quad D_j = \sum_j P_k e^{-\gamma d_{ij}}$$

where A_i represents job accessibility for people living in location i; O_j is the number of job opportunities in location j; γ is an empirically derived impedance function associated with the travel cost. The 2015 National Household Travel Survey (NHTS) is used to obtain the γ for the three metropolitan areas ($\gamma_{atlanta} = -0.04$, $\gamma_{chicago} = -0.084$, $\gamma_{dallas} = -0.024$); D_j is the demand potential (competition) in location j; P_k is the number of job seekers living in location k. The potential job seekers are measured using total working age populations.

3.4. Employment Effects

A probit model is used to measure employment outcomes of Black populations concerning local job accessibility and individual, household, and neighborhood characteristics. The main objective of this analysis is to examine whether metropolitan spatial patterns of job accessibility affect labor market outcomes of Black populations and if there exist differing relations of job accessibility in the city and the suburb and by the share of Black populations in the neighborhood. If the hypothesis holds, the effect of job accessibility will be lower among Black populations who live in highly segregated suburbs due to higher isolation in the suburbs and fewer economic resources [33]. The probit model for estimating the effect of spatial mismatch on employment outcomes can be specified as follows. Let E_I^* be the latent variable related to the employment status E of individual i such that.

$$E_i = \begin{cases} 1 & if\ E_i^* > 0 \\ 0 & otherwise \end{cases}$$

By assuming the Cumulative Distribution Function (CDF) of the standard normal distribution, the model takes the form:

$$\Pr(E_i = 1|x_i) = \Phi(\beta_0 + x\beta)$$

$$\Pr(E_i = 0|x_i) = 1 - \Phi(\beta_0 + x\beta)$$

where E_i represents employment outcome of individuals i, x is the vector of individual and neighborhood characteristics, including age, ethnicity, gender, educational attainment, auto availability, marriage status, having own children, neighborhood characteristics that include job accessibility, residence in the suburb, and Black share in the neighborhood. This model estimates the effects of the local labor market job accessibility on the probability of employment outcome.

3.5. Income Effects

Then, to examine the relationship between earnings and neighborhood job accessibility, a Log-linear model is used that takes the form:

$$\ln(y_i) = \beta_0 + \beta_1 I_i + \beta_2 H_i + \beta_3 N_i + \varepsilon$$

where $\ln(y_i)$ is the natural logarithm of earned income of individual i; variables in I include individual characteristics; H includes household characteristics; N includes neighborhood characteristics.

For both employment and income effects models, an interaction term is used to examine differing effects of job accessibility on labor market outcomes as a function of residence in the suburb, neighborhood share of Black (three dummy variables—low, moderate, and high Black share), and having auto ownership.

3.6. Blinder-Oaxaca Decomposition

Blinder-Oaxaca decomposition is used to examine whether the difference in employment and income is due to differences in individual and neighborhood characteristics or whether it is due to group differences associated with living in the city or the suburb. The decomposition method divides the employment and income differences between two groups into 'explained' and 'unexplained' by the differences in explanatory variables. The unexplained part may be the result of an unobserved effect, but may also represent labor market discrimination and differences or the gap in reservation wages in the city and the suburb. Blinder-Oaxaca analysis is often used to examine racial and gender wage discrimination [45,46] to determine whether the observed variables can explain the differences in labor market outcomes. Although regression analysis is helpful for measuring the relationships between individual and neighborhood characteristics and labor market outcomes, it is difficult to determine the factors contributing to the differences between the two groups. Therefore, by analyzing the differences in employment and income for those living in the city and the suburb, this analysis explains the extent to which differences in labor market outcomes are due to differences in individual and neighborhood characteristics, and how much is unobserved.

Given that outcome (Y) is explained by a set of predictors ($x_1 \cdots x_k$) for two groups (city (C) and suburb (S), the mean predicted outcome for the two groups is as follows [47]:

$$\overline{Y}^C = \beta_0^C + \sum_{i=1}^{k} \beta_i^C \overline{x_i}^C$$

$$\overline{Y}^S = \beta_0^S + \sum_{i=1}^{k} \beta_i^S \overline{x_i}^S$$

The mean difference between the two groups is:

$$\Delta\overline{Y} = \left(\beta_0^C - \beta_0^S\right) + \sum_{i=1}^{k}\left(\beta_i^C \overline{x}^C - \beta_i^S \overline{x_i}^S\right)$$

The first component is the basic differences in the intercepts, this is part of the effects of unobservable variables not taken into account. The second component can be further decomposed by creating a hypothetical term with the $\overline{x}$ of city residents and β of the suburban residents. Including the term into the above equation can be expressed as the following:

$$\Delta\overline{Y} = \left(\beta_0^C - \beta_0^S\right) + \sum_{i=1}^{k}\left(\beta_i^C \overline{x}^C - \beta_i^S \overline{x_i}^S\right) + \beta_i^C \overline{x_i}^S - \beta_i^C \overline{x_i}^S$$

Then, the standard linear Blinder-Oaxaca decomposition model can be expressed as follows:

$$\Delta\overline{Y} = \left[\sum_{i=1}^{k}\left(\overline{x_i}^C - \overline{x_i}^S\right)\beta_i^C\right] + \left[\left(\beta_0^C - \beta_0^S\right) + \sum_{i=1}^{k}\left(\beta_i^C - \beta_i^S\right)\overline{x_i}^S\right]$$

The first component is the 'explained' part, which represents the mean differences in the outcome explained by the differences in the mean values of the explanatory variables. The second component is the 'unexplained' or 'discrimination effect', due to differences in intercepts and unobservable variables [48]. The Stata software program version 11 is used to run the Blinder-Oaxaca decomposition using oaxaca command [49]. The oxaca command can also be used for binary outcomes with the linear probability model.

4. Results

4.1. Descriptive Statistics

Table 1 shows the means and the standard deviations of the dependent variables, individual, household, and neighborhood characteristics for each metropolitan area: Atlanta, Dallas, and Chicago.

Table 1. Descriptive statistics of variables in the city and the suburb.

	Atlanta		Chicago		Dallas	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Dependent variables						
Employment status (=1)						
City	0.82	(0.38)	0.78	(0.42)	0.89	(0.31)
Suburb	0.89	(0.31)	0.85	(0.35)	0.92	(0.28)
ln(earned income)						
City	9.99	(1.25)	10.06	(1.24)	10.12	(1.14)
Suburb	10.19	(1.16)	10.24	(1.22)	10.3	(1.07)
Total personal earned income						
City	USD 28,673	(USD 45,205)	USD 28,284	(USD 48,398)	USD 31,502	(USD 39,592)
Suburb	USD 32,086	(USD 42,208)	USD 35,100	(USD 51,981)	USD 36,870	(USD 46,451)
Individual characteristics						
Age	41.21	(11.88)	41.50	(12.38)	41.69	(11.79)
Hispanic	0.01	(0.12)	0.02	(0.13)	0.02	(0.13)
Gender (male = 1)	0.46	(0.50)	0.45	(0.50)	0.47	(0.50)
Education Attainment						
Less than Highschool	0.07	(0.26)	0.08	(0.27)	0.06	(0.23)
Highschool equivalent	0.28	(0.45)	0.29	(0.45)	0.29	(0.45)
College	0.65	(0.48)	0.63	(0.48)	0.65	(0.47)
Household Characteristics						
Auto ownership (=1)	0.90	(0.30)	0.74	(0.44)	0.91	(0.29)
Married with spouse	0.48	(0.50)	0.37	(0.48)	0.51	(0.50)
Own child under age 5	0.14	(0.34)	0.11	(0.32)	0.13	(0.34)
Neighborhood Characteristics						
Residence in suburb	0.86	(0.35)	0.49	(0.50)	0.71	(0.45)
Black population percentage	0.50	(0.28)	0.46	(0.24)	0.24	(0.17)
Black population percentage (grouped)						
City						
Low (<30%)	0.10		0.16		0.57	
Moderate (30–60%)	0.28		0.28		0.43	
High (>60%)	0.62		0.56		-	
Suburb						
Low (<30%)	0.22		0.59		0.74	
Moderate (30–60%)	0.30		0.23		0.17	
High (>60%)	0.49		0.18		0.09	
Job accessibility	0.64	(0.41)	0.47	(0.52)	0.45	(0.42)
(by Black population percentage)						
City						
Low (<30%)	1.70	(0)	0.97	(1.43)	0.74	(0.63)
Moderate (30–60%)	1.69	(0)	0.27	(0.04)	0.16	(0.01)
High (>60%)	0.49	(0)	0.22	(0.08)	-	
Suburb						
Low (<30%)	0.62	(0.43)	0.69	(0.27)	0.48	(0.35)
Moderate (30–60%)	0.58	(0.26)	0.44	(0.04)	0.19	(0.04)
High (>60%)	0.50	(0.36)	0.48	(0)	0.30	(0)

