Title
An Analysis of the Spatial Determinants and Long-Term Consequences of Youth Joblessness

Author
Raphael, Steven P.

Publication Date
1996

An Analysis of the Spatial Determinants and Long-Term Consequences of Youth Joblessness

by

Steven Paul Raphael

B.A. (San Diego State University) 1990

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Economics

in the

GRADUATE DIVISION

of the

UNIVERSITY of CALIFORNIA, BERKELEY

Committee in Charge:

Professor Michael Reich, Chair
Professor Clair Brown
Professor Jonathan Leonard

1996

The dissertation of Steven Paul Raphael is approved:

Michael Reich 4-23-96

Chair Date

Claire Brown 4-22-96

Date

4/23/96

Date

University of California, Berkeley

1996

An Analysis of the Spatial Determinants and Long-Term Consequences of Youth Joblessness

Table of Contents

List of Figures

List of Tables

Acknowledgements

The input, support, and encouragement that I received from family, fellow students, and faculty over the past five years have been invaluable. I would like to thank Melissa Appleyard, Kelly Baldwin, Robert Cervero, William Dickens, Eric Evenhouse, Hillary Hoynes, Jonathan Leonard, John Quigley, Siobhan Reilly, Eugene Smolensky, Dennis Toseland, Vince Valvano, and John Wald for feedback that has greatly improved my research. I would especially like to thank my mentors at the Institute of Industrial Relations, Clair Brown and Lloyd Ulman, and my advisor, Michael Reich, for providing continual input and direction. Many thanks to the participants of the Berkeley Labor Seminar who provided valuable input during the early stages of my research. I am most indebted to the staff members of the Institute of Industrial Relations for their expert support and, most of all, their comradery.

I would like to thank the Institute of Industrial Relations, John Quigley, and Kenneth Train for providing financial support for data acquisition. In addition, I am indebted to Ray Brady of the Association of Bay Area Governments and Charles Purvis of the Bay Area Metropolitan Transportation Commission for providing data integral to this project.

I would like to thank my mother and father, my brothers, Joshua, Billy, and Richard, and my sister Patricia, for their love and support.

Most of all, I would like to thank my wife, Kelly, whose love and unwavering faith in me have been bottomless wells of inspiration.

Chapter 1: Introduction and Overview

One of the most pressing and pervasive problems facing contemporary American society concerns the alarmingly high rates of joblessness suffered by inner-city African-American youth. Rates of black youth unemployment and joblessness far exceed those of white youth. For the year 1995, the unemployment rate for black youth workers between 16 and 19 years of age was approximately 37 percent for young black men and 34 percent for young black women. Furthermore, the rate of joblessness stood at 75 percent for black male youth and 74 percent for black female youth. In contrast, the comparable unemployment rates for white male and white female youth were 15 and 13 percent, respectively, while the corresponding rates of joblessness were 49 and 48 percent.

The relatively high rate of black youth joblessness raises several important questions concerning the causes and consequences of inner-city youth unemployment. Particularly, what explains the consistently large disparity between white and black youth unemployment rates? Is employment discrimination to blame? Do black youth workers lack the skills or personal characteristics demanded by the employers of youth labor? Alternatively, are there systematic demand-side differences in the local labor markets faced by the average white and black youths? Moreover, can studying the determinants of inter-racial differences in youth unemployment provide partial explanations of the large inter-racial differences that exist for adult workers?

To be sure, unemployment for all youth workers has consistently hovered at nearly triple that of the entire work force. Figure 1.1 graphs the unemployment rates for

Figure 1.1

Source: Economic Report of the President, 1996

workers between 16 and 19 years of age and for all workers 16 and over between 1954 and 1995. The youth unemployment series clearly exceeds that for all workers and exhibits greater variation over the business cycle. Several hypotheses potentially explain the relatively high youth unemployment rates, including lower rates of automobile ownership, employer preferences for older more experienced workers, and the relative geographic immobility of youth -- i.e., youths confined to their parent's home are unable to move to take a job or search for employment. Moreover, weaker labor force attachment because of school attendance and the existence of other family income offer partial explanations for relatively high joblessness rates.

Nonetheless, within the youth population, large racial unemployment differentials exist that resemble exaggerated images of racial labor market differences for the work force as a whole. Figure 1.2 plots unemployment series for workers 16 to 19 years of age by race and gender. While the youth unemployment rates for white male and female workers are high, they are consistently lower than rates for black youths of both genders. While care must be taken in inferring trends in the youth racial unemployment differentials due to a 1972 change in racial categorization,[1] the racial differential exhibits a slight upward trend before and after the definitional change. Racial differentials in youth joblessness, however, increased unambiguously over the period shown. From 1950 to 1995, the proportion of black male youths without employment increase from approximately one-half to three-quarters, while over the same period the proportion of white youth without jobs remained stable at roughly one-half. Over the same period, the jobless rate for black female youth declined from roughly four-fifths to three-quarters, while that of white female youth declined from two-thirds to one-half (*Economics Report of the President,* 1996).

Superimposing recent developments in poor inner-city neighborhoods against the evolution of the black youth employment crisis heightens the sense of urgency. Wilson

---

[1]Prior to 1972, the black unemployment series includes all non-white workers. The change in definition from non-white to black in 1972 did increase the calculated unemployment rate by approximately 2 percent.

Figure 1.2

Source: Economic Report of the President, 1996

(1986) links the declining labor market position of young black men to increasing out-of-wedlock child bearing among African-American young women, arguing that the poor economic position of young black men inhibits family formation and has reduced marriage rates within the black community. Mare and Winship (1991) test this hypothesis for the post-war period and find that the declining economic position of young black males explains one-fifth of the decline in marriage rates. Over the past two decades, rates of crime victimization and perpetration have increased disproportionately among young black men (Dilulio 1996), a trend that may be directly driven by increased inner-city joblessness (Freeman 1995). In addition to the immediate consequences of criminal activity including incarceration and personal injury, felony convictions and gaps in employment history may permanently limit future legitimate employment opportunities and result in lower lifetime earnings and future difficulty in locating and retaining acceptable jobs (Freeman 1996).

In this study, I present a detailed analysis of several aspects of the youth labor market with the dual aim of understanding systematic racial employment differentials within the youth population, and of evaluating the effect of early joblessness on future employment and earnings. First, I revisit an old and unsettled debate concerning the geographic determinants of black joblessness. An argument that has been debated quite actively in the economics literature and in the inter-disciplinary body of literature on the underclass concerns the effect of racial segregation on the employment prospects of black inner-city residents. The spatial mismatch hypothesis contends that involuntary racial segregation in the housing market coupled with the metropolitan decentralization of low and semi-skilled employment opportunities has created a geographic mismatch between the supply of and demand for black low-skilled labor. Moreover, the resulting systematic racial differences in proximity to areas of high employment opportunity (spatial accessibility) partially explains systematic racial differences in employment and earnings. The following chapter presents a spatial analysis of the San Francisco Bay Area's youth labor market. Specifically, I present a new employment-based measure of intra-metropolitan accessibility to employment opportunity that, in direct contrast to past measures, provides strong evidence in support of the spatial mismatch hypothesis. The measure is constructed to capture intra-metropolitan variation in the net growth of employment rather than variation in employment levels. The principal spatial disadvantage suffered by black male youth is that they live in areas of weak or negative employment growth. I find that differential accessibility explains between 30 and 50 percent of the neighborhood employment rate differential between the average white and black male youths.

The following analysis of 1990 San Francisco Bay Area data uses the same methodological framework and dependent variable as studies of 1970 data for Chicago (Ellwood 1986) and 1980 data for Los Angeles (Leonard 1985). These previous studies failed to find substantial relationships between various measures of accessibility and neighborhood youth employment-to-population ratios. Several potential causes of these conflicting results include differences between the metropolitan areas studied, differences in time period, and differences in the measurement of accessibility. To rule out the first two possibilities, I reproduce the accessibility measures used in the past with the San Francisco data. Using this alternative set of accessibility measures, I find no significant effects of spatial accessibility on neighborhood employment rates. Hence, rather than differences in the metropolitan area studied or differences in time period, differences in the construction of the accessibility measures explain the divergence in results from past studies. This calls into question the robustness of past studies that are often offered as key evidence against the importance of the spatial mismatch hypothesis.

Next, chapter 3 presents an analysis of the spatial distribution of the journey-to-work trips of employed male youths. The chapter demonstrates the importance of the spatial distributions of employment demand and competing labor supply in determining the commute patterns of youth workers. Past empirical studies of journey-to-work flows find a strong inverse relationship between the aggregate flow of labor between an origin and destination zone and the intervening distance between the zones. I find that controlling for the intervening opportunities and the intervening competing labor supply between a given origin and destination reduces the estimated negative effect of distance on the inter-zonal flow of labor by nearly eighty percent. Nonetheless, physical distance has a significant and substantial negative effect on intra-metropolitan youth labor flows, even after controlling for the other spatial variables. Despite the high correlation between intervening opportunities and intervening competing workers, both spatial variables have sizable and independent effects on labor flows. I interpret these findings as evidence of the importance of spatial search models that emphasize the correlates of distance -- i.e., the cumulative intervening opportunities and the increasing stock of competing workers -- as well as distance itself in impeding intra-metropolitan labor mobility.

After discussing the spatial determinants of youth joblessness, chapter 4 then presents an analysis of the long-term consequences of youth joblessness. Specifically, the chapter examines the long-term effects of youth joblessness on future employment and earnings. I explicitly account for the importance of one's initial labor market segment of employment. I weigh the impact on future labor market outcomes of a) experience foregone against b) a worker's initial industry of employment. Moreover, I allow the return to experience to vary across labor market segments. Analysis of a sample of young men taken from the National Longitudinal Survey of Youth finds that accounting for labor market segmentation diminishes the estimated effect of past work experience on future wages. Furthermore, the return to work experience is significantly lower in the secondary sector. In contrast to previous studies, early unemployment is found to have a moderately negative effect on future employment.

The strong evidence indicating the severity and importance of spatial mismatch in explaining racial differences in youth employment rates and the finding that early spells of joblessness adversely affect future employment and earnings indicate the need for future policy-oriented research on the spatial causes and long-term consequences of youth joblessness. While the spatial mismatch literature has not reached a consensus on the relative importance of spatial isolation from employment opportunities, there is now mounting evidence that space matters, that systematic differences in the local labor markets immediately accessible to black and white youth play a role in explaining racial differences in labor market outcomes, and that there are substantial barriers in the housing market that prevent the spatial adjustment of metropolitan labor markets. Future research should focus on the exact mechanisms by which physical isolation from areas of high employment opportunity hinders the labor market prospects of isolated workers. The policies necessary to combat the adverse effects of physical isolation differ substantially depending on how distance from opportunity affects accessibility. For example, do commuting costs prevent inner-city youths from taking jobs in tight suburban labor markets or do inner-city youths simply lack information about these distant employment opportunities (where they are, and the expectations of suburban employers)? Appropriate policy responses critically depend on such questions. To date, much of the mismatch literature has focused on demonstrating the importance of the hypothesis and has provided little information concerning the efficacy of specific policy responses.

Similarly, the analysis here and the few alternative studies of the long-term effect of youth joblessness rely on an overly simple model of the labor market and the evolution of lifetime earnings. Future research should develop richer models of early labor force participation that explore the differences in the possible set of career ladders offered by differing local labor markets, the lure and long-term consequences of involvement in criminal activity, and the role of geographic and inter-firm mobility.

Chapter 2: The Spatial Mismatch Hypothesis of Black Youth Unemployment: Evidence from the San Francisco Bay Area

2.1 Introduction

In popular discourse, the lower employment rates and earnings of African-American youths are often attributed to their geographic and social isolation in ailing inner-city neighborhoods. Abandoned by blue-collar employers and geographically trapped by housing discrimination and suburban land use policy, these workers are victims of what has been aptly labeled a "spatial mismatch" between the geographic distributions of the supply of, and demand for, blue collar labor. Despite the many studies devoted to evaluating the spatial mismatch hypothesis, the economic literature has not reached a consensus. While past research carefully documents both pervasive racial housing segregation (Farley & Frey 1994, Massey & Denton 1993) and the flight of large blue collar employers from the central cities (Kasarda 1986, 1989), past work does not decisively establish a link between these trends and interracial employment and earnings differentials.

The debate can be focused on a single central question: given racial segregation and the continuing decentralization of employment, is the intra-metropolitan mobility of labor sufficient to overcome the spatial disadvantage of inner-city blacks? Past studies provide conflicting answers to this question largely depending on how intra-metropolitan variation in labor demand or, alternatively stated, access to employment opportunities is measured. Studies that employ direct measures of neighborhood labor demand, such as the number of jobs within a given commute time or the ratio of neighborhood jobs to workers, find little evidence in support of the mismatch hypothesis (Ellwood 1986, Hutchinson 1974, Leonard 1985). On the other hand, studies employing indirect measures of neighborhood labor demand, such as the average commute time of a neighborhood's employed low-wage workers, find strong supporting evidence (Ihlanfeldt & Sjoquist 1991, Ihlanfeldt 1993).

This chapter presents a new, employment-based, measure of intra-metropolitan accessibility that, in direct contrast to past measures, provides strong evidence in support of the mismatch hypothesis. Several factors distinguish the measure presented here from accessibility measures employed in the past. First, the measure is constructed to capture intra-metropolitan variation in the net growth of employment rather than spatial variation in employment levels. I show that the principal spatial disadvantage suffered by black male youths is that they live in areas of weak or negative net employment growth. In the metropolitan area studied, while employment levels are relatively high in areas immediately accessible to black youths, the net changes in employment between 1980 and 1990 are considerably higher in the areas immediately accessible to white male youths. Furthermore, dis-aggregating net changes in employment by broad industrial categories reveals large relative employment declines in the immediate vicinity of the average black youth in industries that are staple employers of black blue-collar workers, such as manufacturing, transportation, construction, and public utilities. I argue that accessibility measures that fail to account for the intra-metropolitan distribution of employment growth by industrial sector miss the important differences between the local labor markets faced by black and white youths.

Second, the measure employed here accounts for a neighborhood's proximity to all other areas within the local labor market. Specifically, I use the distance-decay function from a gravity equation to discount distant employment opportunities. Since the gravity equation empirically models the intra-metropolitan commute patterns of employed youth, the actual behavior of youth workers provides the discounting parameter. This is an improvement over past employment-based accessibility measures that rely on arbitrary boundaries to define the region accessible to a given neighborhood and that do not adequately incorporate the continuous effect of distance on accessibility.

The analysis focuses on the San Francisco-Oakland-San Jose Consolidated Metropolitan Statistical Area (CMSA) for the year 1990. Compared with other large metropolitan areas, the Bay Area CMSA is moderately segregated and has experienced changes in the geography of its industrial base similar to those of other cities. Hence, there is little reason to believe that the recent experience of the area is atypical. The analysis combines data from several sources including local planning agencies, publicly available data from the 1990 Census, and a set of special tabulations from the Census Bureau. I find that differential accessibility explains between 30 and 50 percent of the neighborhood employment rate differential between average white and black male youths. Furthermore, I find that spatial variation in access to employment opportunity explains nearly half the relationship between neighborhood poverty rates and the employment rates of male youths. I interpret these results as strong evidence in support of the mismatch hypothesis.

This chapter will proceed as follows. First, I provide a selective review of the spatial mismatch literature and other related research in urban economics and urban history. This is followed by a critique of the prior studies and documentation of the important differences between the spatial distributions of the level of employment and the growth of employment. Next, I present the methodology behind the construction of the accessibility measures, a description of the data, and the main results of the paper. A discussion of the appropriateness of generalizing from a study of a single metropolitan area follows. Finally, I offer conclusions.

2.2 Distance, Information, and Employment Opportunity

The spatial mismatch hypothesis rests on four conditions: (1) the ongoing decentralization of traditionally blue collar industry and employment, (2) racially segregated metropolitan areas with blacks mostly concentrated in or around central cities, (3) market imperfections such as housing discrimination and suburban land-use policy that impede adjustment in the housing market and maintain racial segregation patterns, and (4) spatial frictions that prevent adjustment in the labor market. The first three conditions create the mismatch between black blue-collar workers and employers of blue-collar labor. The fourth condition provides a potential source of racial employment and earnings differentials. Most past studies investigating the mismatch hypothesis take the first three conditions as given and attempt to measure the extent of the mismatch and its importance in determining spatial variation in employment probabilities. Before discussing specific studies, however, the first three conditions merit closer examination.

Kasarda (1986, 1989) carefully documents that over the past half century, American central cities have been steadily changing from centers of goods production and distribution to centers of administration and information processing. During the late 19th and early 20th centuries, proximity to transportation terminal points coupled with the nearby residential concentration of abundant immigrant labor made the central city the prime location for manufacturing. With the subsequent shift from railroad to truck transportation, the increasing horizontal land needs of mass production technology, and the spread of public services to the suburbs, the central city's comparative advantage as a location for heavy industry eroded.

As goods producing industries relocated in the suburbs, information processing industries began to concentrate in the central city. The physical structure of central cities did not hinder these industries as they were able to cope with relatively higher land rents by substituting capital for land via vertically organizing operations in tall buildings. Since the education requirements of information processing industries are higher than that of such blue-collar industries as manufacturing and transportation, the composition of labor demand shifted to the detriment of less educated central city workers. The demand for unskilled inner-city labor further eroded with a parallel decentralization of personal services. These services followed suburban-bound movements in population as income levels rose and new housing was constructed on metropolitan peripheries (Mieszkowski & Mills 1993).

Concurrently, the residential choice of low-income central city blacks was, and is, severely constrained. During the post-World War II internal migration of African Americans from the rural south to northern metropolitan areas, blacks mainly settled in the oldest and least expensive central city housing. Constrained by overt housing discrimination prior to the passage of the Fair Housing Act in 1968[2] and by covert discrimination thereafter, many blacks, especially those with fewer resources, were unable to follow manufacturing and service employment to the suburbs. Furthermore, suburban zoning policy, intended to maintain the homogeneity and tax base of periphery communities and to avoid income redistribution through local government spending, further constrained the residential location of low-income blacks (Mieszowski & Mills 1993).

There is little disagreement over the first three necessary conditions of the hypothesis. Changes in the spatial configuration of industry follow the patterns described above in most large metropolitan statistical areas (Kasarda 1986, 1989). While it can be argued that the poor quality of inner-city labor has driven the decentralization of heavy industry, several technological factors clearly favor suburban over central city locations -- e.g., cheaper land, and accessibility to highway systems. Racial segregation, while declining in some cities, is still an important phenomena (Farley 1991, Massey & Denton 1993, Farley & Frey 1994). Furthermore, the two national Fair Housing Audits carried out by the Department of Housing and Urban Development firmly establish the ubiquity of housing discrimination against blacks (Turner 1992). The main area of disagreement

---

[2]During the first half of the twentieth century, several institutions openly restricted the residential distribution of blacks. Restrictive covenants to deeds that precluded property being occupied by minorities for a given period of time were not uncommon in the inter-war period (Farley & Frey 1994). Furthermore, the practice of redlining was openly encouraged by the Federal Housing Administration and the Code of Ethic for Realtors prevented realtors from "introducing into a neighborhood ... members of any race, nationality, or any individual whose presence will clearly be detrimental to property values in that neighborhood" (Cited in Wienk 1992).

concerns the magnitude of the mismatch and the ability of the labor market to adjust through intra-metropolitan commuting.

Theoretically, distance obstructs access to employment opportunities in two ways. First, the worker must traverse this distance at a cost, namely the commute costs in time and money. These costs lower the effective wage, possibly below the worker's reservation wage, which in turn lessens the acceptability of any particular job. Second, physical distance between a worker and an area of high employment opportunity impedes the flow of employment information traveling through informal channels. This is particularly important for young workers as youths tend to rely on informal job search methods -- i.e., directly applying to help-wanted signs, or checking with friends and relatives (Holzer 1988). In a search theoretical framework, the rate at which job offers are received will be relatively lower for those searching workers with poorer access to informal information networks.[3]

The employment effect of differential access to opportunities depends on the degree of wage flexibility in the central city labor market. Assuming complete racial segregation, a finite elasticity of substitution between otherwise equal black and white

---

[3]A lower job offer arrival rate for blacks is not sufficient to generate systematic racial differentials in the length of unemployment spells or the overall incidence of joblessness. A change in the arrival rate has two offsetting effects on the probability of locating acceptable employment. First, a lower arrival rate decreases the probability of finding an acceptable match simply because the searcher receives less offers per unit of time. Second, a lower arrival rate will diminish the choosiness of the searching worker, thus partially countering the first effect. The net effect on the length of the unemployment spell is ambiguous (Van den Berg 1994). Nevertheless, unemployed workers with relatively lower job offer arrival rates --i.e., poorer access to employment information -- suffer in terms of search costs incurred and the range of possible employment opportunities encountered.

workers,[4] and flexible wages, then the excess supply of black blue-collar workers will depress the wages of black workers in the central city. When labor markets clear, black workers who commute to employment outside their areas of residence will be compensated for the costs of commuting to the point where the wages of black workers net of commuting costs are uniform over space. This gives rise to a wage gradient for black workers that increases with distance from the central city (Straszheim 1980). Hence, with flexible wages, while otherwise similar black workers earn less than their white counterparts, differential accessibility does not affect the ability of blacks to obtain employment. Differential accessibility, however, may lower the employment-to-population ratio for black workers, since lower wages will induce some workers to withdraw from the formal labor market. On the other hand, when wages are downwardly rigid due to minimum wage constraints or alternative opportunities in the informal sector, poor access to employment opportunity will affect the ability of a neighborhood's workers to locate employment. If searching workers compete for jobs that pay the minimum wage, both neighborhood employment and unemployment rates will depend on the neighborhood's spatial access to opportunities.

Kain (1968) first tested the mismatch hypothesis with data on the Chicago and Detroit labor markets. In his seminal work, Kain examined the effect of distance from the major black ghettos on the percentage of total employment held by black workers in geographically defined work place areas. He found that distance from the ghetto had a

[4]As noted by Ihlanfeldt (1992), differential wage gradients for black and white workers are possible only if race plays a role in the hiring decision.

large negative effect on the percentage of black employment and concluded that residential desegregation would have substantially increased black employment, especially in Chicago. Kain's results were soon attacked by Offner and Saks (1971) who, using the same data, showed that Kain's conclusions regarding the positive employment effects of desegregation were sensitive to the specification of his original regressions. In fact, an alternative specification of Kain's employment equation yielded the prediction that residential desegregation would have a negative effect on total black employment. Mooney (1969) further dissented, finding that while physical isolation from suburban employment reduced total black employment, the effect of distance was minuscule when compared to the impact of temporal variation in aggregate demand.

Among the more recent papers that attempt to evaluate the employment effects of differential accessibility, Ellwood (1986) provides the strongest evidence against the spatial mismatch hypothesis. Using 1970 data for Chicago, the author presents a set of linear regressions of youth census tract employment rates on various neighborhood characteristics and a set of accessibility measures. Ellwood uses several accessibility measures including the proportion of jobs within a 30 minute commute of a given neighborhood, the ratio of neighborhood jobs to workers, and the average travel time of neighborhood workers. All the accessibility measures perform poorly; effects on neighborhood employment rates are statistically significant but small. Furthermore, the accessibility measures do not explain any of the relationship between neighborhood youth employment rates and the percentage of neighborhood residents that are black. Leonard (1985) reproduces Ellwood's analysis with 1980 data for Los Angeles and arrives at similar results.

Recent evidence affirming the mismatch hypothesis is offered in several papers by Ihlanfeldt (1988, 1993) and Ihlanfeldt and Sjoquist (1990, 1991). The authors reexamine the effects of spatial access on youth employment probabilities and earnings using individual microdata instead of aggregate census tract variables. In both comparisons across SMSAs (Ihlanfeldt & Sjoquist 1991) and an analysis of a single metropolitan area (Ihlanfeldt & Sjoquist 1990), the average commute time of low wage workers in an individual's area of residence significantly and substantially affects the probability that a particular youth is employed. In an analysis of the Philadelphia metropolitan area they find that differential accessibility explains between 33 and 54 percent of the black-white differential in employment probabilities. Similar magnitudes are found in the cross-SMSA analysis.

2.3 Shortcomings of Past Research

Past employment-based accessibility measures suffer two important shortcomings: (1) they are based on spatial variation in employment levels rather than employment growth, and (2) they fail to adequately characterize a neighborhood's location relative to all other areas in the local labor market. The first shortcoming points to a qualitative flaw in defining the sources of employment opportunities for new labor market entrants. The second shortcoming concerns the technical difficulties encountered in reducing a two-dimensional phenomena -- i.e., the location of a given neighborhood in urban space -- to a one-dimensional variable --i.e., an accessibility measure. I now turn to an independent discussion of each issue.

A. Employment Levels vs. Employment Growth

Job opportunities for new labor market entrants come from two sources: vacancies created by non-layoff labor turnover (quits, discharges, and retirement), and vacancies created by job growth. Assuming uniform turnover rates over space, accessibility measures based on employment levels capture the variation in vacancies created by turnover. However, these measures do not capture the net contribution to local vacancies from job growth and decline. The geographical distribution of employment growth depends on such factors as the spatial distributions of land prices, accessibility to transportation routes, and accessibility to the relevant product markets: all factors in which central cities are now at a disadvantage. There are no a priori reasons to believe that the level of employment within an area is positively correlated with the region's net employment growth. In fact, given the difference in population densities between central cities and suburbs, the opposite may be the case.[5] Accessibility measures based on employment levels miss the contribution of employment growth entirely.

