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Spatial Choice of Residence and Workplace and Minority Economic Welfare*

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1. Introduction

Transportation improvement, changes in production technology, spread of public services and a huge supply of single-family housing throughout the suburban rings after World War II have been the important factors of industrial and residential suburbanization(Fainstein and Fainstein, 1986). Although suburbanization was the growth mechanism for the U.S. economy since World War II, it also provided a base for the subsequent decline of central cities. The economic restructuring process since early 1970s also accelerated the deterioration of central cities and manufacturing communities, especially in the old manufacturing region, and seriously affected both urban residents' daily lives and communities through firm management strategies such as relocation and plant closure(Clark, 1989).

In the context of the deterioration of the central city economy, many social scientists have been concerned about racial segregation and employment problems of central city minorities. Many spatial mismatch studies have investigated the spatial effect of the suburbanization of blue-collar and service jobs on the economic welfare and employment opportunities of central city minorities(see Holzer, 1991 and Kain, 1992 for extensive review). Many researchers have argued that there are serious urban problems such as housing market discrimination against non-whites and lower employment prospects of central city minorities. Since Kain's paper (1968) published in Quarterly Journal of Economics, a number of studies(see Wilson, 1987 ; Ihlanfeldt, 1988 ; Kasarda, 1989 ; and Ihlanfeldt and Sjoquist, 1990a, 1990b, and 1991 for most recent studies) have supported Kain's original spatial mismatch hypothesis that residential segregation has limited employment opportunities and earnings potentials for blacks, especially blacks in central city ghettos. However, there have been some critiques about spatial mismatch hypothesis. Critics such as Harrison(1972) and Ellwood(1986) have argued that a key factor of racial inequality in earnings and employment opportunities is not space, but labor market discrmination against blacks throughout the entire metropolitan areas regardless of the central city and the suburbs.

As Ihlanfeldt and Sjoquist(1989 and 1990a) note, however, it is not surprising that the empirical tests for the spatial mismatch hypothesis have provided controversial and divergent results, partly because of differences in data(aggregate vs. individual), and partly because of differ-

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ences in comparison(workplace vs. residence). One-sided comparison by either residence or workplace tends to overlook the fact that workplace choice is to a high extent conditioned on a given residence for a certain group of workers or that both workplace and residence tend to be simultaneously chosen. While some past analyses use either place of work or place of residence as a spatial unit, the preferable approach would be to account for both location of residence and of work. Then differences in employment opportunities and earnings among demographic groups which arose from spatial barriers to either choice of work location or residence location or their joint choice could be examined. This suggests that earnings functions should be estimated so that they treat both workplace and residence as endogeneous variables.

Our model is intended to extend the traditional spatial mismatch approach, [which usually dichotomizes workers into central city and suburban categories based on either place of residence or place of employment.] In our analysis, we divide workers into four groups defined by the central city/suburban split of both residence and workplace. This allows us to systematically analyze earnings differentials within race and gender among these four categories and between races and genders within each of these categories. One difficulty with focussing on ordinary least squares earnings regressions for each of the four categories is that if there are barriers to location selection which differ by race or gender, the unobservable characteristics of individuals in each of the four choices will reflect these differences in barriers. For example, if blacks face costly barriers in moving to the suburbs, only the most successful blacks will live in the suburbs. Unless this non-random assignment of both residence and workplace is accounted for, the earnings regressions will not be consistently estimated.

Therefore, in addition to examining ordinary least squares earnings regressions for each of the four categories, a multinomial selection model is estimated. The model first estimates the probability of being in each of the four categories, conditional on demographic characteristics, educational attainment, and occupation. These probabilities are used to "correct" the coefficients of earnings regressions for the non-random assignment. The full measure of differences between races or between genders within location groups accounts for both differences in the earnings functions and differences in the non-random assignment of residence and workplace.

On the basis of the 1980 Public Use Microdata Sample(PUMS) of the Pittsburgh SMSA, our estimation results of a multinomial logit sample selection model provide a variety of evidence of spatial mismatch for central city minorities, especially for black males. Regardless where they work, suburban non-white males have significantly higher earnings than those residing in the central city. One interesting finding is that even after controlling for personal attributes, non-white reverse commuters do not earn more than non-white central city local workers, whereas white reverse commuters have significantly higher earnings than white central city local workers. In addition, non-white suburban local workers have still higher earnings than both non-white central city local workers and reverse commuters. We also find that the degree of labor market discrimination against non-whites is higher for central city residents, especially for reverse commuters, than for suburban residents. In contrast to the findings for non-white males, for non-white females, we do not find any spatial mismatch or discrimination against non-whites. However, it is found that female workers, regardless of race, are seriously discriminated over the entire labor market.

The present paper is organized in the following manner : In section 2, a multinomial sample selection model is introduced, and then the allocation of residence and workplace and its effect on wage determination are analyzed. In section 3, earnings differentials among worker groups with different location assignment are investigated, using a new decomposing method. Finally, section 4 summarizes principal findings and provides policy implications.

2. Multinomial Logit Sample Selection Model

Urban economists find that suburban resident workers have relatively higher earnings than those of central city counterparts. This may be explained by the fact that workers with more positive earnings characteristics(e. g. better human capital) tend to select residence in the suburbs. However, suburban residents can be categorized into two groups : commuters to the central city and suburban local workers who both live and work in the suburbs. In a same way, central city resident workers are also categorized into two groups : reverse commuters and central city local workers. Even though the earnings of suburban resident workers are still higher than those of central city counterparts after controlling for personal attributes, it does not provide evidence that suburban jobs pay better because we cannot figure out whether higher earnings are caused by higher wages of suburban jobs or by the larger proportion of higher earning commuters to the central city.

For example, differences in earnings between central city non-whites and suburban non-whites would be overestimated if we compare those by residence only, and underestimated if we compare those by workplace only. This may be caused by the fact that the effect of suburban high income non-whites commuting to the central city may be ignored by one-sided comparison. Therefore, one-sided comparison would cause a selection bias on the estimates of earnings regressions because of unobservable heterogeneity among workers related to the choices of residence and workplace.

Thus, we develop a joint model of residence and workplace assignment and wage determination. This framework allows us not only to control for unobserved heterogeneity among workers, but also to explain explicitly differences in the wage setting mechanism for worker groups with the various combination of residence and workplace.[1)]

Lee(1983) describes an estimation method for the sample selection model with multiple choice selection equations. At the first stage, a multinomial logit model for the category choice of residence and workplace is estimated by the maximum likelihood method, and then MNL selectivity variables. λ_j, are calculated for each of joint categories. At the second stage, the wage equations including a MNL selectivity variable are estimated by the ordinary least square method :

$$P_j = \exp(\xi_j Z) \ / \ \sum_{j=0}^{J} \exp(\xi_j Z) \qquad (1)$$

where

- P_j : the probability of choosing a joint category of workplace and residence
- Z : the individual characteristic vector; and
- ξ_j : the coefficient vector for a chosen category j.

Based on the probability of choosing a joint category of residence and workplace, wage equations are established as the following reduced form such as

$$\begin{aligned}(\ln W_j \mid P_j) &= \psi_j X_j + \theta_j \phi(H_j(P_j)) / \\ &\quad \Phi(H_j(P_j)) + \eta_j \\ &= \psi_j X_j + \theta_j \lambda_j + \eta_j \qquad (2)\end{aligned}$$

where

$\ln W_j$: the log weekly wage of an individual in an alternative j ;

X : the individual characteristic vector ;

ψ : the coefficient vector of the individual characteristic variables ;

θ : the estimated parameter of the MNL selectivity variable ;

and where the function H_j is defined as $\Phi^{-1}(\cdot)$, that is, the inverse standard normal cumulative density function evaluated at P_j(see Lee, 1983 and Greene, 1989, pp280~283), hence $\Phi(H_j(P)_J)$ is equal to P_j;the functions ϕ and Φ are the probability density function(pdf) and the cumulative density function(cdf) of the standard normal distribution ; and η_j denotes the random disturbances, which are assumed to be independent of X and independently and identically distributed as type 1 extreme-value.