The employment rate of Black individuals is shown separately for the city and the suburb. On average, the employment rate is around 5.6 percent higher, and earned income is USD 5199 higher in the suburbs. The difference in employment and earnings is quite significant in Atlanta and Chicago, and there is only a slight gap in Dallas. Regarding neighborhood characteristics, as expected, 86 percent of the Black population in Atlanta lives in the suburbs, followed by 71 percent in Dallas and 49 percent in Chicago. The Black population percentage in the PUMA is approximately 50 percent in Atlanta, followed by 46 percent in Chicago and 24 percent in Dallas.

The shares of Black populations in the PUMA are grouped into three: low (less than 30 percent of the overall population in PUMA is Black), moderate (between 30–60 percent of the population in PUMA is Black), and high (over 60 percent of the population in PUMA is Black). In Chicago, around 59 percent of the population samples live in areas with low shares of the Black population. In contrast, in the city, only 16 percent of the population live in low Black share areas, and 56 percent live in areas with high shares of Black populations. In Dallas, there is no PUMA in the city, with more than 60 percent of the population being Black, and thus 57 percent of the population in the city live in low Black share areas, and 43 percent live in moderate Black share areas. In the suburbs, 74 percent of the population live in a low Black percentage area, suggesting that Black residents are more likely to live in areas with a lower share of Black populations. In Atlanta, around half of the population in the suburbs live in areas with high shares of Black populations, where over 60 percent of populations are Black—highly segregated neighborhoods.

Figure 2 shows the estimated job accessibility of three metropolitan areas. Geographical boundaries are PUMAs, and a bold line represents the boundaries of the city. A PUMA with the highest accessibility score is in dark brown, while a PUMA with the lowest accessibility score is in light yellow. Job accessibility is highest in areas with low Black population percentage in all three metropolitan areas. In Atlanta and Dallas, the average job accessibility is higher in the city where the neighborhood percentage of Black is low and moderate. This suggests that job accessibility is lower in the suburbs where large share of Black population resides. Job accessibility is lowest in highly segregated neighborhoods where over 60 percent of the population is Black. In contrary to the traditional assumption that job accessibility is higher in the suburbs, the finding here suggests that job accessibility is higher in the inner city than suburbs with high percentage of Black population. In these South metropolitan areas, moving into the segregated suburbs in the south may not lead to increased job accessibility than in the city. In Chicago, however, job accessibility is higher in the suburbs, with a moderate and high share of Black populations. In Chicago, the northwest suburbs have the highest job accessibility, whereas the southern inner city has the lowest accessibility to job opportunities.

4.2. Probit Regression Results

The results of employment outcomes are shown in Table 2. Model (1) in the first column examines the relationship between neighborhood characteristics and employment outcome, but without any interactions. The second column, model (2), shows the relationship between each neighborhood's characteristics (specifically, shares of Black populations in the neighborhood and job accessibility) and employment by the place of residence in the city and the suburb. Model (3) in the third column shows the relationship between neighborhood characteristics and employment by auto ownership, which allows distinguishing between those with and without auto ownership. The fourth column shows model (4), which shows the relationship between job accessibility and employment outcomes by the shares of Black populations in the neighborhood—the Black share is low (less than 30 percent is Black), moderate (30 to 60 percent is Black), and high (over 60 percent is Black).

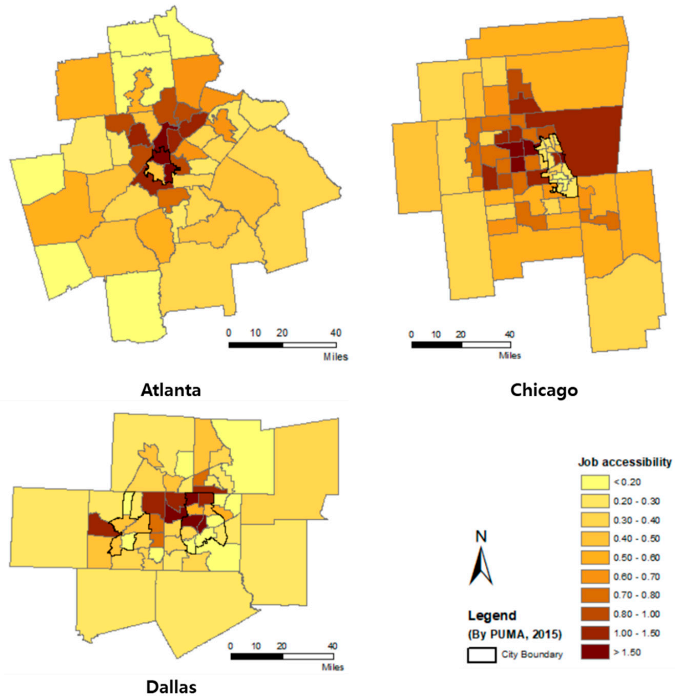

Figure 2. Job accessibility index in three metropolitan areas, 2015.

Table 2. Probit model results of employment outcomes.

	Model 1			Model 2 (Job Accessibility * Puma Suburb)			Model 3 (Job Accessibility * Auto)		
Emp	**Atlanta**	**Chicago**	**Dallas**	**Atlanta**	**Chicago**	**Dallas**	**Atlanta**	**Chicago**	**Dallas**
Individual characteristics									
Age	0.0395 ***	0.0444 ***	0.0593 ***	0.0395 ***	0.0447 ***	0.0592 ***	0.0395 ***	0.0445 ***	0.0585 ***
	(0.0101)	(0.0107)	(0.0120)	(0.0101)	(0.0106)	(0.0122)	(0.0101)	(0.0106)	(0.0122)
Age^2	−0.0004 ***	−0.0003**	−0.0006 ***	−0.0004 ***	−0.0003 **	−0.0006 ***	−0.0004 ***	−0.0003 **	−0.0006 ***
	(0.00012)	(0.0001)	(0.0001)	(0.00012)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Hispanic	0.0904	0.518 ***	0.436 **	0.0929	0.524 ***	0.435 **	0.0884	0.520 ***	0.436 **
	(0.171)	(0.201)	(0.202)	(0.172)	(0.198)	(0.203)	(0.171)	(0.199)	(0.202)
Male	−0.0299	−0.196 ***	−0.0498	−0.0305	−0.197 ***	−0.0502	−0.0304	−0.196 ***	−0.0506
	(0.0458)	(0.0461)	(0.0470)	(0.0460)	(0.0465)	(0.0470)	(0.0459)	(0.0459)	(0.0469)
Highschool graduate	0.332 ***	0.300 ***	0.143 **	0.331 ***	0.301 ***	0.142 **	0.333 ***	0.299 ***	0.141 **
	(0.0564)	(0.0362)	(0.0641)	(0.0566)	(0.0352)	(0.0646)	(0.0567)	(0.0367)	(0.0646)
College graduate	0.568 ***	0.583 ***	0.414 ***	0.566 ***	0.584 ***	0.411 ***	0.569 ***	0.582 ***	0.412 ***
	(0.0617)	(0.0398)	(0.0709)	(0.0619)	(0.0384)	(0.0716)	(0.0622)	(0.0397)	(0.0713)
Household characteristics									
Auto availability	0.424 ***	0.547 ***	0.536 ***	0.421 ***	0.551 ***	0.535 ***	0.524 ***	0.497 ***	0.789 ***
	(0.0411)	(0.0389)	(0.0604)	(0.0423)	(0.0393)	(0.0602)	(0.136)	(0.132)	(0.130)
Married with spouse	0.272 ***	0.295 ***	0.242 ***	0.271 ***	0.295 ***	0.241 ***	0.271 ***	0.295 ***	0.241 ***
	(0.0379)	(0.0511)	(0.0613)	(0.0378)	(0.0507)	(0.0607)	(0.0379)	(0.0510)	(0.0609)
Own child under age 5	−0.0385	0.149 ***	0.0448	−0.0378	0.151 ***	0.0446	−0.0372	0.148 ***	0.0480
	(0.0552)	(0.0509)	(0.0610)	(0.0552)	(0.0508)	(0.0609)	(0.0550)	(0.0509)	(0.0613)
Neighborhood characteristics									
Suburb	0.0418	−0.177 **	0.0352	−0.331 ***	−0.330 *	0.0821	0.0367	−0.177 **	0.0344
	(0.0348)	(0.0696)	(0.0487)	(0.0709)	(0.179)	(0.184)	(0.0341)	(0.0703)	(0.0488)
Black percentage *Interaction: (City; Auto = 0)*	−0.279 ***	−0.458 ***	−0.0939	−0.680 ***	−0.571 ***	-0.101	−0.309 **	−0.500 ***	0.385
	(0.0782)	(0.132)	(0.135)	(0.0356)	(0.196)	(0.384)	(0.149)	(0.193)	(0.352)
Job accessibility *Interaction: (City; Auto = 0)*	0.00495	0.122 ***	0.0118	−0.106 ***	0.108**	0.0609	0.131 *	0.112 ***	0.232 **
	(0.0527)	(0.0389)	(0.0660)	(0.0136)	(0.0445)	(0.0833)	(0.0707)	(0.0400)	(0.109)