Moreover, the level of employment in a given area may be a poor gauge of vacancies created by non-layoff turnover as turnover behavior and local employment growth are not independent of one another. In areas of relative decline, poor employment

---

[5]In an alternative test of the mismatch hypothesis, Ellwood (1986) compares black youth unemployment rates for the west and south sides of Chicago and finds little difference even though employment levels were much higher on the west side. Kasarda (1989) disputes the validity of the test based on a similar argument to the one offered here. Specifically, Kasarda disputes the relative superiority of the west side labor market citing (1) the loss of 75 percent of industries and businesses between 1960 and 1970 in North Lawndale, the economic core of the west side, and (2) the economic devastation which befell this area as a result of the severe rioting of 1968 following the assassination of Dr. Martin Luther King Jr.

growth lowers the area arrival rate of job offers (relative to other employment areas) and increases the costs of job search for resident workers. Workers that live and work in these areas will be more reluctant to quit and more careful not to shirk on the job.[6] Furthermore, low or negative employment growth limits opportunities for employment-to-employment inter-firm labor mobility. In such areas, the relative stability of existing job matches would make the prospects of new labor market entrants (such as youths) particularly dependent on the few vacancies created by employment growth. Hence, the assumption that permits the use of employment stocks as a measure of job vacancies, specifically that non-layoff turnover rates are uniform over space, is suspect.[7]

To illustrate the interaction between the spatial distribution of employment growth and racial residential patterns, Table 2.1 presents cumulative employment changes for the Bay Area CMSA between 1980 and 1990 by industry and by the 1990 racial composition of census tracts.[8] The table provides the 1990 levels of employment located within census

---

[6]This line of reasoning is consistent with the well-documented observation that black workers are much less likely to quit than white workers (Blau & Kahn 1981).

[7]This argument parallels the model of Akerlof et. el. (1988) that offers an explanation of the fact that voluntary inter-firm labor mobility is strongly pro-cyclical. Autonomous job vacancies --e.g., employment growth -- set off vacancy chains, defined as the number of job switches, on average, per autonomous vacancy. The length of vacancy chains, and in turn, the amount of voluntary turnover, increases during periods of strong employment growth since opportunities for job switching expand in tight labor markets. Conversely, voluntary turnover is low when unemployment is high since the probability that a vacancy is filled by an unemployed worker (effectively ending the chain since the unemployed worker does not create an additional vacancy) increases with the unemployment rate. This model applies directly to the analysis of spatial variation in non-layoff turnover where spatial variation in autonomous vacancy creation is substituted for temporal variation.

[8]Tract level employment data for 1990 and 1980 were furnished by the Association of Bay Area Governments. The data are matched to racial population counts from the 1990 Census Summary Tape File 1A.

Table 2.1
Changes in Employment 1980 to 1990 by Neighborhood Racial Composition, and by Broad Industry Categories for the San Francisco-Oakland-San Jose CMSA

Neighborhood Racial Composition	Total	Manu-facturing	Wholesale Trade	Retail Trade	Services	Combined[a]
Entire CMSA						
1990	3,073,735	494,622	183,961	515,014	1,019,437	825,591
1990 - 1980	538,106	-5,859	69,246	116,687	308,627	52,854
% Change	23.12%	-1.17%	60.36%	29.29%	43.42%	6.84%
< 20% Black						
1990	2,725,951	444,504	160,113	470,589	905,186	711,798
1990 - 1980	513,168	5,713	65,354	107,656	280,968	56,552
% Change	23.19%	1.3%	68.96%	29.66%	45.01%	8.63%
20% < Black ≤ 40%						
1990	157,449	19,252	9,626	21,632	59,547	46,936
1990 - 1980	11,718	-5,287	448	3,152	11,774	1,769
% Change	8.04%	-21.55%	4.88%	17.06%	24.66%	3.92%
40% < Black ≤ 60%						
1990	76,816	7,280	6,028	9,344	25,945	28,815
1990 - 1980	3,816	-4,208	1,165	-105	4,200	2,849
% Change	5.23%	-36.63%	23.96%	-1.11%	19.31%	11.41%
60% < Black ≤ 80%						
1990	39,984	10,570	2,964	3,865	12,413	9,860
1990 - 1980	-9,203	-5,549	286	573	3,978	-8,466
% Changes	-18.71%	-34.06%	10.68%	17.41%	47.16%	-46.2%
80% < Black						
1990	33,832	4,433	2,967	3,634	10,067	12,652
1990 - 1980	243	-4,669	327	612	2,512	1,488
% Change	.72%	-51.30%	12.39%	20.25%	33.25%	13.33%
Unpopulated						
1990	39,635	8,583	2,263	5,950	6,279	16,530
1990 - 1980	18,364	8,051	1,666	4,799	5,190	-856
% Change	82.26%	1,513%	279%	416%	476%	-4.92%

Data furnished by the Association of Bay Area Governments.
a. The combined industry category includes transportation, communication, other public utilities, construction, and public administration.

tracts of a given racial composition, the absolute changes in employment between 1980 and 1990, and the percentage changes in employment. Employment growth in predominantly black census tracts was substantially below the rate of growth for the entire region. While total employment increased by 23 percent for the entire CMSA, employment grew by less than 10 percent in census tracts with resident populations above 20 percent black. For census tracts that are 60 to 80 percent black, total employment actually declined by nearly 20 percent.

Net employment growth in individual industries follows similar patterns of growth and decline, with the largest racial differences in manufacturing. While manufacturing employment declined slightly for the entire CMSA, employment in this industry increased by nearly 6,000 jobs in tracts with less than 20 percent of the population black. The percentage change in manufacturing employment declines sharply with the percentage of residents that are black. For census tracts between 20 and 40 percent, 60 to 80 percent, and greater than 80 percent black, the percentage changes in manufacturing employment were -21, -34, and -51 percent, respectively. Similarly, wholesale and retail trade employment grew at a rate below that of the region as a whole in all census tracts in the 20 percent and above categories. Employment growth in services and the combined industry category are not uniformly below the CMSA growth rate. Service industry employment growth was relatively higher in census tracts between 60 and 80 percent black and employment growth in the combined industry category was higher for census tracts between 40 and 60 percent and greater than 80 percent black.

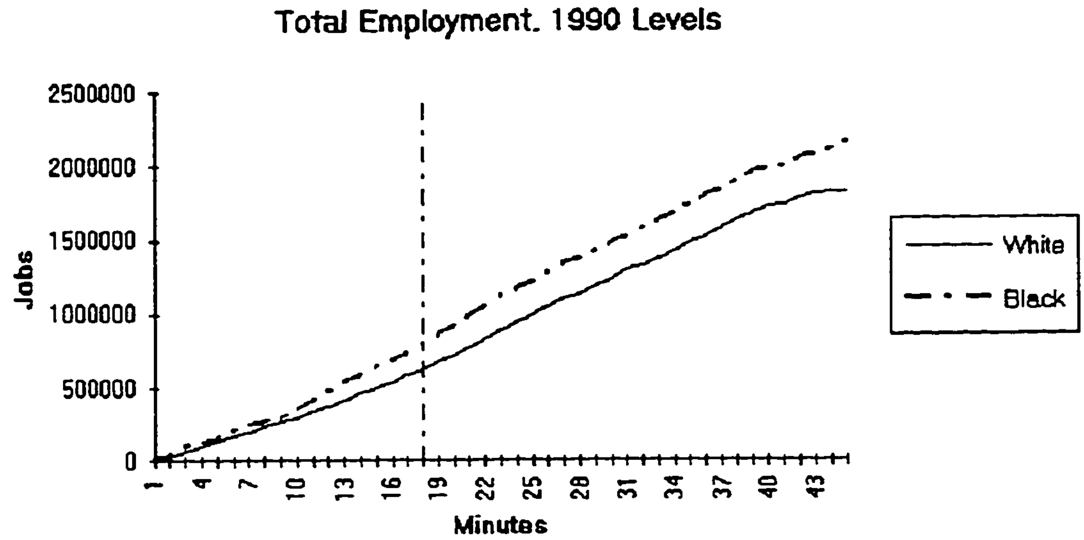
Looking beyond racial differences in employment growth within neighborhoods, are there systematic differences in employment growth in the areas surrounding the neighborhoods of the typical white and black youths? Figures 2.1 through 2.6 provide a graphical illustration of the relative location of black male youths within the metropolitan area's spatial distributions of employment levels and employment growth. The figures show the levels of employment in 1990 and the change in employment between 1980 and 1990 within a 45 minute private transportation commute from the residences of the average black and white youths.[9] The graphs are constructed as follows. For each neighborhood,[10] I calculate the number of jobs within a one minute private transportation commute of the neighborhood, the number of jobs within a two minute commute, and so on until 45 minutes, for the year 1990. Next, I repeat the calculation for each neighborhood substituting the decade change in employment for the 1990 employment level. I then compute weighted averages by race of the level and change profiles using as weights the 1990 neighborhood counts of 16 to 19 year old black and white youths. Hence, a point on the level profile for the average white youth is interpreted as the number of jobs located within x minutes of the average white youth's residence while a point on the change profile is the net change in employment between 1980 and 1990 within x minutes of the average white youth's residence. Separate profiles are computed for total employment and employment by broad industrial groups. In all of the figures, a dashed vertical line is drawn at 18 minutes, marking the average one-

---

[9]Nearly 99 percent of employed Bay Area male youths work within a 45 minute commute from their homes.

[10]Neighborhoods are defined in terms of modified regional travel analysis zones that are slightly larger than census tracts. A full discussion of the data and the relevant geography is presented below.

Figure 2.1


Total Employment. 1990 Levels
2500000
2000000
1500000
1000000
500000
0
Jobs
1
4
7
10
13
16
19
22
25
28
31
34
37
40
43
Minutes
White
Black

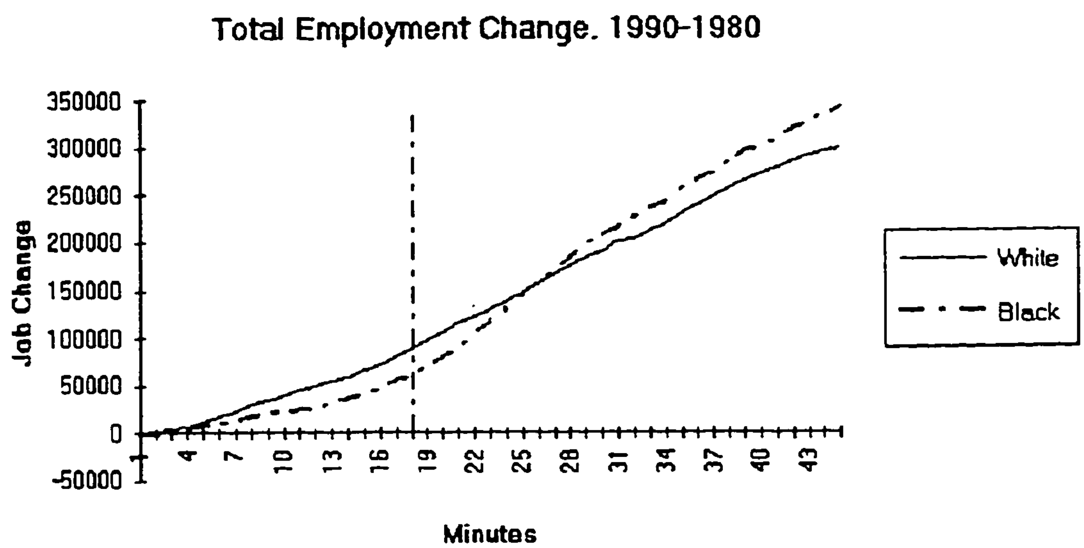
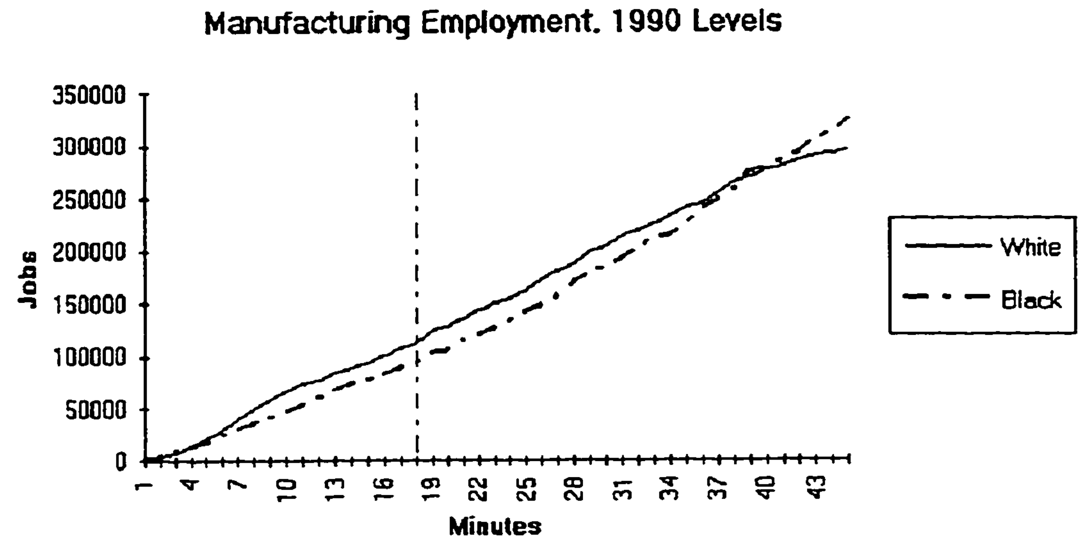

Total Employment Change. 1990-1980
350000
300000
250000
200000
150000
100000
50000
0
-50000
Job Change
4
7
10
13
16
19
22
25
28
31
34
37
40
43
Minutes
White
Black

Figure 2.2


Manufacturing Employment. 1990 Levels
350000
300000
250000
200000
150000
100000
50000
0
Jobs
1
4
7
10
13
16
19
22
25
28
31
34
37
40
43
Minutes
White
Black

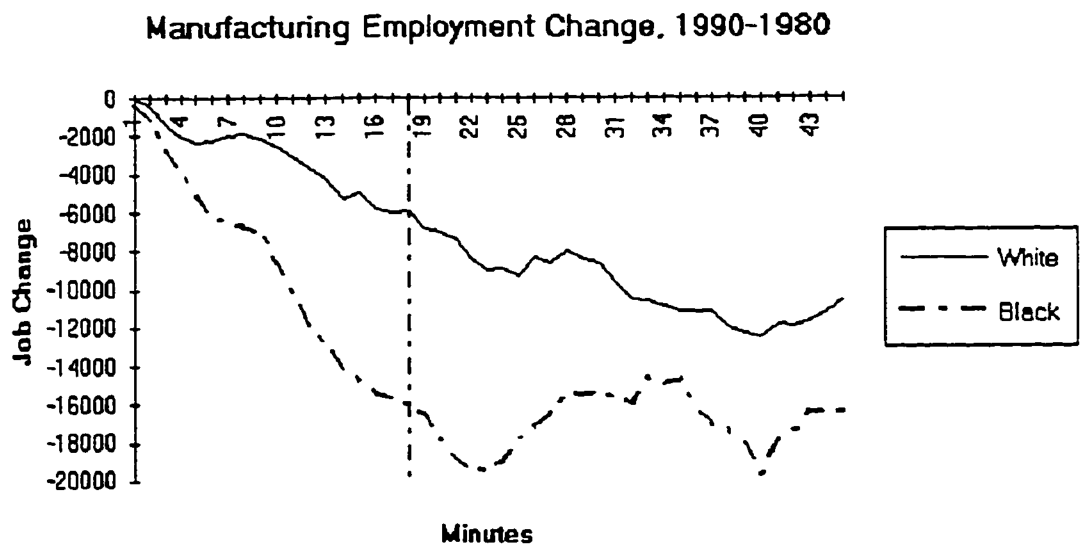
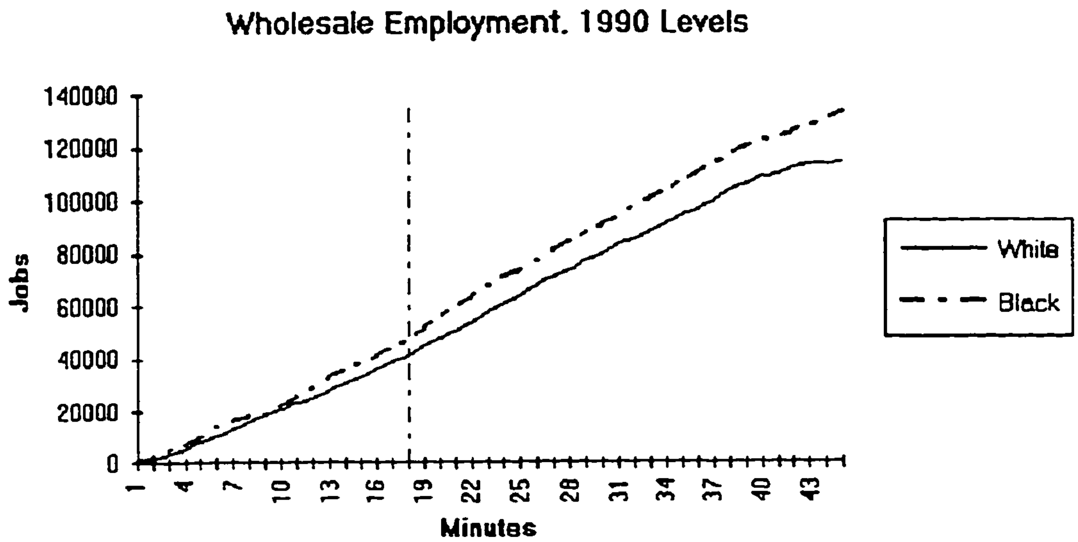

Manufacturing Employment Change. 1990-1980
0
-2000
-4000
-6000
-8000
-10000
-12000
-14000
-16000
-18000
-20000
Job Change
1
4
7
10
13
16
19
22
25
28
31
34
37
40
43
Minutes
White
Black

Figure 2.3


Wholesale Employment. 1990 Levels
Jobs
140000
120000
100000
80000
60000
40000
20000
0
1
4
7
10
13
16
19
22
25
28
31
34
37
40
43
Minutes
White
Black

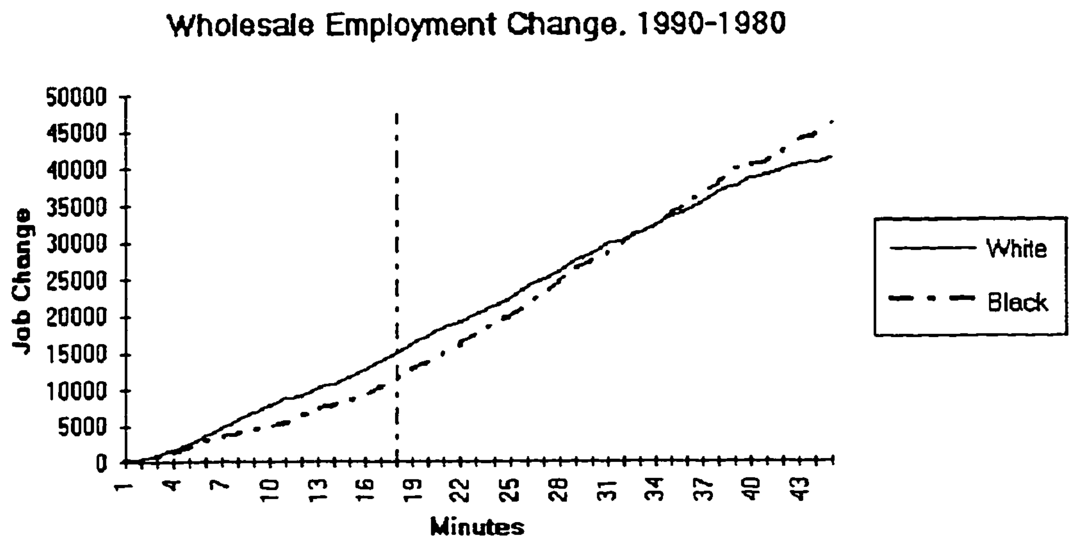
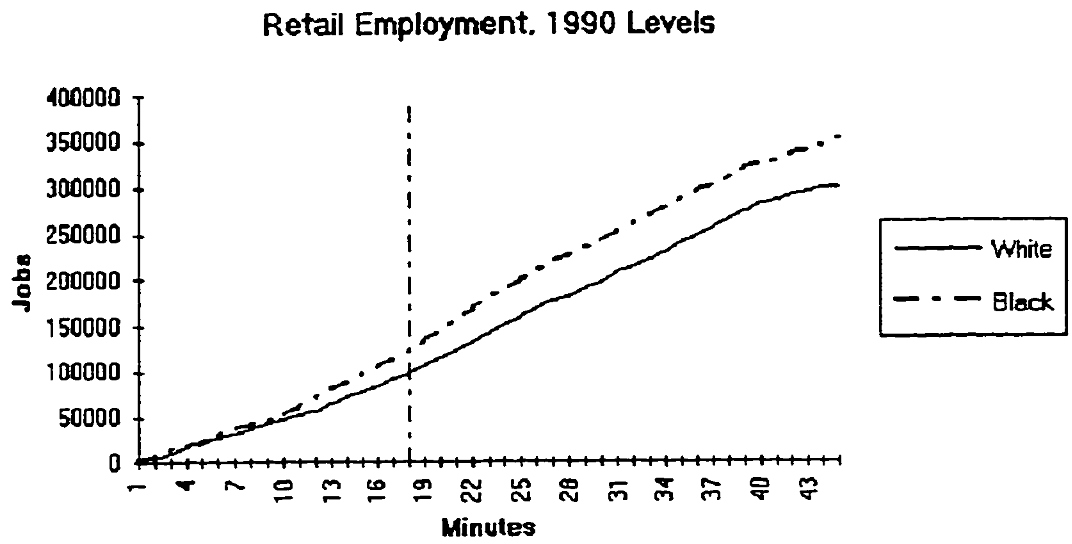

Wholesale Employment Change. 1990-1980
Job Change
50000
45000
40000
35000
30000
25000
20000
15000
10000
5000
0
1
4
7
10
13
16
19
22
25
28
31
34
37
40
43
Minutes
White
Black

Figure 2.4


Retail Employment, 1990 Levels
Jobs
400000
350000
300000
250000
200000
150000
100000
50000
0
1 4 7 10 13 16 19 22 25 28 31 34 37 40 43
Minutes
White
Black

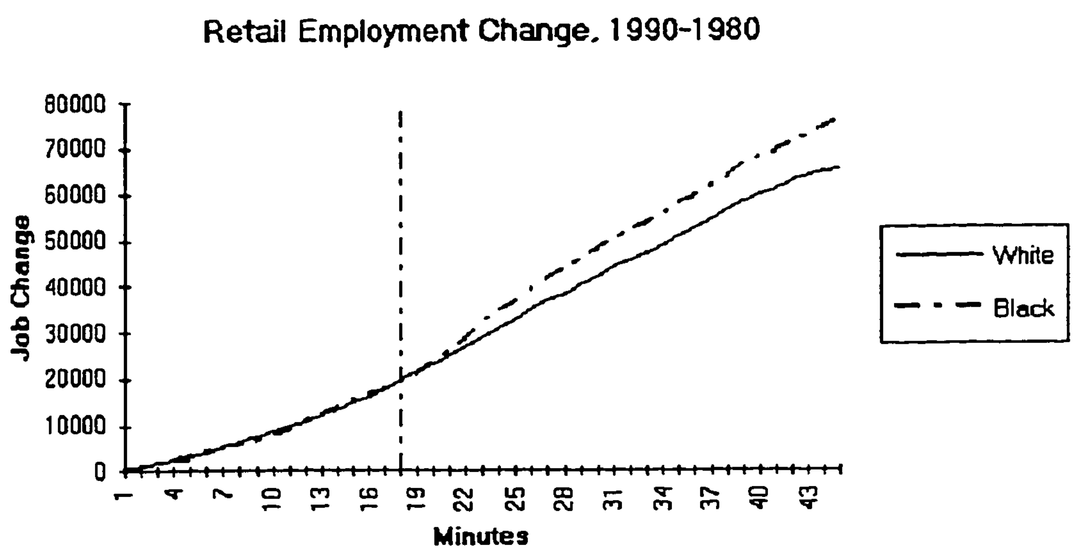
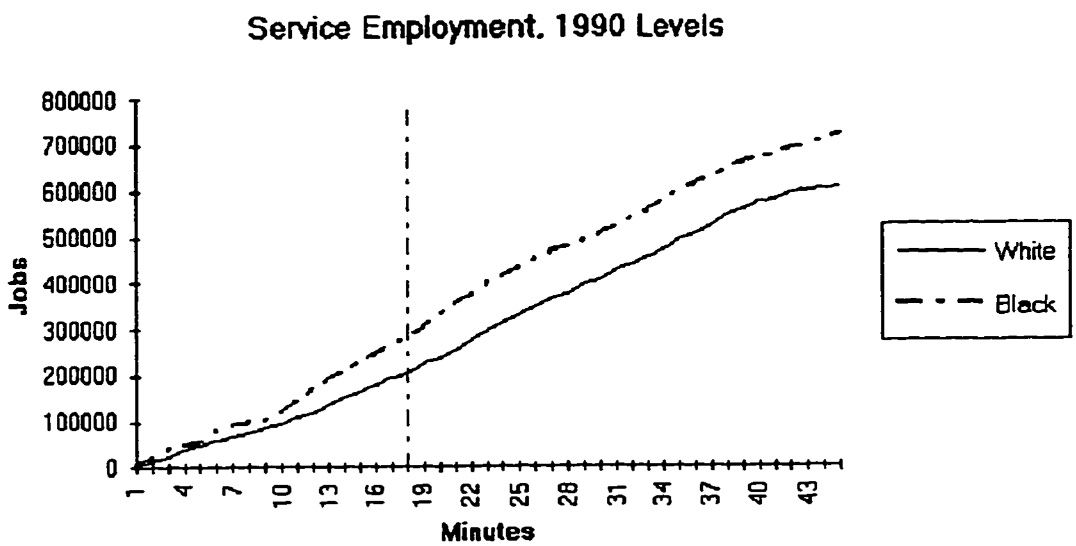