Because $E(\eta_j \mid P_j, X_j) = 0$, the parameters of the equation (2) are estimated consistently by OLS regressions of log weekly wage $\ln W_j$ on individual characteristic variables X_j and a selectivity variable λ_j in the relevant subsamples. A formal test for presence of selectivity involves the simple t-test of the null hypothesis, $\theta_j = 0$. The positive(negative) signs of θ_j will indicate that the estimated earnings of workers in the category j are higher(lower) than those of randomly drawn workers with identical characteristics.

3. Empirical Specification and Estimation Results

Our MNL selection model first estimates the probability of choosing one of four categories from the combination of residence and workplace based on personal attributes and household characteritics: 1) both residence and workplace in the central city(CC : central city local workers); 2) central city residence and suburban workplace(CS : reverse commuters); 3) suburban residence and central city workplace(SC : commuters to the central city); 4) both residence and workplace in the suburbs(SS : suburban local workers). Then earnings equations, conditioned on the location selection, are estimated by the Heckman-type two stage OLS method(see Heckman, 1979 and Lee, 1983). The basic explanatory variables in wage equations are human capital components and occupation dummy variables. A selectivity variable, which is estimated from the probability of choosing one of the four categories, is also included in a relevant wage equation.[2)]

The dependent variable in each of wage equations is the natural logarithm of weekly earnings. For the purpose of examining spatial differences of the wage setting mechanism in the private sector, public, self-employed, and farm workers have been excluded in our sample. Table 1 reports varible definition and sample statistics.

The conceptual framework of our MNL selection model is as follows : If residence and workplace are randomly allocated within the entire metropolitan area, there will not exist spatial variations in earnings by either residence or workplace and even by race. However, the non-random assignment of residence and workplace may affect the spatial earnings distribution partly because of spatial differences in the distribution of personal attributes and partly because of employer discrimination against locally bound disadvantaged workers. Workers possessing positive earnings characteristics tend to choose suburban residence and hold high-paying occupations in either the central city or the suburbs. If it is the case, the selectivity variables are expected to have positive signs in wage equations for suburban residents, indicating that suburban resident workers will have higher earnings than randomly drawn workers with identical characteristics. This implies that higher earnings of suburban residents relative to central city residents may be caused by both higher personal attributes and by the positive selection effect. However, whether reverse commuters residing in the central city earn more than central city local workers or suburban local workers with identical characteristics is really an empirical matter.

Especially for central city minorities, earnings comparison between reverse commuters and central city local workers will provide an important policy implication given the steady dispersal of relatively high-paying manufacturing jobs from the central city. Our MNL selection model will provide an answer about whether the non-random assignment of residence and workplace will affect worker's earnings potentials. Furthermore, our model will show how much the selection effect exerts influence on earnings differences among worker groups with the different combinations of residence and workplace, from decomposing such earnings differentials into a portion by attributes, a portion by coefficients, and a portion by selection.

Table 1. Variable Definition and Sample Statistic

Variable	Definition		Sample Mean(std)	
Binary	1	0	Male	Female
Personal Characteristics				
AGE1	if aged 16 − 19(reference category)			
AGE2	if aged 20 − 34	Otherwise	0.410(0.49)	0.439(0.50)
AGE3	if aged 35 − 54	Otherwise	0.388(0.49)	0.345(0.48)
AGE4	if aged 55 and over	Otherwise	0.153(0.36)	0.142(0.35)
DIPLOMA	if finished highschool	Otherwise	0.808(0.39)	0.849(0.36)
PROF	if professional, managerial, or technical occupations	Otherwsie	0.358(0.48)	0.291(0.45)
CRAFT	if production-related	Otherwsie	0.465(0.50)	0.084(0.28)
SERVICE	if service or sales	Otherwsie	0.108(0.31)	0.293(0.46)
CLERK	if clerical or adm. support	Otherwsie	0.069(0.25)	0.332(0.47)
BLACK	if non-whites	Otherwise	0.050(0.22)	0.063(0.24)
Household Characteristics				
CHILD	if presence of child(ren)	Otherwise	0.476(0.50)	0.369(0.48)
FEHEAD	if female-headed household	Otherwise	0.062(0.24)	0.336(0.47)
NOFAMILY	if non-family household	Otherwise	0.095(0.29)	0.167(0.37)
Continuous			Male	Female
Personal Characteristics				
AGE	age of a worker		39.125 (13.77)	37.410 (14.46)
AGES	age squared		1,720.477(1,142.95)	1,605.639(1,173.15)
GRADE	highest grade attended		13.015 (2.77)	12.761 (2.30)
GRADES	grade squared		177.044 (74.98)	168.115 (61.02)
HOURS	weekly working hours		41.015 (9.57)	34.230 (10.94)
Household Characteristics				
HGRADE	grade of a household head		12.824 (2.93)	12.597 (2.87)
NETHINC	household income net worker's income(unit : $ 1,000)		9.098 (11.78)	17.174 (13.86)

Dummy Interaction Variables : (e. g. BAGE means BLACK * AGE)
Variables starting with "B" indicates Black Dummy Interaction Terms

Table 2 reports MNL estimates of the assignment of residence and workplace.[3] The estimation result shows that worker's residence and workplace are not randomly assigned. This non-random assignment of residence and workplace is significantly associated with worker's educational attainment, occupation, and family status.

Table 2. Multinomial Logit Estimates of Residence and Workplace Choice

Variable	Male			Female		
	CS	SC	SS	CS	SC	SS
CONSTANT	−0.5623	1.1197	3.5356	−3.3801	1.2447	2.1554
	(0.823)	(2.802)**	(9.778)**	(3.981)**	(3.053)**	(5.822)**
AGE2	0.2766	−0.1466	−0.6868	0.2041	0.2780	0.0205
	(0.692)	(0.618)	(3.426)**	(0.509)	(1.333)	(0.113)
AGE3	0.2603	0.4918	−0.2996	0.0611	0.2679	0.1896
	(0.641)	(2.052)**	(1.472)	(0.151)	(1.284)	(1.051)
AGE4	0.4153	0.1330	−0.5941	0.0073	0.3011	0.3248
	(0.963)	(0.518)	(2.699)**	(0.016)	(1.295)	(1.608)
GRADE	−0.0518	−0.0854	−0.1348	0.0516	−0.0992	−0.0747
	(1.008)	(2.658)**	(4.648)**	(0.844)	(3.312)	(2.717)**
DIPLOMA	0.3684	0.8418	0.9944	0.7187	0.6305	0.5111
	(1.587)	(5.836)**	(7.562)**	(1.885)*	(3.668)**	(3.498)**
PROF	0.3266	0.7128	0.5218	0.0775	−0.0810	0.2163
	(1.103)	(4.222)**	(3.347)**	(0.272)	(0.629)	(1.775)*
CRAFT	0.5528	0.4247	0.8448	0.3946	−0.4569	0.5531
	(1.969)**	(2.579)**	(5.626)**	(0.951)	(2.213)**	(3.046)**
SERVICE	−0.2036	0.0049	0.2819	0.4473	−0.9066	0.4039
	(0.579)	(0.025)	(1.611)	(1.663)*	(6.628)**	(3.400)**
BLACK	−0.9780	−0.6994	−2.1282	−0.0091	−1.3055	−1.9557
	(1.118)	(1.396)	(4.293)**	(0.011)	(2.564)**	(4.595)**
BDIPLOMA	0.1063	−0.6539	−0.2855	−0.9868	−0.2985	0.5111
	(0.234)	(1.921)*	(1.023)	(1.470)	(0.636)	(3.498)**
BPROF	0.4566	−0.3564	0.7899	0.7821	0.2641	0.3801
	(0.502)	(0.706)	(1.570)	(1.125)	(0.812)	(1.082)
BCRAFT	0.7352	−0.3202	0.6621	1.0965	0.5771	1.6802
	(0.870)	(0.659)	(1.375)	(1.049)	(0.877)	(3.167)**
BSERVICE	0.3541	−0.9756	−0.0312	0.6526	0.2111	0.1964
	(0.391)	(1.811)*	(0.062)	(0.925)	(0.540)	(0.552)
HGRADE	−0.0518	0.0401	0.0153	−0.0399	0.0500	0.0099
	(1.228)	(1.479)	(0.635)	(0.959)	(2.416)**	(0.525)
CHILD	0.2339	0.0043	0.0410	0.3915	0.1022	0.4643
	(1.355)	(0.042)	(0.430)	(1.716)*	(0.915)	(4.536)**
FEHEAD	0.1392	−0.5049	−0.5887	0.1760	−0.2369	−0.6052
	(0.615)	(3.257)**	(4.314)**	(0.708)	(1.954)*	(5.454)**
NOFAMILY	0.2037	−1.0143	−0.8465	0.3290	−0.2284	−0.2050
	(0.968)	(7.351)**	(6.945)**	(1.147)	(1.631)	(1.599)
NETHINC	0.0004	−0.0128	−0.0102	0.0190	0.0079	0.0068
	(0.070)	(3.312)**	(2.949)**	(2.254)**	(1.805)*	(1.669)*
Log-Likelihood :		−8984.2			−6,272.6	
Sample Size :		10,325			7,061	
Goodness of Fit :		0.656			0.636	