Table 2. *Cont.*

	Model 1			Model 2 (Job Accessibility * Puma Suburb)			Model 3 (Job Accessibility * Auto)		
Emp	**Atlanta**	**Chicago**	**Dallas**	**Atlanta**	**Chicago**	**Dallas**	**Atlanta**	**Chicago**	**Dallas**
Black percentage * Suburb				0.413 ***	0.276	0.0126			
				−0.0849	−0.24	−0.407			
Job accessibility * Suburb				0.0935	0.0504	−0.118			
				−0.0701	-0.125	−0.156			
Black percentage * Auto							0.0337	0.0718	−0.543
							−0.143	−0.191	−0.351
Job accessibility * Auto							−0.161 *	0.0305	−0.267 ***
							−0.084	−0.0986	−0.101
Constant	−0.499 **	−0.884 ***	−0.879 ***	−0.117	−0.819 ***	−0.892 ***	−0.576**	−0.858 ***	−1.079 ***
	(0.238)	(0.251)	(0.268)	(0.214)	(0.282)	(0.294)	(0.266)	(0.275)	(0.262)
Observations	22,695	19,204	13,070	22,695	19,204	13,070	22,695	19,204	13,070
Pseudo R-squared	0.0781	0.1352	0.0874	0.0782	0.1356	0.0876	0.0784	0.1352	0.0882

	Model 4 (Job Accessibility * Black Percentage)		
Emp	**Atlanta**	**Chicago**	**Dallas**
Individual characteristics			
Age	0.0396 ***	0.0447 ***	0.0591 ***
	(0.0101)	(0.0108)	(0.0121)
Age^2	−0.0004 ***	−0.0003**	−0.0006 ***
	(0.00012)	(0.0001)	(0.00015)
Hispanic	0.0874	0.517 ***	0.432 **
	(0.173)	(0.199)	(0.201)
Male	−0.0317	−0.197 ***	−0.0493
	(0.0462)	(0.0460)	(0.0471)
Highschool graduate	0.327 ***	0.293 ***	0.144 **
	(0.0573)	(0.0373)	(0.0650)
College graduate	0.559 ***	0.570 ***	0.416 ***
	(0.0623)	(0.0412)	(0.0719)
Household characteristics			
Auto availability	0.418 ***	0.557 ***	0.540 ***
	(0.0431)	(0.0380)	(0.0605)
Married with spouse	0.272 ***	0.296 ***	0.243 ***
	(0.0378)	(0.0506)	(0.0604)
Own child under age 5	−0.0346	0.147 ***	0.0449
	(0.0551)	(0.0517)	(0.0613)
Neighborhood characteristics			
Suburb	0.0694 **	−0.316 ***	0.0472
	(0.0346)	(0.0837)	(0.0598)
Black percentage group	−0.0207	−0.367 ***	0.135
Interaction: (job accessibility = 0)	(0.0372)	(0.0829)	(0.197)
Job accessibility (Black pop. group = 1, Low)	0.194 **	0.0761	0.0100
	(0.0803)	(0.0493)	(0.0734)
Job accessibility * Black pop. group = 2 (Moderate)	−0.194 **	0.450 ***	−0.979
	(0.0763)	(0.147)	(0.909)
Job accessibility * Black pop. group = 3 (High)	−0.283 ***	1.264 ***	−1.237
	(0.101)	(0.292)	(1.303)
Constant	−0.621 **	−0.441	−1.032 ***
	(0.253)	(0.329)	(0.316)
Observations	22,695	19,204	13,070
Pseudo R-squared	0.0793	0.1377	0.0877

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Results of model 1 in Table 2 show that the shares of Black populations in the neighborhood are negatively associated with Black employment in Atlanta and Chicago. In Chicago, job accessibility is positively associated with Black employment, suggesting that individuals who live in neighborhoods with high job accessibility are more likely to be employed. Most coefficients of individual and household characteristics are as expected. Higher education attainment is positively and significantly associated with the likelihood of being employed and auto ownership in the household. Marital status with a spouse has a strong positive relationship with employment. However, the coefficient for being male is negatively associated with employment outcomes, suggesting that Black females are more likely to be employed than Black males.

Model 2 and model 3 in Table 2 show that the shares of Black populations in the neighborhood are negatively associated with Black employment—especially in the city and those without access to the auto. It also shows that in all three metropolitan areas, job accessibility is positively associated with Black employment for individuals who do not have access to auto. For individuals with auto, job accessibility was negatively associated with employment, suggesting that employed individuals with auto access tend to live in areas with low job accessibility. At the same time, the interaction between job accessibility and the neighborhood location (the city and suburb) shows different results. In Atlanta, job accessibility in the city is negatively associated with employment (−0.106), whereas job accessibility in the inner city of Chicago shows a positive relationship with Black employment (0.108). This suggests that the probability of employment in Atlanta is higher in the inner city, although job accessibility is lower. However, in Chicago, employment is higher in neighborhoods with higher job accessibility. This reflects a differing relationship between job accessibility on labor market outcome by the neighborhood location—Depending on whether living in the inner city is advantageous over living in the suburb, and the spatial pattern of mismatch in the metropolitan area.

Model 4 further examines the relationship between job accessibility and employment by the shares of Black populations in the neighborhood—low, moderate, and high Black population shares. Results show that in Atlanta, job accessibility is significantly and positively associated with Black employment in neighborhoods with a low share of Black populations (less than 30 percent of the population is Black). However, the relationship is negative in moderate and high Black share neighborhoods. This implies that although an increase in job accessibility is positively associated with the probability of being employed, the relationship becomes negative if the neighborhood composition is predominantly Black (more than 60 percent of the population is Black). In Chicago, such interactions exist—The association between job accessibility and employment depends on the share of Black populations; however, having higher Black shares do not negate the effect of job accessibility on employment. Instead, an increase in job accessibility in the predominantly Black neighborhood is associated with a higher probability of being employed, suggesting higher marginal effects of job accessibility on Black employment.