Retail Employment Change, 1990-1980
Job Change
80000
70000
60000
50000
40000
30000
20000
10000
0
1 4 7 10 13 16 19 22 25 28 31 34 37 40 43
Minutes
White
Black

Figure 2.5


Service Employment. 1990 Levels
800000
700000
600000
500000
400000
300000
200000
100000
0
Jobs
1
4
7
10
13
16
19
22
25
28
31
34
37
40
43
Minutes
White
Black

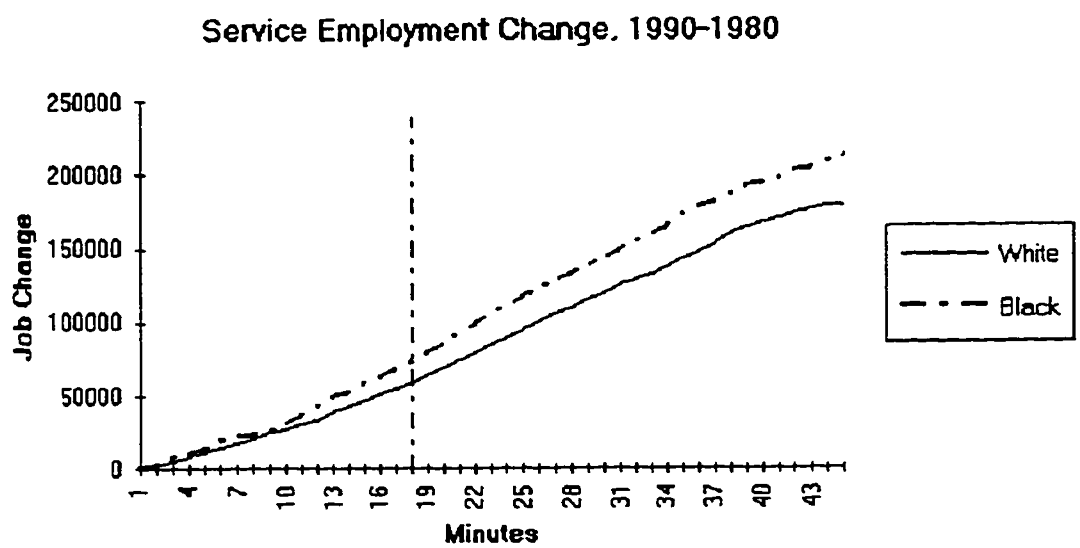
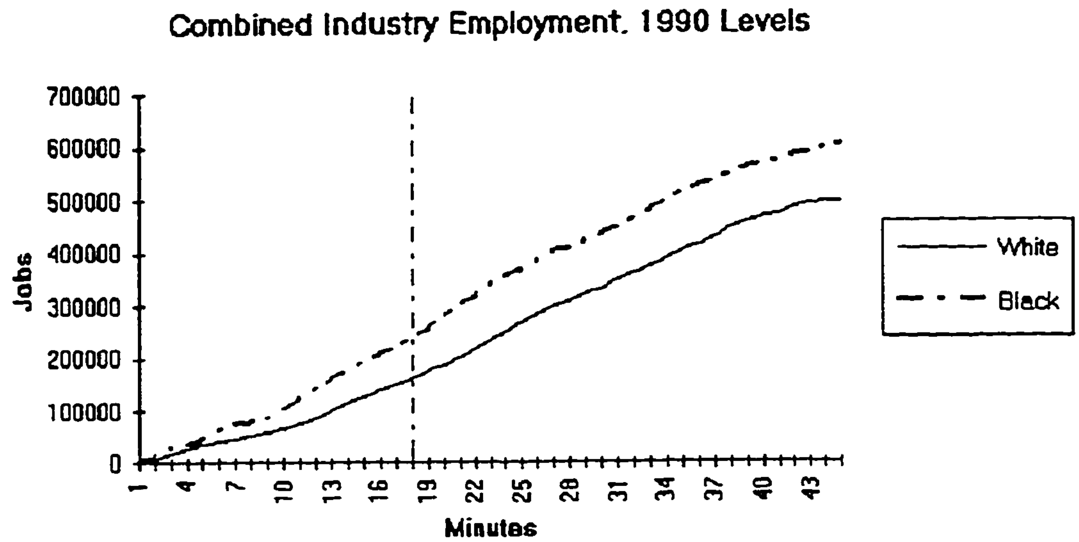
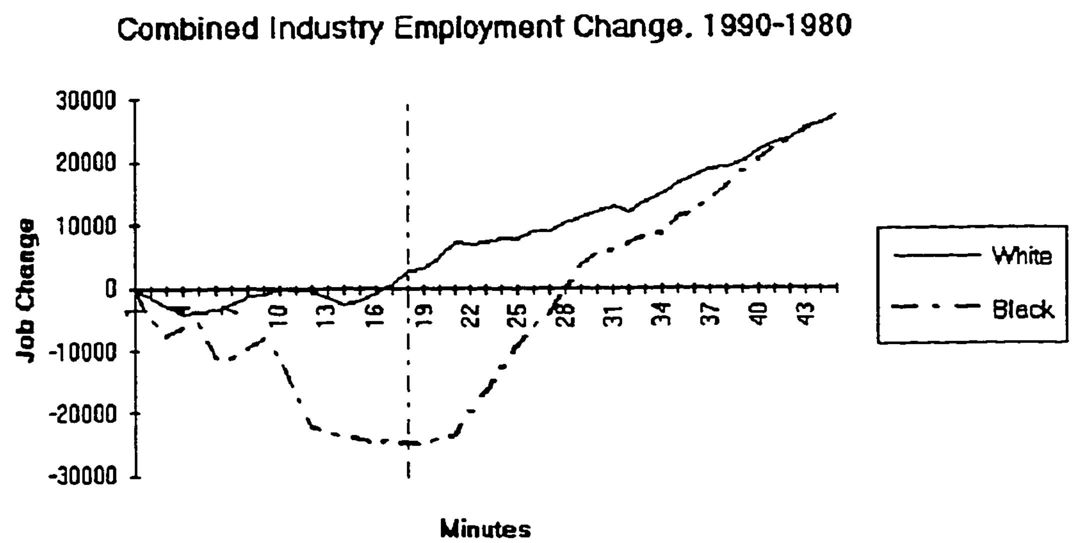

Service Employment Change. 1990-1980
250000
200000
150000
100000
50000
0
Job Change
1
4
7
10
13
16
19
22
25
28
31
34
37
40
43
Minutes
White
Black

Figure 2.6





Note: The combined industries category includes transportation, communication, other public utilities, construction, and public administration.

way commute time of employed Bay Area male youths.

Except for manufacturing, all figures show 1990 employment levels that are higher in the immediate vicinity of the average black youth. For example, while Figure 2.1 shows approximately 300,000 jobs within a 10 minute commute of the average white youth's residence, there are nearly 340,000 jobs within 10 minutes of the average black youth's residence. Similarly, the level profiles for the average black youth are everywhere above those of the average white youth for wholesale trade, retail trade, services, and the combined graph of transportation, communication, public utilities, construction, and public administration.

The change profiles, however, paint an entirely different picture. Starting with employment growth in all industries, approximately 2,000 jobs were lost between 1980 and 1990 within two minutes of the average black youth's residence, while for the average white youth 2,000 jobs were gained. Within 10 minutes of the average black youth's residence, 20,000 jobs were added compared to a net gain of 40,000 jobs within 10 minutes of the average white youth. Moreover, the change profile for black youths is below that of white youths up to 26 minutes. Note, this is substantially above the 18 minute average commute of male youths.

The most dramatic differences between the level and change profiles are found in manufacturing (Figure 2.2) and in the combined industries category (Figure 2.6). At 20 minutes, the change profile for the average black youth indicates a loss of 19,000 manufacturing jobs while the similar figure for the average white youth is a loss of 7,000 jobs. Furthermore, the time-change profile for black youth is everywhere below that of white youth. In Figure 2.6, approximately 25,000 jobs are lost within 20 minutes of the residence of the average black youth while for the average white youth 3,000 jobs are gained. The implications of Figures 2.2 and 2.6 are particularly severe since a fifth of black male youths and slightly more than half of low-skilled adult black males are employed in manufacturing; transportation, communication & public utilities; or public administration.[11]

The mismatch hypothesis links the relatively low employment and earnings of inner-city blacks to segregation and the decentralization of blue-collar employment. Employment growth is an important source of job opportunities, especially for recent labor market entrants such as youths. In terms of nearby employment growth, black youths are at a clear disadvantage. Direct employment based measures of spatial accessibility must account for this important factor.

B. The Spatial Characterization of Individual Neighborhoods

The second major shortcoming of past employment-based accessibility measures concerns the spatial characterization of a given neighborhood's location in relation to the metropolitan distribution of employment opportunities. Past measures rely on arbitrary boundaries to define accessibility, such as the area within a 30 minute public transit commute from a neighborhood. By choosing an arbitrary commute length, the accessibility measure fails to capture large employers beyond the defined radius who may exert significant pull on workers of the neighborhood that the measure is meant to

[11]Calculations from the 1990 Public Use Microdata Sample (PUMS) show that 52 percent of employed black males between 20 and 55 years of age and with a high school degree or less are employed in the industries described by Figures 2 and 6.

characterize.

Moreover, within the arbitrarily defined area, past measures fail to adequately account for the effect of distance on accessibility. It is implicitly assumed that all employment opportunities within the defined area are equally accessible whether they are 5 or 30 minutes away. The observed commute behavior of employed youth, however, indicates that this is not the case. Fully half of all employed male youths in the study commute less than 15 minutes while 75 percent commute less than 25 minutes. Assuming that the residential locations of youths are exogenously given (which, in general, is the case as the majority of youths live at home),[12] the sharply declining aggregate commute flow of youth with increasing distance indicates a strong attenuating effect of distance on accessibility.

The shortcomings of past employment-based accessibility measures provide some guidelines to constructing a new measure of spatial access to employment opportunity. First, employment opportunities should be defined by net changes in employment rather than levels of employment. This will better measure the geography of intra-metropolitan industrial change and provide a more concise measure of employment opportunities available to inner-city youth. Second, the neighborhood accessibility measure should account for the neighborhood's proximity to *all other neighborhoods* within the local labor

[12]Defining youths living at home as those who state their relationship to the household head as either son, stepson, grandchild, or those who are the children of a subfamily where the family head is not a householder, calculation from the 1990 5% PUMS indicate that 78 percent of 16 to 19 year old male youths in Bay Area CMSA were living at home at the time of the 1990 census. For employed youth, this figure is only slightly lower at 76 percent. Furthermore, of the remaining 24 percent, the majority were in living arrangements that reflect a geographically constrained housing choice – e.g., living with alternate relatives or living in a university dormitory.

market. This means that in addition to accounting for the employment opportunity in every other neighborhood, the measure should account for the distance between all other neighborhoods and the neighborhood for which accessibility is being measured. Furthermore, the incorporation of distance should be based on the observed commute behavior of already employed workers rather than arbitrary speculation.

2.4 Empirical Framework, Data, and Results

Following Ellwood (1986) and Leonard (1985), I regress neighborhood male youth employment-to-population ratios on a set of geographically defined accessibility measures and a host of neighborhood characteristic variables to evaluate the importance of spatial accessibility in explaining youth employment rates in general, and the racial difference in youth employment rates in particular. In this section, I first present the methodology behind the construction of the accessibility measures. A description of the data and the specification of the neighborhood employment equations follows. Finally, I present my main results.

In what follows I assume that the residential distribution of youths is exogenously given. This assumption is justified by the fact that for most youths the residential location decision has been made for them by a parent or guardian (see footnote 12).

A. Constructing the Accessibility Measures

Here, I construct an employment-based accessibility measure that speaks directly to the criticisms outlined above. The accessibility measures are based on employment changes rather than levels, account for a given neighborhood's proximity to all other areas of the local labor market, and incorporate distance based on the observed commute behavior of employed young men. First, I estimate a simple trip-distribution gravity model in order to isolate the effect of distance on intra-metropolitan youth labor mobility. Next, the distance parameter is combined with neighborhood net employment changes between 1980 and 1990 to construct the accessibility measures.

Specifically, partitioning the Bay Area CMSA into I origin and J destination neighborhoods, I estimate the gravity equation

$$T_{ij} = kL_i^{\alpha}E_j^{\beta}\exp(-\gamma d_{ij}) , \tag{1}$$

where i=(1,...,I) indexes origin neighborhoods, j=(1,...,J) indexes destination neighborhoods, T_{ij} is the count of youths that live in neighborhood i and work in neighborhood j, L_i is the count of youth workers residing in i, E_j is the count of jobs located in j, d_{ij} is the distance between neighborhoods i and j measured by private vehicle commute time, and α, β, γ, and k are parameters to be estimated. The gravity equation models the aggregate spatial interaction between two areas, here the interaction being the aggregate commute flow of youth labor from an origin to a destination neighborhood. The origin labor supply and destination labor demand capture the possible scale of interaction. By entering labor supply and demand multiplicatively, the potential scale of interaction increases in the total possible combinations of worker-job matches. The inclusion of these scale variables provides a more precise estimate of the relationship between aggregate mobility and distance.

The parameter, γ, in the "distance-decay" function is of primary interest. The specific functional form of the decay function in equation (1) is a more general form of the function often used in transportation planning models (Gray & Sen 1983). The exponential decay function is directly derived from entropy maximization and implies that the aggregate flow of labor declines proportionately with distance.

As the dependent variable in equation (1) is the count of workers that flow between given neighborhoods, estimation requires the use of an empirical model that takes the dependent variable as being generated from a discrete probability process. I estimate equation (1) with a negative-binomial count model. The estimator is superior to a simple log-linear OLS estimator as it constrains the predicted values of the dependent variable to non-negative integers and is able to incorporate observations where the dependent variable takes the value of zero. I present a detailed discussion of the estimator and the estimation results in the appendix.

Assuming an exogenously given residential distribution, the observed spatial distribution of work trips can be interpreted as the result of spatial job search from fixed residential locations. Moreover, the attenuating effect of distance on aggregate commute flows provides information concerning the accessibility of distant employment opportunity. I use the estimate of the distance-decay function in equation (1) to discount distant employment opportunities. Specifically, let $CHANGE_j$ be the total change in employment in neighborhood j between 1980 and 1990. Then the number of accessible employment opportunities created over the decade for workers in neighborhood i is

$$ACCESS_i = \sum_{j=1}^{j=J} CHANGE_j * \exp(-\bar{\gamma} d_{ij}) \,, \tag{2}$$

where the line over γ indicates the parameter estimate. The accessibility measure is similar to the gravitational potential measure specified by Isard (1960). In addition to increasing in the employment growth of the base neighborhood, the measure increases in the employment growth of immediately surrounding neighborhoods. Furthermore, the measure places less weight on relatively distant employment opportunities. Hence, neighborhoods that are relatively removed from areas of high employment growth will have lower accessibility. I calculate the accessibility measure in equation (2) for all employment and individually for the five industrial groupings presented in Figures 2.2 through 2.6.

While the accessibility measures derived from equations (1) and (2) capture the spatial variation in labor demand, they do not account for spatial variation in labor supply. Controlling for spatial differences in labor supply is particularly important when analyzing racial differences in youth employment rates, since inner-city youths live in more densely populated areas with higher concentrations of low-skilled workers than those of their suburban counterparts. To incorporate geographic differences in the supply of labor, I construct a neighborhood labor supply variable that accounts for the neighborhood's location within the spatial distribution of low-skilled labor. Since adult low-skilled workers compete directly with teenagers for job vacancies, I base the measure on both the competition from other teenagers and the competition from adult low-skilled workers. Let $SUPPLY_j$ be the sum of all teenagers and of adults with less than a high school education residing in neighborhood j. Again, employing the estimated distance-decay function from equation (1), I define the directly competing supply of labor to teenage workers in neighborhood i as

$$COMPETING\ LABOR_i = \sum_{j=1}^{j=J} SUPPLY_j * \exp(-\bar{\gamma} d_{ij}) \,. \qquad (3)$$

The accessibility measures from equation (2) and spatial measure of labor supply in equation (3) are the principal geographic measures used in the analysis.

B. Description of the Data and Specification of the Neighborhood Employment Equations

The data employed here are for the San Francisco-Oakland-San Jose CMSA and come from four sources. Census tract-level demographic variables come from the 1990 Census Summary Tape File 3A. By request, the Census Bureau provided aggregate tract-to-tract youth commute flows and tract-level counts of 16 to 19 year old male youths by employment status and by race. A complete matrix of zone-to-zone AM peak-period travel times comes from the Bay Area Metropolitan Transportation Commission (MTC). These data give the estimated travel time by private vehicle and public transit between all origin-destination pairs of regional traffic analysis zones. Finally, the Association of Bay Area Governments (ABAG) provided tract-level employment counts by broad industrial groupings for the years 1980 and 1990. ABAG compiles these counts from state ES-202 files.

Before proceeding to the specification of the employment equation a brief discussion of the unit of analysis is necessary. While the demographic data, employment data, and journey-to-work flow data are calculated at the census tract-level, the MTC calculates the travel-time matrix for its own Regional Traffic Analysis Zone (RTAZ) system. For the most part, the 1,382 Bay Area census tracts are nested within the MTC's 700 RTAZ system and matching the data simply requires the appropriate aggregation of the Census Bureau data. In a hand full of cases, however, the MTC system splits census tracts into two or more RTAZs. In these cases, I aggregate the inter-zonal travel times to the tract level by averaging. After all necessary adjustments, the matched data set describes 660 zone-based neighborhoods. After eliminating zones without teenage residents, 634 zones remain. In estimating the gravity equation, I exclude all origin-destination pairs with zero origin counts of teenagers or zero destination employment counts. In all, 423,776 origin-destination observations remain after imposing these restrictions.

Unfortunately, aggregation qualitatively affects the dependent variable. Specifically, aggregating from census tracts to the modified RTAZ system reduces the racial differential in neighborhood employment rates. Calculating the racial employment differential by comparing the tract-level youth employment-to-population ratio for the average white and black male youths yields a racial employment differential of 14 percent. A similar calculation with the modified zone system gives a racial differential of approximately 11 percent. Aggregation dilutes spatial differences in employment rates as areas with relatively low employment rates are combined with relatively high employment areas. Furthermore, aggregation reduces variation in the accessibility measures and all other demographic variables used. As I am constrained by the geography of the travel-time matrix, I can only acknowledge the problem.

The empirical strategy is to first regress neighborhood male youth employment rates (defined in terms of the modified zone system) on a variable measuring the proportion of neighborhood residents that are black (Black) and then next to re-estimate the equation including the geographic accessibility and labor supply variables. If black youth are systematically disadvantaged by poor spatial accessibility, the coefficient on "Black" should decrease with the inclusion of the accessibility and competing supply variables. In addition to the spatial variables and the variable "Black", I include other neighborhood characteristics in the employment equations. The additional neighborhood variables fall into one of two categories: variables measuring the educational attainment of youth and adult labor and variables that measure the adverse concentration effects resulting from the social isolation of poor neighborhoods. The education variables include the proportion of all 16 to 19 year olds that are high school dropouts (Dropout), the proportion of 16 to 19 year olds that are enrolled in school (Enrolled), and the proportion of adult residents with less than a high school education (< High School). The proportion of teenagers enrolled in school affects the dependent variable in two ways. First, the higher the percentage attending school the higher the average quality of teenage labor. Hence, in neighborhoods with high attendance rates, one would expect relatively high quality teenage labor, on average. Similar reasoning justifies the inclusion of the "Dropout" variable. On the other hand, as the dependent variable measures the employment-to-population ratio for all male teenagers regardless of enrollment status, the proportion enrolled may also indicate the extent to which neighborhood youths are available to work.

I include the proportion of adult residents with less than a high school education for several reasons. First, the average level of adult human capital provides additional information about the human capital endowment of the neighborhood teenage population.

Since it is impossible to control for personal characteristics with summary data, I include as many variables as possible that capture spatial variation in the underlying heterogeneity of teenage labor. Second, aside from the technological arguments offered to explain employment decentralization, such as shifts in transportation modes and the horizontal land needs of goods-producing industry, one can argue that employers of blue collar labor leave poor depressed areas because labor in these areas does not meet the necessary skill requirements. In this scenario, the skill deficiencies of inner-city neighborhoods would be driving any observed relationship between employment rates and employment decentralization. Hence, in order to account for this possible omitted variables bias, I include a measure of the average education of all neighborhood workers.

The second set of neighborhood variables captures the effects of the concentration of poverty and the social isolation of poor neighborhoods on the employment prospects of local youth. Wilson (1986) argues that the flight of the black middle class from predominantly black inner-city neighborhoods has eroded informal employment information networks. As the concentration of poverty, welfare dependence, and unemployment increases in inner-city communities, the efficacy of informal channels of employment information erodes. Hence, in addition to being physically removed from areas of high employment opportunity, the geographic concentration of unemployment and poverty socially isolates inner-city youths from the labor market, further reinforcing the adverse effects of physical isolation. These self-reinforcing aspects of spatially concentrated poverty are what Wilson calls "concentration effects". O'Regan and Quigley (1990) test for these effects and find that direct familial contacts to the labor market, such as having an employed parent or sibling, and neighborhood poverty concentration significantly impact youth labor market outcomes. To control for such effects, I include the average neighborhood household income, the proportion of residents living in poverty (Poverty), and the proportion of households headed by a single parent (Single Parent).

Table 2.2 provides the descriptive statistics for all Bay-Area male youths and Bay-Area male youths by race. All figures are neighborhood weighted averages where the weights are the 1990 neighborhood counts of the respective youth population and neighborhoods are defined by the 660 zone system. There is approximately an 11.5 percentage point differential between the neighborhood employment rate of the average white youth and that of the average black youth. The spatial variables indicate a clear accessibility disadvantage for black youths. With the exception of retail trade and services, the accessibility measures are relatively lower for black youths. Furthermore, the immediately competing labor supply is higher for black youths. With respect to the other neighborhood variables, black youths, relative to white youths, live in neighborhoods with lower household incomes, higher poverty rates, higher proportions of families headed by a single parent, lower levels of adult educational attainment, high teenage high school dropout rates, and lower school attendance rates.

Table 2.3 presents the means of the spatial accessibility measures and the competing labor supply variable for specific areas within the Bay Area CMSA. The first column of data provides the means of the accessibility measures for zones that do not lie within predominantly black areas. The remaining columns provide the averages for the predominantly black neighborhoods in Oakland, South San Francisco, Menlo Park, and

Table 2.2
Neighborhood Descriptive Statistics for Bay-Area Male Youths, Total and by Race[a]

Variables	Total Sample	White	Black
Neighborhood Employment Rate	.447	.464	.351
Spatial Accessibility Variables			
All Industries	22,105	22,890	17,456
Manufacturing	-1,500	-994	-4,499
Wholesale Trade	-3,504	3,582	3,044
Retail Trade	5,056	5,003	5,373
Services	15,022	14,379	18,833
Combined[b]	239	1,122	-4,993
Competing Labor	23,286	21,825	31,356
Other Neighborhood Variables			
Black	.089	.049	.328
<High School	.081	.076	.110
Single Parent	.105	.094	.175
Poverty	.080	.068	.148
Dropout	.083	.075	.131
Enrolled	.815	.825	.761
Average Household Income	$54,056	$56,384	$40,262

a. The means are calculated by taking the weighted average of the neighborhood variables where the weights are either the count of all white and black youths, white youths only, and black youths only.
b. Combined industrial category includes transportation, communication, other public utilities, construction, and public administration.