Notes : Reference group is CC(workers who live and work in the central city) ;
* : significant at the 10 percent level ; and
** : significant at the 5 percent level.

The assignment of residence and workplace is also significantly different between races and between genders. This is due largely to residential segregation for blacks and household responsibilities for women. Additionally, employer discrimina-

Table 3. OLS Estimates of Wage Equations without selection

	Male				Female			
	CC	CS	SC	SS	CC	CS	SC	SS
CON-STANT	1.3233	2.5196	1.1091	1.4003	2.5570	1.3202	2.0809	2.4879
	(2.981)**	(3.010)**	(5.666)**	(10.888)**	(5.874)**	(0.759)	(8.206)**	(15.812)**
AGE	0.1213	0.1000	0.1040	0.1061	0.0569	0.0349	0.0382	0.0247
	(12.225)**	(5.581)**	(18.522)**	(30.628)**	(5.504)**	(1.413)	(6.007)**	(6.217)**
AGES	-0.013	-0.0011	-0.0010	-0.0011	-0.0006	-0.0004	-0.0004	-0.0002
	(10.736)**	(4.952)**	(16.160)**	(27.027)**	(5.123)**	(1.300)	(5.315)**	(4.826)**
GRADE	0.1188	-0.0407	0.1464	0.0876	-0.0346	0.2230	0.0740	-0.0118
	(2.185)**	(0.431)	(7.159)**	(5.813)**	(0.623)	(0.995)	(0.730)	(0.571)
GRADES	-0.0034	0.0032	-0.0041	-0.0020	0.0017	-0.0081	0.0007	0.0024
	(1.725)*	(0.894)	(5.055)**	(3.322)**	(0.837)	(1.075)	(0.534)	(2.922)**
HOURS	0.0122	0.0218	0.0136	0.0184	0.0336	0.0356	0.0365	0.0341
	(5.361)**	(3.750)**	(10.586)**	(24.199)**	(13.990)**	(8.017)**	(24.463)**	(40.211)**
PROF	0.3602	0.2427	0.3511	0.3539	0.5347	0.3304	0.4252	0.3317
	(4.044)**	(1.490)	(6.582)**	(11.553)**	(6.447)**	(2.177)	(8.579)**	(11.015)**
CRAFT	0.2535	0.2970	0.4098	0.4300	0.2270	0.0772	0.3337	0.3559
	(3.413)**	(2.097)**	(8.929)**	(17.277)**	(2.096)**	(0.391)	(4.834)**	(10.382)**
CLERK	0.1486	0.1732	0.1805	0.2232	0.3481	0.1766	0.3249	0.2416
	(1.482)	(0.857)	(2.948)**	(5.827)**	(4.898)**	(1.277)	(7.523)**	(9.352)**
BLACK	0.6849	-2.8963	0.9092	1.6070	-0.0196	-2.9499	-1.9268	-0.0702
	(0.773)	(1.394)	(1.018)	(2.691)**	(0.013)	(1.138)	(0.941)	(0.063)
BAGE	0.0316	-0.1054	-0.0028	-0.0133	0.0090	0.1302	0.0167	0.0638
	(1.354)	(1.520)	(0.081)	(0.887)	(0.394)	(1.628)	(0.448)	(2.802)**
BAGES	-0.0004	0.0014	0.0000	0.0002	0.0000	-0.0012	-0.0003	-0.0008
	(1.344)	(1.712)*	(0.042)	(1.209)	(0.115)	(1.199)	(0.564)	(2.956)**
BGRADE	-0.1907	0.0067	-0.1624	-0.2773	-0.1592	-0.0443	0.2078	-0.1689
	(1.585)	(0.036)	(2.155)**	(3.781)**	(0.725)	(0.128)	(0.791)	(1.114)
BGRADES	0.0064	0.0040	0.0049	0.0111	0.0086	0.0042	-0.0076	0.0065
	(1.435)	(0.535)	(1.643)	(3.957)**	(1.033)	(0.309)	(0.876)	(1.198)
BHOURS	-0.0014	0.0734	-0.0017	0.0026	0.0151	-0.0202	0.0069	-0.0061
	(0.288)	(4.677)**	(0.274)	(0.733)	(2.697)**	(1.459)	(1.046)	(1.447)
BPROF	0.0019	0.4898	0.2268	-0.1774	-0.6673	0.3903	-0.1512	0.0831
	(0.010)	(1.176)	(0.989)	(1.181)	(3.973)**	(1.017)	(0.786)	(0.542)
BCRAFT	-0.1108	0.6482	0.2572	-0.0390	-0.1287	1.5445	-0.1454	0.3813
	(0.768)	(2.183)**	(1.383)	(0.360)	(0.463)	(2.934)**	(0.513)	(2.520)**
BCLERK	0.1904	1.3003	0.2650	-0.1408	-0.1705	0.8300	-0.0197	-0.1078
	(0.930)	(2.124)**	(1.102)	(0.695)	(1.171)	(2.232)**	(0.115)	(0.691)
LAMBDA	-0.0156	-0.1333	0.6929	0.4258	0.0075	0.3812	0.4327	0.5003
	(0.042)	(0.188)	(2.477)**	(2.659)**	(0.034)	(0.822)	(2.878)**	(4.449)**
R-SQUARED	0.4105	0.4501	0.3925	0.4165	0.4449	0.5338	0.4175	0.4453
N	782	281	2503	6759	782	142	1704	4433
TEST	0.9032	5.1329**	2.0631**	2.9653**	3.1275**	2.5875**	1.1869	3.6917**

Note : The number in parenthesis indicates the absolute value of t-ratio ;
* : Significant at the 10 percent level ;
** : Significant at the 5 percent level ;
N : Sample size; and
TEST : Joint F-test of a null hypothesis that all the coefficients of black interaction terms are zero.

tion may also limit the workplace choice of blacks or women at the given residence. If workers were free to choose residence and workplace, they would choose a combination of residence and workplace, which provides maximum utility in terms of expected returns in each workplace, commuting costs, and housing amenities. However, if the choice of either residence or workplace were restricted for some groups of workers, employer's monopsonic power or discrimination over those workers may be possible. If this is the case for disadvantaged workers, the metropolitan labor market could not be a single, homogeneous labor market, at least for workers with restrained choice. Instead the labor market would be spatially segmented by the choice limitations of those workers, and to the extent of the degree of monopsonic power or employer discrimination, the earnings gap between workers with restrained choice and workers with free choice would become greater than otherwise might be.