For all models, McFadden's Pseudo R-squared is used to interpret the probit models. McFadden's pseudo-R-squared value is lower than the regular R-squared value, and a value between 0.2 and 0.4 is considered to have a good model fit [50]. The Pseudo R-squared for the employment model ranges between 0.07 and 0.13. Even though the model fit suggests the variance in the employment outcome is not well explained by the independent variables, each of the variables is statistically significant, indicating a high correlation between the variables and employment outcomes. In Figure 3, the predictive margins are shown to better explain the model performance, especially the relationship between job accessibility and the probability of employment. The predictive margins with 95 percent confidence intervals are presented for neighborhoods with low, moderate, and high Black population percentages.

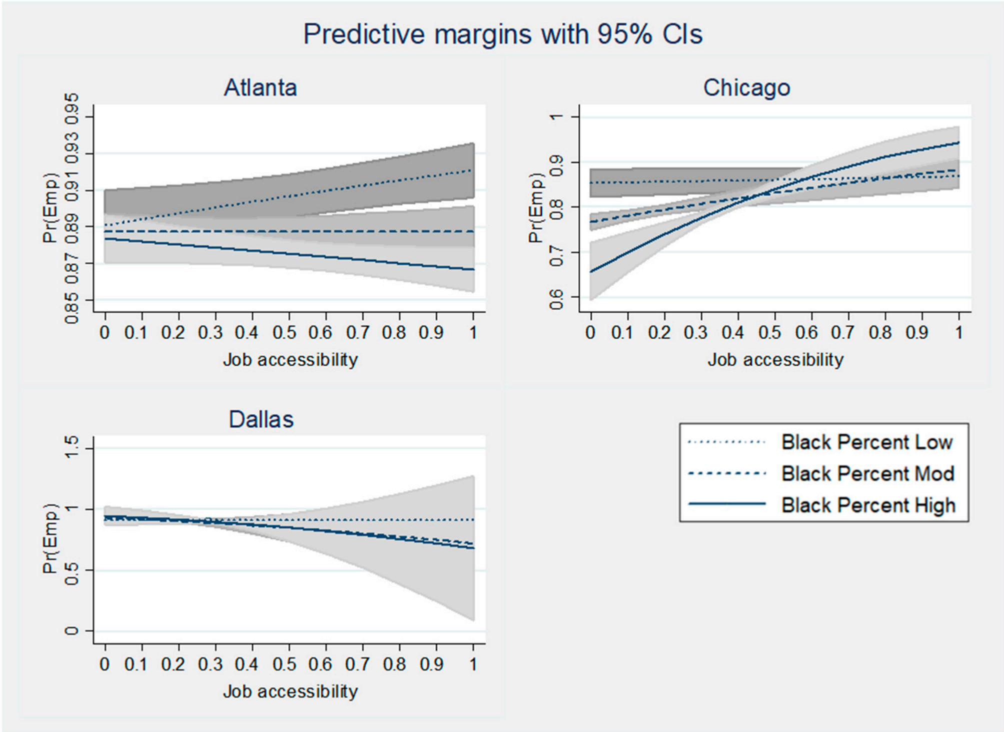

Figure 3. Predictive margins of employment outcome over neighborhood Black share with 95% confidence intervals.

In Atlanta, individuals who live in predominantly Black neighborhoods have a lower probability of employment as job accessibility increases. On the other hand, in neighborhoods with lower shares of Black populations, an increase in job accessibility is positively associated with Black employment. In Chicago, the changes in job accessibility in neighborhoods with low shares of the Black population are not associated with employment. However, in predominantly Black neighborhoods, the marginal increase in job accessibility is positively associated with Black employment. This suggests that unlike in Atlanta, where the neighborhood share of Black populations counteracts the effect of job accessibility on the probability of being employed, an increase in job accessibility in highly segregated areas leads to higher chances of employment in Chicago. In Dallas, predicted margins show job accessibility is negatively associated with employment in neighborhoods with moderate and high shares of Black populations similar to Atlanta. The wider confidence interval at a job accessibility score of over 0.5 suggests that the sample is small, meaning that in neighborhoods with moderate and high shares of Black populations, job accessibility is more likely to be below 0.5.

4.3. Regression Results on Earned Income

In the same manner as the employment model, the relationship between job accessibility and the log of earned income is shown in Table 3. Model (1) examines the relationship between neighborhood characteristics (shares of Black populations in the neighborhood and job accessibility) and log earned income, but without any interactions. Models (2) and (3) report interactions between neighborhood characteristics and log earned income in the city and the suburb and by auto ownership. Lastly, model (4) shows the relationship between job accessibility and employment outcomes by the shares of Black populations in the neighborhood.

Table 3. Linear model results of log income.

	Model 1			Model 2 (Job Accessibility * Puma Suburb)			Model 3 (Job Accessibility * Auto)		
Ln (Income)	**Atlanta**	**Chicago**	**Dallas**	**Atlanta**	**Chicago**	**Dallas**	**Atlanta**	**Chicago**	**Dallas**
Individual characteristics									
Age	0.0883 ***	0.0869 ***	0.104 ***	0.0883 ***	0.0871 ***	0.104 ***	0.0882 ***	0.0871 ***	0.104 ***
	(0.00763)	(0.00613)	(0.00812)	(0.00762)	(0.00620)	(0.00814)	(0.00762)	(0.00615)	(0.00816)
Age^2	−0.0009 ***	−0.0009 ***	−0.0011 ***	−0.0009 ***	−0.0009 ***	−0.0011 ***	−0.0009 ***	−0.0009 ***	−0.0011 ***
	(9.21×10^{-5})	(6.89×10^{-5})	(8.93×10^{-5})	(9.20×10^{-5})	(6.97×10^{-5})	(8.94×10^{-5})	(9.20×10^{-5})	(6.92×10^{-5})	(8.97×10^{-5})
Hispanic	−0.0350	−0.109	−0.00364	−0.0329	−0.107	−0.00232	−0.0354	−0.106	−0.00349
	(0.0628)	(0.0829)	(0.0805)	(0.0626)	(0.0816)	(0.0802)	(0.0634)	(0.0831)	(0.0805)
Male	0.126 ***	0.116 ***	0.127 ***	0.126 ***	0.116 ***	0.127 ***	0.126 ***	0.116 ***	0.127 ***
	(0.0185)	(0.0232)	(0.0180)	(0.0185)	(0.0232)	(0.0182)	(0.0185)	(0.0232)	(0.0181)
Highschool graduate	0.173 ***	0.150 **	0.275 ***	0.172 ***	0.152 **	0.271 ***	0.172 ***	0.150 **	0.276 ***
	(0.0400)	(0.0574)	(0.0426)	(0.0398)	(0.0579)	(0.0426)	(0.0402)	(0.0575)	(0.0429)
College graduate	0.503 ***	0.417 ***	0.598 ***	0.501 ***	0.418 ***	0.594 ***	0.502 ***	0.416 ***	0.600 ***
	(0.0422)	(0.0642)	(0.0505)	(0.0421)	(0.0646)	(0.0503)	(0.0424)	(0.0642)	(0.0507)
Household characteristics									
Auto availability	0.341 ***	0.336 ***	0.339 ***	0.338 ***	0.339 ***	0.338 ***	0.309 ***	0.242 ***	0.412 ***
	(0.0333)	(0.0321)	(0.0447)	(0.0331)	(0.0314)	(0.0450)	(0.102)	(0.0729)	(0.117)
Married with spouse	0.157 ***	0.128 ***	0.166 ***	0.156 ***	0.127 ***	0.165 ***	0.157 ***	0.127 ***	0.166 ***
	(0.0208)	(0.0168)	(0.0230)	(0.0209)	(0.0167)	(0.0232)	(0.0208)	(0.0170)	(0.0230)
Own child under age 5	0.0362	0.0470	0.0468	0.0369	0.0495	0.0462	0.0371	0.0469	0.0468
	(0.0225)	(0.0368)	(0.0368)	(0.0225)	(0.0364)	(0.0367)	(0.0225)	(0.0366)	(0.0366)
Neighborhood characteristics									
Suburb	0.00609	−0.0530	0.0852 ***	−0.286 ***	−0.0179	0.0796	0.00195	−0.0516	0.0863 ***
	(0.0294)	(0.0370)	(0.0253)	(0.0409)	(0.0799)	(0.0648)	(0.0285)	(0.0365)	(0.0256)
Black percentage *Interaction: (City; Auto = 0)*	−0.102 **	−0.0953	-0.0178	−0.429 ***	−0.152 **	−0.170	−0.197 *	−0.196 **	0.276
	(0.0450)	(0.0610)	(0.0791)	(0.0186)	(0.0595)	(0.137)	(0.116)	(0.0932)	(0.299)
Job accessibility *Interaction: (City; Auto = 0)*	0.0646 **	0.0839 ***	0.0693 *	−0.0193 ***	0.0959 ***	0.0994 **	0.0919	0.0580 ***	0.0659
	(0.0305)	(0.0260)	(0.0368)	(0.00599)	(0.0146)	(0.0440)	(0.0589)	(0.0186)	(0.0912)
Interaction:									
Black percentage * Suburb				0.337 ***	0.0847	0.184			
				(0.0442)	(0.108)	(0.154)			
Job accessibility * Suburb				0.0688 *	−0.137 *	−0.101 *			
				(0.0374)	(0.0746)	(0.0600)			
Black percentage * Auto							0.103	0.142	−0.311
							(0.100)	(0.111)	(0.303)
Job accessibility * Auto							−0.0337	0.0498	0.00764
							(0.0506)	(0.0426)	(0.102)
Constant	7.411 ***	7.544 ***	6.910 ***	7.713 ***	7.567 ***	6.947 ***	7.450 ***	7.606 ***	6.839 ***
	(0.132)	(0.161)	(0.202)	(0.156)	(0.162)	(0.193)	(0.171)	(0.167)	(0.214)
Observations	16,664	13,480	10,544	16,664	13,480	10,544	16,664	13,480	10,544
R-squared	0.095	0.090	0.127	0.096	0.091	0.127	0.096	0.090	0.127