Table 2.3
Means of Accessibility Measures for Specific Black Neighborhood within the Bay Area CMSA

Variables	Zones Not in Black Areas	Oakland	South San Francisco	Menlo Park	Richmond
Neighborhood Employment Rate	.462	.273	.298	.349	.346
Spatial Accessibility Variables					
All Industries	23,060	10,458	17,148	27,845	13,469
Manufacturing	-949	-8,843	-7,508	-6,670	-2,931
Wholesale Trade	3,605	1,971	4,879	6,087	1,094
Retail Trade	5,050	4,561	8,031	5,358	4,086
Services	14,351	19,436	35,386	21,206	14,511
Combined[a]	1,206	-6,717	-23,044	2,234	-3,100
Competing Labor	22,002	37,474	52,385	23,868	21,016

The means are calculated by taking the weighted averages of the neighborhood variables where the weights are the count of youths living in the zones. The predominantly black areas within the cities of Oakland, Menlo Park, and Richmond, and within South San Francisco are defined as all zones where the percentage of neighborhoods residents that are black is at least 20 percent.
a. Combined industrial category includes transportation, communication, other public utilities, construction, and public administration.

Richmond. With the exception of Menlo Park, the means of the "All Industries" variable is lower for the predominantly black neighborhoods than for the neighborhoods that are not within black areas. Furthermore, in all of the individual black areas, manufacturing losses exceed those in predominantly white neighborhoods. In the black neighborhoods of Oakland and South San Francisco, the numbers of directly competing workers far exceed the supply of competing labor in the predominantly white neighborhoods of the Bay Area CMSA. In the black neighborhoods of Menlo Park and Richmond (areas that are further from the area's central cities) the supply of competing labor is comparable to that of the predominantly white neighborhoods. Moreover, in these more suburbanized black communities, the average youth employment-to-population ratios are approximately five percentage points higher than in the inner-city black communities of Oakland and San Francisco.

C. Empirical Results

In this section, I present the main results of the chapter. First, I discuss the performance of the constructed accessibility measures in linear neighborhood employment regressions and how controlling for accessibility alters the estimated effects of other neighborhood variables. Next, I use the racial differences in average accessibility presented in Table 2.2 and the parameter estimates from the employment equations to evaluate the importance of differential accessibility in explaining the racial difference in neighborhood employment rates. All regressions reported in this section are weighted by the count of neighborhood male teenagers. While weighting improves the fit of the equations, it does not qualitatively affect the results.

Table 2.4 presents regressions of male youth employment rates on the competing labor and all industry variables, on competing labor and each individual industry measure, and on competing labor and the full set of industry-specific accessibility measures. For the regressions on individual accessibility measures, with the exception of services, the estimated effects of the spatial accessibility variables have the expected signs and are highly significant. The competing labor supply variable has a negative effect on neighborhood employment rates in all regressions and is statistically significant in all of

Table 2.4
Regressions of Neighborhood Male Teenage Employment Rates on Spatial Accessibility Measures and Competing Labor Supply

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	.4444 (33.61)	.4974 (48.11)	.4901 (47.26)	.4589 (30.32)	.5097 (44.76)	.4574 (35.92)	.4746 (29.34)
Competing Labor Supply	-3.13×10^{-6} (-8.19)	-1.70×10^{-6} (-4.37)	-4.13×10^{-6} (-8.98)	-3.70×10^{-6} (-7.26)	-1.23×10^{-6} (-1.677)	-4.78×10^{-6} (-.987)	-2.45×10^{-6} (-2.95)
All Industries	3.44×10^{-6} (6.81)	-	-	-	-	-	-
Manufacturing	-	6.93×10^{-6} (5.28)	-	-	-	-	4.25×10^{-6} (2.65)
Wholesale Trade	-	-	1.53×10^{-5} (6.411)	-	-	-	1.18×10^{-5} (3.89)
Retail Trade	-	-	-	1.48×10^{-5} (3.91)	-	-	4.03×10^{-6} (.73)
Services	-	-	-	-	-2.23×10^{-6} (-1.76)	-	-1.71×10^{-6} (-.886)
Combined[a]	-	-	-	-	-	5.01×10^{-6} (5.89)	1.07×10^{-6} (.849)
R^2	.121	.097	.115	.079	.062	.106	.146
N	634	634	634	634	634	634	634

T-statistics are in parenthesis. All regressions are weighted by the neighborhood count of teenage males.
a. The combined industry category includes transportation, communication, other public utilities, construction, and public administration.

the estimated equations except for the regression on services only and on the combined industry category. In the first equation of Table 2.4, the accessibility measure based on all industries performs fairly well. Combined with the competing labor supply variable, accessibility to all jobs explains approximately 12 percent of the variance in neighborhood male youth employment rates. Replacing the all industries accessibility measure by the set of industry-specific measures improves the fit, as can be seen in the higher R^2 in equation (7) of approximately 15 percent. Hence, the geographically-defined measures alone explain a substantial portion of the intra-metropolitan variation in male youth employment rates.

Table 2.5 provides a regression of neighborhood employment rates on the proportion of residents that are black, a set of regressions on the variable "Black" and the individual accessibility measures, and a regression on the variable "Black" and the full set of industry-specific spatial variables. Similar to the findings of Ellwood (1986) and Leonard (1985), the variable "Black" has a strong negative effect on neighborhood employment rates. Contrary to their results, however, adding the spatial accessibility measures substantially reduces the estimated negative employment effect of the percentage of residents that are black. Adding the all industries accessibility measure and the competing labor supply variable to the specification of equation (1) results in a 29 percent decrease in the estimated coefficient on "Black" from -.3394 to -.2422. Replacing the all industries accessibility measure by the set of industry-specific measures causes a larger decrease of 32 percent. In all of the regressions with single industry-specific measures the coefficient on "Black" declines. Again, the direction of the estimated effects of all

Table 2.5
Regressions of Neighborhood Male Youth Employment Rates on Spatial Accessibility Measures, Competing Labor Supply, and the Proportion of Neighborhood Residents that are Black

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	.4777 (74.69)	.4697 (35.00)	.5053 (50.36)	.5001 (49.18)	.4796 (32.61)	.5170 (47.68)	.4743 (38.14)	.481 (30.43)
Black	-.3394 (-9.74)	-.2422 (-6.38)	-.2643 (-7.00)	-.2471 (-6.48)	-.2832 (-7.81)	-.3012 (-8.42)	-.2671 (-7.41)	-.2309 (-5.77)
Competing Labor Supply	-	-2.15×10^{-6} (-5.39)	-1.22×10^{-6} (-3.21)	-2.72×10^{-6} (-5.50)	2.43×10^{-6} (-4.73)	-2.75×10^{-7} (-.389)	-1.69×10^{-7} (-.362)	-1.04×10^{-6} (-1.23)
All Industries	-	2.24×10^{-6} (4.28)	-	-	-	-	-	-
Manufacturing	-	-	3.85×10^{-6} (2.88)	-	-	-	-	1.21×10^{-6} (.733)
Wholesale Trade	-	-	-	9.36×10^{-6} (3.77)	-	-	-	6.65×10^{-6} (2.15)
Retail Trade	-	-	-	-	9.82×10^{-6} (2.68)	-	-	6.57×10^{-6} (1.21)
Services	-	-	-	-	-	-2.41×10^{-6} (-1.99)	-	-2.93×10^{-6} (-1.54)
Combined[a]	-	-	-	-	-	-	3.77×10^{-6} (4.53)	1.21×10^{-6} (.984)
R^2	.130	.175	.162	.169	.160	.156	.177	.189
N	634	634	634	634	634	634	634	634

T-statistics are in parenthesis. All regressions are weighted by the number of neighborhood male teenagers.
a. The combined industry category includes transportation, communication, other public utilities, construction, and public administration.

of the spatial accessibility measures, with the exception of services in equations (5) and (8), are as expected. While only one of the coefficients of the six geographical variables in regression (8) is statistically significant, an F-test of equation (8) against equation (1) strongly rejects the hypothesis that all six coefficients equal zero.

Table 2.6 adds the neighborhood labor quality and social isolation variables to the basic regressions. Here, I omit the regressions with the individual industry-specific accessibility measures as the results are analogous to the regressions in Tables 2.4 and 2.5. The effects of the neighborhood variables on the male youth employment rate are as expected with the exception of average household income and the proportion of families headed by a single parent. The coefficients on "Single Parent" are statistically insignificant in all the regressions. I interpret the negatively significant coefficients on average household income as reflecting the higher non-labor incomes of youths from relatively wealthy homes (recall, the dependent variable measures the employment rate of all male youths regardless of enrollment status). The labor quality variables (Enrolled, Dropout, and <High School) negatively affect neighborhood employment rates. The negative effects of the proportion of youths that dropout and the proportion of the adult population with a high school education or less reflects the effect of neighborhood human capital on male youth employment rates. The estimated negative effect of "Enrolled" indicates that the variable partially captures the percentage of youths available for work.

In regression (1), the proportion of neighborhood residents living in poverty has a strong negative effect on the neighborhood employment rate. Using the racial difference for the poverty rate variable presented in Table 2.2, the negative employment

Table 2.6
Regressions of Neighborhood Male Youth Employment Rates on Spatial Measures and All Other Neighborhood Variables

Variables	(1)	(2)	(3)
Constant	1.0022 (11.80)	.9466 (11.34)	.9815 (11.63)
Average Household Income	-2.01×10^{-6} (-6.02)	-2.05×10^{-6} (-6.28)	-2.18×10^{-6} (-6.53)
Enrolled	-.4069 (-4.63)	-.3674 (-4.26)	-.3647 (-4.24)
Dropout	-.3036 (-3.45)	-.3187 (-3.71)	-.3310 (-3.86)
Poverty	-.5601 (-4.38)	-.3593 (-2.74)	-.2851 (-2.08)
Single Parent	.2644 (1.43)	.1594 (.877)	.1217 (.648)
<High School	-.5237 (-2.37)	-.3973 (-1.82)	-.5317 (-2.32)
Black	-.3379 (-5.97)	-.2735 (-4.81)	-.2459 (-4.16)
Competing Labor Supply	-	-2.02×10^{-6} (-4.93)	-1.50×10^{-6} (-1.75)
All Industries	-	2.41×10^{-6} (4.76)	-
Manufacturing	-	- -	2.32×10^{-6} (1.47)
Wholesale Trade	-	-	9.23×10^{-6} (3.06)
Retail Trade	-	-	-3.01×10^{-6} (-.547)
Services	-	-	2.64×10^{-7} (.127)
Combined[a]	-	-	2.10×10^{-6} (1.70)
R^2	.228	.267	.278
N	634	634	634

T-statistics are in parenthesis. All regressions are weighted by the count of neighborhood male youths.
a. The combined industry category includes transportation, communication, other public utilities, construction and public administration.

effect of "Poverty" estimated in the first regression predicts a 4.5 percentage point differential between the neighborhood employment rate of the average white youth and that of the average black youth (-.56501*(.148-.068)). Note, this is nearly 40 percent of the total racial differential in neighborhood employment rates. The coefficient on "Black" in the first equation is nearly identical to the estimated effect of this variable when the neighborhood quality and isolation variables are omitted.

Adding the spatial variables to the equation yields several interesting results. Starting with regression (2), adding the all industries accessibility measure and the competing labor supply variable reduces the estimated coefficient on the variable "Black" by 20 percent (from -.3379 to -.2753). Furthermore, the coefficient estimate on "Poverty" drops considerably, from -.5601 to -.3591. The estimated effects of all other variables change very little with the exception of "<High School". Both of the coefficients on the competing labor supply and the all industry variables have the expected sign and are highly significant.

Replacing the all industries accessibility measure by the set of industry-specific accessibility measures yields even larger changes. The estimated coefficient on the variable "Black" drops by 27 percent, from -.3379 in regression (1) to -.2459 in regression (3). The largest change occurs in the estimated effect of the proportion of residents living in poverty. The coefficient estimate drops by nearly half, from -.5601 to -.2851. While in regression (1) the difference in neighborhood poverty rates between that of the average white male youth and that of the average black male youth predicts a 4.5 percentage point differential in neighborhood employment rates, the smaller coefficient on "Poverty" in regression (3) predicts a 2.3 percentage point differential. All of the other coefficients in regression (3) are similar to the estimates in regression (1). Again, while only one of the six coefficient on the spatial variables is statistically significant (wholesale trade), an F-test of regression (3) against regression (1) strongly rejects the hypothesis that the effect of all six variables is statistically insignificant.

Having discussed the basic estimation results, I now turn to the relative importance of differential accessibility in explaining the racial differential in neighborhood employment rates. Table 2.7 combines the average racial differences in the accessibility measures presented in Table 2.2 with the parameter estimates of Tables 2.4, 2.5, and 2.6. For each table, I calculate four figures. First, using the regressions on the all industries accessibility measure and the competing labor supply variable, I calculate the neighborhood employment rate differential predicted by the spatial variables using the average differences between black and white male youths. The same figure is also calculated for the regressions on the competing labor supply variable and the full set of industry-specific accessibility measures. I then compute the ratios of the predicted to the actual racial differentials.

The percentage of the actual racial differential predicted by differential accessibility varies from a low of 29 percent, in the regression with all neighborhood controls and the all industries accessibility measure, to 51 percent in the regression with the competing supply variables and the set of industry-specific measures alone. In each table, the specification with the set of industry-specific accessibility measures predicts a larger racial differential than the regression on the all industries accessibility measure.

Table 2.7
Predicted Racial Employment Differentials and the Ratio of Predicted to Actual Racial Employment Differentials, by Equation Specifications

Specification	All Industry Measure and Competing Labor Supply	Industry-Specific Measures and Competing Labor Supply
Spatial Variables Only		
Predicted Differential	4.82%	5.70%
Predicted/Actual	.43	.51
Spatial Variables and %Black		
Predicted Differential	3.25%	3.57%
Predicted/Actual	.29	.32
Spatial Variables, %Black, and other Neighborhood Variables		
Predicted Differential	3.21%	4.00%
Predicted/Actual	.29	.36

While the percentage of the racial employment differential explained by differential accessibility varies with the specification, the percentage never falls below approximately 30 percent.

D. Comparison to Accessibility Measures Used in the Past

The results presented in Tables 2.4 through 2.7 stand in stark contrast to the findings of similar studies of Chicago (Ellwood 1986) and Los Angeles (Leonard 1985). These previous studies failed to find substantial relationships between various measures of spatial accessibility and neighborhood youth employment-to-population ratios. Moreover, the small measurable effects of the accessibility measures used did not explain the strong negative relationship between youth neighborhood employment rates and the percentage of neighborhood residents that are black. In addition to the differences between past work and this study in the measuring of spatial accessibility, several factors may explain the conflicting results independently of the specific accessibility measure used. For example, the geography of the Bay Area is quite distinct from that of Chicago or Los Angeles and may aggravate the extent and effects of black spatial isolation from employment opportunities. Furthermore, the current study uses data for 1990 while Ellwood's Chicago study uses data for 1970 and Leonard's Los Angeles study uses data for 1980. If the extent of the mismatch has increased over the past two decades or if parallel developments -- e.g., the exodus of the black middle class from inner city neighborhoods emphasized by Wilson (1986) -- has created a situation were inner-city black youth employment rates are now, more than ever, exceedingly sensitive to the amount of immediately accessible opportunities, then mismatch studies focusing on different time periods will yield conflicting results.

In order to investigate such possibilities, I reproduce Ellwood's Chicago employment regressions using similar accessibility measures and 1990 Bay Area data. While significant differences exist between the geographic units of analysis in Ellwood's study and this study,[13] the data do allow me to construct rough approximations of Ellwood's accessibility measures. Specifically, as alternative measures of accessibility I construct variables measuring the average commute time of all neighborhood workers,

[13]Ellwood's dependent variable is defined at the census tract level and accessibility is measured for "neighborhood areas" that are larger than census tracts. Here, the geographic unit of the dependent variable and the unit used for the accessibility measures are the same. Moreover, the modified traffic analysis zones discussed in the previous section are slightly larger, in terms of area and population, than census tracts.

the average commute time of neighborhood male youths with jobs, the ratio of jobs to workers within the residence zone, and the ratio of jobs to workers within 30 minutes of the residence zone. For the jobs-to-workers ratios, at the zone level and within 30 minutes, I use several alternative numerators including employment in all industries, manufacturing employment, and "blue collar" employment, defined simply as the sum of manufacturing, retail, and service employment. Since I am unable to reproduce Ellwood's blue collar import ratios exactly (the ABAG employment data is dis-aggregated by industry only), I experimented with several possible combinations of industries as measures of blue collar employment. The results did not differ significantly for different definitions of blue collar employment.

Table 2.8 presents results from regressing neighborhoods male youth employment rates on the full set of neighborhood controls and the Ellwood accessibility measures. Each row of the table corresponds to an individual regression. For a point of reference, the first row presents the regression results omitting accessibility measures. This is the same regression presented in the first column of Table 2.6. I omit the full set of coefficient estimates as they do not differ substantially from the results in Table 2.6 and do not change as a result of including the alternative accessibility measures in the specification.[14] Table 2.8 gives several statistics. The second column presents the coefficient estimate for each individual accessibility measure, the third column gives the coefficient on the variable measuring the proportion of neighborhood residents that are

[14]The full regression results for the specification including the entire set of neighborhood controls, as well as regression results from the alternative specifications used in Tables 2.3 and 2.4 are available from the author upon request.

Table 2.8
Regressions Results and Predicted Racial Employment Differentials with Alternative Accessibility Measures

Accessibility Measures	Coefficient Estimate (t-statistic)	Coefficient on Black (t-Statistic)	R^2	Predicted % Point Differential (Predicted/Actual)
None	-	-.3379 (-5.97)	.228	-
Average Travel Time				
All Workers	-.0014 (-1.11)	-.3358 (-5.93)	.230	.17% (.02)
Male Youths	.0011 (.946)	-.3247 (-5.70)	.232	.05% (.00)
Ratio of Zone-Level Jobs to Workers				
All Industries	-.0003 (-.584)	-.3359 (-5.92)	.229	.00% (.00)
Manufacturing	.0060 (1.75)	-.3419 (-6.04)	.233	.02% (.00)
Blue Collar*	.0010 (.611)	-.3413 (-6.00)	.229	.00% (.00)
Ratio of Jobs to Workers Within 30 Minutes of Zone				
All Industries	-.1071 (-2.57)	-.3222 (-5.68)	.237	.45% (.04)
Manufacturing	.1943 (2.74)	-.3101 (-5.42)	.238	.71% (.06)
Blue Collar*	-.0403 (-.713)	-.3388 (-5.98)	.229	.00% (.00)

All regressions control for neighborhood average household income, the proportions of youth enrolled in school, proportions of youths that drop out, the neighborhood poverty rate, the proportion of households headed by a single parent, and the proportion of adults with less than a high school education.
* Blue collar employment is the aggregation of manufacturing, retail, and service jobs.

black, while the fourth column provides the R^2 of the regression. The final column uses the coefficient estimates of the accessibility measures and the mean differences of the accessibility measures between the average white and black youth to compute a predicted racial differential in the neighborhood youth employment-to-population ratio. The numbers in parenthesis in the final column give the ratio of the predicted to actual racial employment differential.

Of the eight accessibility measures shown in Table 2.8, only two have statistically significant effects on the neighborhood youth employment rates (the "all industries" and "manufacturing" jobs-to-workers ratio within 30 minutes of the zone), one of which has the wrong sign (all industries). The average travel time measures have no discernable effect on the dependent variable as do none of the zone level jobs-to-workers ratios. Similar to Ellwood's findings, adding these accessibility measures does not substantially effect the coefficient estimate on the variable measuring the proportion of neighborhood residents that are black. The largest decline in the coefficient estimate for the variable "Black" occurs when the 30 minute manufacturing jobs-to-workers ratio is added to the employment equation (declining from -.3379 to -.3101).

None of the eight accessibility measures presented in Table 2.8 predict a substantial portion of the racial employment differential. The proportion of the actual racial differential in neighborhood employment rates predicted by these accessibility ranges from .00 to .06, with the high being the .71% differential predicted by the 30 minute manufacturing ratio. This contrasts sharply with the results presented in Table 2.7 where it is shown that (in similarly specified equations) the geographic accessibility measures presented in this paper predict racial neighborhood employment rate differentials equivalent to between 29 and 36 percent of the actual differential. Hence, rather than differences in the metropolitan areas studied or differences in time periods, differences in the construction of the accessibility measures appear to explain the divergence in results from past studies.

2.5. Generalizability of the Results

The major shortcoming of intra-metropolitan studies of the mismatch hypothesis that focus on a single or limited number of metropolitan areas is the difficulty in assessing the generalizability of the results. Each urban area has a distinctive public transit system, employment base, and social and economic history. Particularities of a region's geography or system of highways may act to isolate, or integrate, the given black population living within the metropolitan area. While at present, I do not have data to extend the analysis to other major cities, it is possible to compare the underlying conditions that create a spatial mismatch in the Bay Area CMSA to those of other large metropolitan areas. This comparison provides some indication of the severity of racial segregation and employment decentralization in the Bay Area relative to other cities.

Table 2.9 provides two measures of the racial segregation between blacks and non-hispanic whites for the five Bay Area Primary Metropolitan Statistical Areas (PMSA) and for the 20 non-Bay Area PMSAs with the largest black populations in 1990. The data for the segregation measures come from the 1990 Census Summary Tape File 1A. The dissimilarity index is interpreted as the percentage of black residents that would have to

Table 2.9
Segregation Indices for Bay Area PMSAs and Other Major Metropolitan Areas

PMSA	Dissimilarity Index[a]	Isolation Index[b]
Bay Area PMSAs		
Oakland	68	46
San Francisco	64	31
San Jose	43	5
Santa Rosa-Petaluma	34	2
Vallejo-Fairfield-Napa	49	21
Weighted Average	62	35
PMSAs With Largest Black Populations		
New York	82	62
Chicago	84	77
Washington D.C.	65	61
Detroit	87	71
Los Angeles-Long Beach	73	42
Philadelphia	77	67
Atlanta	67	64
Baltimore	71	69
Houston	67	53
New Orleans	68	69
St. Louis	77	69
Dallas	62	50
Newark	83	69
Memphis	68	74
Norfolk	49	53
Cleveland	83	76
Miami-Hialeah	72	61
Boston	67	38
Richmond-Petersburg	59	59
Birmingham	72	70
Weighted Average	74	64
Weighted Average 45[c]	73	61

Calculated from the 1990 Census Summary Tape Files 1A. Averages are weighted by the black populations of the PMSAs.
a. The dissimilarity index is interpreted as the percentage of black residents that would have to move to create a perfectly even residential distribution.
b. The isolation index measures the percentage of the population that is black in the neighborhood of the average black resident.
c. Computed with the 45 PMSAs with the largest black populations.

move to create a perfectly even residential distribution. The isolation index measures the percentage of the population that is black in the neighborhood of the average black resident.[15] All indices are computed with census tract data. In addition to presenting weighted averages for the twenty non-Bay Area PMSAs listed, Table 2.9 also provides the weighted average for the 45 PMSAs with the largest black population in 1990.

Relative to the areas listed in Table 2.9, the Bay Area PMSAs are moderately segregated. For both the dissimilarity index and the isolation index, the segregation scores for the individual PMSAs are below the weighted averages for the 20 largest and 45 largest metropolitan areas. The segregation scores vary considerably within the Bay Area. For example, the index of dissimilarity varies from 35 for the Santa Rosa-Petaluma PMSA to 68 for the Oakland PMSA. Despite the low segregation scores for three of the Bay Area PMSAs, the overall measures for the entire area are closer to the higher scores of San Francisco and Oakland as the majority of blacks reside in these two PMSAs. Hence, like other major American cities, the San Francisco-Oakland-San Jose CMSA is segregated. The degree of segregation, however, is moderate and should not create an atypically large mismatch between the resident black population and areas of high employment opportunity.

Measuring employment decentralization is relatively more difficult as geographically detailed employment data, by industry, and at two points in time, are hard to come by. Nonetheless, employment data by broad industry categories are available at

---

[15]For a full methodological exposition of these and other measures of segregation, see Massey and Denton (1988).

five year intervals for the central city and non-central city portions of large PMSAs. Table 2.10 presents percent changes in PMSA employment over the period from 1977 to 1987 by central city status and by industry. The table provides figures for the three Bay Area PMSAs with identifiable central cities and for the ten non-Bay Area PMSAs with the largest black populations. Several patterns emerge that are quite similar across all PMSAs. First, with the exception of San Jose and Houston, the declines in manufacturing were relatively less severe in the non-central city portions of the PMSAs. In fact, non-central city manufacturing employment grew in 8 of the 13 metropolitan areas in the table. Manufacturing employment increased in only three of the central cities. Moreover, central-city manufacturing jobs increased at a higher rate than non-central city employment in San Jose only.

