EFFECTS OF JOB ACCESS AND NEIGHBORHOOD DISADVANTAGE ON
EMPLOYMENT SUCCESS OF FEMALE FORMER WELFARE RECEPIENTS

by

SEOK-JOO KIM

Submitted in partial fulfillment of the requirements
For the degree of Doctor of Philosophy

Dissertation Adviser: Dr. Claudia Jane Coulton

MANDEL SCHOOL OF APPLIED SOCIAL SCIENCES
CASE WESTERN RESERVE UNIVERSITY
May, 2013
We hereby approve the thesis/dissertation of

SEOK-JOO KIM

candidate for the Doctor of Philosophy degree*. 

(signed) Dr. Claudia Jane Coulton
(chair of the committee)

Dr. David E. Biegel

Dr. David Crampton

Dr. Jill E. Korbin

(date) March 20, 2013

*We also certify that written approval has been obtained for any proprietary material contained therein.
List of Contents

Chapter One: Introduction  

1.1. Purpose and overview ........................................................................................................... 1
1.2. Context of welfare reform .................................................................................................. 2
1.3. Why this study is important ............................................................................................... 3  
   1.3.1. Importance of employment success of welfare recipients ........................................... 3
   1.3.2. Job access as a barrier of employment ......................................................................... 3
   1.3.3. Effect of neighborhood disadvantage on employment success ................................. 5
1.4. Research context ................................................................................................................. 7
1.5. Implications for social policy, program, and community development ......................... 8
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>Welfare reform of 1996</td>
<td>9</td>
</tr>
<tr>
<td>2.2</td>
<td>Employment and human capital of TANF recipients</td>
<td>13</td>
</tr>
<tr>
<td>2.2.1</td>
<td>Employment of TANF recipients</td>
<td>11</td>
</tr>
<tr>
<td>2.2.2</td>
<td>Human capital of former TANF recipients</td>
<td>14</td>
</tr>
<tr>
<td>2.3</td>
<td>Job access</td>
<td>18</td>
</tr>
<tr>
<td>2.3.1</td>
<td>Theoretical background</td>
<td>18</td>
</tr>
<tr>
<td>2.3.2</td>
<td>Previous studies</td>
<td>26</td>
</tr>
<tr>
<td>2.4</td>
<td>Neighborhood disadvantage</td>
<td>33</td>
</tr>
<tr>
<td>2.4.1</td>
<td>Theoretical background</td>
<td>33</td>
</tr>
<tr>
<td>2.4.2</td>
<td>Concept of neighborhood disadvantage</td>
<td>35</td>
</tr>
<tr>
<td>2.4.3</td>
<td>Previous studies</td>
<td>37</td>
</tr>
<tr>
<td>2.5</td>
<td>Conceptual framework and research questions</td>
<td>44</td>
</tr>
<tr>
<td>2.5.1</td>
<td>Conceptual framework</td>
<td>44</td>
</tr>
<tr>
<td>2.5.2</td>
<td>Research questions and hypotheses</td>
<td>47</td>
</tr>
</tbody>
</table>
### 3.1. Study design

- **3.1.1. Data manipulation**
  - 3.1.1.1. TANF data
  - 3.1.1.2. Quarterly Wage Records
  - 3.1.1.3. 2000 Census data

- **3.1.2. Sampling criteria**

### 3.2. Timeframe and operational definition of variables

- **3.2.1. Timeframe**
  - 3.2.1.1. Cash assistance period
  - 3.2.1.2. Post-cash assistance period

- **3.2.2. Dependent variables**

- **3.2.3. Individual-level variables**
  - 3.2.3.1. Covariates
  - 3.2.3.2. Individual job access

- **3.2.4. Neighborhood-level variables**
  - 3.2.4.1. Neighborhood disadvantage
  - 3.2.4.2. Neighborhood public transportation access
Chapter Four: Results

4.1. Descriptive analysis ......................................................... 89
   4.1.1. Dependent variables ................................................. 89
   4.1.2. Individual-level variables ........................................... 97
   4.1.3. Neighborhood-level variables ...................................... 100
      4.1.3.1. Neighborhood disadvantage .................................. 100
      4.1.3.2. Neighborhood public transportation access ............... 101
   4.1.4. Bivariate correlations ................................................ 105
### 4.2. Job retention

<table>
<thead>
<tr>
<th>Model</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.2.1. Model 1: Null model</td>
<td>109</td>
</tr>
<tr>
<td>4.2.2. Model 2: Random-intercept model</td>
<td>109</td>
</tr>
<tr>
<td>4.2.3. Model 3: Random-intercept regression model</td>
<td>110</td>
</tr>
<tr>
<td>4.2.4. Model 4: Random-intercept ANCOVA model</td>
<td>111</td>
</tr>
</tbody>
</table>

### 4.3. Two-year employment

<table>
<thead>
<tr>
<th>Model</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.3.1. Model 5: Null model</td>
<td>115</td>
</tr>
<tr>
<td>4.3.2. Model 6: Random-intercept model</td>
<td>115</td>
</tr>
<tr>
<td>4.3.3. Model 7: Random-intercept regression model</td>
<td>116</td>
</tr>
<tr>
<td>4.3.4. Model 8: Random-intercept ANCOVA model</td>
<td>117</td>
</tr>
</tbody>
</table>

### 4.4. Average quarterly earnings

<table>
<thead>
<tr>
<th>Model</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.4.1. Model 9: Null model</td>
<td>121</td>
</tr>
<tr>
<td>4.4.2. Model 10: Random-intercept model</td>
<td>122</td>
</tr>
<tr>
<td>4.4.3. Model 11: Random-intercept regression model</td>
<td>123</td>
</tr>
<tr>
<td>4.4.4. Model 12: Random-intercept ANCOVA model</td>
<td>124</td>
</tr>
</tbody>
</table>
Chapter Five: Discussion  

5.1. Summary ........................................................................................................ 130  

5.1.1. Background ................................................................................................. 130  

5.1.2. Method .......................................................................................................... 131  

5.1.3. Summary of results ....................................................................................... 132  

5.2. Discussion and implications ......................................................................... 137  

5.2.1. Effects of neighborhood disadvantages .................................................... 137  

5.2.2. Job access and public transportation access ............................................. 142  

5.2.3. Public assistance program and policy ......................................................... 148  

5.3. Limitations and future study ...................................................................... 151  

5.3.1. Limitations .................................................................................................. 151  

5.3.2. Future study ................................................................................................. 154  

Reference ............................................................................................................... 157
# List of Tables