	Model 4 (Job Accessibility * Black Percentage)		
Ln (Income)	**Atlanta**	**Chicago**	**Dallas**
Individual characteristics			
Age	0.0884 ***	0.0870 ***	0.105 ***
	(0.00766)	(0.00617)	(0.00814)
Age^2	−0.0009 ***	−0.0009 ***	−0.0011 ***
	(9.24×10^{-5})	(6.95×10^{-5})	(8.94×10^{-5})
Hispanic	−0.0345	−0.108	−0.00131
	(0.0624)	(0.0810)	(0.0802)
Male	0.126 ***	0.116 ***	0.127 ***
	(0.0185)	(0.0231)	(0.0181)

Table 3. *Cont.*

	Model 4 (Job Accessibility * Black Percentage)		
Highschool graduate	0.173 ***	0.150 **	0.272 ***
	(0.0397)	(0.0584)	(0.0427)
College graduate	0.503 ***	0.414 ***	0.596 ***
	(0.0420)	(0.0656)	(0.0502)
Household characteristics			
Auto availability	0.340 ***	0.340 ***	0.337 ***
	(0.0331)	(0.0337)	(0.0451)
Married with spouse	0.157 ***	0.127 ***	0.165 ***
	(0.0210)	(0.0168)	(0.0236)
Own child under age 5	0.0366	0.0472	0.0469
	(0.0224)	(0.0363)	(0.0368)
Neighborhood characteristics			
Suburb	0.00822	−0.0902 **	0.0716 **
	(0.0262)	(0.0390)	(0.0298)
Black percentage group Interaction: (job accessibility = 0)	−0.0330	−0.0935 ***	−0.123 **
	(0.0238)	(0.0323)	(0.0608)
Job accessibility (Black pop. group=1, Low)	0.0851 **	0.0767 ***	0.0688 *
	(0.0363)	(0.0284)	(0.0370)
Job accessibility * Black pop. group=2 (Moderate)	−0.0283	0.147	0.646 **
	(0.0325)	(0.133)	(0.278)
Job accessibility * Black pop. group=3 (High)	−0.0253	0.385 ***	1.011 **
	(0.0735)	(0.141)	(0.410)
Constant	7.427 ***(0.170)	7.655 ***(0.170)	7.038 ***(0.193)
Observations	16,664	13,480	10,544
R-squared	0.096	0.090	0.127

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As reported in the first column of Table 3, the shares of Black populations in the neighborhood are negatively associated with earned income, which is consistent with the observations of the employment model. Job accessibility is positively associated with earned income in all three metropolitan areas, suggesting that neighborhoods with high job accessibility are likely to have higher earnings. In Dallas, residence in the suburb is positively associated with earned income, implying that Black individuals who live in the suburbs tend to have higher earnings. Coefficients of individual and household variables are as expected, in which individuals with higher education levels, having access to auto, and married with a spouse are significantly and positively associated with earned income. Additionally, although the result of the employment model in the previous section showed that males have a lower probability of being employed, the results in Table 3 show that male workers have higher earned income. A potential explanation is that although women have a higher probability of being employed but are more likely to work at lower-paying jobs. In other words, Black male workers are more likely to look for a higher-paying job than female workers, and female workers are willing to accept a job for less pay than to be unemployed. The vicinity to the job opportunities may be a more critical consideration for their decision to work. The differences in earned income between men and women may also indicate gender wage gaps.

The results of model 2 in Table 3 show interactions between neighborhood characteristics and the city and suburb residence on earnings. Metropolitan differences exist in the relationship between job accessibility and earned income. In Atlanta, job accessibility in the city is negatively associated with earnings, whereas the relationship is positive in the suburb. In other words, Black individuals who live in the city tend to have lower earnings if the neighborhood job accessibility is high. In comparison, those who live in the suburb have higher earnings if the job accessibility is high. This suggests that suburbs have better access to higher-paying jobs, which increases the amount of earned income as accessibility increases. In Chicago and Dallas, the relationship is the opposite—job accessibility in the city is positively associated with earnings, and the relationship is negative in the suburb. These results suggest that Black individuals have higher earnings if they live in a city with high job accessibility. In the suburb, individuals who earn higher income tend to live in neighborhoods with lower job accessibility, a pattern expected for those who self-select into neighborhoods based on their preferences other than access to jobs. Results of model 3 report that the association between neighborhood characteristics and earnings is only significant for individuals without auto ownership. This is consistent with the employment model since those without automobiles are more likely to be lower-income and, thus, more influenced by neighborhood characteristics.

Model 4 shows the associations between job accessibility, earned income, and the interactions with the share of Black populations in the neighborhood. Job accessibility is significantly and positively associated with earnings in all three metropolitan areas, while the magnitude of the associations varies. Marginal effects of job accessibility on earnings are highest in neighborhoods with less than 30 percent of Black in Atlanta. However, the marginal effect in Chicago and Dallas is highest in predominantly Black neighborhoods (over 60 percent of the population is Black), suggesting that increases in job accessibility have the most considerable effect in segregated neighborhoods.

Differing relationships by the percentage of the Black population in each neighborhood are further shown in Figure 4, which shows predictive margins over job accessibility scores. Overall, job accessibility is positively associated with earnings, suggesting that individuals who live in neighborhoods with better job accessibility earn a higher income. However, in Atlanta, the marginal increase is more significant in neighborhoods with low shares of Black populations than in Chicago and Dallas, where a marginal increase is more significant in predominantly Black neighborhoods. This is consistent with the findings of the employment model that show the marginal increase in job accessibility has a more significant effect in neighborhoods with a higher share of Black populations.

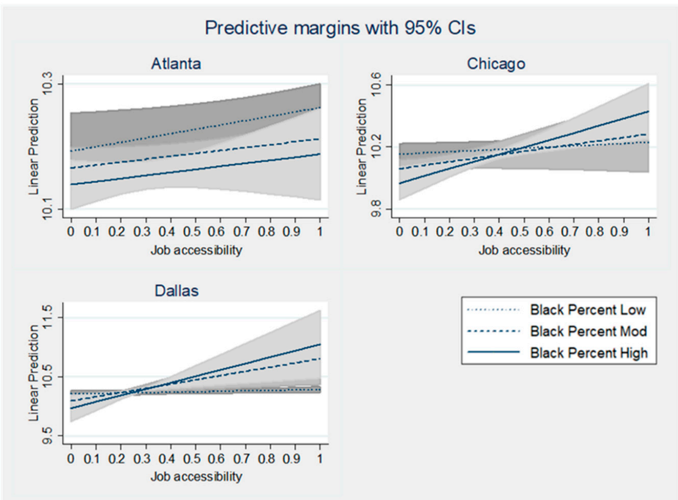

Figure 4. Predictive margins of log income over neighborhood Black share with 95% confidence intervals.