Table 3 reports the OLS estimation results of wage equations with a selectivity variable.[4] All equations are highly significant and the personal attribute varibles are generally significant with the expected signs. From the F-test, the null hypothesis, that all the coefficients on black dummy interaction terms are zero, cannot be accepted at the 5 percent level for six of eight wage equations. This indicates that wages are usually differently determinated between whites and non-whites.

One interesting result is that the coefficients of selection variables(lambda's) are significantly positive at the 5 percent in wage equations for suburban resident workers(SC and SS) for both male and female. The magnitudes of coefficients on lambda's were unstable and varied with the slightly different specification of wage equations. However, the coefficients on lambda's for suburban resident workers (SC and SS) were always positive and significant for both male and female.

This implies that the estimated earnings of suburban resident workers are higher than those of randomly drawn workers with identical characteristics. Given that the majority of blacks live in the central city and the majority of whites live in the suburbs, this implies that black workers tend to earn less, at the average, than white workers with identical characteristics. This also implies that suburban resident black workers earn more than central city resident black workers with identical characteristics, even though they choose a same workplace either in the central city or in the suburbs.

4. Decomposition of Earnings Differentials between Worker Groups

1) A Decomposing Method for the Measure of Labor Market Differentials

Labor market differentials are often defined as the portion of the earnings gap unexplained by individual characteristics. As initially proposed by Blinder(1973) and applied recently by Price and Mills (1985), Goldin and Polachek(1987), Ihlanfeldt(1988), and Boston(1990), the difference in mean earnings between two groups can be decomposed into two portions : A portion by attribute differences (the former term of RHS in equation (3)) and another portion by different returns to those attributes(the latter term of RHS in equation (3)) as follows :

$$\overline{\ln W_i} - \overline{\ln W_j} = \beta_i(\overline{X}_i - \overline{X}_j) + (\beta_i - \beta_j)\overline{X}_j \quad (3)$$

where

$\overline{\ln W}$ indicates the natural log of predicted mean earnings;

$\overline{X}$ denotes a vector of mean personal attributes;

β represents a vector of the estimated coefficients of earnings regressions; subscripts i and j denote comparable categories.

In equation (3), the first term of RHS represents the difference in log mean earnings resulting from differences in attributes, and the second term of RHS is usually interpreted as the portion of the labor market differentials in earnings. However, equation (3) can be rewritten as follows :

$$\overline{\ln W_i} - \overline{\ln W_j} = \beta_j(\overline{X}_i - \overline{X}_j) + (\beta_i - \beta_j)\overline{X}_i \quad (4)$$

The left hand sides of equations (3) and (4) are exactly same, but two terms of the right hand side are different between equations (3) and (4). As Goldin and Polachek(1987) and Boston(1990) point out, this is due to the different reference earnings function, although two approaches are considered equally correct formulas. In order to correct this problem, Boston(1990) uses the simple mean of values yielded by the two approaches. Since the simple averaging method seems not to consider the sample distribution, however, we propose a weighted averaging method such as

$$\overline{\ln W_i} - \overline{\ln W_j} = \frac{(\beta_i N_j + \beta_j N_i)(\overline{X}_i - \overline{X}_j)}{N_i + N_j} + \frac{(\beta_i - \beta_j)(\overline{X}_j N_j + \overline{X}_i N_i)}{N_i + N_j} \quad (5)$$

In the second term of RHS in equation (5), the weighted mean attributes of two subsample, $(\overline{X}_j N_j + \overline{X}_i N_i)/(N_i + N_j)$, is equal to the overall sample mean attributes, $\overline{X_{i+j}}$. Thus, if the weighted mean method is used, then so-called the index number problem is solved. For our MNL selection model, earnings differences between different worker groups by the assignment of residence and workplace can be decomposed into three portions : a portion by attribute differences, a portion by different returns to those attributes, and a portion by selection :

$$\overline{\ln W_i} - \overline{\ln W_j} = \frac{(\beta_i N_j + \beta_j N_i)(\overline{X}_i - \overline{X}_j)}{N_i + N_j} + \frac{(\beta_i - \beta_j)(\overline{X}_j N_j + \overline{X}_i N_i)}{N_i + N_j} + (\theta_i \lambda_i - \theta_j \lambda_j) \quad (6)$$

where β_i and β_j indicates that the coefficient vector except a coefficient θ on a selectivity variable λ for categories i and j, respectively.

When using wage equations without a selectivity variable, the earnings differences between two groups can be decomposed into two portions as in equation (5). Following Blinder's (1973) definition, the latter term is considered the labor market discrimination portion.[5] The decomposition in equation (6) continues to represent labor market discrimination by the second term. The third term represents the differences in earnings from the differences in unobservable characteristics related to the assignment of individuals to workplace and residence location. The differences in assignment may result from discrimination in the spatial choice of either the housing market or the labor market or both of them due to different mixes of attributes for each demographic group. For our model, how much the inclusion of selectivity variable affect both a portion by attributes and a portion by returns can be directly tested by comparison between decomposition of wage equations with correction for selectivity and that of wage equations without selection.

Table 4 shows the differences in log mean wages and the decomposition of the differences among non-white male worker groups with the different assignment of residence and workplace. As expected, the decomposed portion by returns plus by selection (E: C+D) from wage equations with selection is similar to the portion by returns only (G) from wage equation without selection. This result is consistent regardless of race and gender(see Table 6 for non-white females, and Table A. 2 in Appendix for white males and females, respectively.) Only the slight differences of the two portions between wage equations with selection and without selection are due to the changes of coefficients by correcting selectivity in wage equations with selection.[6)]

This implies that labor market differentials unexplained by personal attributes, from wage equations with selection, are represented by both a portion by different returns and a portion by selection, while those are represented by a portion by returns only from wage equations without selection. As also expected, a portion by intercept differences plus a portion by selection from wage equations with selection are similar to a portion by intercept differences only from wage equations without selection. Following Blinder's(1973) definition of the labor market discrimination portion(a portion by intercept differences plus a portion by different returns to attributes), thus, a portion by selection is interpreted to be a part of the discrimination portion, which is not explained but hidden in a portion by intercept differences when using wage equations without selection.

2) Can Blacks Improve their Welfare in the Suburbs?

(1) Analysis for Non-White Males

As shown in Table 4, among non-white male workers, mean wage is the lowest for reverse commuters who live in the central city and work in suburbs (CS), and the highest for workers who commute from suburbs to the central city(SC). The results also show that non-white male workers residing in the central city tend to earn less than those living in suburbs, although they would have identical characteristics with suburban resident workers. For non-white male workers, earnings differentials are in general explained by both positive earnings attributes of higher wage groups and the positive portion by selection outweighing the negative portion by returns. Two cases are in contrast to such a pattern of wage decomposition: One from decomposition of the earnings difference between central city local workers (CC) and reverse commuters (CS), and another from decomposition between suburban commuters to the central city (SC) and suburban local workers (SS).

Non-white central city local workers (CC) earn around 7 percent more than non-white reverse commuters (CS) in terms of mean wage. Where the negative portion by attributes is offset by the larger positive portion by discrimination. This indicates that if both groups of workers would have identical attributes, earnings differentials would be much greater. This also indicates that reverse commuters (CS) would be better off if they could obtain jobs relevant to their personal characteristics in the central city instead commuting to the suburbs.

If so, why do they commute to the suburbs at the lower wages and without compensation for transportation costs? Is it indeed the case for white reverse commuters? The more detailed decomposition of the portion by attributes shows that the negative portion by attributes is due largely to more working hours and the higher proportion of blue-collar workers among non-white male reverse commuters (CS) than among central city local workers (CC). This implies that some non-white reverse commuters have to accept suburban blue-collar jobs despite relatively lower wages, because the central city does not provide any longer enough blue-collar jobs nearby their residence. As Danziger and Weinstein(1976) state, non-white reverse commuters seem not to be motivated by higher suburban wage rates, but to be induced by the trade-off between employment and unemployment given relatively higher non-white unemployment rates in the central city.