<table>
<thead>
<tr>
<th>Table IV-1. Previous studies on job access and employment of welfare recipients</th>
<th>32</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table III-1. Job locations in Metropolitan Statistical Areas</td>
<td>60</td>
</tr>
<tr>
<td>Table III-2. Composition of variables</td>
<td>71</td>
</tr>
<tr>
<td>Table IV-1. Dependent variables: Employment success</td>
<td>91</td>
</tr>
<tr>
<td>Table IV-2. Individual-level variables</td>
<td>99</td>
</tr>
<tr>
<td>Table IV-3. Neighborhood-level variables and PCA of neighborhood disadvantage</td>
<td>102</td>
</tr>
<tr>
<td>Table IV-4. Bivariate correlations at individual level</td>
<td>108</td>
</tr>
<tr>
<td>Table IV-5. HGLM with a Poisson distribution of job retention</td>
<td>113</td>
</tr>
<tr>
<td>Table IV-6. HGLM with a Bernoulli distribution of two-year employment</td>
<td>119</td>
</tr>
<tr>
<td>Table IV-7. HLM of average quarterly earnings</td>
<td>127</td>
</tr>
</tbody>
</table>
List of Figures

| Figure II-1. Caseload of welfare recipients in the U.S. | 12 |
| Figure II-2. Employment rates of welfare recipients in the U.S. | 17 |
| Figure II-3. Conceptual framework | 46 |
| Figure III-1. Data manipulation | 54 |
| Figure III-2. Sample by neighborhoods | 58 |
| Figure III-3. Job locations in Metropolitan Statistical Areas | 59 |
| Figure III-4. Time frame | 64 |
| Figure III-5. Applications of multi-level analyses | 83 |
| Figure IV-1. Distribution of job retention | 92 |
| Figure IV-2. Distribution of average quarterly earnings | 93 |
| Figure IV-3. Geographic distribution of job retention | 94 |
| Figure IV-4. Geographic distribution of two-year employment | 95 |
| Figure IV-5. Geographic distribution of average quarterly earnings | 96 |
| Figure IV-6. Geographic distribution of neighborhood disadvantage | 103 |
| Figure IV-7. Geographic distribution of neighborhood public transportation access | 104 |
| Figure IV-8. Neighborhood disadvantage and job retention | 114 |
| Figure IV-9. Neighborhood disadvantage and two-year employment | 120 |
| Figure IV-10. Neighborhood disadvantage and average quarterly earnings | 128 |
| Figure IV-11. Public transportation access and average quarterly earnings | 129 |
Acknowledgements

Numerous and invaluable supports have allowed me to complete the long journey of my doctoral program. First of all, Dr. Claudia Jane Coulton, my academic advisor, has mentored me since my master program. She has always highlighted my strengths and gave me many opportunities for my academic achievements and self-growth. She has shown me the best role models of a teacher, researcher, scholar, mentor, and human.

I appreciate my dissertation committee: Drs. David E. Biegel, David Crampton, and Jill Korbin. Their sharp critiques and warm comments made my improvised dissertation more affluent. The faculty that has supported me in-and-outside of classes: Drs. Chatterjee, Hokenstad, Singer, Farkas, Tracy, Townsend, Groza, and Meeyoung Oh. I have a special appreciation for Ms. Soad Mansour’s unconditional and consistent care since my first day at this school.

I thank the staff (Nina, Tusi, April, Curtis, Jessie, & Michael) and professors (Drs. Milligan, Collins, Fisher, & Chupp) at the Center on Urban Poverty and Community Development. I appreciate the school staff (Ms. Helen Menke, Doris, & Dennis) as well as my internship supervisors (Dr. Garrity and Mr. Williams) at the Alcohol, Drug Addiction, and Mental Health Services Board of Cuyahoga County.

I can never forget my happiest times with my fellow doctoral students (Drs. Susie, Sue, & Diwakar) and with other Korean folks at the university (Nakyung’s parents, Dr. Sunghee, Dr. Heeyoul, Minso, Yunsung’s parents, Young-yun, Youngmin, Min-Hyung, Culho, and Dr. Wonik).
I would like to extend my appreciation to my former professors in Korea: Drs. Kyungseok Choi, Sungchun Kim, Sulki Chung at Chung-Ang Univ. (CAU), Inyoung Han at Ewha Womans Univ., and Jung-won Lim at Kangnam Univ.

Moreover, I appreciate for my CAU alumni’s support: Dr. Seogoo, Dr. Yongwoo, Jong-Min, Wong-Hyung, Do-Kyun, Sung-Ho, Sang-Hoon, Eunjoo, An-Jin, Sung-Man, Minseok, Fr. Joseph Na, and LIBERO (soccer club) members. I am especially appreciative of Dr. Hyunsoo Kim’s constant friendship. My childhood friends should be happy for me: Hun-wook, Jun-ho, Jay-Hyuk, Hyuk-Bae, Young-Jin, and Min-Woo.

Many Korean families in Cleveland have also supported my doctoral program: Doosik, Simon Lee, Dr. Ko, Ju-hyun, Hee-Chuel, Sung-Tae, and Joon. Furthermore, I appreciate that Boston Mills/Brandywine ski patrol made my afterschool life happier. I also thank Jonathan Metcalfe who carefully checked my English grammars.

What is more, I expand my appreciations to the extended families, especially Dr. Jay Kim’s family, and Mrs. Nam-Soon You & Mr. Tae-Hyun Kwon couple. I also remember my grandparents who passed away before and during my doctoral program.

I appreciate the long-term support of my elder sister (Eun-Joo) and brother-in-law (Sung-Han Kim). Like my mother, my elder sister has always looked after and worried about me since I was born. I am very excited to see her first baby this fall.

My mother, Kyung-Ja You, has provided the full lifetime warranty services to me. Her patience, sacrifice, and love made me complete this program. Finally, my dissertation is dedicated to my father, Jae-Young Kim, who had passed away. I am sure that he is very proud of me. Mom and dad, thank you for your endless love!
Effects of Job Access and Neighborhood disadvantage on Employment Success of Female Former Welfare Recipients

Abstract

by

SEOK-JOO KIM

Purpose and backgrounds: This study aimed to test the effects of job access and neighborhood disadvantage on the employment success of female former welfare recipients. It mainly addressed vital policy concerns on employment issues of Temporary Assistance for Needy Family (TANF) recipients who exited cash assistance. This study was grounded on two theoretical perspectives: (1) the Spatial Mismatch Hypothesis (SMH) that explained job access as a barrier to employment and (2) Wilson’s observation that neighborhood disadvantage negatively affected employment.