Second, employment in wholesale trade, retail trade, and services grew at much higher rates in the non-central city balances of the PMSAs than in the respective central cities. Again, San Jose provides the sole exception. Growth in service sector employment provided the largest source of new jobs in both central cities and the non-central city areas. Even in the city of Detroit, where there were large percentage declines in all other industries, service employment increased by 25 percent. The Bay Area PMSAs appear to follow much the same pattern as the other large PMSAs, with the exception of San Jose, which experienced abnormally strong employment growth in all industries. As the majority of the Bay Area black population resides in the cities of San Francisco and Oakland, their exposure to the adverse effects of employment decentralization does not appear to differ from the experience of blacks in other large

Table 2.10
Percentage Changes in Employment 1977 to 1987 by Central City and Balance of Metropolitan Area

PMSA/MSA	Manufacturing	Wholesale Trade	Retail Trade	Services
Oakland				
Central City	-26	17	3	113
Balance of PMSA	-1	95	55	243
San Francisco				
Central City	2	7	39	104
Balance of PMSA	6	31	41	168
San Jose				
Central City	77	128	36	243
Balance of PMSA	45	122	40	147
New York				
Central City	-28	1	10	76
Balance of PMSA	13	25	26	144
Chicago				
Central City	-40	-23	-14	53
Balance of PMSA	-30	37	2	122
Washington D.C.				
Central City	-9	-18	16	100
Balance of PMSA	104	104	68	224
Detroit				
Central City	-33	-29	-20	25
Balance of PMSA	-8	54	39	184
Los Angeles				
Central City	-4	31	24	113
Balance of PMSA	14	41	35	145
Philadelphia				
Central City	-39	-12	7	76
Balance of PMSA	-5	52	38	174
Atlanta				
Central City	1	-7	14	105
Balance of PMSA	80	129	137	362
Baltimore				
Central City	-31	-2	1	100
Balance of PMSA	1	74	77	249
Houston				
Central City	-23	13	26	104
Balance of PMSA	-27	57	49	129
New Orleans				
Central City	-21	-23	7	54
Balance of PMSA	3	67	63	190

Source: County and City Data Book, 1994, 1983.

metropolitan areas. If anything, the degree of decentralization is less severe.

2.6 Conclusion

This chapter has demonstrated the importance of urban geography and the distribution of employment growth in determining the differential employment rates of black and white youth in one large Consolidate Metropolitan Statistical Area. Differential accessibility to areas of high employment growth is sufficient to explain between 30 and 50 percent of the racial differential in neighborhood youth employment rates. As the CMSA studied is only moderately segregated relative to other large metropolitan areas and has experienced changes in the spatial configuration of industry similar to other cities, there is little reason to believe that these results are atypical. In fact, one would expect a more stark mismatch in such hyper-segregated cities as Chicago and Detroit. In future research, I intend to extend the analysis to additional metropolitan areas.

An important question that has been left unanswered concerns the divergence in results between accessibility measures based on employment changes and accessibility measures based on levels. In future research, I will attempt to reconcile this divergence by comparing the actual number of jobs held by youth in a given area to recent area employment growth. The 1990 Public Use Micro Data sample includes geographic identifiers for the Public Use Microdata Area (PUMA) for the residence and work place of the person being observed. While PUMAs are considerably larger than the Regional Traffic Analysis Zones used in this study, nearly 100 separate PUMAS are identified for the Bay Area CMSA. Comparing employment growth by sector within each PUMA to the total number of jobs held by youth workers will provide information on the relationship between local area employment growth and the stock of employment opportunities available to youth workers.

Note, this chapter only examines a single aspect of how the constrained residential choice of African-Americans affects their employment and earnings prospects. The racial disparity in accessibility may widen as young workers mature and gain control over their residential choices. With the ability to move, the geographic area in which a worker will search for employment expands, since relocating to be nearer to one's place of work is now an option. With severe racial discrimination in the housing market, however, the search area of blacks is still constrained to employment areas in, or within the immediate vicinity of, predominantly black neighborhoods. On the other hand, the search area of white workers now encompasses the entire metropolitan area since their residential choices are not constrained by housing discrimination and they can more easily relocate for employment purposes. Future research on racial differences in geographic mobility, both within and between metropolitan areas, would provide a more complete assessment of how housing discrimination impacts the employment prospects of African Americans.

Appendix 2.A

In the past, researchers estimating the unconstrained gravity equation often assumed a log-normally distributed dependent variable which allows one to simply take the log of equation (1) and apply ordinary least squares. This approach is inappropriate when there are many small or zero flows as is often the case with journey-to-work data (Flowerdew & Aitken 1982). Furthermore, the simple log-normal model tends to underpredict large flows and underpredict the total of all flows (Senior 1979). For these reasons, recent research has modelled the dependent variable as a discrete probability process, an approach which is clearly more appropriate in the analysis of count data (Flowerdew & Aitkin 1982, Guy 1987, Yun & Sen 1994). The estimation procedure used here will follow this latter line of research.

The simplest statistical model of count data is the Poisson regression. Let X_{ij} be the observed commute flow of male teenage workers between neighborhoods i and j. Assuming that the movement of individuals are independent and that the flow of workers from i to j has a Poisson distribution, then for the basic model of equation (1),

$$Prob(X_{ij}=x_{ij}|\lambda_{ij}) = \frac{\exp(-\lambda_{ij})\lambda_{ij}^{x_{ij}}}{x_{ij}!}, \tag{A.1}$$

where

$$E(X_{ij}) = V(X_{ij}) = \lambda_{ij} = kL_i^{\alpha}E_j^{\beta}\exp(-\gamma d_{ij}). \tag{A.2}$$

Equation (A.1) is simply the Poisson distribution with parameter λ_{ij}. The parameters are estimated by constructing the maximum likelihood function with (A.1) and employing an iterative optimization procedure.

The main drawback of the Poisson model is that the variance of the dependent variable is constrained to being equal to the mean. While this does not affect the consistency of the estimates, the presence of overdispersion in the data -- i.e., the variance being greater than the mean -- causes a downward bias in the standard errors of the parameter estimates. Applying a test for overdispersion derived by Cameron & Trivedi (1990) to initial Poisson regression estimates with the data used here revealed strong evidence of overdispersion. Hence, a distribution which relaxes the variance constraint is necessary.

One solution is to suppose that the Poisson parameter itself has a random distribution (Hausman et. al. 1984). Assume that λ_{ij} has a gamma distribution with parameters (θ_{ij},δ), where we specify $\theta_{ij}=kE_i^{\alpha}L_j^{\beta}\exp(-\gamma d_{ij})$ and δ as constant across all origin-destination pairs. Using the gamma distribution to take expectations of equation (A.1) yields the negative binomial distribution

$$Prob(X_{ij}=x_{ij}|\theta_{ij},\delta) = \frac{\Gamma(\theta_{ij}+x_{ij})}{\Gamma(\theta_{ij})\Gamma(x_{ij}+1)}\frac{\delta^{\theta_{ij}}}{(1+\delta)^{\theta_{ij}+x_{ij}}}, \qquad (A.3)$$

with the conditional mean and variance

$$E(X_{ij}) = \frac{\theta_{ij}}{\delta}, \quad V(X_{ij}) = \theta_{ij}\frac{(1+\delta)}{\delta^2}. \qquad (A.4)$$

Similar to the Poisson regression, the ratio of the variance to the mean is constant. Unlike the Poisson model, however, the variance-mean ratio is greater than one -- i.e., $V(X_{ij})/E(X_{ij}) = (1+\delta)/\delta > 1$. In the estimation reported below, estimates of the parameter δ are on the order of .03 implying a variance to mean ratio of approximately

34. This clearly illustrates the restrictiveness of the variance assumptions in the Poisson regression model.

I estimate the negative binomial model in equations (A.3) and (A.4) using maximum likelihood techniques. Multiplying the conditional probabilities of equation

$$\log(\mathcal{L}) = \sum_i \sum_j [\log\Gamma(\theta_{ij}+x_{ij}) - \log\Gamma(\theta_{ij}) - \log\Gamma(x_{ij}+1) + \theta_{ij}\log(\delta) - (\theta_{ij}+x_{ij})\log(1+\delta)] .$$

(A.3) for all i and j and taking logs gives the log-likelihood function

After substituting the parameratization of θ_{ij},, the likelihood function is maximized with respect to the parameters of the model using iterative numerical optimization techniques. The parameter estimates for the basic gravity equation are presented in Table A1. All parameters have the expected signs and are highly significant.

Table 2A.1
Parameter Estimates for the Basic Gravity Equation

Parameter	Coefficient
ln(Constant)	-12.362 (.1419)
Exponent on Origin Labor	.8101 (.0187)
Exponent on Destination Employment	.6545 (.0116)
Distance Coefficient	-.1618 (.0014)
δ	.0281 (.0009)
N	423,776
Log of Likelihood	-37,616

Chapter 3: Intervening Opportunities, Competing Searchers, and the Intra-Metropolitan Flow of Male Youth Labor

3.1 Introduction

The geographic mobility of labor is a vital adjustment mechanism in all modern industrialized economies. As the spatial configuration of employment changes with technological innovation and population shifts, residential mobility permits individual workers to adapt to the evolving economic landscape and supports the equalization of wages and unemployment rates over space. For many segments of the population, however, the residential location decision is severely constrained. For example, African Americans suffering from housing discrimination, low-income workers, teenagers living at home, and dual-earner families face various limitations to residential mobility. For these workers, geographically accessible opportunities are limited to the set of jobs within a reasonable distance of their residential locations. Overall accessibility to employment opportunities will be sensitive to the particular spatial distribution of employment and the distribution of the competing labor supply within the local labor market. Furthermore, one's access to employment opportunities may strongly affect one's wages and the relative ease of locating acceptable employment.

Given the fact that the workers with the most constrained residential choices are also among the most vulnerable in the labor market, a sound understanding of the spatial aspects of job search may provide important clues to understanding the relatively poor labor market performance of geographically constrained groups. For workers that search from a fixed residential location, job search is a form of spatial interaction that determines a worker-employer match and a concurrent journey-to-work path. The probability of a given residence-work place interaction will depend on a host of variables that describe the relative proximity of the work place location to the residential location. Conventional spatial models of the labor market emphasize the importance of commute costs that increase with distance (Strazheim 1980) or employment information flows that erode with distance (Ihlanfeldt 1992). Recent theoretical advances in the modelling of spatial search processes (Jayet 1990a, 1990b) stress the importance of the geographic distribution and density of competing job searchers and intervening opportunities in affecting the spatial partitioning of existing residence-work place matches. Few papers attempt to empirically disentangle the relative importance of various aspects of accessibility in explaining the fluidity of labor within a given local labor market.

This chapter analyzes the determinants of the journey-to-work commute patterns for male teenage workers within a single local labor market: the Oakland Primary Metropolitan Statistical Area. Aggregate commute flows between origin and destination traffic analysis zones are analyzed. I find that controlling for the intervening opportunities and the intervening labor supply between a given origin and destination reduces the estimated negative effect of distance on the inter-zonal flow of labor by nearly eighty percent. Nonetheless, physical distance has a significant and substantial negative effect on intra-metropolitan youth labor flows, even after controlling for the other spatial variables. Despite the high correlation between intervening opportunities and intervening competing workers, both spatial variables have sizable, and independent, effects on labor flows. I interpret these findings as evidence of the importance of spatial search models that emphasize the correlates of distance -- i.e., the cumulative intervening opportunities and the increasing stock of competing workers -- as well as distance itself in impeding intra-metropolitan labor mobility. These findings are important in that they highlight the need for geographic accessibility measures that, in addition to physical distance, incorporate the spatial distributions of labor supply and labor demand.

The remainder of this chapter is organized as follows. First, I provide a theoretical discussion of distance related frictions to labor mobility, their implications for theoretical models of spatial job search, and the implications for the specification of empirical models of aggregate spatial interaction. Various specification of the gravity model are offered as tests for competing theories of spatial search and interaction. Next, the negative binomial regression used to estimate the gravity models is presented. A description of the data and the presentation of the main results follows. Finally, I offer conclusions.

Throughout the chapter I assume that workers obtain employment through job search from a fixed residential location -- i.e., residential locations are exogenously given. The focus on male youth labor flows justifies this assumption, since the overwhelming majority of male teenagers are either living with their parents or another relative. In the absence of exogenously given residences, it is difficult to empirically interpret the distribution of work trips, as journey-to-work flows are determined by two search processes, job search and the search for housing.

3.2 Distance, Competition, and Labor Mobility

The inter-zonal commuting of labor is one form of spatial interaction between individual neighborhoods or zones within a local economy. Economic geographers and sociologists who study aggregate spatial interaction, such as migration or the distribution of shopping trips, liken such interactions to the gravitational attractions between two physical masses. Analogous to gravitational force, the population or characteristics of a given destination zone exert an attractive pull on the population of a given origin. Also akin to gravitational force, "demographic force" exerted by one region on another erodes with the friction injected by the intervening distance.

Extending the gravity analogy to intra-metropolitan labor mobility, the factors that determine aggregate commute flows between neighborhoods fall into three categories: (1) the supply of labor in the given origin, (2) the demand for labor at a given destination, and (3) the distance between the origin and destination. This provides the specification of the unconstrained gravity model,

$$T_{ij} = \frac{kL_i^{\alpha}E_j^{\beta}}{d_{ij}^{\gamma}}, \qquad (1)$$

where $i=(1,\ldots,I)$ indexes the origin neighborhoods, $j=(1,\ldots,J)$ indexes destination neighborhoods, T_{ij} is the aggregate flow of labor between zones i and j, L_i is the supply of labor in the origin zone i, E_j is the demand for labor in the destination zone j, d_{ij} is the distance between neighborhoods i and j, k is a constant, and α, β, and γ are positive parameters. The scale of the possible labor flow between zones is captures by the origin labor supply and destination labor demand. By entering labor supply and demand multiplicatively, the potential scale of interaction is increasing in the total possible combinations of workers and jobs.

The inverse relationship between distance and the total flow of workers in equation (1) represents the spatial content of the model. Here, distance is measured by commute time so as to neutralize any geographic structure that creates a divergence between physical distance and the facility of a particular commute. Several factors motivate the inverse relationship between distance and labor flows. First, commuting is costly both in terms of direct cash outlays and time. All else held equal, workers prefer jobs closer rather than farther from home. Second, distance impedes the flow of information travelling through informal channels. In a search theoretical framework, the rate at which job offers from a given work place location are received decreases with distance from the location. Hence, both workers' preferences and the geography of information flows yield an inverse relationship between the aggregate commute flow between a pair of zones and the intervening distance.

Several researchers argue that the gravity model in equation (1) is mis-specified. Specifically, it is argued that the negative relationship between spatial interactions and distance is driven by the correlates of distance rather than physical distance itself. As the distance between two regions increases, so does the volume of intervening opportunities between the regions. Hence with increasing distance, the probability of locating an acceptable opportunity closer to home increases. This criticism was first offered by Stouffer (1940) and has been empirically tested with inter-metropolitan migration data by Haynes et. al. (1973).

Two recent papers by Jayet (1990a, 1990b) provide a rigorous connection between spatial search theory and aggregate spatial interaction models and demonstrate the theoretical importance of variables that are highly correlated with distance. Jayet (1990a) defines three set of factors that determine the probability that a worker searching from a fixed location obtains employment at a given point in space. First are those factors under the worker's control, such as search intensity and the sequence of areas visited. Next, are the spatial and temporal aspects of the process that generates new opportunities. Finally, are the interactions of the search process and residential locations of other competing searchers. These factors together determine the shape of the spatial search hazard function, defined as the probability that a worker with a fixed residential location searching for a time t will locate employment in the time interval $t+dt$ within a given location.

The spatial element of this model and the implication for aggregate labor flows comes from assumptions concerning the spatial trajectory of the search process. Jayet defines a sequential search process where space is partitioned into three area, a starting point (or area), a core, and an ending point. The starting point is the area in the immediate vicinity of a worker's neighborhood. The search process is defined as sequential if the probability of locating an acceptable opportunity in the starting area decreases with the length of the search spell and the probability of locating an opportunity in the final area increases with the time spent searching.

In equilibrium, the probability that a particular residence-work place match occurs, or alternatively stated, that a given journey-to-work path is realized, depends on the volume of intervening opportunities between the residence and potential work place and a law of vacancy duration for the given employment opportunity. While the spatial distribution of employment determines the intervening opportunities between a pair of origin and work place zones, the sequential search processes of competing searchers determine the durations of particular job vacancies. In this model, the probability of a given residence-work place match decreases with distance. The inverse relationship between distance and the probability of a given journey to work, however, is not dependent on distance related costs but rather on the increasing number of intervening opportunities and competing labor supply.

The attractive feature of this model is that it provides a direct link between spatial search and aggregate spatial interaction. The aggregation of the set of individual intervening opportunity models for the residents of each origin zone determines the aggregate commute patterns between neighborhoods. The resulting aggregate interaction (or flow) function is strikingly similar to the basic gravity equation. Labor flows between areas are proportional to the count of workers in the origin and the count of jobs in the destination. However, the arrival rate of competing searchers per unit of time qualifies the attracting force of jobs in the destination zone. Furthermore, the total flow declines with increasing intervening opportunities rather than with increasing distance. In fact, distance does not enter the aggregate interaction function (Jayet 1990b).

While it is difficult to empirically implement an aggregate labor flow function which depends on the destination-specific arrival rates of competing searchers, it is possible to re-specify equation (1) in a manner implied by Jayet's theoretical argument.

Specifically, defining the quantity of intervening opportunities by the variable

$$IO_{ij} = \sum_k E_k \ \forall (k|d_{ik}<d_{ij}) \tag{2}$$

and the quantity of competing labor by

$$IC_{ij} = \sum_k L_k \ \forall (k|d_{kj}<d_{ij}) \ , \tag{3}$$

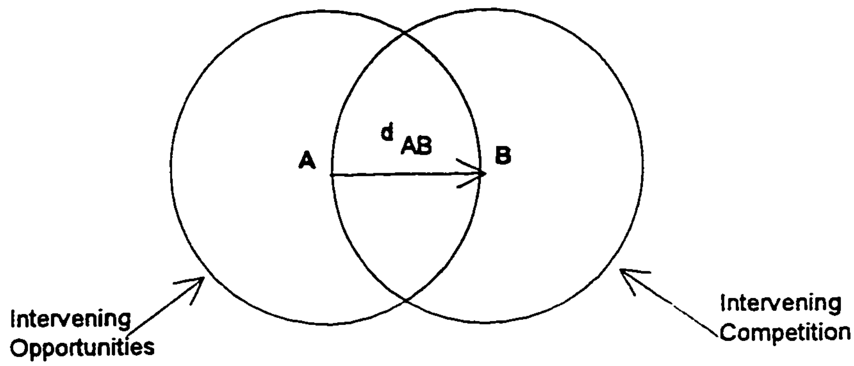
the aggregate flow function suggested by Jayet's spatial search model is

$$T_{ij} = kL_i^{\alpha} E_j^{\beta} IC_{ij}^{\delta} IO_{ij}^{\eta} . \tag{4}$$

The theory suggests positive values for the parameters, α and β, and negative values for the parameters, δ and η. Figure 3.1 graphically depicts the intervening opportunities and intervening competition variables for a typical origin-destination observation. Labor flows from the origin neighborhood, A, to the destination neighborhood, B, travelling the distance, d_{AB}. Drawing a circle of radius, d_{AB}, around the point of origin, A, and summing all employment opportunities within the area of the circle provides the intervening opportunities between A and B. Similarly, sweeping a ray of length d_{AB} around the destination point, B, and summing the labor supply within the area of this circle gives the number of workers who are in direct competition with the workers in A for job opportunities in B.

Showing the spurious negative correlation in the model of equation (4) between the total flow of labor and physical distance is simple when employment and labor supply are uniformly distributed over space. Let D_e by the density per square unit of distance for employment and D_l be the densities per square unit of distance for labor supply.

Figure 3.1



Given the uniformity assumptions and employing the formula for the area of a circle, intervening opportunities and intervening competition can be rewritten as $IO_{ij} = D_e \pi d_{ij}^2$, and $IC_{ij} = D_l \pi d_{ij}^2$. Substituting into equation (4) gives

$$T_{ij} = C L_i^{\alpha} E_j^{\beta} d_{ij}^{2(\delta+\eta)}, \tag{5}$$

where $C = k(D_l\pi)^{\delta}(D_e\pi)^{\eta}$. Given that the theory predicts η, $\delta < 0$, there is a negative empirical relationship between distance and the total labor flow. Nonetheless, no causal relationship exists.

The models of equations (1) and (4) represent extreme versions of the competing hypotheses concerning the relationship between distance and spatial interaction. The relative importance of each hypothesis in explaining the intra-metropolitan flow of youth labor is an empirical question that is the main purpose of this paper. The empirical strategy is to fit equation (1) to the flow data for Oakland and generate an initial estimate of the effect of distance between zones (measured in travel time) on the aggregate flow of teenage labor. Next, I add intervening opportunities and intervening competition to the equation individually, and simultaneously, and analyze the changes in the estimated effect of distance. Before proceeding to the main results, the next sections describes the statistical model used.

3.3 Estimation Methodology

In the past, researchers estimating the unconstrained gravity equation often assumed a log-normally distributed dependent variable which allows one to simply take the log of equation (1) and apply ordinary least squares. This approach is inappropriate when there are many small or zero flows as is often the case with journey-to-work data (Flowerdew & Aitken 1982). Furthermore, the simple log-normal model tends to underpredict large flows and underpredict the total of all flows (Senior 1979). In realization of these short comings, recent research has modelled the dependent variable as a discrete probability process, an approach more appropriate in the analysis of count data (Flowerdew & Aitkin 1982, Guy 1987, Yun & Sen 1994). In the estimation procedure used here, I follow this latter line of research.

The simplest statistical model of count data is the Poisson regression. Let X_{ij} be the observed commute flow of male teenage workers between neighborhoods i and j. Assuming that the movement of individuals are independent and that the flow of workers from i to j has a Poisson distribution, then for the basic model of equation (1),

$$Prob(X_{ij}=x_{ij}|\lambda_{ij}) = \frac{\exp(-\lambda_{ij})\,\lambda_{ij}^{x_{ij}}}{x_{ij}!}, \tag{6}$$

where

$$E(X_{ij}) = V(X_{ij}) = \lambda_{ij} = \frac{kL_i^{\alpha}E_j^{\beta}}{d_{ij}^{\gamma}}. \tag{7}$$

Equation (6) is the Poisson distribution with parameter λ_{ij}. The parameters are estimated by constructing the maximum likelihood function with (6) and employing an iterative optimization procedure.

The main drawback of the Poisson model is that the variance of the dependent variable is constrained to being equal to the mean. While this does not affect the consistency of the estimates, the presence of overdispersion in the data -- i.e., the variance being greater than the mean -- causes a downward bias in the standard errors of the parameter estimates. Applying a test for overdispersion derived by Cameron & Trivedi (1990) to initial Poisson regression estimates of equations (1) and (4) with the data used here revealed strong evidence of overdispersion. Hence, a distribution that relaxes the variance constraint is necessary.

One solution is to suppose that the Poisson parameter itself has a random distribution (Hausman et. al. 1984). Assume that λ_{ij} has a gamma distribution with parameters (θ_{ij},δ), where $\theta_{ij}=kE_i^{\alpha}L_j^{\beta}/d_{ij}^{\gamma}$ and δ is constant across all origin-destination pairs. Using the gamma distribution to take expectations of equation (6) yields the negative binomial distribution

$$Prob(X_{ij}=x_{ij}|\theta_{ij},\delta) = \frac{\Gamma(\theta_{ij}+x_{ij})}{\Gamma(\theta_{ij})\Gamma(x_{ij}+1)}\frac{\delta^{\theta_{ij}}}{(1+\delta)^{\theta_{ij}+x_{ij}}}, \tag{8}$$

with the conditional mean and variance

$$E(X_{ij}) = \frac{\theta_{ij}}{\delta}, \quad V(X_{ij}) = \theta_{ij}\frac{(1+\delta)}{\delta^2}. \tag{9}$$

Similar to the Poisson regression, the ratio of the variance to the mean is constant. Unlike the Poisson model, however, the variance-mean ratio is greater than one -- i.e., $V(X_{ij})/E(X_{ij}) = (1+\delta)/\delta > 1$. In the estimations below, estimates of the parameter δ are on the order of .03, implying a variance to mean ratio of approximately 34. This clearly illustrates the restrictiveness of the variance assumptions in the Poisson regression model.

I estimate the negative binomial model in equations (8) and (9) using maximum likelihood techniques. Multiplying the conditional probabilities of equation (8) for all i

$$\log(\mathcal{L}) = \sum_i\sum_j [\log\Gamma(\theta_{ij}+x_{ij}) - \log\Gamma(\theta_{ij}) - \log\Gamma(x_{ij}+1) + \theta_{ij}\log(\delta) - (\theta_{ij}+x_{ij})\log(1+\delta)]. \tag{10}$$

and j and taking logs gives the log-likelihood function

After substituting the parameratization of θ_{ij} into equation (9), the likelihood function is maximized with respect to the parameters of the model using iterative numerical optimization techniques.

3.4 Description of the Data and Empirical Results

The data used here are for 1990 and are drawn from several sources. By special request, the Census Bureau calculated an inter-zonal labor flow matrix for male teenager workers in the San Francisco-Oakland-San Jose Consolidated Metropolitan Statistical Area. The matrix gives the aggregate, inter-zonal journey-to-work flows for male teenagers between all possible origin-destination combinations of 1990 census tracts in the Bay Area CMSA. The flows were computed from the Census Bureau's confidential microdata files. The tabulations were calculated in the exact same manner as the journey-to-work flows for all workers in the Urban Element of the 1990 Census Transportation and Planning Package, with the sole difference being the restriction of the sample to male workers between the ages of 16 and 19 years of age. In addition, tract-level population counts of male teenage workers by employment status were obtained in the special tabulations request. The Bay Area Metropolitan Transportation Commission (MTC) provided a complete zone-to-zone matrix of AM peak period travel times by private vehicle. Finally, the Association of Bay Area Governments provided tract-level employment totals. These data are calculated from state ES-202 files.