Table 4. Decomposition of Earnings Differentials of Non-White Males

	Wage Equations with selection					
	CC-CS	SC-CC	SS-CC	SC-CS	SS-CS	SC-SS
A. Difference in Log Mean Wages	0.0688	0.4746	0.3626	0.5434	0.4314	0.1120
B. By Attributes	−0.0820	0.2726	0.0826	0.2387	0.0872	0.1126
Age	0.0236	0.1538	0.0232	0.0996	0.0092	0.1172
Grade	0.0775	0.0046	0.0048	0.0951	0.0836	0.0124
Hours	−0.0828	0.0127	0.0092	0.0030	−0.0369	0.0069
Occupation	−0.1003	0.1015	0.0550	0.0410	0.0314	−0.0239
C. By Returns	0.0617	−0.3515	−0.0479	−0.3379	−0.0729	−0.2261
Age	2.7147	−1.0011	−1.1055	1.7914	1.6469	0.1177
Grade	−1.2143	0.3416	−0.4432	−0.8857	−1.6684	0.7819
Hours	−3.3541	0.0457	0.4086	−3.3814	−2.9821	−0.3664
Occupation	−0.4696	0.2520	0.0930	−0.2573	−0.4532	0.2295
Intercept	2.3849	0.0102	0.9991	2.9350	3.3840	−0.9889
D. By Selection	0.0891	0.5534	0.3279	0.6426	0.4171	0.2255
E. C+D	0.1508	0.2019	0.2800	0.3047	0.3442	−0.0006
	Wage Equations without Selection					
F. By Attributes	−0.0847	0.2536	0.0746	0.2409	0.0881	0.1240
Age	0.0238	0.1451	0.0231	0.0969	0.0093	0.1092
Grade	0.0771	0.0059	−0.0051	0.0969	0.0840	0.0149
Hours	−0.0826	0.0124	0.0092	0.0029	−0.0368	0.0068
Occupation	−0.1032	0.0928	0.0474	0.0450	0.0315	−0.0069
G. By Returns	0.1536	0.2183	0.2880	0.3026	0.3434	−0.0120
Age	2.7181	−1.2439	−1.0948	1.5461	1.6608	−0.1364
Grade	−1.2794	0.3689	−0.4763	−0.9236	−1.7677	0.8413
Hours	−3.3435	0.0309	0.4015	−3.3865	−2.9785	−0.3741
Occupation	−0.4793	0.2086	0.0525	−0.3261	−0.5140	0.2083
Intercept	2.5377	0.8540	1.4051	3.3917	3.9428	−0.5511
Wage Ratio 1	1.0713	1.6074	1.4371	1.7219	1.5394	1.1185
Wage Ratio 2	1.1628	1.2237	1.3231	1.3562	1.4109	0.9994
Wage Ratio 3	1.1660	1.2440	1.3338	1.3534	1.4097	0.9881

Notes : CC, CS, SC, and SS : First letter and second letter indicate residence and workplace, respectively(C : central city; and S : suburbs); for example, CS indicates living in the central city and working in the suburbs.

Ratio 1 : actual mean wage ratio between two groups(e. g. W_{CC}/W_{CS})

Ratio 2 : mean wage ratio when workers have identical characteristics and no selection; calculated by anti-logarithm of the Row E.

Ratio 3 : mean wage ratio when workers have identical characteristics; calculated by anti-logarithm of the Row G.

This seems not to be the case for white male workers. As shown in Table A. 2 in Appendix, however, white male reverse commuters earn more than white male central city local workers in terms of both actual earnings and adjusted earnings. Table 5 also shows that both earnings gap between whites and non-whites and labor market discrimination against non-whites are the greatest for reverse commuters. As shown in Table 4, the comparison between non-white suburban local workers (SS) and non-white reverse commuters (CS) shows that although both of them

Table 5. Decomposition of Earnings Differentials between White Males and Non-White Males

	Wage Equations with Selection			
	$CC_w - CC_b$	$CS_w - CS_b$	$SC_w - SC_b$	$SS_w - SS_b$
A. Difference in Log Mean Wage	0.1681	0.4405	0.1118	0.0227
B. By Attributes	0.0182	0.1867	0.0007	−0.0127
Age	−0.0592	0.0044	−0.0535	0.0008
Grade	0.0056	0.0701	0.0028	−0.0253
Hours	0.0088	0.0439	0.0097	0.0165
Occupation	0.0630	0.0682	0.0417	−0.0047
C. By Returns	0.1455	0.2188	0.2777	0.1437
Age	−0.5824	1.6671	0.0854	0.1586
Grade	1.3380	−0.7734	1.2546	1.6556
Hours	0.0547	−3.0127	0.0689	−0.1061
Occupation	0.0935	−0.5585	−0.2220	0.0426
Intercept	−0.6849	2.8963	−0.9092	−1.6070
D. By Selection	0.0044	0.0350	−0.1667	−0.1083
E. C+D	0.1499	0.2538	0.1110	0.0354
	Wage Equations without Selection			
F. By Attributes	0.0182	0.1874	0.0091	−0.0138
Age	−0.0591	0.0046	−0.0483	0.0011
Grade	0.0055	0.0705	0.0069	−0.0275
Hours	0.0088	0.0438	0.0094	0.0164
Occupation	0.0630	0.0686	0.0411	−0.0037
G. By Returns	0.1499	0.2531	0.1027	0.0365
Age	−0.5830	1.6595	0.4306	0.2102
Grade	1.3420	−0.8207	1.2500	1.6897
Hours	0.0543	−3.0001	0.0862	−0.0946
Occupation	0.0193	−0.5717	−0.1429	0.0905
Intercept	−0.6826	2.9862	−1.5212	−1.8592
Wage Ratio 1	1.1831	1.5535	1.1183	1.0230
Wage Ratio 2	1.1617	1.2890	1.1174	1.0360
Wage Ratio 3	1.1617	1.2880	1.1082	1.0372

Notes : See Notes in Table 4 for CC, CS, SC, SS, Ratio 1, Ratio 2, and Ratio 3 ; and subscripts w and b indicate whites and non-whites, respectively.

have jobs in the suburbs, both the discrimination portion and mean wage ratios (SS/CS) are the highest in all the cases of non-white male wage comparison. Furthermore from the comparison between white and non-white male workers, as shown in Table 5, it is found that racial discrimination at workplace is the lowest for subruban local workers(SS_W and SS_b), while that is the highest for reverse commuters(CS_W and CS_b).[7)]

These findings indicate that non-white male reverse commuters are seriously suffering from relatively lower earnings than suburban non-white local workers or white reverse commuters despite same workplace. Just improvement of personal attributes is not enough to offset the earnings differentials.[8)] This may be caused by employer discrimination due to suburban employers' local evaluation criteria for recruitments and wage contracts, especially for central city minorities potentially searching for suburban jobs.

Our findings are highly consistent with the spatial mismatch hypothesis. In contrast to Danziger and Weinstein's(1976) findings, we find that non-white reverse commuters have 7 percent(16 percent) lower weekly wage(adjusted mean wage) than non-wihte males working in the central city, and that the percentage of non-white male reverse commuters to non-white central city residents is lower than that of white counterparts by around 8 percent.[9] The fact that non-white reverse commuters are willing to accept suburban jobs at lower wages than central city jobs also supports the spatial mismatch hypothesis in that it reflects scarcity of central city jobs relevant to their personal attributes.