Method: As a non-experimental design, this longitudinal study merged two local administrative datasets with 2000 Census data. This study selected female former welfare recipients (N=13,788) (1) who exited cash assistance and were employed between 2000 and 2003, and (2) who resided in 405 census tracts of Cuyahoga County. Employment success was measured by: job retention, two-year employment, and average quarterly
earnings. In addition to demographic and human capital variables, the independent variables that were measured: (1) individual job access (distances), (2) neighborhood public transportation access, and (3) neighborhood disadvantage. As a main analysis, Hierarchical Generalized Linear Model (HGLM) and Hierarchical Linear Model (HLM) were conducted to test the nested effects of job access and neighborhood disadvantage on employment success. Furthermore, this study used spatial analysis (mapping and spatial auto-correlation) to support the main analysis.

**Results:** This study found variances of the employment success among neighborhoods. The results showed that neighborhood disadvantage adversely affected the employment success of female former welfare recipients; however, shorter job distances and higher public transportation access only increased average quarterly earnings.

**Discussion:** The results suggested three domains for implication on social work programs and social policy: (1) neighborhood disadvantage, (2) individual job access and neighborhood public transportation access, and (3) cash assistance program and policy. In particular, this study recommended community development and residential programs should ameliorate the job access barriers and neighborhood disadvantage of welfare recipients. The implementation of cash assistance programs should consider the effects of job access and neighborhood disadvantage.
CHAPTER ONE: INTRODUCTION

1.1. Purpose and overview

The purpose of this study was to examine the effects of job access and neighborhood disadvantage on the employment success of former Temporary Assistance for Needy Family (TANF) recipients. The target population was female former welfare recipients of Cuyahoga County, Ohio who were employed after exiting cash assistance. This study mainly addressed three policy concerns surrounding the 1996 welfare reform: (1) the employment success of female former welfare recipients who were mandated to participate in work-related activities and exit cash assistance within a time limit, (2) job access, as many available workplaces have been suburbanized in the past few decades and there are limited options for transportation, and (3) neighborhood disadvantage, as many TANF recipients lived in economically disadvantaged neighborhoods that may have lowered their employment chances. First, this chapter briefly explains the policy shift of cash assistance program from Aid to Families with Dependent Children (AFDC) to TANF. Next, it discusses the contribution this study can make toward enhancing employment success of female former welfare recipients. Finally, this chapter suggests the necessity of this study for social policy and social research on welfare recipients.
1.2. Context of welfare reform

The Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA) eliminated the AFDC program and embarked on TANF program (P.L. 104-193). Compared to AFDC, TANF places a stronger work requirement on its recipients. As well, TANF limits the length of receiving cash assistance. TANF regulates that its recipients cannot receive cash assistance for more than five years. In Ohio, a three year time limit on cash assistance was adopted (Ohio Department of Job and Family Services [ODJFS], 2001). Although the Ohio TANF program assists its recipients with cash assistance up to a life-time maximum of 60 months, its recipients must wait two years before again qualifying after completing their initial 36 months of cash assistance (ODJFS, 2001). Therefore, self-sufficiency and employment of welfare recipients who exited cash assistance are vital policy concerns raised by the 1996 welfare reform.
1.3. Why this study is important

1.3.1. Importance of employment success of welfare recipients

A study of factors affecting employment success of female former welfare recipients is important because retaining a job after exiting cash assistance can be problematic. Under the policy context mentioned earlier, the first concern of this study was to focus on the importance of employment success among female former welfare recipients who exit cash assistance. The employment rate of the closed TANF adults, those who exited cash assistance, has declined from 37.9 percent in 2000 to 25.7 percent in 2009 (U.S. Department of Health and Human Services [HHS], 2012). The average monthly non-TANF income of former TANF family was $1,018; only 25.0 percent of former TANF family cases earned income in the 2009 fiscal year (HHS, 2012). This employment status of female former welfare recipients did not satisfy the initial purpose of TANF which emphasizes promoting self-sufficiency of welfare recipients. Therefore, the employment success of female former welfare recipients should be persistently considered and assessed.

1.3.2. Job access as a barrier of employment success

A potentially significant barrier to employment success was the problem of geographic job access for female former welfare recipients. Because of increasing suburbanization of low-skilled job opportunities, the concentration of welfare recipients in inner cities, and welfare recipients’ dependency on public transportation, job access
was one of the important factors that affected the employment of female former welfare recipients (Allard, 2002; Allard & Danziger, 2003; Bania, Coulton, & Leete, 1999; 2003; Bloom, Riccio, & Verma, 2005; Blumenberg & Manville, 2004; Blumenberg & Ong, 1998; Blumenberg & Shiki, 2003; Gurley & Bruce, 2005; Gurmu & Smith, 2006; Ihlanfeldt & Sjoquist, 1998; Ong, 1996; Pan, Jensen, Fuller, & Mohanty, 2006). The phenomenon of job suburbanization has attenuated an employment likelihood of low-skilled workers who were unable to move from the inner cities to the suburbs (Blumenberg & Marville, 2004; Coulton, 2003; Holzer & Ihlanfeldt, 1996; Ihlanfeldt & Sjoquist, 1998; Ihlanfeldt, 1994; Kain, 1968; 1974). A high portion of female former welfare recipients can be regarded as low-skilled workers in a labor market. Fifty-two percent of closed TANF recipients did not have a high-school diploma in the 2009 fiscal year (HHS, 2012). Further, female former welfare recipients have less work-experience; only two of ten active TANF recipients worked in the fiscal year 2009 (HHS, 2012).

With regards to job suburbanization, TANF recipients often confronted a job access barrier to their workplaces because many of them reside in poor inner-cities and rely on public transportation (Bloom et al., 2005; Blumenberg & Manville, 2004; Blumenberg & Ong, 1998; Blumenberg & Shiki, 2003; Ong, 1996; Ong & Blumenberg, 1998; Sanchez, Qing, & Peng, 2004). In 2001, 748,000 mothers, ages 15 to 44, received TANF cash assistance (U.S. Census Bureau, 2012). Eighty one percent of them resided in metropolitan areas; fifty percent of metropolitan TANF recipients lived in inner-cities (U.S. Census Bureau, 2012). Given these characteristics, former welfare recipients are exposed to job access barriers to employment. However, few empirical studies have been conducted on testing the relationship between job access and the employment of welfare
1.3.3. Effect of neighborhood disadvantage on employment success

An additional factor considered in this study was the effect of neighborhood disadvantage on the employment success of female former welfare recipients. There is some evidence that the socio-economic characteristics of neighborhoods are associated with the self-sufficiency and employment of welfare recipients (Austin & Lemon, 2005; Allard & Danziger, 2003; Coulton, 2005; Gurmu, Ihlanfeldt, & Smith, 2008; Mendenhall, DeLuca, & Duncan, 2006). During the transformation of public assistance policy from AFDC to TANF, neighborhood effects based on an ecological perspective emerged as an important factor of welfare recipients' employment (e.g., Allard & Danziger, 2003; Allen & Kirby, 2000; Austin & Lemon, 2005; Chow, Johnson, & Austin, 2005; Casiano & Massey, 2008; Coulton, 2003; Deverteuil, 2005; Gurmu et al., 2008; Ihlanfeldt & Sjoquist, 1998; O’Connor, 2000; Vartanian, 1999). Concentrated disadvantage in inner city neighborhoods has been recognized as a serious concern since the 1970s (Briggs, 2005; Massey & Denton, 1993; Massey, Gross, & Shibuya, 1994; Wilson, 1987; 1996).