4.4. Decomposition of Employment and Income Gaps

In addition to the differing effects of job accessibility, the contributions of individual, household, and neighborhood characteristics to the differential in labor market outcomes by the residents in the city and suburb are examined using the Oaxaca-Blinder (OB) decomposition method. The two-fold decomposition uses the coefficients from a pooled model over two groups as the reference [51]. The two-fold model decomposes the mean difference in the dependent value between the two groups into the "explained" and "unexplained" component, in which the explained portion represents the differences in estimated outcome is attributable to the group differences in explanatory variables. In this research, the unexplained component may refer to unobserved factors that affect individuals living in the city and in the suburb that is not observed from the independent variables in the model.

Table 4 shows the decomposition of the differences in the labor market outcomes based on the estimation of probit regression to explain the likelihood of being employed and linear regression to explain log income. It shows how much the variables in the analysis can explain the differences in labor market outcomes in the (explained component) and how much each individual, household, and neighborhood characteristics contribute to the explained component. The difference in the employment rate in the city and the suburbs among Black individuals were 7.7 percent in Atlanta, 7.8 percent in Chicago, and 2.7 percent in Dallas. Overall, Dallas's employment rate is relatively high compared to Atlanta and Chicago, and the differences in employment outcomes in the city and the suburb are not as substantial. However, in Atlanta and Chicago, employment rate differences for the city and suburban residents are quite significant, considering the employment rate gap between Black and White populations in 2015 was around 4.97 percent.

The decomposition analysis results also indicate that the differences in characteristics can explain around 88.5 percent, 139.9 percent, and 83.2 percent of the employment gap in the city and the suburb in Atlanta, Chicago, and Dallas, respectively. The explained component is quite significant in Chicago, accounting for 139.9 percent of the total gap of 7.8. This implies that if the city residents had the same characteristics as the suburban residents but kept their coefficient, the employment gap would become even more significant (10.9 percent). This suggests that the difference in the characteristics in the city and suburb is significant, especially auto ownership (which explains 38.3 percent of the total gap, calculated by $-0.0418/-0.109$) and the percent Black in the neighborhood (27.2 percent of the total gap, calculated by $-0.0297/-0.109$). In Atlanta, around 59.3 percent of employment gaps come from household characteristics (especially auto ownership and marital status), and neighborhood characteristics explain around 16.9 percent. In total, 12.5 percent of the employment gap in the city and the suburb are unobserved in the analysis. This may be attributed to housing location choices or other neighborhood effects that are not captured by the share of Black populations and job accessibility. In Dallas, 62.7 percent of the employment gap is attributable to the difference in household characteristics, and individual characteristics explain around 35.1 percent. However, an unexplained component is the largest among the three metropolitan areas, around 16.8 percent of the differences are unobserved characteristics that affect the employment gap in the city and the suburb.

The decomposition of the log income model shows that the difference in earnings in the city and the suburb is most significant in Atlanta, followed by Dallas and Chicago. The portions explained by the differences in characteristics account for 97 percent in Atlanta and 130.7 percent in Chicago, suggesting that the model can explain the differences in earnings in the two metropolitan areas. The detailed decomposition shows that in both Atlanta and Chicago. Auto ownership explains around 42.6 percent ($-0.0829/-0.1948$) and 45.4 percent ($-0.1024/-0.2257$) of the differences in income, respectively. This implies that around half of the mean differences in income (that is, an income gap of USD 3413) among the city residents and suburban residents are attributable to the differences in auto ownership, in which individuals without access to auto in the household have lower incomes. In Chicago, consistent with the employment model, the characteristic differences explain the income gap beyond the actual income gap, suggesting that the income gap would increase if the city residents had the characteristics of the suburban residents.

Table 4. Decomposition of the differences in employment and log income by the residence in the city and the suburb.

	Employment Model						**Log Income Model**					
	Atlanta		**Chicago**		**Dallas**		**Atlanta**		**Chicago**		**Dallas**	
		(%)		(%)		(%)		(%)		(%)		(%)
City	81.80%		77.50%		89.00%		9.99		10.06		10.12	
Suburb	89.50%		85.30%		91.70%		10.19		10.24		10.30	
Raw Difference	−7.70%		−7.80%		−2.70%		−0.20		−0.17		−0.18	
Explained Component	−0.068	88.5%	−0.109	139.9%	−0.023	83.2%	−0.19	97.0%	−0.23	130.7%	−0.09	52.7%
Individual characteristics	−0.0163	23.8%	−0.017	15.6%	−0.008	35.1%	−0.0809	41.5%	−0.0508	22.5%	−0.0518	54.5%
Age	−0.0184		−0.0179		−0.0036		−0.1783		−0.1302		−0.0144	
	(0.0041)		(0.0032)		(0.0026)		(0.0307)		(0.0208)		(0.0268)	
Age^2	0.0134		0.0108		0.0015		0.1450		0.1122		−0.0020	
	(0.0036)		(0.0029)		(0.0020)		(0.0266)		(0.0183)		(0.0233)	
Hispanic	−0.0001		−0.0012		−0.0003		0.0002		0.0009		0.0000	
	(0.0003)		(0.0006)		(0.0002)		(0.0003)		(0.0007)		(0.0000)	
Male	0.00019		0.0018		(3.92×10^{-5})		−0.0035		−0.0044		−0.0012	
	(0.0001)		(0.0003)		(0.0000)		(0.0017)		(0.0012)		(0.0013)	
Highschool graduate	0.0046		0.0032		0.00152		0.0096		0.0061		0.0142	
	(0.0010)		(0.0006)		(0.0006)		(0.0031)		(0.0022)		(0.0037)	
College graduate	−0.0160		−0.0137		−0.0072		−0.0539		−0.0352		−0.0485	
	(0.0019)		(0.0012)		(0.0012)		(0.0078)		(0.0052)		(0.0073)	
Household characteristics	−0.0405	59.3%	−0.05529	50.7%	−0.01429	62.7%	−0.1207	62.0%	−0.1279	56.7%	−0.0488	51.4%
Auto availability	−0.0255		−0.0418		−0.0078		−0.0829		−0.1024		−0.0259	
	(0.0026)		(0.0022)		(0.0010)		(0.0097)		(0.0089)		(0.0039)	
Married with spouse	−0.0152		−0.0132		−0.0064		−0.0368		−0.0249		−0.0221	
	(0.0017)		(0.0013)		(0.0010)		(0.0049)		(0.0047)		(0.0034)	
Own child under age 5	0.00021		−0.0003		−0.0002		−0.0010		−0.0006		−0.0008	
	(0.0002)		(0.0001)		(0.0001)		(0.0007)		(0.0004)		(0.0006)	
Neighborhood characteristics	−0.0116	16.9%	−0.0368	33.7%	−0.00049	2.1%	0.0068	−3.5%	−0.0471	20.8%	0.0056	−5.9%
Black percentage	−0.01198		−0.0297		−0.0007		−0.0186		−0.0264		−0.0006	
	(0.0018)		(0.0028)		(0.0007)		(0.0061)		(0.0117)		(0.0022)	
Job accessibility	0.0004		−0.0071		0.0002		0.0253		−0.0207		0.0062	
	(0.0030)		(0.0017)		(0.0007)		(0.0099)		(0.0059)		(0.0025)	

Further, the neighborhood characteristics explained around 20.8 percent of the income gap—The differences in the share of Black populations and job accessibility in the city and the suburb explain 20.8 percent of the income difference in Chicago. In Dallas, the differences in characteristics only explain about half of the income gap (USD 6859) in the city and the suburb. Around half of the income differences are unobserved in the model. This suggests that compared to the employment model in Dallas, the individual, household, and neighborhood characteristics in the log income regression model only explain half of the income gap.