While the journey-to-work flow calculations received from the Census Bureau are calculated at the tract level, the MTC travel time matrix is computed for their own regional travel analysis zone (RTAZ) system. For the most part, the 1,382 census tract system of the Bay Area CMSA is nested within the 700 RTAZ system of the MTC and matching the journey-to-work and employment data simply requires the appropriate aggregation of the Census Bureau data. In a hand full of cases, however, the MTC system split census tracts into two or more RTAZs. In these cases, inter-zonal travel times are aggregated to the tract level by averaging. After all the necessary adjustments, the matched data set encompasses a 660 zone system with 435,600 origin-destination observations.

The origin supply of male teenage labor is defined as all male teenagers in the origin zone. Destination employment opportunities is measured by the count of jobs located in the destination zone. Distance between zones is measured by the private vehicle, AM peak period travel time and is measured in minutes. Intervening opportunities and intervening competing labor are calculated as follows. For the intervening opportunities variable, the data are sorted in ascending order by the origin zone codes and by inter-zonal travel times. A variable is then created by cumulating destination employment counts, with a new running total starting for each new origin. I then subtract destination employment from the cumulative variable for each observation to obtain the number of jobs between a given origin and destination that are closer to the origin than the employment located in the particular destination. For intra-zonal observations -- i.e., T_{ij}, where $i=j$ -- the intervening opportunities variable is set equal to one.

Similarly, intervening competing labor is calculated by sorting the observations in ascending order by destination zone codes and travel time, and by then creating running totals of origin labor within destinations. Origin labor for each observation is then subtracted from the running total yielding the count of workers for a given origin-destination pairing who are physically closer to the employment in the destination zone than workers in the origin zone. Again, the intervening competing labor is set to one for intra-zonal observations.

In the estimations below, I restrict the sample to all observations with origins in the Oakland PMSA. Given that the Oakland PMSA is the most centrally located of the five PMSAs in the region and the fact that the only constraint placed on destinations is that they lie within the much larger CMSA, the set of possible destinations most likely encompasses the complete set of employment opportunities available to male teenage workers living in Oakland. I further restrict the sample to observation where origin labor supply and destination labor demand are positive. Note, when either variable is equal to zero, the predicted flows of equation (1) and (4) above are zero. After the various restrictions, there are 158,008 origin-destination observations.

Table 3.1 presents basic descriptive statistics for the sample. Panel A gives the means and standard deviation for each variable. The average zone has approximately 116 potential teenage workers and the average destination has approximately 4,700 jobs. The average totals of intervening opportunities and intervening competition between zones are large. This is as expected given that both counts are increasing in the square of the distance between zones. The average time between zones is a little over a half of an hour. The minimum travel time recorded is slightly over a minute for one intra-zonal observation while the maximum travel time is slightly over two hours. As can be seen, the average flow between zones is quite small (.1358). This is due to the fact that the overwhelming majority of observation are zero flows (approximately 95 percent). This is a common characteristic in intra-metropolitan journey-to-work data.

Table 3.1

Descriptive Statistics

Panel A

Variables	Mean	Standard Deviation
$Flow_{ij}$	.1358	2.4821
Origin Labor	115.59	77.56
Destination Employment	4,684.11	7209.26
Intervening Opportunities	1,571,426	910,133
Intervening Competition	31,865	18,607
Drive Alone Travel Time	34.59	17.84

Panel B

Variables	$Flow_{ij}$	Intervening Opportunities	Intervening Competition	Travel Time
$Flows_{ij}$	1	-	-	-
Intervening Opportunities	-.0826	1	-	-
Intervening Competition	-.0785	.7224	1	-
Travel Time	-.0844	.8761	.8209	1

There are 158,008 observation.

Panel B of Table 3.1 provides the correlation matrix for the total flow variable and the three spatial determinants: distance, intervening opportunities, and intervening labor competition. All three spatial variables are highly correlated. As argued by proponents of intervening opportunity models, distance is strongly correlated with both the intervening opportunities variable (.88) and the competition variable (.82). Moreover, intervening competition and opportunities are highly correlated (.72). The correlations of the spatial variables with the total flow are all of similar magnitude and have the expected signs

Table 3.2 presents the estimation results for four specifications of the negative binomial gravity model: the basic model of equation (1), equation (1) controlling for intervening opportunities, equation (1) controlling for intervening labor competition, and equation (1) with both intervening opportunities and intervening competition. In all regressions, the spatial variables have the expected signs and are highly significant. The most striking pattern is the decline in the distance parameter as the spatial variables are sequentially added to the basic specification of the first regression. Adding intervening labor competition in regressions (2) causes a drop in the coefficient on travel time from 1.5115 to .8999. Controlling for intervening opportunities causes an even larger decrease in the travel time coefficient estimate to .6335. When both spatial variables are entered together, the distance coefficient drops to .3416, an eighty percent decrease in the decaying effect of distance relative to the estimate in the first regression.

In order to judge the relative magnitude of the decaying effect of distance on intra-metropolitan youth labor flows, Figure 3.2 plots the effects of distance on aggregate commute flows implied by the parameter estimates in the first and fourth regressions of Table 3.2. Note, the distance effects implied by regressions (1) and (4) are implicitly independent of the decaying effects of intervening opportunities and intervening labor competition. The figure plots the functions, $1/d^{1.5115}$ and $1/d^{.3416}$, effectively normalizing

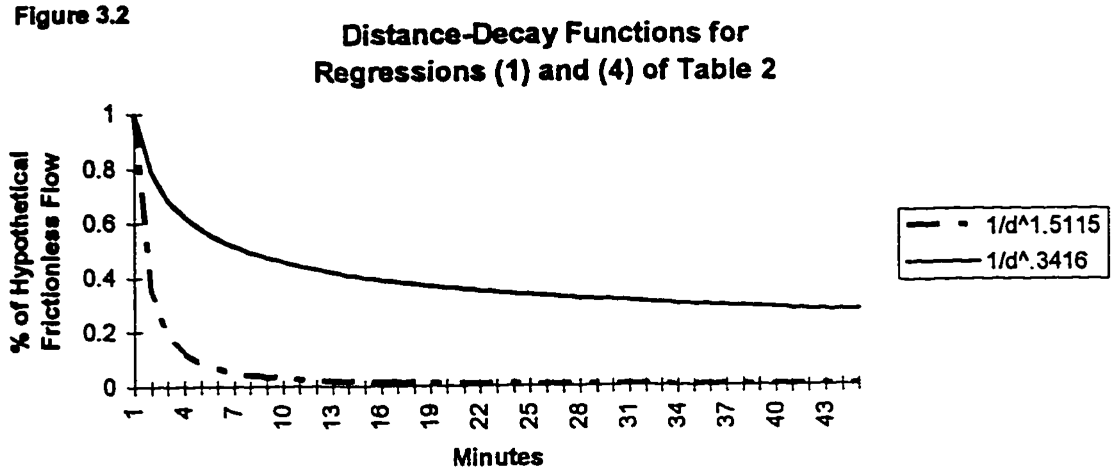
Table 3.2
Estimation Results from Various Specifications of the Negative Binomial Gravity Model, Dependent Variable=Inter-Zonal Flow of Male Teenage Labor in the Oakland PMSA (t-statistics)

Variables	(1)	(2)	(3)	(4)
ln(Constant)	-10.5639 (-50.02)	-8.4979 (-35.48)	-6.2840 (-25.79)	-5.3768 (-20.00)
Origin Labor	.7449 (24.38)	.7996 (26.41)	.7832 (25.13)	.8072 (26.13)
Destination Employment	.6779 (35.68)	.7040 (37.84)	.7906 (41.13)	.7960 (42.04)
1/Drive Alone Travel Time	1.5115 (-107.89)	.8999 (-21.80)	.6335 (-18.73)	.3416 (-7.04)
Intervening Competition	-	-.4562 (-16.51)	-	-.2681 (-8.72)
Intervening Opportunities	-	-	-.6060 (-30.37)	-.5581 (-25.08)
δ	.0334	.0335	.0344	.0345
Log of Likelihood	-13,728	-13,655	-13,478	-13,455
N	158,008	158,008	158,008	158,008

The inter-zonal flows include all labor flows originating in the Oakland PMSA with destinations anywhere in the 9-county Bay Area CMSA. The intervening opportunities and intervening competition variables include job opportunities and competing labor outside of the Oakland PMSA.

the impact of all other variables. Hence, one minus the vertical coordinate is interpreted as the percentage reduction in the total flow of labor below the hypothetical flow that would occur in the absence of distance-injected frictions. The predicted flow drops off

Figure 3.2



quickly with distance using the parameter estimate from regression (1). Within three minutes, the estimated labor flow is eighty percent less than that which would exist in the absence of a distance effect. At twenty minutes, there is a 99 percent reduction.

Controlling for intervening opportunities and intervening competition, however, significantly flattens the independent effect of distance. At five minutes, the estimated flow is 62 percent of the hypothetical frictionless flow, at ten minutes 45 percent, at twenty minutes 36 percent, and at thirty minutes 31 percent. Hence, while the independent decaying effect is still quite substantial after controlling for the other spatial variables, its independent effect is reduced considerably. Nonetheless, combined with the effects of the other spatial variables, the parameter estimates of the fourth equation in Table 3.2 imply a strong observable drop of the size of labor flows with distance. In Section 3.3 above, equation (5) provided the observable decline in labor flows with distance in the hypothetical case where employment and workers are uniformly distributed over space and where there is no real distance effect. Equation (5) can easily be modified to allow for a true independent effect of distance by simply adding distance with its own exponential parameter. Assuming this modified version of equation (5), the expected empirical flow-distance profile without controlling for intervening opportunities and intervening competition would be that characterized by a distance exponent of -1.994={2*(-.2681-.5581)-.3416}.

Another interesting finding in Table 3.2 is the fact that all three spatial variables have significant and strong effects on intra-metropolitan labor flow, even when all variables are included simultaneously. This is especially surprising given the high correlations shown in Panel B of Table 3.1. For example, intervening opportunities and intervening labor competition have a correlation coefficient of .72. Nevertheless, when entered together, their estimated effects remain strong and highly significant. In fact, the estimated effect of intervening opportunities barely drops (from -.6060 to -.5581) when intervening labor competition is added to the equation. Furthermore, despite the large drop in the coefficient on distance, the independent decaying effect of distance remains quite strong, as can be seen in Figure 3.2. Again, this is surprising given the extremely high correlations of distance with the other spatial variables (.88 with intervening opportunities and .82 with intervening labor competition).

3.5 Conclusions

Understanding how geographic accessibility to employment opportunities varies across space requires a sound understanding of the determinants of accessibility and of how labor moves within local labor markets. Researchers wishing to investigate systematic differentials in accessibility by race and residential location within metropolitan areas need to develop measures of accessibility that accurately capture the spatial distribution of labor supply and demand. This paper has illustrated the independently important effects of distance, the spatial distribution of competing workers, and the spatial distribution of employment opportunities in determining intra-metropolitan commute patters. The results carry several implication for the measurement of physical accessibility. To start, as is already emphasized in the literature, physical distance to employment opportunity matters. A point less emphasized in the literature, and empirically more difficult to implement, is the effect of the geography of competing workers on accessibility.

Chapter 4: The Long Term Effects of Youth Joblessness in a Segmented Labor Market

4.1 Introduction

This chapter examines the long term economic effects of youth unemployment on future employment and earnings. The approach here differs from previous research by incorporating the qualitative aspects of the individual's initial employment. Specifically, I weigh the relative impact on future earnings and employment of past experience foregone against the relative effect of one's initial industry of employment and the return to experience in one's labor market segment. Labor market segmentation theory provides the set of nonmarket-clearing tools for analysis. Specifically, in assessing the impact of youth unemployment on later unemployment, one must account for low job security in secondary employment and the barriers to entry into primary employment. In estimating the costs of foregone experience, one must allow for the differential returns to experience across labor market segments. Including labor market structure in the empirical analysis significantly alters the interpretation of the path by which early unemployment will impact later employment and earnings.

The effects of youth unemployment extend beyond the individual's concurrent loss of income. It is often cited that chronic levels of youth unemployment are correlated with higher crime rates, youth violence, teen pregnancy, suicide and a host of other social ills (Freeman & Medoff, 1982). Perhaps the most dangerous effects of early unemployment are the potential long run economic implications. The failure to accumulate early work experience is a failure to invest in one's own human capital and may result in permanently lower earnings throughout the duration of the work life. Furthermore, in a world of imperfect information, potential employers may use the continuity of past work history as a signal of the ability of prospective employees. This provides a path by which past unemployment may generate recurrent unemployment and weak labor force attachment. Effective public policy intended to counter these adverse effects requires a careful assessment of their magnitudes.

Nevertheless, focusing on the length of unemployment spells alone without taking into account the characteristics of the segment of the youth population most affected may lead to distorted conclusions and inappropriate policy prescriptions. The incidence of youth unemployment is heavily concentrated among high school drop-outs, minorities, and inner-city youth. The jobs available to this group consist largely of secondary employment characterized by low pay, little or no room for advancement, and low job security. If the socioeconomic mobility of this group is limited, a future track of unfavorable employment may be more the result of initial dead-end jobs rather than initial unemployment. Under these conditions, policy aimed at indiscriminately generating jobs will be ineffective in combating the longer lasting threats of youth joblessness.

I analyze a sample of young men taken from the National Longitudinal Survey of Youth. It is found that controlling for industry of employment and allowing for differential returns to experience across industry-based labor market segments diminishes the estimated impact of foregone experience on future earnings. The effect on future earnings diminishes for the sample as a whole and even more so for those employed in the secondary sector. A more general model of wage determination which does not rely on an a priori classification of labor market segments confirms this finding. In contrast to previous studies, early unemployment is found to have a moderately negative effect on future employment. Moreover, correction of the effective censoring of the weeks worked dependent variable yields a larger negative effect. Early industry of employment is found to have no statistically significant effect on future unemployment.

The chapter is organized as follows. Section 4.2 will elaborate on the differences between the human capital and the labor market segmentation interpretations of the potential long-term effects of youth unemployment. Emphasis will be placed on the importance of labor market structure and the presence of labor market institutions. Section 4.3 discusses the estimation methodology used to evaluate the arguments presented. Section 4.4 presents a description of the sample taken from the National Longitudinal Survey of Youth which is used in the empirical section of the paper. Section 4.5 presents estimates of an employment determination equation and several wage equations in order to evaluate the relative importance of past industry of employment and early unemployment. Finally, Section 4.6 concludes.

4.2 Labor Market Segmentation Theory and Youth Unemployment

Human capital theory predicts that foregone experience is the only avenue by which early unemployment affects future labor market outcomes. Early work experience is equivalent to a capital investment which will earn a return throughout one's working-life. The foregone investment caused by early unemployment will imply permanently lower earnings and a flatter age-earnings profile. Since the entire earnings profile is shifted to the right and downwards the potential losses are substantial. The theory does not predict any lasting effect of early unemployment on future unemployment.

Most previous studies on youth unemployment have implicitly employed human capital theory in trying to estimate the long-term consequences. Using the 1965 National Longitudinal Survey of Young Men, Ellwood (1982) estimates that at the upper bound 26 weeks of unemployment in the first year out of high school decreases wages 10 years later by approximately 12 percent relative to the wage that would exist given a full year of employment. He arrives at this figure by regressing log wages on several individual characteristics and an experience variable constructed from the number of weeks worked in the year after the individual had permanently left school. Corocon (1982) finds a similar effect using the National Longitudinal Survey of Young Women. While Ellwood fails to find any persistent effect on future employment, Corocon finds that after controlling for heterogeneity the probability of being employed is significantly reduced by unemployment in the previous year. Both studies fail to include labor market structure in their analyses.

I argue that in addition to foregone experience, one's initial labor market segment partially shares the blame for low future earnings. Specifically, obtaining a "good job" today may depend on having had a good job in the past. Labor market segmentation theory predicts that omitting controls for early industry of employment and imposing the constraint of a constant return to experience across labor market segments will overestimate the relative impact of foregone experience on future wages, especially for those in the secondary sector. Furthermore, the theory provides an avenue by which early unemployment can lead to future unemployment. Before discussing these lines of reasoning at length, a brief description of labor market segmentation theory is necessary in order to clarify the arguments presented.

A. Labor Market Segmentation Theory

Dickens and Lang (1992) define the essential tenets of labor market segmentation theory as 1) a labor market composed of separate segments with distinct wage determination mechanisms, and 2) an excess supply of qualified labor in the higher paying segments. The crucial departure from human capital theory is that there is queuing for primary employment opportunities. Rather than an efficient labor market paying each person a merited return to human capital endowments, markets fail and jobs are rationed by non-price mechanisms. Institutional structures, such as limited points of entry to internal labor markets and the internal filling of job vacancies, insulate the price and quantity of primary employment from excess labor supply in the external sector. Hence, competitive pressures do not eliminate non-competitive wage differentials and labor mobility is restricted between segments.

Broadly speaking, available employment can be classified as being in either the primary or secondary sectors. Primary sector jobs are characterized by high pay, room for advancement, employment security, returns to experience or seniority, and internal labor markets. Secondary sector employment can be described as jobs with poor working conditions, low pay, little or no job security, and little opportunity for advancement.

The main body of supporting empirical evidence is the extensive documentation of inter-industry wage differentials (Dickens & Katz 1988, Krueger & Summers 1989). The thrust of this evidence lies in the proposition that inter-industry differentials are evidence of true market failures. Much of the recent literature has focused on the testing of market clearing hypotheses which are consistent with the observed industrial wage structure. Krueger and Summers (1989) find that after controlling for several job characteristics, wage differentials are increased, thus rejecting the compensating differential argument. Gibbons and Katz (1989), Krueger and Summers (1989), and Murphy and Topel (1987) have independently tested the hypothesis that unobserved heterogeneity drives the wage structure estimated in cross section log-wage equations. Of the three studies, only Murphy and Topel find that unobserved heterogeneity explains a significant portion of interindustry wage differentials.[16] Nevertheless, the research to date does not provide strong support for market-clearing explanations.

With respect to the issue at hand, applying labor market segmentation theory to an analysis of the long-term impact of youth unemployment begs two questions which are essentially ignored by the human capital approach described above. First, to what extent are the institutional structures that determine the structure of inter-industry wage

[16]However, Murphy and Topel's results are suspect. The three studies mentioned employ a test where unobserved heterogeneity is assumed to have a time-invariant effect on wages. Consecutive yearly observations are first-differenced in order to eliminate the nuisance parameter and industry effects are measured by the change in wages realized by those who have switched industries. The major problem with this technique is the extent of false industry switching reported in most micro data sets. If many of the individuals in the sample hold the same jobs across both periods while reporting a switch in industries the estimated interindustry wage differentials will be biased downwards. While Krueger and Summers derive a correction for this problem and Gibbons and Katz use a sample of exogenously displaced workers, Murphy and Topel fail to take this into account.

differentials contributing to the length and incidence of unemployment spells and how does this affect future earnings and employment? Second, given the existence of labor market segments, how important is the return to experience in explaining low future earnings for the group most affected by youth unemployment?

B. *Industry Affiliation and Employment Security*

Under the assumption that primary employment is more concentrated in some industries than others, weeks of unemployment suffered by an individual in a given year will be partially determined by that person's industry of employment. High turnover and low job security in the secondary sector is the result of weak commitments on behalf of both the employer -- due to the low levels of investment made by secondary sector employers in their workers -- and the employee -- due to the lack of incentive to stick around. Those who work in more unionized industries and industries with higher incidence of internal labor markets will have more job security and more of an interest in a continuous employment relationship. If employers use continuity of previous employment, and the type of previous employment itself, as a signal for such desirable worker traits as dependability or punctuality, large gaps in one's employment history will reduce the probability of primary employment and increase the probability of future unemployment.

Here lies the hypothesized link between early industry affiliation and future employment and earnings. Essentially, the probability of having a good stable job in the future (and in turn, higher earnings) is increased by having had good jobs in the past.

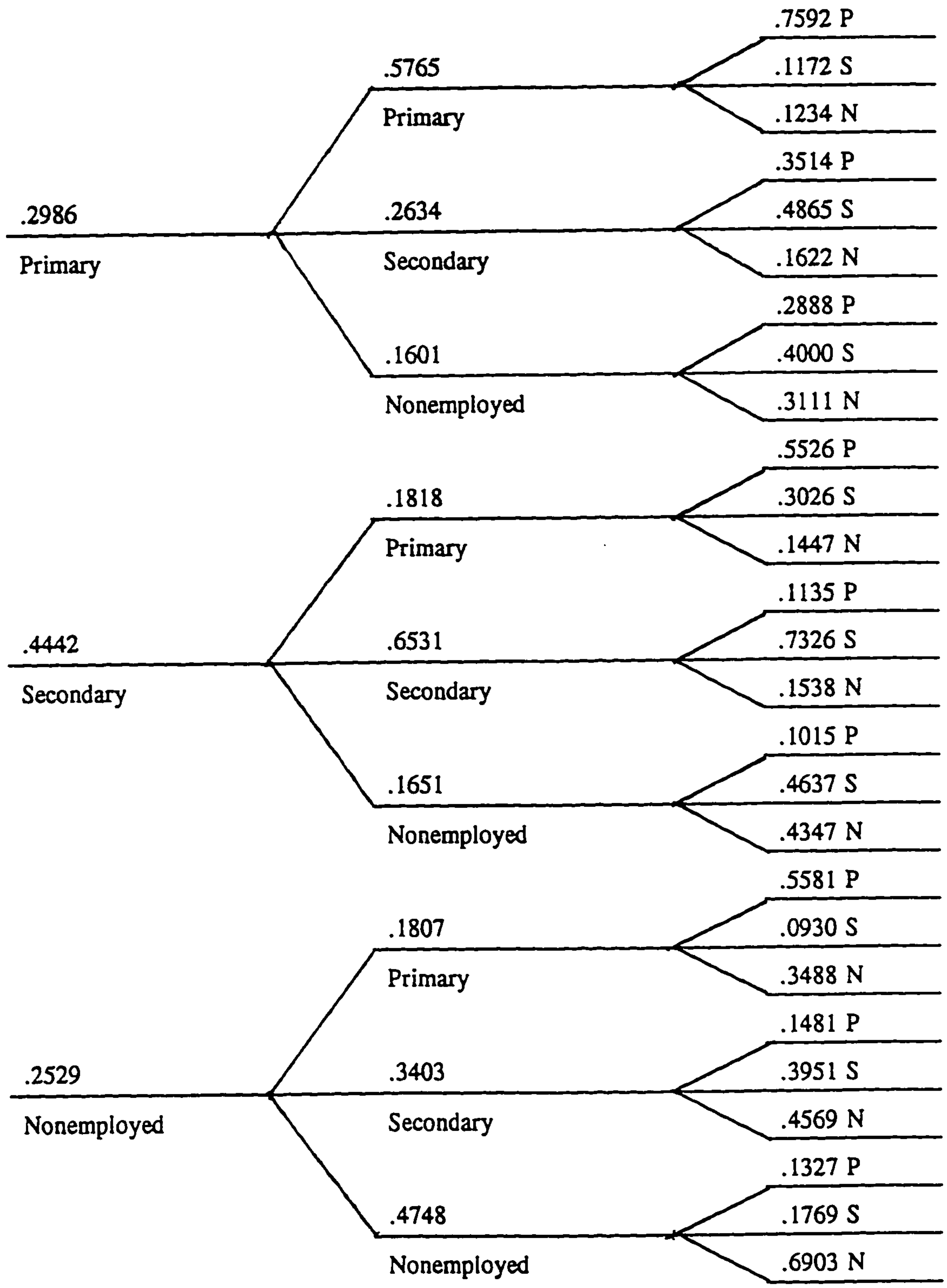
On the other hand, secondary employment begets more secondary employment with its accompanying low pay and low job security. It is through this link that individuals can be tracked into an undesirable chain of secondary sector jobs.

One implication of this argument is that there is little mobility across labor segments. Figure 4.1 presents a probability tree which describes the employment experience of a sample of workers taken from the National Longitudinal Survey of Youth over the first three years of the panel. The sample includes 941 young men with 14 or fewer years of education in 1990 who were between the ages of 14 and 22 in 1979 and had permanently left school. Workers are classified as being primary sector workers, secondary sector workers, or nonemployed. The classification of workers as in the primary or secondary sectors is by three-digit industry following Davidson and Reich (1988).[17] The figure is interpreted as follows. The first set of branches describes the status of the sample in 1979, the top branch for primary sector, the middles branch for secondary sector, and the lower branch for the nonemployed. The following sets of branches describe the status in subsequent years conditional on the status in the previous year. For example, the proportion of individuals in this sample who were in the primary sector in 1980 given that they were in the primary sector in 1979 is .5765.

The figure implies that there is limited movement from nonemployment and secondary sector employment into the primary sector. Furthermore, there appears to be downward rigidity in movement from the primary sector even given nonemployment or secondary employment two periods prior. Specifically, the probability of primary

[17]The primary/secondary coding scheme is provided in appendix 4B.