Basic statistics illustrate the skewed distribution of income and poverty between inner cities and suburbs; the median household income of the suburbs ($56,140) was greater than that of inner cities ($44,409) in 2010 (DeNavas-Walt, Proctor, & Smith, 2011). It was also estimated that 46 million people, which was 15.1 percent of the U.S. population, lived below the federal poverty threshold in 2010 (DeNavas-Walt et al., 2010). Among them, 38 million lived in metropolitan areas, including 19 million in inner cities and 8 million in the suburbs (DeNavas-Walt et al., 2010).
Similar to median household income, there was a difference in the poverty rate between inner cities and suburbs; the poverty rates of inner cities and the suburbs were 19.7 percent and 11.8 percent, respectively (DeNavas-Walt et al., 2010). An additional problem is that the concentrated poverty in inner-city neighborhoods is associated with other indicators of some distress. The influence of concentrated poverty in inner-cities has been expanded to measure a broad concept of the level of neighborhood disadvantage (Deverteuil, 2005; Sampson, Morenoff, & Earls, 1997). Because many TANF recipients reside in urban areas, their economic activities (i.e., employment) are expected to be understood by the level of neighborhood disadvantage where they reside.

Moreover, neighborhood disadvantage adversely affects various outcomes of low-income families including TANF recipients. For example, low-income families in concentrated areas of poverty are exposed to negative individual, familial, and social outcomes such as unemployment, crime, mortality, teenage childbearing, low birth weight, physical and mental health issues, child development issues, and adolescent behavioral problems (e.g., Austin & Lemon, 2005; Chow et al., 2005; Fauth, Leventhal, & Brooks-Gunn, 2005; Goering & Feins, 2003; Katz, Kling, & Liebman, 2001; Kling, Liebman, & Katz, 2007; Ludwig, Duncan, & Pinkston, 2005; Sampson & Sharkey, 2008). Related to this study, welfare recipients who exit cash assistance and reside in poor inner-city neighborhoods encounter economic challenges, such as unemployment and low earnings.
1.4. Research context

Despite their potential importance, many studies have paid little attention to the influence of job access and neighborhood disadvantage on female former welfare recipients’ employment success. Few studies have analyzed the effects of job access or neighborhood disadvantage on the employment of welfare recipients, yielding inconsistent results due to different theoretical perspectives, research methods, and analytical tools. Most of the existing studies on neighborhood influences were done on the AFDC program, not the TANF program that replaced it. Therefore, it is necessary to explore TANF recipients as they are subject to a more demanding set of work requirements than the old program. Hence, this study was focused on female former welfare recipients who resided in neighborhoods within Cuyahoga County, Ohio. Cuyahoga County includes many poor neighborhoods, particularly within the City of Cleveland and the City of East Cleveland, which are persistently and extremely poor urban cities in the U.S.
1.5. Implications for social policy, program, and community development

This study examined how job access and neighborhood disadvantage influenced the employment success of female former welfare recipients. Overall, the results of this study can contribute to social policies and programs related to TANF implementation. If neighborhood disadvantage undermines the employment success of female former welfare recipients, various approaches need to be considered to overcome the neighborhood disadvantage. For example, residential mobility programs along with community development strategies would need to be emphasized. If job access problems also limit employment success, alternative transportation assistance may be an additional policy option regarding expansion. These place-based policy considerations would expand the thinking about TANF implementation to go beyond the usual human capital programs to encompass practices that help female former welfare recipients to overcome limitations based on a residential and employment and location context.
CHAPTER TWO: LITERATURE REVIEW

This study investigated the effects of job access and neighborhood disadvantage on the employment of female former welfare recipients. This chapter begins with a review of policy context of the 1996 welfare reform. Then, it reviews the literatures on the employment of recipients and the employment barriers that they face from a human capital perspective. Next, it discusses the relevant background of literature and theory regarding job access and neighborhood disadvantage. Finally, it turns to the theoretical and empirical literature pertinent to job access and the effects of neighborhoods on employment of female former welfare recipients.

2.1. Welfare reform of 1996

PRWORA of 1996, known as welfare reform, terminated the AFDC program and replaced it with TANF. The primary goal of TANF was to facilitate economically marginalized people to become self-sufficient and ultimately to live without cash assistance from the welfare system (PRWORA; P.L. 104-103). Specifically, this act aimed to shift welfare support from income support to job placement (Blank & Blum, 1997; Falk, 2012). Therefore, employment of welfare recipients is one of the key issues of TANF (Falk, 2012).

The main differences between TANF and AFDC can be summarized by two attributes: time-limit on cash assistance and work requirements (Falk, 2012; Gilbert & Terrell, 2000). Generally, the cash assistance of TANF is limited to a cumulative period
of five years (60 months). Further, the consecutive period of cash assistance is limited depending on each state’s policy. For example, the Ohio Works First (OWF) program, a TANF program in the State of Ohio, enacted a 36-month time limitation for its recipients (ODJFS, 2001). Although the federal government finances the TANF program via a fixed basic federal grant, it provides incentive funds to state governments depending on the performance of each state (i.e., reducing out-of-wedlock, child bearing and caseload) (Falk, 2012; Gilbert & Terrell, 2000).

The eligibility for TANF is usually determined by an initial assessment of a recipient’s need, income, family size, resources, and skills (Gilbert & Terrell, 2000; ODJFS, 2001). TANF supports cash assistance to its recipients within a limited time. Along with the cash benefit, other in-kind benefits (i.e., childcare vouchers, food stamps, and Medicaid) are available to recipients during and after TANF program (Falk, 2012; ODJFS, 2001). One particularly utilized benefit is childcare vouchers, which are eligible for TANF recipients who participate in work or community services (Dologoff & Feldstein, 2000; Falk, 2012). Approximately 4.4 million people and 1.8 million families received TANF benefits; 3.3 million children enlisted in the TANF program in 2010 (HHS, 2010). The average monthly cash benefit for the recipients’ families on TANF was $360 in 2004 (HHS, 2006).