While the earnings difference between central city non-white local workers (CC) and non-white reverse commuters (CS) is due to unexplained labor market different -ials, slightly higher earnings of non-white suburban resident commuters (SC) than non-white suburban local workers (SS) is mostly explained by a portion by attributes. This implies that residence itself affects non-white males workers' earnings potentials more seriously than workplace does. For white males, however, note that earnings differences by workplace for workers with same residence are higher for central city residents than for suburban residents, and that earnings differences by residence for workers with same workplace is higher for central city workers than suburban workers, as shown in Table A.2 in Appendix.

For non-white male workers, the comparison between suburban local workers (SS) and central city local workers (CC) provides a meaningful finding in favor of the spatial mismatch hypothesis. Suburban non-white local workers (SS) have weekly earnings that are around 40 percent higher than central city non-white local workers(see unadjusted mean wage ratio in Table 4).[10] Even after controlling for personal attributes, suburban non-white local workers earn around 30 percent more than central city non-white local workers. The decomposition of the differences in earnings between two groups shows that only 22 percent of the differences in earnings is explained by a portion by attributes, while 78 percent of the gap reflects labor market differentials between the suburbs and the central city. The comparison between white and non-white males also shows that both the earnings gap(in both actual and adjusted earnings) and labor market discrimination against non-whites are lower for suburban local workers than for central city local workers. This finding indicates that if central city minorities would relocate their residence to the suburbs, they would be better off. As mentioned before., however, only the change of job locations from the central city to the suburbs would not improve their welfare, at least for the case of the Pittsburgh metropolitan area. Furthermore, transportation improvement to link central city residential areas and suburban work areas will be more likely to enhance the welfare of white males rather than that of non-white males.

Non-white males residing in the suburbs and working in the central city (SC) have around 61 percent higher weekly earnings than central city non-white local workers (CC). Around half of this earnings difference is explained by attribute differences, but another half is ascribed to the unexplained portion, e. g. labor market differentials. The unexplained portion may be caused by occupational differences in the wage setting mechanism, in which wages are non-linearly determined as suggested by dual labor market hypothesists (see Gordon et als, 1982, Boston, 1990, and Gindling, 1991). Given that suburban commuters (SC) have better personal attributes, especially in schooling, than central city local workers (CC), the formers tend to have jobs in the higher paying primary segment, while the latters usually work in the secondary segment. Such difference in the occupational allocation may be associated with the assignment of residence and workplace, and thus spatial configuration of earnings.

This may be also the case for earnings differentials between non-white central city local workers (CC) and non-white reverse commuters(CS). Our selection effect on the wage determination is also interpreted by spatial differences in the occupational allocation associated with workers' choice of residence and workplace. While discrimination literature stresses racial discrimination to explain labor market differentials, it must be borne in mind that occupational segmentation may be attributable to unexplained labor market differentials between whites and non-whites and even within same race. From this respect, we suggest that labor market policy must be concerned about deep-rooted wage differentials between occupational segments as well as racial discrimination.

Table 6. Decomposition of Earnings Differentials : Non-White Females

	Wage Equations with Selection					
	CC−CS	SC−CC	CC−SS	SC−CS	SS−CS	SC−SS
A. Difference in Log Mean Wage	0.1216	0.2586	0.0979	0.3802	0.0238	0.3564
B. By Attributes	0.1486	0.1800	−0.0125	0.4373	0.2013	0.2321
Age	−0.0682	0.0374	−0.0128	0.0139	−0.0212	0.0444
Grade	0.0918	0.0322	−0.0157	0.1342	0.0739	0.0349
Hours	0.0203	0.0808	0.0481	0.0585	−0.0038	0.1140
Occupation	0.1047	0.0296	−0.0321	0.2308	0.1524	0.0389
C. By Returns	0.2809	−0.2898	0.5335	−0.1177	−0.2928	0.1790
Age	−3.2371	−0.4337	−0.1939	−2.6213	−1.9831	−0.6476
Grade	2.3807	2.5469	0.0768	0.1558	−2.4240	2.6053
Hours	1.1976	−0.1937	0.7218	1.0466	0.4419	0.5531
Occupation	−0.5601	0.1741	−0.2008	−0.4825	−0.3750	−0.0682
Constand	4.1670	−2.383	0.1196	1.7838	4.0474	−2.2637
D. By Selection	−0.3079	0.3684	0.4231	0.0606	0.1153	−0.0547
E. C+D	−0.0270	0.0786	0.1104	−0.0571	−0.1775	0.1243
	Wage Equations without Selection					
F. By Attributes	0.1506	0.1867	−0.0065	0.4416	0.1903	0.2562
Age	−0.0712	0.0391	−0.0126	0.0157	−0.0243	0.0460
Grade	0.0951	0.0336	−0.0178	0.1365	0.0755	0.0335
Hours	0.0190	0.0827	0.0480	0.0561	−0.0036	0.1169
Occupation	0.1077	0.0313	−0.0241	0.2333	0.1427	0.0598
G. By Returns	−0.0290	0.0719	0.1044	−0.0614	−0.1665	0.1002
Age	−2.7799	−0.3313	−0.2251	−2.6590	−2.0891	−0.5759
Grade	−2.4499	2.3215	0.3485	−0.1369	−2.7610	2.6522
Hours	1.2497	−0.1312	0.7386	1.1642	0.4857	0.6213
Occupation	−1.5454	0.1893	−0.2107	−0.4504	−0.3456	−0.0739
Intercept	3.9966	−1.9765	−0.5469	2.0200	4.5435	−2.5235
Wage Ratio 1	1.1293	1.2951	1.1028	1.4626	1.0241	1.4282
Wage Ratio 2	0.9734	1.0818	1.1167	0.9445	0.8374	1.1324
Wage Ratio 3	0.9714	1.0745	1.1100	0.9404	0.8466	1.1054

Note : see Notes in Table 4 for CC, CS, SC, SS, Ratio 1, Ratio 2, and Ratio 3

(2) Analysis for Non-White Females

As shown in Table 6, among non-white female workers, log mean wage is the lowest for reverse commuters (CS), and the highest for workers commuting from the suburbs to the central city (SC). This is also the case for white female workers, as shown in Table A.2. In contrast to the case of non-white male workers, however, non-white female central city local workers (CC) have higher earnings than non-white female suburban local workers (SS). While non-white male suburban local workers earn more than non-white male reverse commuters by 54 percent, estimated earnings of non-white female suburban local workers are higher than those of non-white female reverse commuters by only 2.4 percent. Furthermore, non-white female reverse commuters would earn more than other comparable workers with identical personal characteristics.

Contrary to the findings from analysis of non-white males, these findings do not support that non-white female central city residents have labor market disadvantag-

Table 7. Decomposition of Earnings Differentials between White Females and Non-White Females

	Wage Equations with Selection			
	$CC_w - CC_b$	$CS_w - CS_b$	$SC_w - SC_b$	$SS_w - SS_b$
A. Difference in Log Mean Wage	0.016	0.1339	0.0717	0.0074
B. By Attributes	−0.0156	0.0772	0.1116	0.1288
Age	−0.0160	−0.1484	0.0488	0.0322
Grade	0.0442	0.1278	0.0120	0.0124
Hours	−0.0494	−0.0468	0.0658	0.0459
Occupation	0.0057	0.1446	−0.0150	0.0382
C. By Returns	0.0337	0.1498	−0.1657	−0.2810
Age	−0.2860	−2.8293	0.1969	1.0335
Grade	0.5652	0.6659	1.3834	−1.0731
Hours	−0.5304	−0.4658	0.2526	−0.2013
Occupation	0.2652	2.9499	−0.0687	0.0301
Intercept	0.0196		−1.9269	−0.0702
D. By Selection	−0.0019	−0.0931	0.1228	0.1596
E. C+D	0.0318	0.0567	−0.0399	−0.1214
	Wage Equations without Selection			
F. By Attributes	−0.0156	0.0812	0.1146	0.1211
Age	−0.0161	−0.1537	0.0518	0.0331
Grade	0.0442	0.1345	0.0126	0.0140
Hours	−0.0494	−0.0440	0.0683	0.0457
Occupation	0.0056	0.1445	−0.0180	0.0283
G. By Returns	0.0318	0.0527	−0.0429	−0.1137
Age	−0.2866	−2.9426	0.2457	1.0017
Grade	0.5656	−0.1529	1.1453	−1.3314
Hours	−0.5300	0.7284	0.2900	−0.2279
Occupation	0.2655	−0.4256	−0.0685	0.0207
Intercept	0.0175	2.8462	−1.6553	0.4234
Wage Ratio 1	1.0163	1.1433	1.0743	1.0074
Wage Ratio 2	1.0323	1.0583	0.9609	0.8857
Wage Ratio 3	1.0323	1.0541	0.9580	0.8925