5. Discussion

The role of neighborhood job accessibility in the labor market outcomes of Black individuals is examined for metropolitan areas with different spatial patterns of mismatch. Different associations between job accessibility and labor market outcomes are examined by the residence in the city and the suburb, auto ownership, and neighborhood share of Black populations. The purpose of this research is to identify how job accessibility affects differ by the location of residence, as well as whether there is an interaction effect between the neighborhood share of Black populations and job accessibility. The research findings support the spatial mismatch hypothesis, in which neighborhood job accessibility affects the probability of employment and earnings. Labor market outcomes were closely associated with job accessibility, especially among Black individuals who do not have access to automobiles, suggesting that these individuals are likely to be most dependent on neighborhood characteristics. As for individuals with access to automobiles, neighborhood job accessibility was negatively associated with employment outcomes, suggesting that these individuals may have self-selected into neighborhoods with lower job accessibility but other desirable neighborhood characteristics.

In addition, the findings highlight varying levels of job availability in the city and the suburb by the proportion of Black residents in the neighborhood. In all metropolitan areas, job accessibility was lowest in neighborhoods with a high proportion of Black populations. This is consistent with other studies that found the level of job accessibility within the inner city varies considerably by the neighborhood characteristics [8,41]. Chicago, which represents a traditional spatial pattern of mismatch, job accessibility is lowest in the inner city, where the Black population remains disproportionately segregated. In these areas, an increase in job accessibility has a higher marginal effect on employment in predominantly Black neighborhoods (with more than 60 percent of the population is Black). In metropolitan areas where large shares of Black populations have moved into the suburbs, job accessibility in neighborhoods with low shares of Black populations is positively associated with Black employment. However, accessibility in highly segregated neighborhoods negatively affects employment outcomes. This suggests that the neighborhood shares of Black populations have more significant associations with Black employment than job accessibility in Atlanta.

The results of the income model are consistent with the employment model results. In all three metropolitan areas, job accessibility in the inner city is positively associated with income, suggesting that living in neighborhoods with better access to jobs increases their earned income. However, in the suburbs, job accessibility is negatively associated with earnings, indicating that those with higher incomes live in areas with less job accessibility. This may result from residential location preferences, in which individuals choose to live in areas with neighborhood attributes other than job accessibility.

The results of the Blinder-Oaxaca decomposition show that much of the differences in the labor market outcomes among Black individuals living in the city and the suburbs can be attributable to the differences in the auto ownership and the neighborhood share of Black populations. The findings suggest that much of the variation in the impact of job accessibility on labor market outcomes is associated with spatial patterns of mismatch of metropolitan areas. This is consistent with the study that suggests that in metropolitan areas with smaller spatial separation between workers and jobs, higher job accessibility may not influence employment outcomes. However, higher job accessibility may result in higher household income levels as households may have more job options to choose from [52]. In Chicago, where the spatial pattern of mismatch is most evident, the majority of the Black population is concentrated in the city, and an increase in job accessibility is positively associated with employment and earnings. However, the effect of job accessibility on employment is less evident in the suburbs, where individuals with higher earnings tend to live in neighborhoods with lower job accessibility. In Atlanta, where much of the Black population has suburbanized, living in a neighborhood with higher job accessibility is positively associated with earnings. However, living in neighborhoods with high shares of Black populations offsets the effect of job accessibility. Living in a low Black share neighborhood has higher returns on the labor market outcomes of Black individuals than the neighborhood job accessibility.

Overall, the study findings demonstrate that job accessibility continues to play a critical role in the labor market outcome among the Black population, especially in predominantly Black neighborhoods. At the same time, the impact of job accessibility on labor market outcomes varies by the metropolitan spatial pattern of mismatch. This study moves away from a discussion of whether or not job accessibility affects labor market outcomes, to a discussion of how its impact varies depending on the spatial structure of a metropolitan area, the pattern of residential segregation and the distribution of employment opportunities. In Atlanta, where the neighborhood share of Black populations is higher in the suburbs, residence in the inner city and living in a neighborhood with a lower share of the Black population are positively associated with Black employment and earnings. In Chicago, where the spatial pattern of mismatch follows a traditional inner city Black–suburban job structure, job accessibility continues to play as the strong predictor for Black labor market outcomes, especially in the inner city where the share of the Black population is highest. In all metropolitan areas, job accessibility negatively affected labor market outcomes for households with auto ownership, suggesting a reverse causality between auto ownership and neighborhood job accessibility. This also corresponds with the findings of scholars arguing in favor of modal mismatch, whereby workers with auto ownership can overcome spatial separation and, as a result, have an improved chance of finding a job and have higher earnings [8,9]. The findings also suggest that the re-segregation of the Black population in the suburbs has shifted the geography of disadvantage into the suburbs. Discussions on spatial mismatch and job accessibility need to be carefully examined in metropolitan areas with different spatial structures.

This research is not without its limitations. First, the estimates are based on the microdata sample data that uses PUMA as the geographic unit. Although the use of microdata can identify characteristics of individuals and households that are not observed in aggregated data, neighborhood characteristics at the PUMA level limit the geographic precision. Second, this research does not control the endogeneity problem, and results should be considered in consideration of this issue. The findings indicate a negative relationship between job accessibility and labor market outcomes in the suburbs, which may result from individuals self-selecting into their preferred residences. A randomized controlled experiment, a structural equation model, or spatial modeling could be used in the future to address this issue. Lastly, the model fit for the employment and income model is relatively low. This suggests that there are other variables not observed in the current research that may affect labor market outcomes, such as social capital or racial discrimination.

Funding: This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (2022R1C1C2012727).

Data Availability Statement: Not applicable.

Conflicts of Interest: The author declares no conflict of interest. The sponsors played no role in the design of the study, collection, analysis, and interpretation of data, writing the manuscript, or deciding whether to publish the results.