Following the mandate of TANF, the assessment of TANF program eligibility also includes a personal plan that identifies needed education, training, and job placement activity (Gilber & Terrell, 2002; ODJFS, 2001). Hence, most of TANF participants are required to participate in a job (or related) activity; within two year after the initiating TANF cash assistance, they are mandated to join in job related activities such as
employment, job training, work-experience, community services, or 12 months of vocational training (Dologoff & Feldstein, 2000).

The strict regulation of time-limited cash assistance affected a decrease of TANF caseloads (See Figure II-1). Before the enactment of PRWORA, caseloads began to drop because AFDC work requirements continued to evolve in the 1980s (Falk, 2012). However, the caseload of cash assistance has been dramatically reduced since the implementation of TANF. At the last year of AFDC (the fiscal year 1996), the total caseload of cash assistance including adults and children was approximately 12.5 million (HHS, 2012). In the fiscal year 2009, the caseload of that was approximately four million; and the number of adults and children recipients was approximately one million and three million, respectively (HHS, 2012). During 10 years after implementing TANF (between the fiscal year 1996 and 2006), the total caseload has been decreased by an annual average of 10 percent (HHS, 2012). As shown on Figure II-1., the rapid decrease of the total caseload occurred within five years after the TANF implementation.
Figure II-1. Caseload of welfare recipients in the U.S.

Source: U.S. Department of Health and Human Services, Administration for Children and Families (http://www.acf.hhs.gov/)
2.2. Employment and human capital of TANF recipients

This section explores the trends in employment achievement of welfare recipients. As well, the personal characteristics of welfare recipients including human capitals were reviewed. This section used the data from U.S. Department of Health & Human Services (HHS) (www.acf.hhs.gov/).

2.2.1. Employment of TANF recipients

The employment rate of welfare recipients increased after the TANF implementation due to the emphasis of TANF on work requirements and time-limited cash assistance. In the fiscal year 1996, the employment rate of active AFDC adults was 9.3 percent; in the fiscal year 1999, the employment rate of active TANF adults was 27.2 percent (HHS, 2012). After the fiscal year 2000, the employment rate of active TANF adults had been reduced and became 22.0 percent in the fiscal year 2009 (See Figure II-2).

Because this study focused on female former welfare recipients, it also checked the trend of employment rates among former TANF adults who exited cash assistance. The employment rate of former TANF adults has been persistently higher than active TANF adults. However, the employment rate of former TANF adults has decreased since the fiscal year 2000; the employment rate of former TANF adults was 37.9 percent and 25.7 percent in the fiscal year 2000 and 2009, respectively (HHS, 2012). Although a majority of former welfare recipients are employed when they leave welfare, many
cannot retain their job positions and a large proportion of former welfare recipients return to welfare (Loprest, 2002; Wu, Cancian, Meyer, & Wallace, 2006).

2.2.2. Human capital of female former welfare recipients

Human capital theory suggests that employment success of welfare recipients is limited due to low education, little work-experience, and other personal characteristics that present barriers to work (Danziger, Kalil, & Anderson, 2002; Gurmu et al., 2008). These human capital and personal characteristic of TANF recipients take account of employment success (Danziger et al., 2002; Gurmu et al., 2008).

A number of individual characteristics may affect employment of female former welfare recipients. First, the influence of gender, number of children, and marital status on employment of female former welfare recipients should be jointly considered because they are interconnected. The male employment rate is higher than the female one among TANF recipients. In the fiscal year 2009, 25.5 percent of male TANF adults were employed; but 23.2 percent of female TANF adults were employed (HHS, 2012). Because of childcare issues, female TANF recipients experience fewer opportunities and more disadvantage than male recipients in the labor market (Danziger et al., 2002). By and large, men who are welfare recipients in two parent families have higher job opportunities since they are not solely responsible for childcare. Amongst female former welfare recipients, 68.9 percent were a single and only 15.6 percent of them were married at the point of exiting case assistance in the fiscal year 2009 (HHS, 2012).

Moreover, the portion of not-in labor, which means not looking for work, was higher among female TANF recipients than males. Amongst male and female TANF
adults, 26.5 percent and 29.6 percent respectively, were not in-labor in the fiscal year 2009 (HHS, 2012). Childbearing and childcare make it more difficult for female TANF recipients to gain education or job training and to build a record of employment experience. The data shows that former TANF families had 1.8 children in the fiscal year 2009 (HHS, 2012). Furthermore, 42.7 percent of former TANF families had a child under two years old at least in the fiscal year 2009 (HHS, 2012).

There are some contradictions in the discussion regarding the correlation between age and the employment of welfare recipients. In general, young recipients have a lower possibility of employment than their older counterparts because they are less skilled and experienced in the labor market (Danzinger et al., 2002; Ong & Blumenberg, 1998). On the other hand, younger welfare recipients may be more willing to accept minimum wage position than older welfare recipients, so that is an advantage they have in labor force competition (Ong & Blumenberg, 1998). However, considering the age of welfare recipients, the former explanation is much more reasonable than the latter one. Most of the empirical studies on welfare recipients suggest that older recipients have a higher likelihood of employment than young recipients (Ong & Blumenberg, 1998; Sanchez et al., 2004). The majority of former TANF adults (58.9 percent) were between 20 and 29 years old in the fiscal year 2009 (HHS, 2012). Amongst younger adults, 10.9 percent of former TANF adults were under 20 years old (HHS, 2012).

Human capital is a key factor to determine the employment of welfare recipients in a labor market (Danzinger et al., 2002; Gurmu et al., 2008). Human capital variables of welfare recipients such as educational attainment and the level of work-skills influence on employment of welfare recipients (Danzinger et al., 2002; Gurmu et al., 2008). Most
female former welfare recipients have low levels of human capital in the labor market. Less than half, 43.4 percent, of former TANF adults did not have a high school degree (years of education was below 11 years) and only 3.6 percent of them participated in advanced education (years of education was more than 12 years) in the fiscal year 2009 (HHS, 2012).

The variables related to welfare receipt such as the length on cash assistance or reasons for exiting cash assistance may also affect employment of female former welfare recipients. If TANF recipients exit cash assistance without income sources (especially, employment), they easily encounter serious economic difficulties. In the fiscal year 2009, 17.5 percent of former TANF families exited cash assistance with employment and 13.4 percent of them voluntarily exited cash assistance (HHS, 2012). More critically, many TANF families were forced to exit cash assistance because of the federal time-limit (1.7 percent), state-time limit (0.6 percent), work-related sanction (6.2 percent), state policy (12.1 percent), failure to cooperate (15.1 percent), and so on.

The TANF data above show the disadvantage of TANF recipients’ characteristics in the labor marker. The majority of female former welfare recipients is ethnic minorities (African-Americans or Hispanic), young, has a low level of human capital, and single with childcare burdens. As well, many female former welfare recipients exit cash assistance without appropriate preparation and their employment possibilities are quite low.
Figure II-2. Employment rates of welfare recipients in the U.S.