Note : See Notes in Table 4 for CC, CS, SC, SS, Ratio 1, Ratio 2, and Ratio 3; and subscripts w and b indicate Whites and Non-Whites, respectively.

es relative to suburban counterparts. Rather, these are consistent with Vrooman and Greenfield's(1980) findings that "estimates for hypothetically dispersed black females indicated discrimination in favor of the central city residents." Labor market differentials among four location groups are relatively smaller for females than for males regardless of race. This also implies that the labor market outcomes are different between males and females.

As shown in Table 7, earnings differences between females and non-white females are relatively smaller than those between white male and non-white males for all cases. Furthermore, non-white female subruban residents would have higher earnings than white counterparts with identical personal attributes. This indicates that there is of little evidence of labor market discrimination against non-white females. Our results from analysis of female workers do not support the spatial mismatch hyothesis, while there exists evidence of spatial mismatch for non-white males.

Table 8 reports the differences in labor market outcomes between males and females. Actual earnings ratios(Ratio 1) of males to females range between 1.4 and 2.2 for non-whites, and range between 1.6 and 2.3 for whites, Although males and females have identical characteristics, sex differences in earnings are still higher than racial differences within same gender. Sex differences in earnings are much higher within whites than within non-

Table 8. Decomposition of Earnings Differentials between Males and Females

	Non-Whites			
	CC_m-CC_f	CS_m-CS_f	SC_m-SC_f	SS_m-SS_f
Difference in Log Mean wage	0.3440	0.3967	0.5600	0.8044
By Attributes	0.1199	0.7671	0.1250	0.3925
By Returns	0.2430	0.0457	0.2689	0.5261
By Selection	−0.0189	−0.4146	0.1661	−0.1142
By Returns plus By Selection	0.2241	−0.3689	0.4350	0.4119
Ratio 1	1.4106	1.4869	1.7506	2.2354
Ratio 2	1.2512	0.6915	1.5450	1.5097
	Whites			
	CC_m-CC_f	CS_m-CS_f	SC_m-SC_f	SS_m-SS_f
Difference in Log Mean wage	0.4958	0.7033	0.7436	0.8345
By Attributes	0.1721	0.2994	0.2936	0.3724
By Returns	0.3364	0.6919	0.3276	0.5249
By Selection plus	−0.0127	−0.2880	0.1224	−0.0628
By Returns plus By Selection	0.3237	0.4039	0.4500	0.4621
Ratio 1	1.6418	2.0204	2.1035	2.3037
Ratio 2	1.3822	1.4977	1.5683	1.5874

Note : See Notes in Table 4 for CC, CS, SC, SS, Ratio 1, and Ratio 2; and subscripts m and f indicate male and female, respectively.

whites. This is not surprising because racial differences in earnings of males are much larger than those of females. This implies that both white and non-white females are similarly discriminated over the entire metropolitan labor market relative to males regardless of race. Labor market discrimination against females, combined with spatial mismatch of non-white male central city residents, would result in family income inequality in space and race.

Non-white families with two earners residing in the central city are worse-off relative to both non-white families with two earners residing in the suburbs and white families with two earners. It is due basically to spatial mismatch for non-white males. Non-white male-headed families with a single earner residing in the central city are also badly affected by spatial mismatch of non-white male central city residents. The economic welfare of non-white female-headed families is not much different from that of white female-headed families, but it will be much worse than that of average families because of discrimination against females. Given the larger proportion of non-white female-headed families in the central city, sex discrimination tends to seriously affect the welfare of central city non-white families as spatial mismatch of non-white males does.

5. Conclusion

Despite an abundance of spatial mismatch studies, they do not provide evidence for spatial variations in earnings by the assignment of both residence and workplace. Our estimation results of a MNL sample selection model show that the selectivity variables have significant and positive coefficients on earnings regressions for suburban resident workers. This indicates that estimated earnings of suburban residents are higher than of randomly drawn workers with identical characteristics. After controlling for personal attributes, non-white male reverse commuters do not earn more than non-white central city local workers, whereas white male reverse commuters have significantly higher earnings than white male central city local workers. In addition, non-white male suburban local workers have still higher earnings than both non-white male central city local workers and reverse commuters. The comparison of earnings between non-white and white males shows that labor market discrimination against non-white males is more severe for central city residents, especially for non-white reverse commuters.

These findings suggest that transportation improvement between the central city and the suburbs would provide relatively more benefits for both white reverse commuters and suburban residents commuting to the central city(both whites and non-whites) rather than for central city minorities. For non-white males, suburban jobs without residential relocation do not enhance the economic welfare, and also just the improvement of personal attributes is not sufficient to offset earnings differentials between non-white reverse commuters and white reverse commutres or non-white suburban local workers.

Contrary to the findings for non-white males, we do not observe empirical evidence of spatial mismatch for non-white female workers. However, both white and non-white females are seriously discriminated over the entire metropolitan labor market. Labor market discrimination against females, combined with relatively lower earnings of non-white males residing in the central city, would affect more seriously the economic welfare of central city minority families. This would also result in further family income polarization within non-white families as well as between whites and non-whites (Harrison and Gorham, 1992).

Endnotes

1) For our purpose, two estimation methods, a bivariate probit sample selection model and a multinomial logit sample selection model, can be considered. However, while a bivariate probit model provides only the corrected estimates for each of two independent selection equations, a multinomial logit model enables us to compare differences in individual joint choice behavior among mutually exclusive joint categories. A multinomial logit sample selection model(MNLSM) is also a more general form of the selection model, since MNLSM can be utilized for a model with two or more selection criteria, and for a model with multiple choice selection equations. However, it must be borne in mind that a MNL model assumes independence of irrelevant alternatives(IIA assumption). Thus, it is important to test the IIA property is violated if workers choose first a residence in the central city or in the suburbs, and then choose a workplace, or vice versa. In these cases, the MNL model will be inappropriate. However, the test of the nested nature of residence and workplace choice on the basis of Hausman and McFadden(1984), we conclude that the IIA property holds for our MNL model.
2) Our MNL selection model is separately estimated by gender. Instead separate estimation by occupation or by race, however, occupation dummies and race dummy interaction terms are included in this model, because the disaggregation by occupation and race leads to the insufficient sample size for each category.
3) We use a term 'assignment' instead of 'choice', because residence for some worker groups may be involuntarily selected by other factors such as housing market segregation of family utility than one's real preference.
4) The OLS estimation results of wage equations without a selection variable are reported in Table A.1 in Appendix.
5) Blinder(1973 : 438~439) notes that "the latter [portion], which exists only because the marekt evaluates differently the identical bundle of traits if possessed by members of different demographic groups, is a reflection of discrimination as much as the shift coefficient is."
6) Presence of selectivity(e.g. existence of significant lambda) indicates that the estimated coefficients of wage equations without selection are inconsistent because of the heteroskedastic error distribution. Because we have consistently significant coefficients on lambda for suburban resident workers(SC and SS) regardless of gender and race. The estimation results from wage equations with selection are superior to those from wage equations without selection.
7) Although it is not reported, we also find that there is no significant difference in both actual and adjusted mean wage between non-white suburban local workers (SS_b) and white reverse commuters (CS_W).
8) After controlling personal attributes, white reverse commuters and non-white suburban local workers earn respectively around 30 percent and 40 percent more than non-white reverse commuters.
9) Danziger and Weinstein(1976) found 10 percent higher hourly wage of black reverse commuters relative to black central city local workers and a hihger percentage of blacks than of whites commute to the suburbs.
10) Vrooman and Greenfield(1980) found that black males residing in the suburbs earn almost 40 percent more than those living in the central city, from a Uiversity of Texas survey of households in SMSA's of more than 250,000 population. Given that the majority of suburban blacks tend to have jobs in the suburbs, and most central city black residents work in the central city, this finding is consistent with our result.