Figure 4.1


.2986
Primary
.5765
Primary
.7592 P
.1172 S
.1234 N
.2634
Secondary
.3514 P
.4865 S
.1622 N
.1601
Nonemployed
.2888 P
.4000 S
.3111 N
.4442
Secondary
.1818
Primary
.5526 P
.3026 S
.1447 N
.6531
Secondary
.1135 P
.7326 S
.1538 N
.1651
Nonemployed
.1015 P
.4637 S
.4347 N
.2529
Nonemployed
.1807
Primary
.5581 P
.0930 S
.3488 N
.3403
Secondary
.1481 P
.3951 S
.4569 N
.4748
Nonemployed
.1327 P
.1769 S
.6903 N

employment conditional on being in the primary sector in the previous period is markedly similar for those in the primary sector the first two periods and for those who were either in the secondary sector or nonemployed in the first period and in the primary sector the following two periods (.5765, .5526, and.5581 respectively).

Such immobility is a necessary condition for the path dependence discussed above. However, a few caveats should be mentioned before drawing any conclusions from such an inexact contraption. The numbers given are percentages rather than robust estimations of true probabilities. There are no controls for individual characteristics implying any signs of immobility can also be interpreted as the extent of worker heterogeneity in the sample. Furthermore, classifications are based on the person's status at the time of the interview adding additional noise to the classification scheme. Specifically, those who were classified as primary workers did not necessarily work 52 weeks that year and those classified as non-employed were not necessarily unemployed throughout the year. The figure is intended solely as a descriptive starting point which indicates a possible role for early industry affiliation in explaining future unemployment levels and in specifying the wage equations to be estimated below.

C. Returns to Experience Across Labor Market Segments

Education and experience are rewarded differently in different jobs. This may be due to true increases in worker productivity with time and education, or to institutions such as unions and internal labor markets. For example, an agricultural laborer who picks tomatoes and is paid a piece rate will most likely exhaust any increases in productivity through experience in the first few weeks or even days. On the other hand, a carpenter's apprentice will acquire substantial skills over several years of working under an experienced craftsman. This worker will realize a steady increase in earnings which will peak when the apprentice obtains the experience level of the master carpenter. In addition, if the supply of carpenters is restricted through union-controlled apprenticeship programs, the apprentice will eventually earn a monopoly rent above and beyond his or her marginal product. Regardless of whether the observed returns are returns to actual productivity increases through skill acquisition on the job or are actually some form of unearned rents -- i.e., a situation where the social and private returns to job tenure are misaligned -- it is unarguable that this return will vary considerably with the technological aspects of the job and the presence or absence of institutional structures.

This calls into question the importance of lost experience associated with youth joblessness. As noted above, the incidence of youth unemployment is concentrated among a small relatively homogeneous group who most likely face an employment opportunity set which is far more constrained than that of the average youth. At the extreme, an employment opportunity set which consists solely of bottom-of-the-barrel secondary sector employment implies that lost experience has no real impact. Failure to take into account the qualitative differences between the determination of wages in the primary and secondary sectors will lead to a misinterpretation of the path by which early labor market experiences affects later earnings.

4.3 Estimation Methodology

A. Long Term Effects on Employment

Ellwood (1982) estimates the long term impact of past unemployment on future employment by estimating an employment determination equation of the following form:

$$(1) \qquad WW_{it} = X_{it}'\beta_t + \Sigma_{j=1}^{t-1} \alpha_{t-j} WW_{it-j} + \delta_{it} + \varepsilon_{it}$$

where WW_t is the number of weeks worked in year t, X_{it} is a vector of explanatory variables for individual i at time t (including age, highest grade completed, a race dummy, region dummy variables, and lagged wages), δ_{it} is the individual fixed effect, β_t and α_{t-j} are parameters, and ε_{it} is a normally distributed error term. The individual fixed effect, δ_{it}, is interpreted as capturing all relevant characteristics not included in the vector of explanatory variables. If δ_{it} were observable, its inclusion in equation (1) would yield unbiased estimates of the coefficient on past weeks worked. However δ_{it} is not observed and is most likely positively correlated with the number of weeks worked in a given year. Hence, in addition to capturing any effect of past weeks worked on future weeks worked, the past weeks worked coefficient will also capture variation in the dependent variable due to unobserved heterogeneity. Cross-section estimates of the α_{t-j} will be biased upwards.

Ellwood corrects for this omitted variable bias by estimating the first difference of equation (1). Assuming that δ has a time-invariant effect on the dependent variable -- i.e., $\delta_{it} = \delta_i$ -- differencing across years will eliminate the heterogeneity term from the equation. Ellwood's estimation of (1) finds a large significant coefficient on past weeks worked which disappears after differencing. A bias in the opposite direction which Ellwood mentions but fails to correct for is the downward bias on the coefficients in (1) which results from the fact that the dependent variable is limited. An individual cannot work more than 52 or less than 0 weeks per year. If several observations in the sample work a full year or don't work at all, this bias can be substantial[18].

Below I re-estimate equation (1) and its first difference using the specification above and an alternative specification that includes dummies for past industry of employment. Segmentation theory predicts that weeks worked in a given year will be correlated with industry of employment. If past industry has an effect on future employment, the inclusion of past industry dummies should yield significant coefficients and decrease the estimated coefficient on weeks worked. I also correct for the effective top and bottom censoring of the dependent variable by re-estimating the undifferenced equation with a two-sided Tobit model. While this does not account for the heterogeneity bias, it gives some idea of the magnitude of the bias incurred by applying a linear estimator. The likelihood function for this estimator is derived in appendix A.

---

[18] Here, a linear estimator is clearly unsuitable. Linear estimators will force the regression line within the confined interval of the dependent variable and will underestimate the effects of the explanatory variables. Rather than being continuously distributed, the density of the dependent variable will have point masses at 0 and 52 weeks of work. The peculiarities of this distribution must be dealt with in order to obtain consistent estimates of the parameters in equation (1). See appendix A for the derivation of the correction for the discontinuous distribution.

B. The Long Term Effects on Earnings

An attempt to isolate the impact of early experience on wages should control for early industry of employment and allow for variation of the return to experience across labor market segment. The wage-determination process hypothesized here is expressed as

$$(2) \quad LW_{it} = X_{it}'\beta_t + \sum_{j=1}^{t-1} \alpha_{tt-j} WW_{it-j} + \sum_{j=0}^{t-1} \sum_{k=1}^{K} \gamma_{ktt-j} IND_{ikt-j} + \sum_{j=1}^{t-1} \theta_{tt-j} WW_{it-j} * SEC_{it-j} + \delta_{it} + \varepsilon_{it},$$

where

LW_{it}	≡ log wages for individual i at time t,
X_{it}	≡ a vector of controls for individual i at time t including age, race, an SMSA dummy, region dummies, and education,
WW_{it-j}	≡ weeks worked by individual i in year t-j,
IND_{ikt-j}	≡ a dummy variable which is one if individual i was employed in industry k during the year t-j,
SEC_{it-j}	≡ a dummy variable which is one if individual i was in the secondary sector in year t-j,
δ_{it}	≡ a heterogeneity term for individual i in year t,
ε_{it}	≡ an error term for individual i in year t.

and β_t, α_{tt-j}, γ_{ktt-j}, and θ_{tt-j} are parameters. The argument here predicts a direction for the biases incurred by omitting past industry dummies and by omitting the interaction term between the secondary sector dummy and past weeks worked. First, assume that labor market segments can be measured by industry. Segmentation theory predicts that the lack of mobility across labor market segments will causes a lower lifetime earnings stream for those who start out in secondary sector employment. If the interindustry wage structure is positively correlated with employment security across industry, weeks worked in a given year will be positively correlated with inter-industry wage differentials. Estimation of equation (1) omitting past industry dummies will overestimate the effect of past unemployment on future earnings. Therefore, adding dummies for past industry of employment should decrease the coefficient on WW_{it-j}.

Second, if the return to experience varies across labor market segments, imposing the constraint of a constant return across all segments will bias the estimated return to experience upward for workers in the secondary sector and downward for workers in the primary sector. When the interaction term $WW_{it-j}*SEC_{it-j}$ is included, the coefficient on WW_{it-j} now becomes the return to experience in the primary sector, while the return in the secondary sector is the sum of the estimated coefficients for the two terms. The theory predicts that the coefficient on the interaction term will be negative and its inclusion should cause an increase in the estimated coefficient for WW_{it-j}.

As with the employment equation, the major difficulty encountered in all wage equation estimations is the fact that it is impossible to control for all personal characteristics due to qualitative data limitations. In most cross section wage regressions, the heterogeneity term is omitted, sweeping all unobserved traits into the error term of the regression. If there is sorting across industries by unobservables, then regressions that find statistically significant coefficients on industry dummies are subject to the criticism that the results are driven by the fact that industry is acting as a proxy for unobserved heterogeneity. Again, assuming that the heterogeneity term is time-invariant, it is possible to first difference and eliminate the nuisance parameter. First differencing equation (2) gives

$$(3) \quad LW_{it} - LW_{it-1} = X_{it}'\beta_t - X_{it-1}'\beta_{t-1} + \sum_{j=2}^{t-1} (\alpha_{tt-j} - \alpha_{t-1t-j})WW_{it-j} + \sum_{j=1}^{t-1}\sum_{k=1}^{K}(\gamma_{ktt-j} - \gamma_{kt-1t-j})IND_{ikt-j} + \sum_{j=2}^{t-1}(\theta_{tt-j} - \theta_{t-1t-j})WW_{it-j}{*}SEC_{it-j} + \alpha_{tt-1}WW_{it-1} + \sum_{k=1}^{K}\gamma_{ktt}IND_{ikt} + \theta_{tt-1}WW_{it-1}{*}SEC_{it-1} + \varepsilon_{it} - \varepsilon_{it-1}.$$

In addition to eliminating the heterogeneity term, first differencing isolates weeks worked in the previous year, contemporaneous industry of employment, and the previous year's experience interaction term. Second differencing will isolate two years of the respective variables, third differencing isolates three years and so on. Estimation of equation (3) gives unbiased estimates of the coefficients on the isolated terms.

Below I estimate three OLS wage equation: (1) log wages on a set of controls and past weeks worked, (2) log wages on the controls, past weeks worked and a set of past industry dummies, and (3) log wages on the controls, past weeks worked, a set of past industry dummies, and the interaction term between the secondary sector dummy and past weeks worked. By consecutively adding factors, one can determine the direction of bias on the weeks worked coefficient incurred by omitting past industry dummies and by constraining the return to experience to be equal across labor market segments. The results of this exercise are subject to two criticisms. First, the coding scheme that classifies an individual as a primary or secondary worker based on industry may be driving the finding that the return to experience varies across labor market segments. Second, finding that the coefficients on past industry dummies are statistically significant in an undifferenced OLS equation may still be interpreted as evidence that there is sorting across industries by unobserved characteristics.

The first criticism is addressed by estimating a switching model with unknown regimes where there is no a priori classification of workers as being in the primary or secondary sector. The wage determination model comes directly from Dickens and Lang (1985). This provides an alternative test of the hypothesis that the return to experience varies across labor market segments. The likelihood function of this model is derived in appendix A. The second criticism is addressed by estimating equation (3) above. If the industry dummies are truly measuring the effects of barriers to inter-sector mobility, the estimated coefficients on the past industry dummies should survive differencing. Furthermore, the coefficients should be of the same signs and magnitudes as the estimates from the undifferenced equation.

4.4 The Data

The sample includes 941 young men taken from the National Longitudinal Survey of Youth who were between the ages of 14 and 22 in 1979 and who had permanently left school by the end of that year. All individuals in the sample have fourteen or less years of education and did not serve in the military during the period 1979 to 1990. Blacks are 25.5 percent of the sample. The sample is intended to represent the non-college bound population of young men as of 1979. Industry of employment was reported for most individuals even for those unemployed at the time of interview. Observations were coded as being in the primary or secondary sector by Bureau of the Census three digit industry code. The secondary-primary coding is provided in appendix B. The classification scheme follows closely that of Davidson & Reich (1988).

There are several justifications for limiting the sample to non-college bound individuals who were not enrolled in school. First, the consequences of unemployment suffered while attending school are unclear. One study by Greenberger and Steinberg (1986) asserts that employment actually hinders educational performance. Second, teenage unemployment is not spread proportionately throughout the teen population but affects a minority of the youth labor force in which high school drop-outs and those with lower education are disproportionately represented. An analysis of youth unemployment that does not adequately isolate the group for which unemployment may carry substantial long-term costs will understate the consequences of the problem.

Table 4.1 offers a descriptive summary of the labor market experiences of the sample. The employment rate increased somewhat over the period covered by the panel, increasing from 74.7 percent in 1979 to 85.2 percent in 1990. As can be seen, a substantial proportion of the sample is employed in the secondary sector throughout the entire period covered. In 1979, 59.4% of individuals were classified as secondary sector workers while in 1990 the comparable figure stood at 52.7%. Most importantly, there is an overall decrease in the relative wages of secondary sector workers. While there was growth in the average wages of secondary sector workers, it was at a much slower rate than that of the average wage for primary workers. Again, this provides conjectural evidence of the importance of differential returns to experience and its affect on the age-earnings profile.

Table 4.1 **Descriptive Employment Statistics For Entire Panel**

Year	Employment Rate	% Employed in Secondary Sector	Ratio of Average Wages, Secondary/Primary
1979	74.7%	59.4%	.893
1980	75.7	60.3	.787
1981	72.4	56.5	.768
1982	73	56.1	.794
1983	70.5	57.5	.765
1984	78.8	57.1	.763
1985	80.1	53.4	.73
1986	82	54.1	.745
1987	85.1	53.3	.818
1988	86	52.8	.751
1989	84.4	52.9	.705
1990	85.2	52.7	.734

Table 4.2 presents the unemployment and nonemployment rates for the entire sample and for blacks individually. The statistics parallel the official CPS figures which also show blacks suffering disproportionately. The numbers suggest that the improvement in the unemployment rate for blacks is misleading. For example, from 1986 to 1990 the nonemployment rate for blacks increased slightly from 25.4 percent to 25.5 percent while the unemployment rate for the respective period dropped by 5.9 percent. The improvement in the unemployment rates appears to be the result of a large portion of blacks in the sample dropping out of the labor force in the later years of the panel. Note, however that while blacks have much higher rates of unemployment and nonemployment, in any given year they constitute a minority of the unemployed persons in the sample. In 1979, 36 percent of the unemployed and 38 percent of the nonemployed were black.

Table 4.2 Unemployment and Nonemployemnt Rates for the Entire Panel and for Black Males Individually

	Entire Panel		Black Males	
Year	Unemployment	Nonemployment	Unemployment	Nonemployment
1979	17.5%	25.3%	26%	35.9%
1980	18.1	24.3	26	33.4
1981	21.1	27.6	25.4	37.8
1982	20.4	27	27.3	36.7
1983	23.5	29.5	30.2	39.2
1984	14.9	21.2	22.8	30.9
1985	14.7	19.1	21.7	30.9
1986	12.1	18	17.3	25.4
1987	8.4	14.9	15.8	26.7
1988	6.9	14	10.7	23
1989	7.8	15.6	16.8	29.6
1990	6.1	14.8	11.4	25.5

Table 4.3 presents the raw correlations for weeks worked across years. As can be seen, the correlations are quite high. All correlations for consecutive years range from .59 to .68. Most striking are the large correlations across longer time periods. Specifically, the correlations of annual weeks worked five years apart range from .38 to .43 while the correlation between weeks worked in 1980 and 1990 is .33. While previous studies have not found a significant independent effect of past unemployment on future unemployment, the high raw correlations in this sample indicate that a more careful analysis that controls for individual characteristics should be carried out. If the findings of previous research that use alternative samples are robust, we should be able to reproduce the results here.

Table 4.3 **Raw Correlation for Weeks Worked Across Years**

Year	'80	'81	'82	'83	'84	'85	'86	'87	'88	'89	'90
'80	1	-	-	-	-	-	-	-	-	-	-
'81	.59	1	-	-	-	-	-	-	-	-	-
'82	.50	.61	1	-	-	-	-	-	-	-	-
'83	.40	.48	.66	1	-	-	-	-	-	-	-
'84	.38	.43	.52	.65	1	-	-	-	-	-	-
'85	.40	.40	.49	.52	.67	1	-	-	-	-	-
'86	.37	.39	.41	.46	.54	.68	1	-	-	-	-
'87	.39	.37	.38	.41	.47	.54	.66	1	-	-	-
'88	.35	.36	.37	.38	.45	.54	.54	.69	1	-	-
'89	.35	.36	.40	.36	.41	.46	.48	.53	.73	1	-
'90	.34	.33	.36	.36	.38	.43	.43	.51	.63	.75	1

4.5 Empirical Results

A. Long Term Effects on Employment

Adding twelve one-digit past industry dummy variables to the employment equation does not yield any significant changes. In the undifferenced OLS equation, only one coefficient is statistically different from zero. While adding the industry dummies causes the coefficient on past weeks worked to drop slightly (from .159 to .139), the log of the likelihood function actually drops. In the two-sided Tobit equation, again, only one industry coefficient is statistically different from zero. A likelihood ratio test between the model with and without industry controls fails to reject the hypothesis that the industry coefficients are equal to zero at the ten percent level of confidence. Hence, the tests used in this paper do not find any significant effect of early industry of employment on future weeks worked. The rest of this section will focus on the direct impact of early unemployment on future employment without controls for industry

Table 4.4 presents three estimated employment equations which regress weeks worked in 1986 on a set of controls and weeks worked five years previous. Similar to Ellwood's findings, the coefficient on WW81 drops substantially after differencing, from .1590 to .0668. This indicates that the estimate from the undifferenced equation suffers a substantial omitted-variables bias due to unobserved heterogeneity. In order to asses the magnitude of these estimates, one can compute the estimated difference in weeks worked in 1986 between a person who worked 26 weeks in 1981 and a person who worked 52 weeks in 1981, all else being equal. The number of weeks for the OLS and differenced equations are 4.134 and 1.73 weeks, respectively. Contrary to Ellwood's findings, the coefficient in the differenced equation is significantly different from zero. However, it is debatable whether 1.73 weeks of unemployment is cause for alarm.

Correcting for the effective censoring of the dependent variable yields a substantially higher estimate of the persistent effect of past unemployment. Specifically, the estimate of the coefficient on weeks worked five years previous increases from .159 in the OLS equation to .259 in the two-sided Tobit model. In the Tobit equation, the difference in estimated weeks worked between a person who worked 26 weeks in 1981 and a person who worked 52 weeks (all else being equal) is 6.73 weeks. This translates into a 12.9% difference in employment when the equation is evaluated at the mean of all other independent variables. The related figure for the OLS equation is 8%. Hence, the downward bias in the first equation appears to be quite substantial, approximately

Table 4.4

Employment Equation for 1986

Independent Variables	OLS Dependent Variable WW86	OLS on First Difference[1] Dependent Variable WW86-WW85	Two-Sided Tobit Dependent Variable WW86
σ	11.2938	12.16	11.5538 (44.436)
Constant	21.9545 (3.261)	-	13.7097 (2.327)
Black	.0677 (.0711)	-	.8348 (.9713)
Education	.3595 (1.542)	-	.8776 (3.686)
Age	.1646 (.6014)	.7472 (1.94)	.0467 (.1862)
Smsa	-.7292 (-.8976)	.9122 (.527)	-1.5051 (-1.961)
Married	2.1933 (2.808)	2.491 (1.857)	4.586 (5.776)
South	.1173 (.145)	-4.388 (-1.2)	.1621 (.217)
Log Wages 1986	4.4449 (4.866)	4.6549 (4.311)	8.2027 (10.722)
WW81	.1590 (6.481)	.0668 (2.247)	.2591 (13.03)
R_2	.153	.033	

t-statistics in parentheses
1. Independent variables have been first differenced.

equal in magnitude to the estimated heterogeneity bias. This precludes concluding from the evidence that there is no persistent effect.

Furthermore, an important caveat must be mentioned concerning the differenced equation. The equation itself is incorrect and suffers from a downward bias. This results from employing a linear estimator on the difference of a limited dependent variable where a large portion of the sample is observed at the upper limit in both years. The bias results from treating the information conveyed by a person who worked 52 weeks in two consecutive years the same as that of a person who worked, say, 20 weeks in both years. While there is no qualitative change for those working 20 weeks, among those working 52 weeks some may be more secure in their employment levels as the result of early high levels of employment. For example, assume that we are able to double the number of weeks in a year. Further assuming that everyone wants to work full time, it would be possible that two people who had both worked 52 weeks a year before we lengthened the year would realize different levels of employment afterwards and that these new levels of employment would be partially determined by weeks worked in years previous. The difference equation will not capture this since a large increase in employment across years in the past will be paired with a zero difference in the future.

While this is an extreme hypothetical example, it illustrates the direction of the bias incurred in estimating the differenced equation. At the extreme, the decrease in the estimated effect of early unemployment that is given by differenced estimation may be entirely due to the downward bias of the estimator. Considering that 386 individuals (45% of the sample) worked 52 weeks in both 1986 and 1985, the results of this equation are highly suspect. While no correction is made here, it is important to keep this point in mind before concluding that heterogeneity explains everything away.

Hence, while the evidence presented here does not determine the magnitude of the bias caused by unobserved heterogeneity, it provides upper bound estimates of the effect of early unemployment on future employment that are not negligible. The next step taken should be the derivation of an estimator that corrects for the discontinuous distribution of the differenced model.

B. Long Term Effects on Earnings

Table 4.5 presents three OLS log-wage equation estimates. Equation (1) includes a set of controls and weeks worked in 1980, equation (2) adds 1980 industry dummies, and equation (3) adds an interaction term between the number of weeks worked in 1980 and a dummy variable which is equal to one if the individual was employed in the 1980 secondary sector. The effect on future log-wages of return to work experience is dwarfed by the effect of past industry. According to equation (2), working 52 weeks in 1980 increase 1987 log-wages by .1144 (52*.0022). Of the seven statistically significant industry coefficient, all have a larger effect on future wages. As predicted, adding the past industry dummies decreases the coefficient on past weeks worked from .0043 to .0022. This reduce by half the predicted effect of past joblessness on future earnings. The predicted percentage differentials in hourly wages between a person who worked 26 weeks in 1980 and a person who worked the full year, all else being equal, are 10.74 percent and 5.47 percent for equations (1) and (2), respectively. Testing the hypothesis that the set of industry coefficients equals zero yields an F-statistic of 3.294, which fails to accept the hypothesis at the one percent level of confidence.

In equation (3), adding an interaction term between the weeks worked variable and the secondary sector dummy variable confirms the argument that the return to experience varies across labor market segment. Specifically, the predictions of a statistically significant coefficient on the interaction term and an increase in the coefficient on WW80 are observed. Adding the coefficients for WW80*SEC80 and WW80 gives the return in

Table 4.5

Wage Equations for 1987

Independent Variables	Equation (1)	Equation (2)	Equation (3)
	Dependent Variable = Log-Wages for 1987		
SCHOOL	.0525 (4.53)	.0548 (4.68)	.0551 (4.71)
AGE	.0365 (7.02)	.0349 (6.58)	.0340 (6.42)
BLACK	-.0844 (-1.79)	-.0563 (-1.19)	-.0547 (-1.16)
SMSA	.1711 (4.19)	.1599 (3.96)	.1552 (3.85)
SOUTH	-.0166 (-.351)	-.0308 (-.648)	-.0228 (-.48)
NORTHEAST	.219 (3.78)	.2063 (3.56)	.2101 (3.65)
WEST	.1749 (3.11)	.1832 (3.28)	.1950 (3.49)
MARRIED	.1559 (4.09)	.1458 (3.87)	.1456 (3.87)
WW80	.0043 (3.31)	.0022 (1.57)	.0037 (2.47)
Agriculture, Forestry, & Fisheries	-	.0567 (.597)	.0860 (.901)
Mining	-	-.0331 (-.241)	-.0675 (-.491)
Construction	-	.3254 (4.52)	.2924 (4.00)
Manufacturing	-	.1419 (2.44)	.1420 (2.45)
Transportation, Comm. & Public Utilities	-	.283 (2.62)	.2535 (2.34)
Wholesale and Retail Trade	-	.1212 (1.98)	.1422 (2.31)
FIRE	-	.3587 (2.08)	.3922 (2.28)
Business & Repair Services	-	.2278 (2.71)	.2208 (2.63)
Personal Services	-	.0784 (.629)	.0873 (.701)
Entertainment & Recreation Serv.	-	-.4254 (-2.22)	-.4199 (-2.20)
Professional & Related Services	-	-.0568 (-.472)	-.0417 (.347)
Public Administration	-	.1683 (.984)	.14601 (.855)
SEC80*WW80	-	-	-.0021 (-2.63)
R^2	.157	.199	.206

T-statistics of coefficient estimates are in parentheses. All industry dummies are for industry affiliation in 1980.

the secondary sector while the coefficient on WW80 alone gives the return in the primary sector. The estimated return to a week of experience in 1980 is .0016 for secondary workers and .0037 for primary workers. As expected, the return to experience is substantially lower for those employed in the 1980 secondary sector.

Furthermore, imposing the constraint of a single return across all labor market segments underestimates the return in the primary sector. The return to experience when the interaction term is omitted (.0022) lies between the return in the secondary sector (.0016) and the return in the primary sector (.0037) when the interaction term is included. Proceeding with calculations of the predicted hourly wage differentials described above, equation (3) predicts a differential of 3.96 percent for a 1980 secondary sector employee and 9.16 percent for a 1980 primary sector employee.