Source: U.S. Department of Health and Human Services, Administration for Children and Families (http://www.acf.hhs.gov/)
2.3. Job access

The problem of job access has largely depended on the geographic distance between residential location and the density of jobs for which the individual is qualified. The theoretical and empirical work on this issue has been driven by the SMH, which is reviewed below.

2.3.1. Theoretical background

The SMH maintains that the location of jobs is an important facet of the context of work in urban labor markets (Kain, 1968). After analyzing two metropolitan cities, (Chicago, IL and Detroit, MI), Kain (1968) proposed the association between housing market segregation and the distribution and level of African-American employment in metropolitan areas during the 1960s (Kain, 1968, 1974). Kain (1968) concluded that spatial separation between residential areas and the labor market exacerbated the economic situation of inner-city African Americans. His hypotheses can be summarized as follows:

“(1) the distance to and difficulty of reaching certain jobs from African-American\(^1\) residence areas may impose costs on African Americans high enough to discourage them from seeking employment there, (2) African Americans may have less information about and less opportunity to learn about jobs distant from their place of residence or those of their friends, (3) employers located outside the ghetto may discriminate against African Americans out of real or imagined fears of retaliation

\(^1\) written as Negro in the original text (Kain, 1968; p.179-80).
from white customers for “bring into all-white residential areas or they may feel little pressure not to discriminate, (4) similarly, employers in or near the ghetto may discriminate in favor of African Americans” (Kain, 1968; p.179-80).

Although Kain’s initial study of the SMH targeted African-American males, its application has been expanded to other disadvantaged populations such as the urban poor, low-skilled workers, and African-American females. In particular, three hypotheses suggested by Ihlanfeldt (1994) elaborated Kain’s hypothesis of spatial segregation: “(1) residential segregation helped shaped the geographical distribution of African-American joblessness, (2) segregation has also increased African-American unemployment, and (3) both of these conditions were aggravated by the decentralization of jobs” (Ihlanfeldt, 1994; p.220). The expanded concept of the SMH relates the employment probability of low-skilled workers to characteristics of their residential location (Allard & Danziger, 2003; Blumenberg & Ong; 1998; Briggs, 2005; Coulton, 2005; Gurmu et al., 2008; Holzer & Ihlanfeldt, 1996; Houston, 2005; Ihlanfeldt, 1994; Kain, 1968; Sanchez et al., 2002; Vartanian, 1999). In sum, the SMH assumes that job suburbanization reduced the employment chances of low-skilled inner city residents who were unable to move their labor supply from the central city to the suburbs (Blumenberg & Marville, 2004; Kain, 1968; 1974; Holzer & Ihlanfeldt, 1996; Vartanian, 1999). This spatial separation has been caused by suburbanization and the attendant movement of low-wage jobs away from the inner cities (Gurmu et al., 2008; Holzer & Ihlanfeldt 1996; Ihlanfeldt, 1994; Kain, 1968; 1974; Wilson, 1987).

Regarding the cause of this spatial separation, Kain’s economic perspective on the employment of low-skilled workers is conceptually congruent with Wilson’s sociological
observation of falling employment in the inner cities, which is discussed in the next section (Kain, 1968; Wilson, 1987). By and large, the empirical studies based on the SMH present evidence that the spatial distance between employment opportunities and residence influence an individual’s employment success (Allard, 2002; Allard & Danziger, 2003; Holzer & Ihlanfeldt, 1996; Ihlanfeldt, 1994; Pan et al., 2006; Vartanian, 1999).

The SMH is a useful theoretical tool for understanding the relationship between job access and employment of welfare recipients in poor neighborhoods (Allard, 2002; Allard & Danziger, 2003; Ong, 1996; Ong & Blumenberg, 1998). Job accessibility in proximity to a neighborhood is associated with employment of welfare recipients because most welfare recipients are low-skilled and reside in poor urban areas as mentioned in the previous section.

In spite of this useful logic of SMH, the empirical studies based on the SMH have been criticized due to their lack of consideration for the characteristics of female workers who are the majority of welfare recipients (Allard & Danziger, 2003). Moreover, the findings regarding effects of the SMH on the employment of welfare recipients have varied depending on research methods such as data, sampling methods, areas, and analytical methods. Nevertheless, the empirical evidence on the SMH is quite extensive and generally supports the conclusion that the relatively low earning and employment of less-educated minorities are partially attributable to the poor accessibility of jobs (Allard & Danziger, 2003; Bania et al., 2003; Gurmu & Smith, 2006; Pan et al., 2006).
Recent studies have applied the SMH to identify one of the economic challenges that welfare recipients encounter in the social policy shift from AFDC to TANF (e.g., Allard & Danziger, 2003; Bania et al., 2003; Pan, et al., 2006; Gurmu & Smith, 2006; Gurmu et al., 2008). Employment opportunities are influenced by distance as well as by travel time and accessibility to different travel modes (Blumenberg & Manville, 2004). Because welfare recipients should exit cash assistance with a limited time and participate in work-activities, they face spatial barriers to employment (Blumenberg & Manville, 2004). However, car ownership among the poor is not universal, and access to reliable public transportation is much less common (Blumenberg & Manville, 2004). In terms of public assistance, the issue of the SMH is potentially serious because welfare recipients reside in areas that are often distant from the concentrations of entry-level jobs and travel to distant suburbs is especially difficult when using public transportation (Blumenberg & Manville, 2004; Blumenberg & Ong, 1998; Blumenberg & Shiki, 2003). For this reason, Ihlanfeldt and Sjoquist (1998) asserted that the SMH was still valid to explain the employment of welfare recipients (Ihlanfeldt & Sjoquist, 1998). Likewise, several studies have asserted that job access was an important predictor in the economic well-being of welfare recipients (Blumenberg & Manville, 2004; Blumenberg & Ong, 1998; Blumenberg & Shiki, 2003; Coulton, 2003).

Although the importance of the SMH has been supported by previous studies, the elements of that provoke controversial debate. First, Kain’s initial work (1968) which introduced the SMH was criticized because of its vague concepts (i.e., operational definition) and analytical problems (i.e., statistical analysis) (Masters, 1974; Offner & Saks, 1971). Specifically, Offner and Saks (1971) replicated the data used in the Kain’s
initial study (Offner & Saks, 1971). Yet, they found a nonlinear relationship between African Americans’ employment and residential segregation—results which were the opposite of Kain’s statistical analysis (Offner & Saks, 1971). The nonlinear relationship led to opposite conclusions about the effect of residential segregation on the employment of African Americans in urban areas (Offner & Saks, 1971).