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Table A.1. OLS estimation results of wage equations without selection

	Male				Female			
	CC	CS	SC	SS	CC	CS	SC	SS
CON-	1.3163	2.4474	1.3318	1.5448	2.5605	1.3926	2.2218	2.6666
STANT	(3.203)**	(3.299)**	(7.650)**	(13.246)**	(6.058)**	(0.803)	(8.911)**	(17.491)**
AGE	0.1212	0.0995	0.1076	0.1085	0.0570	0.0343	0.0399	0.0265
	(12.432)**	(5.617)**	(19.835)**	(32.443)**	(5.525)**	(1.391)	(6.296)**	(6.667)**
AGES	-0.013	-0.0010	-0.0011	-0.0011	-0.0006	-0.0004	-0.0004	-0.0002
	(10.813)**	(4.960)**	(16.819)**	(27.950)**	(5.127)**	(1.211)	(5.389)**	(4.832)**
GRADE	0.1192	-0.0361	0.1352	0.0793	-0.0349	0.2245	0.0159	-0.0234
	(2.242)**	(0.396)	(6.772)**	(5.378)**	(0.636)	(1.003)	(0.483)	(1.138)
GRADES	-0.0034	0.0030	-0.0032	-0.0014	0.0017	-0.0077	0.0013	0.0032
	(1.845)*	(0.890)	(4.406)**	(2.508)**	(0.872)	(1.029)	(1.108)	(3.998)**
ROURS	0.0122	0.0218	0.0137	0.0186	0.0337	0.0360	0.0372	0.347
	(5.364)**	(3.770)**	(10.602)**	(24.374)**	(14.063)**	(8.188)**	(24.110)**	(41.368)**
PROF	0.3586	0.2296	0.4233	0.3960	0.5353	0.3674	0.4558	0.3782
	(4.469)**	(1.562)	(9.468)**	(15.110)**	(6.606)**	(2.538)**	(9.395)**	(13.364)**
CRAFT	0.2544	0.3066	0.3715	0.4032	0.2267	0.0624	0.3008	0.3299
	(3.608)**	(2.324)**	(8.588)**	(17.710)**	(2.103)**	(0.318)	(4.408)**	(9.745)**
CLERK	0.1473	0.1646	0.2390	0.2555	0.3486	0.2147	0.3493	0.2819
	(1.543)	(0.838)	(4.227)**	(7.031)**	(5.054)**	(1.650)	(8.231)**	(11.626)**
BLACK	0.6826	-2.9862	1.5212	1.8592	-0.0175	-2.8462	-1.6553	0.4234
	(0.772)	(1.480)	(1.771)*	(3.152)**	(0.012)	(1.101)	(0.807)	(0.380)
BAGE	0.0316	-0.1053	-0.0181	-0.0157	0.0091	0.1387	0.0198	0.0642
	(1.358)	(1.521)	(0.520)	(1.048)	(0.399)	(1.751)*	(0.531)	(2.818)**
BAGES	-0.0004	0.0014	0.0002	0.0002	0.0000	-0.0014	-0.0003	-0.0009
	(1.349)	(1.718)*	(0.438)	(1.348)	(0.121)	(1.344)	(0.652)	(3.058)**
BGRADE	-0.1915	0.0127	-0.1560	-0.2813	-0.1591	-0.0373	0.1810	-0.1991
	(1.612)	(0.070)	(2.069)**	(3.835)**	(0.725)	(0.108)	(0.688)	(1.312)
BGRADES	0.0064	0.0039	0.0045	0.0112	0.0086	0.0036	-0.0069	0.0072
	(1.468)	(0.517)	(1.503)	(3.992)**	(1.033)	(0.264)	(0.800)	(1.334)
BHOURS	-0.0013	0.0731	-0.0021	0.0023	0.0150	-0.0221	0.0080	-0.0069
	(0.286)	(4.691)**	(0.342)	(0.654)	(2.702)*	(1.621)	(1.200)	(1.637)
BPROF	0.0033	0.5128	0.1231	-0.2540	-0.6679	0.3220	-0.1834	0.0199
	(0.017)	(1.290)	(0.545)	(1.722)*	(4.004)**	(0.861)	(0.953)	(0.130)
BCRAFT	-0.1093	0.6580	0.1747	-0.0085	-0.1298	1.4504	-0.1916	0.3774
	(0.781)	(2.255)**	(0.954)	(0.080)	(0.470)	(2.826)**	(0.675)	(2.488)**
BCLERK	0.1888	1.3217	0.2860	-0.1296	-0.1704	0.7886	0.0098	-0.0796
	(0.938)	(2.202)**	(1.189)	(0.639)	(1.172)	(2.144)**	(0.059)	(0.510)
R-SQUARED	0.4105	0.4500	0.3910	0.4159	0.4449	0.5312	0.4147	0.4428
N	782	281	2503	6759	782	142	1704	4433
TEST	1.3406	6.7951**	1.4417	2.5754**	3.1669**	2.5597**	1.0104	2.3756**

Note :

The number in parenthesis indicates the absolute value of t-ratio ;

* : Significant at the 10 percent level ;

** : Significant at the 5 percent level ;

N : Sample size; and

TEST : Joint F-test of a null hypothesis that all the coefficients of black interaction terms are zero.

Table A.2. Decomposition of Earnings Differentials : Whites

	CS−CC	SC−CC	SS−CC	SC−CS	SS−CS	SC−SS
	Wage Equations with Selection : White Males					
Difference in Log Mean wage	0.2036	0.4183	0.2172	0.2147	0.0136	0.2011
By Attributes	0.0511	0.2078	0.0850	0.1240	0.0099	0.1003
By Returns	0.2110	−0.1720	−0.0831	−0.3502	−0.2701	−0.0664
By Selection	−0.0585	0.3824	0.2153	0.4409	0.2738	0.1671
By Returns plus By Selection	0.1525	0.2104	0.1322	0.0907	0.0037	0.1007
	Wage Equations without Selection : White Males					
Difference in Log Mean Wage	0.2036	0.4183	0.2172	0.2147	0.0136	0.2011
By Attributes	0.0539	0.2111	0.0843	0.1214	0.0104	0.1338
By Returns	0.1497	0.2071	0.1329	0.0933	0.0032	0.0673
	Wage Equations with Selection : White Females					
	CS−CC	SC−CC	SS−CC	SC−CS	SS−CS	SC−SS
Difference in Log Mean wage	0.0039	0.1706	0.1215	0.1745	0.1176	0.2920
By Attributes	0.0726	0.1134	0.0910	0.1858	−0.0117	0.2015
By Returns	0.1480	−0.1903	0.2958	−0.0420	0.1779	0.1085
By Selection	−0.2167	0.2475	−0.2653	0.0307	−0.0486	−0.0180
By Selection plus By Selection	−0.0687	0.0572	0.0305	−0.0113	0.1293	0.0905
	Wage Equations without Selection : White Females					
Difference in Log Mean Wage	0.0039	0.1706	0.1215	0.1745	0.1176	0.2920
By Attributes	0.0765	0.1144	0.0927	0.1939	−0.0053	0.2158
By Returns	−0.0726	0.0562	0.0288	−0.0194	0.1229	0.0762