Hence, the evidence presented in Table 4.5 leads to two conclusions: (1) early industry of employment has a substantial influence on future earnings which in some industries is greater in magnitude then the effect of lost experience, and (2) in the secondary sector, in addition to the lack of experience, the lack of return to experience shares the blame for low future earnings. Next, the sensitivity of these results to the industry-based classification scheme and the extent of the contamination of the industry and experience estimates by unobserved heterogeneity must be addressed.

Estimation of the more general switching model further confirms the result that the return to past experience differs across labor market segments. Table 4.6 presents the results of this model along with a similarly specified OLS wage regression. The return to experience in the OLS equation (.0052) lies between the predicted returns in

Table 4.6
Log-Wage Equations Estimated by OLS and Switching Model

	Dependent Variable = Log Wages 1987			
Independent Variables	OLS	Primary	Secondary	Switching Equation
Constant	.9235 (8.98)	-2.6938 (-2.222)	1.1035 (8.00)	-3.4315 (-3.478)
SMSA	.1897 (5.48)	.3708 (1.893)	.1716 (3.365)	.2277 (1.011)
Married	.1043 (3.16)	.2193 (1.149)	.0894 (1.84)	.2055 (.9419)
Education	.0645 (6.96)	.2712 (2.987)	.0395 (2.844)	.2569 (3.061)
Black	-.1247 (-3.23)	-.1841 (-.1865)	.0093 (.1368)	-2.2865 (-4.259)
WW80	.0052 (4.92)	.0081 (2.184)	.0041 (3.484)	-
σ	.5026	.9253 (6.842)	.4222 (22.216)	-
σ_{wp}	-	1.01 (19.95)	-	-
σ_{ws}	-	-	-2.08 (-12.51)	-

t-statistics in parentheses

the primary (.0081) and the secondary (.0041) sectors. In accordance with the findings of Dickens and Lang (1985), the estimated primary and secondary sector wage equations conform with the predictions of labor market segmentation theory. Specifically, the returns to experience and education are much lower in the secondary sector. Furthermore, the parameters of the switching equation indicate that being black significantly reduces the propensity to be in the primary sector while a higher education significantly increases the propensity. Since the switching model and the OLS equations are nested, the significance of the switching equation and the second wage equation can be tested with a simple likelihood ratio test. This gives a test statistic of 55.98 which fails to reject the hypothesis of two wage equations at the .0004% level of confidence.

Lastly, Table 4.7 presents the results from the estimation of the differenced equation (3) from section 4.3. The differenced equation is used to eliminate the heterogeneity bias and should give some indication of the true effect of past weeks worked and past industry on earnings. In the first equation, log wages in 1983 are regressed on a set of controls, weeks worked in the previous four years, concurrent industry dummies, and the industry dummies for the previous four years. The second equation is a second-differenced version of the first equation. Second differencing isolates concurrent and one year lagged industry dummies, and two previous years of weeks worked.

Most interestingly, the coefficients on past weeks worked in 1982 and 1981 increase slightly after differencing. This suggests that the return to experience estimated in undifferenced equations is independent of unobserved heterogeneity. However, the differenced estimates are not independent of the contemporary and past industry dummies. Estimation of equation (2) excluding past and present industry dummies gave a slightly higher estimate (.0046) of the coefficient on WW82 and a substantially higher estimate (.0066) of the coefficient on WW81. This finding is consistent with the argument that the correlation between weeks of employment and industry will lead to biased estimates

Table 4.7
Undifferenced and Second Differenced Log-wage Equations

Explanatory Variables Isolated by Differencing	Dependent Variable = LW83	Dependent Variable = LW83 - LW81
WW82	.0046 (3.07)	.0044 (2.44)
WW81	.0039 (2.29)	.0047 (1.96)
Agriculture, Forestry, & Fisheries '83	-.1097 (-1.19)	-.1534 (-1.51)
Mining '83	.2891 (2.15)	.3561 (2.50)
Construction '83	.1875 (2.32)	.0872 (.978)
Manufacturing '83	.2557 (3.89)	.1788 (2.44)
Trans. Commun. & Public utilities '83	.2785 (3.11)	.2175 (2.29)
FIRE '83	.377 (1.71)	.3439 (1.33)
Business & Repair Services '83	.0774 (1.05)	.0729 (.916)
Personal Services '83	-.0439 (-.432)	-.1798 (-1.56)
Entertainment & Recreation Services '83	-.2113 (-1.31)	-.1694 (-.706)
Professional & Related Services '83	-.0073 (-.069)	.0959 (.7557)
Public Administration '83	-.0575 (-.545)	.1037 (.826)
Agriculture, Forestry, & Fisheries '82	-.12526 (-1.27)	.0121 (.101)
Mining '82	.2774 (1.94)	.3306 (2.17)
Construction '82	.0804 (.999)	.1717 (1.88)
Manufacturing '82	-.0692 (-1.13)	.0322 (.478)
Trans., Commun, & Public Utilities '82	.1389 (1.60)	.0874 (.867)

Table 4.7
Undifferenced and Second Differenced Log-wage Equations

Explanatory Variables Isolated by Differencing	Dependent Variable = LW83	Dependent Variable = LW83 - LW81
FIRE '82	-.2396 (-1.11)	-.2554 (-1.13)
Business & Repair Services '82	-.1467 (-1.92)	-.0292 (-.342)
Personal Services '82	-.0871 (-.676)	.1361 (.939)
Entertainment & Recreation Services '82	-.0204 (-.087)	-.0344 (-.11)
Professional & Related Services '82	.0108 (.084)	.0258 (.081)
Public Administration '82	-.0481 (-.42)	.1303 (.949)
R_2	.396	.179

Regressions include the explanatory variables AGE, SMSA, SOUTH, NORTHEAST, WEST, and MARRIED. T-statistics are in parentheses.

of the impact of work experience when past industry dummies are omitted.

With respect to industry, the results in Table 4.7 suggest that the concurrent industry effects are largely independent of the heterogeneity term. Of the four coefficients that are statistically significant in the first equation, only one becomes insignificant. Two of the twelve coefficients change signs. However, neither of the two are significant before or after differencing. The coefficients on the one year lagged industry dummies are not so well behaved. Before differencing, only one coefficient is statistically significant while after differencing there are two. Four of the coefficients change signs. This poor results may be due in part to the small sample sizes and the high correlation between the industry dummies across time. Specifically, in 1982 five of the twelve industry cells had less than 15 observations each.

In sum, both early work experience and early industry of employment are found to have a significant impact on future wages, with early industry having the larger effect. In addition, the return to experience is found to vary across labor market segments. While the results of the differenced equation are unclear with respect to past industry, the estimate of past experience on future earnings does not suffer from a heterogeneity bias.

4.6 Conclusion

The results of this chapter illustrate the complexities of analyzing the youth labor market. Specifically, the incidence and duration of youth unemployment interact in a complicated manner with the set of employment opportunities available to the group of youths most affected. The evidence presented supports the argument that the qualitative aspects of early employment are equally as important to the path of future earnings as being employed at all. Failing to account for labor market segment overestimates the effect of experience lost.

The practical implication of this argument is that policy should focus on the type of employment available to youths in addition to the number of jobs available. The evidence here indicates that having had a job in a high paying industry contributes much more to future wages than having past work experience. Even if the estimated industry effects are being driven by unobserved heterogeneity, the potential gains from aggressively attacking supply side disparities are much larger than the gains from providing low-wage work experience.

The finding that early unemployment has a negative effect on future employment is a significant departure from the previous literature. One of the main conclusions of the NBER's 1982 inquiry into the causes and consequences of youth unemployment is that early unemployment does not lead to future unemployment (Freeman & Wise 1982, Ellwood 1982). Perhaps this conclusion is incorrect. The estimation technique employed in Ellwood's study is biased towards the finding of no effect. Future work should focus on deriving a consistent estimator which disentangles the true independent effect of early unemployment on later unemployment from the effect due to heterogeneity.

Appendix 4.A

1. Derivation of the Likelihood Function for the Two-Sided Tobit Equation

Each individual is observed in one of three states:

state 1: WW (weeks worked) = 0
state 2: 0 < WW < 52
state 3: WW = 52

Define P_{ij} as equal to one if individual i is in state j, and zero otherwise. The continuous latent variable is defined by

(1) $$WW_i^* = X_i\beta + \varepsilon_i.$$

WW and WW* are related by the identity

(2) $$WW = \begin{cases} 0, & WW^* \leq 0 \\ WW^*, & 0 < WW^* < 52 \\ 52, & WW^* \geq 52. \end{cases}$$

The probability of each state is

(3) $$\begin{aligned} \Pr(\text{state } 1) &= \Pr(WW_i^* \leq 0\,) = \Pr(\varepsilon_i \leq -X_i\beta) \\ \Pr(\text{state } 2) &= \Pr(WW_i^* = WW_i) = \Pr(\varepsilon_i = WW_i - X_i\beta) \\ \Pr(\text{state } 3) &= \Pr(WW_i^* \geq 52) = \Pr(\varepsilon_i \geq 52 - X_i\beta) \end{aligned}$$

Assuming that ε is normally distributed with mean 0 and variance σ^2 gives the likelihood function

(4) $\Pi^{n}_{i=1}\Phi(-X_i\beta/\sigma)^{Pi1}.(1/\sigma\phi((WW_i - X_i\beta)/\sigma)^{Pi2}.(1 - \Phi((52 - X_i\beta)/\sigma))^{Pi3}$

where Φ is the cumulative standard normal distribution and ϕ is the standard normal density.

2. Derivation of the Likelihood Function for the Switching Model

The following derivation comes directly from Dickens and Lang (1985, p.802). The system consists of two wage equations and an equation that determines the sector of employment. The equations are

(1) $\ln W_i = X_i\beta_p + \varepsilon_{pi},$

(2) $\ln W_i = X_i\beta_s + \varepsilon_{si},$

(3) $y^*_i = Z_i\delta + \varepsilon_{wi},$

where $\ln W_i$ is log wages, X_i and Z_i are vectors of independent variables, and ε_{pi}, ε_{si}, and ε_{wi} are the error terms. Equation (1) determines wages in the primary sector while equation (2) determines wages in the secondary sector. Equation (3) defines a latent variable where $y^*_i > 0$ indicates that the individual is employed in the primary sector.

There are two possible states neither of which are directly observed. An individual is employed in the primary sector if $\varepsilon_{wi} > -Z_i\delta$ and $\varepsilon_{pi} = \ln W_i - X_i\beta$ while an individual is employed in the secondary sector if $\varepsilon_{wi} \leq Z_i\delta$ and $\varepsilon_{si} = \ln W_i - X_i\beta$. Assuming that ε_w, ε_p, and ε_s are normally distributed and normalizing σ_w to one, the likelihood function is

$$(4) \qquad \Pi^{n}_{i=1}[\{1 - \Phi((-Z_i\delta - (\rho_{pw}/\sigma_p)\varepsilon_p)/(1 - \rho_{pw}^{2})^{.5})\}.\{1/\sigma_p\phi((\ln W_i - X_i\beta_p)/\sigma_p)\}$$

$$+ \{\Phi((-Z_i\delta - (\rho_{sw}/\sigma_s)\varepsilon_s)/(1 - \rho_{sw}^{2})^{.5})\}.\{1/\sigma_s\phi((\ln W_i - X_i\beta_s)/\sigma_s)\}],$$

where Φ is the standard cumulative normal distribution, ϕ is the standard normal density, ρ_{sw} is the correlation coefficient between ε_w and ε_s, and ρ_{pw} is the correlation coefficient between ε_w and ε_p.

Appendix 4.B
Primary-Secondary Classification by 1970 Census of Population Industrial Classification System

Labor Market Segment	Industry Description (3 Digit Coding)
Secondary	Agriculture, Forestry, and Fisheries (017 - 028)
Primary	Mining (047 - 077)
Primary	Construction (067 - 077)
Secondary	Lumber and Wood products (107 - 118)
Secondary	Stone, Clay, and Glass products (119 - 138)
Primary	Metal Industries (139 - 157)
Secondary	Metal Industries (158 - 169)
Primary	Machinery Except Electrical (177 - 198)
Primary	Electrical Machinery, Equipment and Supplies (199 - 209)
Primary	Transportation Equipment (219 - 238)
Primary	Professional and Photographic Equipment & Watches (239 - 257)
Primary	Ordnance (258)
Secondary	Miscellaneous Manufacturing Industries (259)
Secondary	Food & Kindred Products (268 - 298)
Primary	Tobacco Manufactures (299)
Secondary	Textile Mill Products (307 - 318)
Secondary	Apparel and other Fabricated Textile products (319 - 327)
Primary	Paper and Allied Products (328 - 337)
Secondary	Printing Publishing and Allied Industries (338 -339)

Appendix 4.B
Primary-Secondary Classification by 1970 Census of Population Industrial Classification System

Labor Market Segment	Industry Description (3 Digit Coding)
Primary	Chemical and Allied Products (347 - 387)
Secondary	Leather and Leather Products (388 - 398)
Primary	Transportation, Communications, and other Public Utilities (407 - 479)
Secondary	Wholesale Trade (507 - 588)
Secondary	Retail Trade (607 - 698)
Secondary	Banking (707)
Secondary	Credit Agencies (708)
Primary	Security, Commodity Brokerage, and Investment Companies (709)
Primary	Insurance (717)
Secondary	Real Estate (718)
Secondary	Business and Repair Services (727 - 759)
Secondary	Personal Services (769 - 798)
Primary	Entertainment & Recreation Services (807 - 809)
Primary	Professional & Related Services (849, 879, 888, 889)
Secondary	Professional & Related Services (828 - 848, 857 - 878, 887, 897)
Primary	Public Administration (907 - 937)

References

Akerlof, George; Rose, Andrew; and Janet Yellen (1988), "Job Switching and Job Satisfaction in the U.S. Labor Market," Brookings Papers on Economic Activity, 2: 495-594.

Blau, Francine D. and Lawrence M. Kahn (1981), "Race and Sex Differences in Quits By Young Workers," Industrial and Labor Relations Review, 34(4): 175-225.

Cameron, Colin and Pravin Trivedi (1990), "Regression Based Estimates for Overdispersion in the Poisson Model," Journal of Econometrics, 46: 347-364.

Cameron, Colin and Pravin Trivedi (1986), "Econometric Models Based on Count Data: Comparisons and Applications of Some Estimators and Tests," Journal of Applied Econometrics, 1: 29-53.

Carrothers, Gerald S.P. (1950) "An Historical Review of the Gravity and Potential Concepts of Human Interaction," Journal of the American Institute of Planners, 22: 94-102.

Corcoran, M. (1982), "The Employment and Wage Consequences of Teenage Women's Unemployment," in Freeman, R. and D. Wise (eds.), The Youth Labor Market Problem: Its Nature, Causes, and Consequences, Chicago: The University of Chicago Press.

Davidson, C. and M. Reich (1988), "Income Inequality: An Inter-Industry Analysis," Industrial Relations, 263-286.

Dickens, W. and L. Katz (1988), "Inter-Industry Wage Differences and Theories of Wage Determination," NBER Working Paper #2271, June.

Dickens, W. and K. Lang (1985), "A Test of Dual Labor Market Theory," The American Economic Review, 75: 792-805.

Dickens, W. and K. Lang (1992), "Labor Market Segmentation Theory: Reconsidering the Evidence," NBER Working Paper #4087, June.

DiIulio, John J. Jr. (1996), "Help Wanted: Economists, Crime and Public Policy," The Journal of Economic Perspectives, 10(1): 3-24.

Doeringer, P. and M. Piore (1971), Internal Labor Markets and Manpower Analysis, Lexington Mass.: D.C. Heath & Co.

Ellwood, D. (1982), "Teenage Unemployment: Permanent Scars or Temporary Blemishes?," in Freeman, R. and D. Wise (eds.), The Youth Labor Market Problem: Its Nature, Causes, and Consequences, Chicago: The University of Chicago Press.

Ellwood, David T. (1986), "The Spatial Mismatch Hypothesis: Are there Teenage Jobs Missing in the Ghetto?," in Freeman, Richard B. and Harry J. Holzer (eds.), The Black Youth Employment Crisis, Chicago: The University of Chicago Press.

Farley, Reynolds (1991), "Residential Segregation of Social and Economic Groups Among Blacks, 1970-1980," in Jencks, Christopher and Paul E. Peterson (eds.), The Urban Underclass, Washington, D.C.: The Brookings Institution.

Farley, Reynolds and William H. Frey (1994), "Changes in the Segregation of Whites From Blacks During the 1980s: Small Steps Toward a More Integrated Society," American Sociological Review, 59: 23-45.

Flowerdew, Robin and Murray Aitkin (1982), "A Method of Fitting the Gravity Model Based on the Poisson Distribution," Journal of Regional Sciences, 22(2): 191-202.

Freeman, Richard B. (1995), "The Labor Maket," in Wilson, J.Q. and Joan Petersilia (eds.) Crime, San Francisco: Institute for Contemporary Studies, 171-195.

Freeman, Richard B. (1995), "Why Do So Many Young American Men Commit Crimes and What Might We Do About It?," The Journal of Economic Perspectives, 10(1): 25-42.

Freeman, R. and J. Medoff (1982), "The Youth Labor Market Problem in the United States: An Overview," in Freeman, R. and D. Wise (eds.), The Youth Labor Market Problem: Its Nature, Causes, and Consequences, Chicago: The University of Chicago Press.

Gibbons, R. and L. Katz (1989), "Does Unmeasured Ability Explain Inter-Industry Wage Differences?," NBER Working Paper #3182, November.

Greenberger, E. and L. Steinberg (1986), When Teenagers Work:The Psychological and Social Costs of Adolescent Employment, New York: Basic Books.

Grey, Robert H. and Ashish K. Sen (1983), "Estimating Gravity Model Parameters: A Simplified Approach Based on the Odds Ratio," Transportation Research B, 17B(2): 117-131.

Guy, C.M. (1987), "Recent Advances in Spatial Interaction Modelling: an Application to the Forecasting of Shopping Travel," Environment and Planning A, 19: 173-186.

Hanson, Susan and Geraldine Pratt (1988), "Reconceptualizing the Links Between Home and Work in Urban Geography," Economic Geography, 64(4): 299-321.

Hausman, Jerry; Hall, Brownwyn and Zvi Griliches (1984), "Econometric Models for Count Data with an Application to the Patents-R & D Relationship," Econometrica, 52(4): 909-938.

Haynes, Kingsley; Poston, Dudley; and Paul Schnirring (1973), "Intermetropolitan Migration in High and Low Opportunity Areas: Indirect Tests of the Distance and Intervening Opportunities Hypothesis," Economic Geography, 49: 68-73.

Haynes, Kingsley and Stewart Fotheringham (1984), Gravity and Spatial Interaction Models, Beverly Hills: Sage Publications.

Holzer, Harry J. (1988), "Search Method Use by Unemployed Youth," Journal of Labor Economics, 6(1): 1-20.

Holzer, Harry J. (1991), "The Spatial Mismatch Hypothesis: What has the Evidence Shown," Urban Studies, 28(1): 105-122.

Hutchinson, P. (1974), "Residential Segregation and the Economic Status of Black Workers: New Evidence for an Old Debate," in G. Van Furstenburg, B. Harrison and A. Horowitz (eds.) Patterns of Racial Discrimination Volume 1, Lexington, MA: Lexington Books.

Ihlanfeldt, Keith R. (1988), "Intra-Metropolitan Variation in Earnings and Labor Market Discrimination: An Econometric Analysis of the Atlanta Labor Market," Southern Economic Journal, 55: 123-140.

Ihlanfeldt, Keith R. (1992), Job Accessibility and the Employment and School Enrollment of Teenagers, Kalamazoo: W.E. Upjohn Institute for Employment Research.

Ihlanfeldt, Keith R. (1993), "Intra-Urban Job Accessibility and Hispanic Youth Employment Rates," Journal of Urban Economic, 22: 254-271.

Ihlanfeldt, Keith R. and David L. Sjoquist (1990), "Job Accessibility and Racial Differences in Youth Employment Rates," The American Economic Review, 80(1): 267-276.

Ihlanfeldt, Keith R. and David L. Sjoquist (1991), "The Effect of Job Access on Black and White Youth Employment: A Cross-Sectional Analysis," Urban Studies, 28(2): 255-265.

Isard, Walter (1960), Methods of Regional Analysis: An Introduction to Regional Science, New York: The Technology Press of MIT.

Jayet, H. (1990a), "Spatial Search Processes and Spatial Interaction: 1. Sequential Search, Intervening Opportunities, and Spatial Search Equilibrium," Environment And Planning A, 22(6): 583-599.

Jayet, H. (1990b), " Spatial Search Processes and Spatial interaction: 2. Polarization, Concentration, and Spatial Search Equilibrium," Environment and Planning A, 22(7): 719-732.

Jencks, Christopher and Paul E. Peterson (1991), The Urban Underclass, Washington D.C.: The Brookings Institution.

Kain, John F. (1968), "Housing Segregation, Negro Employment, and Metropolitan Decentralization," Quarterly Journal of Economics, 82(2): 175-197.

Kain, John F. (1993), "The Spatial Mismatch Hypothesis: Three Decades Later," Housing Policy Debates, 3(2): 371-460.

Kasarda, John (1985), "Urban Change and Minority Opportunity," in Paul E. Patterson (ed.), The New Urban Reality, Washington D.C.: The Brookings Institution.

Kasarda, John (1989), "Urban Industrial Transition and the Underclass," The Annals of the American Academy of Political and Social Science, 501: 26-47.

Kerr, C. (1954), "The Balkanization of Labor Markets," in E. Wright Bakke, et.al., Labor Mobility and Economic Opportunity, Cambridge, MA.

Krueger, A. and L. Summers (1988), "Efficiency Wages and the Inter-Industry Wage Structure," Econometrica, 56: 259-93.

Leonard, Jonathon S (1985), "Space, Time, and Unemployment," Unpublished Manuscript, University of California, Berkeley.

Leonard, Jonathon S. (1986), "Comment on David Ellwood's `The Spatial Mismatch Hypothesis: Are there Teenage Jobs Missing in the Ghetto?'," in Freeman, Richard B. and Harry J. Holzer (eds.), The Black Youth Employment Crisis, Chicago: The University of Chicago Press.

Mare, Robert D. and Christopher Winshop (1991), "Socioeconomic Change and the Decline of Marriage for Blacks and Whites," in Jencks, Christopher and Paul E. Peterson (eds.), The Urban Underclass, Washington, D.C.: The Brookings Institution.

Massey, Douglas S. and Nancy A, Denton (1988), "The Dimensions of Racial Segregation," Social Forces, 67:281-315.

Massey, Douglas S. and Nancy A. Denton (1993), American Apartheid: The Making of the Underclass, Cambridge: Harvard University Press.

Mieszowski, Peter and Edwin S. Mills (1993), "The Causes of Metropolitan Suburbanization," Journal of Economic Perspectives, 7(3): 135-147.

Mills, Edwin S. (1972), Urban Economics, Illinois: Scott Foresman and Company.

Mooney, Joseph D. (1969), "Housing Segregation, Negro Employment and Metropolitan Decentralization: An Alternative Perspective," Quarterly Journal of Economics, May: 299-311.

Murphy, K and R. Topel (1987) "Unemployment Risk and Earnings," in K. Lang and J. Leonard (eds.), Unemployment and The structure of Labor Markets, London: Basil Blackwell.

Offner, Paul and Daniel H. Saks (1971), "A Note on John Kain's `Housing Segregation, Negro Employment and Metropolitan Decentralization'," Quarterly Journal of Economics, 191:147-160.

O'Regan, Katherine M. and John M. Quigley (1990), "Labor Market Access and the Labor Market Outcomes for Urban Youth", Center for Real Estate and Urban Economics Working Paper Series, no. 90-185.

Senior, Martyn L. (1979), "From Gravity Modelling to Entropy Maximization: A Pedagogic Guide," Progress in Human Geography, 3:175-210.

Singell, L. and J. Lillydahl (1989), "Some Alternative Definitions of Youth Unemployment: A Means for Improved Understanding and Policy Formation," The American Journal of Economics and Sociology, 48: 457-71.

Stouffer, Samuel A. (1940), "Intervening Opportunities: A theory Relating Mobility and Distance," American Sociological Review, 5(6) 845-867.

Straszheim, Marlon R. (1980), "Discrimination and the Spatial Characteristics of the Urban Labor Market for Black Workers," Journal of Urban Economics, 7: 119-140.

Turner, Margery Austin (1992), "Discrimination in Urban Housing Markets: Lessons From the Fair Housing Audits," Housing Policy Debate, 3(2): 185-215.

Van den Berg, Gerard (1994) "The Effects of Changes of the Job Offer Arrival Rate on the Duration of Unemployment," Journal of Labor Economics, 12(3): 478-498.

Wienk, Ronald E. (1992), "Discrimination in Urban Credit Markets: What We Don't Know and Why We Don't Know It," Housing Policy Debate, 3(2): 217-240.

Wilson, Julius William (1987), The Truly Disadvantaged: the Inner City, the Underclass, and Public Policy, Chicago: The University of Chicago Press.

Yun, Seongsoon and Ashish Sen (1994), "Computation of Maximum Likelihood Estimates of Gravity Model Parameters," Journal of Regional Sciences, 34(2): 199-216.