In addition, the previous studies based on SMH have defined job availability and accessibility in various measures (e.g., distance, job growth, employment rates, median income, etc.) (e.g., Allard & Danziger, 2003; Bania et al., 2003; Gurley & Bruce, 2005; Gurmu & Smith, 2006; Gurmu et al., 2008; Sanchez et al., 2004). However, there are still pros and cons of each measure. Therefore, the operational definition of job access is one of the controversial debates in a discussion of the SMH.

Furthermore, the SMH has been criticized because of gender and racial issues. Previous studies on the SMH primarily focused on male employment and focused little attention to the effect of economic restructuring on African-American women, who traditionally work in low-wage jobs (Hanson, Kominiak, & Carlin, 1995; Mendenhall et al., 2006). Results of others’ studies on the SMH find that African-American women are not affected as much by spatial mismatch as African-American men (Mendenhall et al., 2006).

Another substantive criticism of the SMH is that racial segregation exerts a heavier influence on employment of welfare recipients than spatial mismatch (South & Crowder, 1998; 1997). In other words, the barrier of welfare recipients to being employed may not be their location but their racial segregation (Casciano & Massey, 2008; South & Crowder, 1998; 1997). Specifically, the racial segregation of the job
network explains inner-city unemployment and poverty (Briggs, 2005; Coulton, 2003). For example, employers who run their businesses in a highly segregated areas may have a negative view of prospective employees from low-income or minority neighborhoods (Coulton, 2003).

Few SMH studies have considered the issue of public transportation in spite of its significance (Blumenberg & Manville, 2004; Coulton, 2003). In general, newer cities suffer less spatial mismatch because many of their poor residents have access to automobiles, not because their land use patterns are amenable to human mobility (Blumenberg & Manville, 2004; Blumenberg & Shiki, 2003). Particularly, women who depend on mass or public transit to get to work might be the most disadvantaged because they must juggle household and work-related responsibilities (Blumenberg & Manville, 2004). For instance, compounding the task of traveling to works is the necessity to carry out everyday domestic tasks, such as dropping off and picking up children at school or child care centers, and responding to emergencies and other unexpected familial events (Blumenberg & Manville, 2004). Of note, low-income commuters tend to travel shorter distances than those with high-incomes; in particular, welfare recipients who depend on public transportation can reach far fewer jobs than those who travel by automobile (Blumenberg & Manville, 2004; Blumenberg & Ong, 1998; Hanson et al., 1997). For example, when Bania and his colleagues (1999) examined the number of entry level jobs accessible by public transportation in Cleveland, they discovered that the transit dependent female former welfare recipients suffered heavily compared to those who had automobiles (Bania et al., 1999).
With a wider perspective, the criticism of the SMH can be raised in relation to the skill mismatch hypothesis. The debates on the SMH have been spread out to the comparison with a similar hypothesis. There has been a debate between the skills mismatch hypothesis and the SMH in regard to explaining the concentrated unemployment in urban areas (Handel, 2003; Houston, 2005). Similar to the principle of the SMH, the skills mismatch perspective embraces the economic equation of supply (the skills held by job seekers) and demand (the skills demanded by employers) (Handel, 2003; Houston, 2005). However, the skills mismatch cannot be applied solely to explain the employment of welfare recipients in poor urban areas because it cannot directly explain why unemployment is not uniformly distributed in metropolitan areas compared to the SMH (Houston, 2005). Moreover, the skills mismatch perspective assumes that all groups of people have a high level of job and residential mobility (Ross, 1988). Nonetheless, the combination of the skill mismatch perspective and the SMH can enhance the explanatory power of welfare recipients’ employment in poor urban areas. For example, the concept of the SMH (e.g., job accessibility or availability) can be measured with that of the skill mismatch perspective (e.g., different labor market segments in different areas) (Houston, 2005).

Many previous studies have adopted the SMH in order to explain the effect of job access on employment of low-skilled workers in inner cities. In particular, the usefulness of the SMH has emerged after an implementation of the new public assistance policy because job access is one of the key barriers to discourage welfare recipients’ employment (Bania et al., 1999; 2003; Blumenberg & Manville, 2004; Bluemenburg & On, 1998; Coulton, 2003). However, the effect of job access on employment of welfare
recipients varies and is even controversial depending on each previous study. Therefore, it is necessary to test the effect of the SMH on employment of female former welfare recipients.
2.3.2. Previous studies

The early studies on the SMH targeted unemployed males in inner cities (Kain, 1968). However, the theoretical and conceptual expansion of the SMH made it possible to scrutinize economically disadvantaged populations including welfare recipients. The implementation of welfare reform, which forced welfare recipients to join in work activity, suggests the importance of studying job access in poor urban areas where most welfare recipients reside (Blumenberg & Manville, 2003; Blumenberg & Ong, 1998; Blumenberg & Shiki, 2003). However, most previous studies targeted welfare recipients during the era when AFDC was in effect. Like this study, many previous studies analyzed observational data such administrative data from county or state government. This section briefly reviewed the previous studies on the SMH and employment of welfare recipients (See Table II-1).

In anticipation of 1996 welfare reform, Ong (1996) recognized car ownership as one of the geographic barriers to welfare recipients’ employment. His study aimed to observe the relationship between car ownership and employment among welfare recipients (Ong, 1996). For a survey, this study recruited 2,214 AFDC recipients living in four counties of Los Angeles, CA in 1992 (Ong, 1996). Worked-related outcomes were measured in various ways: employment during past months, working hours during past months, monthly earnings, and hourly wages (Ong, 1996). A logit model and multiple regression models included car ownership variable as an independent variable and controlled for other covariates such as race, educational attainment, and so on (Ong, 1996). The results of this study demonstrated that car ownership positively influenced
employment during the past month, working hours during past month, and monthly earnings (Ong, 1996). This study concluded emphasized that welfare reform had to consider reliable transportation in order to facilitate welfare recipients’ employment (Ong, 1996).

Allard and Danziger (2003) analyzed administrative data on welfare dependency and job location from the Multi-city Study of Urban Inequality (MSUI) in order to identify the relationship between job accessibility and the probability of TANF recipients’ employment in Detroit, MI (Allard & Danziger, 2003). Job accessibility was measured by the overall metropolitan score for that particular access measure (Allard & Danziger, 2003). Specifically, job accessibility and the total number of nearby jobs per adult were put into an analytical model based on two temporal frameworks: 1992 and 1997 (Allard & Danziger, 2003). Establishing a logit-model for each temporal framework, they observed the variation of welfare recipients’ employment for two time frameworks: June 1996 (N=56,887) and June 1998 (N=41,169) (Allard & Danziger, 2003). The results of the study demonstrated a significant positive relationship between job accessibility and the employment probability of welfare recipients regardless of ethnicity (Allard & Danziger, 2003). However, the sample of this study was not affected by many of the changes in welfare policy, from AFDC to TANF.