References

1. Kain, J.F. Housing segregation, negro employment, and metropolitan decentralization. *Q. J. Econ.* **1968**, *82*, 175–197. [CrossRef]
2. Farley, J.E. Disproportionate Black and Hispanic unemployment in US metropolitan areas: The roles of racial inequality, segregation and discrimination in male joblessness. *Am. J. Econ. Sociol.* **1987**, *46*, 129–150. [CrossRef]
3. Ellwood, D.T. The spatial mismatch hypothesis: Are there teenage jobs missing in the ghetto? In *The Black Youth Employment Crisis*; University of Chicago Press: Chicago, IL, USA, 1986; pp. 147–190.
4. Stoll, M.A. Spatial mismatch, discrimination, and male youth employment in the Washington, DC area: Implications for residential mobility policies. *J. Policy Anal. Manag.* **1999**, *18*, 77–98. [CrossRef]
5. Hellerstein, J.K.; Neumark, D.; McInerney, M. Spatial mismatch or racial mismatch? *J. Urban Econ.* **2008**, *64*, 464–479. [CrossRef] [PubMed]
6. Houston, D. Employability, skills mismatch and spatial mismatch in metropolitan labour markets. *Urban Stud.* **2005**, *42*, 221–243. [CrossRef]
7. Stoll, M.A. Geographical skills mismatch, job search and race. *Urban Stud.* **2005**, *42*, 695–717. [CrossRef]
8. Grengs, J. Job accessibility and the modal mismatch in Detroit. *J. Transp. Geogr.* **2010**, *18*, 42–54. [CrossRef]
9. Ong, P.M.; Miller, D. Spatial and transportation mismatch in Los Angeles. *J. Plan. Educ. Res.* **2005**, *25*, 43–56. [CrossRef]
10. Chapple, K. Overcoming mismatch: Beyond dispersal, mobility, and development strategies. *J. Am. Plan. Assoc.* **2006**, *72*, 322–336. [CrossRef]
11. Raphael, S. The spatial mismatch hypothesis and black youth joblessness: Evidence from the San Francisco Bay Area. *J. Urban Econ.* **1998**, *43*, 79–111. [CrossRef]
12. Parks, V. Access to work: The effects of spatial and social accessibility on unemployment for native-born Black and immigrant women in Los Angeles. *Econ. Geogr.* **2004**, *80*, 141–172. [CrossRef]
13. Jin, J.; Paulsen, K. Does accessibility matter? Understanding the effect of job accessibility on labour market outcomes. *Urban Stud.* **2018**, *55*, 91–115. [CrossRef]
14. Galster, G.C. Black suburbanization: Has it changed the relative location of races? *Urban Aff. Q.* **1991**, *26*, 621–628. [CrossRef]
15. Lee, B. "Edge" or "edgeless" cities? Urban spatial structure in US metropolitan areas, 1980 to 2000. *J. Reg. Sci.* **2007**, *47*, 479–515. [CrossRef]
16. Delmelle, E.C. Differentiating pathways of neighborhood change in 50 US metropolitan areas. *Environ. Plan. A* **2017**, *49*, 2402–2424. [CrossRef]
17. Massey, D.S.; Tannen, J. Suburbanization and segregation in the United States: 1970–2010. *Ethn. Racial Stud.* **2018**, *41*, 1594–1611. [CrossRef]
18. Ihlanfeldt, K.R. *A Primer on Spatial Mismatch within Urban Labor Markets*; Blackwell Publishing: Hoboken, NJ, USA, 2006.
19. Ihlanfeldt, K.R.; Sjoquist, D.L. The Effect of Job Access on Black and White Youth Employment: A Cross-sectional Analysis. *Urban Stud.* **1991**, *28*, 255–265. [CrossRef]
20. Blumenberg, E.; Manville, M. Beyond the spatial mismatch: Welfare recipients and transportation policy. *J. Plan. Lit.* **2004**, *19*, 182–205. [CrossRef]
21. Aliprantis, D.; Richter, F.G.-C. Evidence of neighborhood effects from Moving to Opportunity: LATEs of neighborhood quality. *Rev. Econ. Stat.* **2020**, *102*, 633–647. [CrossRef]
22. Lens, M.C.; Gabbe, C.J. Employment proximity and outcomes for Moving to Opportunity families. *J. Urban Aff.* **2017**, *39*, 547–562. [CrossRef]
23. Baum-Snow, N. Did highways cause suburbanization? *Q. J. Econ.* **2007**, *122*, 775–805. [CrossRef]
24. Miller, C. *When Work Moves: Job Suburbanization and Black Employment*; National Bureau of Economic Research: Cambridge, MA, USA, 2018.
25. Galster, G.C.; Andersson, R.; Musterd, S. Who Is Affected by Neighbourhood Income Mix? Gender, Age, Family, Employment and Income Differences. *Urban Stud.* **2010**, *47*, 2915–2944. [CrossRef]
26. Galster, G.C. Housing Discrimination and Urban Poverty of African-Americans. *J. Hous. Res.* **1991**, *2*, 87–122.
27. Ihlanfeldt, K.R. The geography of economic and social opportunity in metropolitan areas. In *Governance and Opportunity in Metropolitan America*; National Academies Press: Washington, DC, USA, 1999; pp. 213–252.
28. Weinberg, B.A. Testing the spatial mismatch hypothesis using inter-city variations in industrial composition. *Reg. Sci. Urban Econ.* **2002**, *34*, 505–532. [CrossRef]
29. Gobillon, L.; Selod, H.; Zenou, Y. The Mechanisms of Spatial Mismatch. *Urban Stud.* **2007**, *44*, 2401–2427. [CrossRef]
30. Bania, N.; Leete, L.; Coulton, C. Job Access, Employment and Earnings: Outcomes for Welfare Leavers in a US Urban Labour Market. *Urban Stud.* **2008**, *45*, 2179–2202. [CrossRef]
31. Bunel, M.; Tovar, E. Key Issues in Local Job Accessibility Measurement: Different Models Mean Different Results. *Urban Stud.* **2014**, *51*, 1322–1338. [CrossRef]
32. Kain, J.F. Black suburbanization in the eighties: A new beginning or a false hope. In *American Domestic Priorities*; University of California Press: Berkeley, CA, USA, 1985; pp. 253–284.
33. Gobillon, L.; Selod, H. *The Effect of Segregation and Spatial Mismatch on Unemployment: Evidence from France*; Center for Research in Economics and Statistics: Palaiseau, France, 2007.
34. Zenou, Y. Spatial versus social mismatch. *J. Urban Econ.* **2013**, *74*, 113–132. [CrossRef]

35. Cutler, D.M.; Glaeser, E.L. Are ghettos good or bad? *Q. J. Econ.* **1997**, *112*, 827–872. [CrossRef]
36. Hu, L. Job accessibility of the poor in Los Angeles: Has suburbanization affected spatial mismatch? *J. Am. Plan. Assoc.* **2015**, *81*, 30–45. [CrossRef]
37. Joassart-Marcelli, P. The Spatial Determinants Of Wage Inequality: Evidence From Recent Latina Immigrants In Southern California. *Fem. Econ.* **2009**, *15*, 33–72. [CrossRef]
38. Liu, C.Y. Ethnic enclave residence, employment, and commuting of Latino workers. *J. Policy Anal. Manag.* **2009**, *28*, 600–625. [CrossRef]
39. Painter, G.; Liu, C.Y.; Zhuang, D. Immigrants and the spatial mismatch hypothesis: Employment outcomes among immigrant youth in Los Angeles. *Urban Stud.* **2007**, *44*, 2627–2649. [CrossRef]
40. Essletzbichler, J. The top 1% in US metropolitan areas. *Appl. Geogr.* **2015**, *61*, 35–46. [CrossRef]
41. Shen, Q. Location Characteristics of Inner-City Neighborhoods and Employment Accessibility of Low-Wage Workers. *Environ. Plan. B Plan. Des.* **1998**, *25*, 345–365. [CrossRef]
42. Andersson, F.; Haltiwanger, J.C.; Kutzbach, M.J.; Pollakowski, H.O.; Weinberg, D.H. Job Displacement and the Duration of Joblessness: The Role of Spatial Mismatch. *Rev. Econ. Stat.* **2018**, *100*, 203–218. [CrossRef]
43. Vickerman, R.W. Accessibility, attraction, and potential: A review of some concepts and their use in determining mobility. *Environ. Plan. A* **1974**, *6*, 675–691. [CrossRef]
44. Hansen, W.G. How accessibility shapes land use. *J. Am. Inst. Plan.* **1959**, *25*, 73–76. [CrossRef]
45. Darity, W., Jr.; Guilkey, D.K.; Winfrey, W. Explaining Differences in Economic Performance Among Racial and Ethnic Groups in the USA. *Am. J. Econ. Sociol.* **1996**, *55*, 411–425. [CrossRef]
46. Neumark, D. Employers' Discriminatory Behavior and the Estimation of Wage Discrimination. *J. Hum. Resour.* **1988**, *23*, 279–295. [CrossRef]
47. Sen, B. Using the oaxaca–blinder decomposition as an empirical tool to analyze racial disparities in obesity. *Obesity* **2014**, *22*, 1750–1755. [CrossRef] [PubMed]
48. Rahimi, E.; Hashemi Nazari, S.S. A detailed explanation and graphical representation of the Blinder-Oaxaca decomposition method with its application in health inequalities. *Emerg. Themes Epidemiol.* **2021**, *18*, 12. [CrossRef] [PubMed]
49. Jann, B. OAXACA: Stata module to compute the Blinder-Oaxaca decomposition. In *Statistical Software Components (Statistical Software Components S456936)*; Boston College Department of Economics: Chestnut Hill, MA, USA, 2008.
50. McFadden, D. *Quantitative Methods for Analyzing Travel Behaviour of Individuals: Some Recent Developments. Cowles Foundation Discussion Papers, 474*; Cowles Foundation for Research in Economics: New Haven, CT, USA, 1977.
51. Yun, M.S. Decomposing differences in the first moment. *Econ. Lett.* **2004**, *82*, 275–280. [CrossRef]
52. Delmelle, E.; Nilsson, I.; Adu, P. Poverty suburbanization, job accessibility, and employment outcomes. *Soc. Incl.* **2021**, *9*, 166. [CrossRef]