Likewise, Bania and his colleagues (2003) examined the relationship between job accessibility and the employment of welfare leavers (Bania et al., 2003). They used administrative data of welfare recipients in Cuyahoga County, Ohio and collected job location data from the U. S. Census Bureau’s data file County Business Patterns (CBP) (Bania et al., 2003). The job accessibility was measured by travel time to work (a 20
minute ride by car and a 40 minute ride by public transportation) (Bania et al., 2003). At the same time, the neighborhood effect was examined by the poverty rate of the welfare recipients’ census tract at the time of exiting cash assistance (Bania et al., 2003). The results showed that the job access and the neighborhood poverty rate were not associated with the employment probability of welfare recipients (Bania et al, 2003).

Sanchez and his colleagues (2004) tested the relationship between the transit access and the employment status of TANF recipients who were aged 16 to 65 in June of 1999 and resided in 6 metropolitans (Atlanta, GA; Baltimore, MD; Dallas, TX; Denver, CO; Milwaukee, WI; and Portland, OR). The total sample was 190,405 and 14 percent were employed in June of 1999 (Sanchez et al., 2004). As well, this study combined administrative data on the welfare recipients’ data with data from each metro area’s transit authority in order to measure job accessibility of welfare recipients (Sanchez et al., 2004). As a key variable, job accessibility was measured by three indicators: (1) automobile ownership, (2) evening transit service frequency within a quarter mile walking distance, and (3) employment accessibility measurement (Shanches et al., 2004). This study established six Ordered Multinominal Logistic (OML) regression models for each city; also, these six OML regression models included demographic variables, training/education program participation, transit access/service quality and employment accessibility (Sanchez, et al., 2004). The results demonstrated that TANF recipients with relatively high levels of transit and regional employment access did not have a significantly higher possibility to be employed and to exit welfare than their counterparts (Sanchez, et al., 2004). Moreover, the results suggested that transit and regional employment accessibility was not critical predictor of TANF recipients’ case status.
(Shanchez, et al., 2004). However, the goodness of model fit varied by the six sites; specifically, the explanatory power of OML models in Atlanta, Baltimore, and Denver were very minimal ($R^2 < 0.05$) (Sanchez et al., 2004). As well, the directions of the coefficients in the OML model of each area were not consistent (Sanchez et al., 2004). Therefore, the results of those cities might be not only insignificant but also difficult to be generalized.

By using four wave longitudinal data, Gurley and Bruce (2005) observed the influence of automobile ownership on employment of welfare recipients such as weekly hours of work, and hourly wages of welfare recipients in Tennessee. During four waves (2001 to 2003), Family Assistance Longitudinal Study (FALS) surveyed approximately 1,500 TANF recipients for each wave; among them 1,273 recipients were analyzed by statistical models (Gurley & Bruce, 2005). This study observed the relationship between automobile access at Wave 1 and work related variables at Wave 4 (18-24 month later of Wave I) (Gurley & Bruce, 2005). A variety of demographic and human capital variables (e.g., age, race, and education) were input to multivariate analyses, a multinomial logit model and a regression model (Gurley & Bruce, 2005). The multinomial logit models showed that automobile access increased the likelihood of being employed and leaving welfare among welfare recipients; the multiple regression model found that automobile access increased the work hours of welfare recipients (Gurley & Bruce, 2005). This study demonstrated the relationship between automobile access and employment of welfare recipients in a more rigorous way. Because this study compared two time points (Wave 1 and Wave 4), it controlled for simultaneity of automobile access and employment (Gurley & Bruce, 2005).
Gurmu and Smith (2006) examined the relationship of neighborhood effects and job accessibility with welfare recidivism (Gurmu & Smith, 2006). By using the administrative data from Georgia, they tracked a cohort of welfare leavers (N=25,451) from 1992 to 2001 (Gurmu & Smith, 2006). Specifically, job accessibility was measured by the proximity to job growth in eight industries (i.e., agriculture, construction, finance, manufacturing, retails, service, transportation, and wholesale). As a result, job accessibility significantly influenced the reduction of welfare recidivism. More precisely, the effects of individual access measures varied depending on the race and the residential location of the welfare recipients (Gurmu & Smith, 2006). The neighborhood’s characteristics also affected welfare recidivism; for example, the educational level of the neighborhood was significantly important in reducing welfare recidivism even after controlling for racial groups and residential location (Gurmu & Smith, 2006).

Despite using the same data set from their previous study, Gurmu, Ihlanfeldt, and Smith (2008) presented opposite results in their previous study (Gurmu et al., 2008). By using the administrative data of Atlanta, Georgia, they observed whether proximity to job opportunity and the availability of child care affected the probability of being a full-time employee among TANF recipients (Gurmu et al., 2008). This study found that individual and familial characteristics (i.e., the educational level and the number of children) were important determinants of the employment probability of welfare recipients; however, location-related variables were relatively unimportant (Gurmu et al., 2008).
The previous studies have some similarities, such as they recruited sample from various metropolitan areas in the U.S. and adopted a cross-sectional method to test the relationship between job access and employment of welfare recipients. Unfortunately, they suggested inconsistent results regarding the relationship between job access and employment of welfare recipients. However, a key finding indicated that car ownership of welfare recipients, which is one of the job access measurements, significantly impacted the employment of welfare recipients (Gurley & Bruce, 2006; Ong, 1996).
### Table II-1. Previous studies on job access and employment of welfare recipients

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Year</th>
<th>Sample</th>
<th>Policy</th>
<th>Measurement</th>
<th>Relationship</th>
<th>Areas</th>
<th>Data source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ong</td>
<td>1996</td>
<td>2,124</td>
<td>AFDC</td>
<td>IV: Car ownership&lt;br&gt;DV&lt;sub&gt;1&lt;/sub&gt;: Employment&lt;br&gt;DV&lt;sub&gt;2&lt;/sub&gt;: Working hours&lt;br&gt;DV&lt;sub&gt;3&lt;/sub&gt;: Monthly earnings&lt;br&gt;DV&lt;sub&gt;4&lt;/sub&gt;: Hourly wage</td>
<td>• IV &amp; DV&lt;sub&gt;1&lt;/sub&gt;<em>&lt;br&gt; • IV &amp; DV&lt;sub&gt;2&lt;/sub&gt;</em>&lt;br&gt; • IV &amp; DV&lt;sub&gt;3&lt;/sub&gt;<em>&lt;br&gt; • IV &amp; DV&lt;sub&gt;4&lt;/sub&gt;</em></td>
<td>LA, CA</td>
<td>Survey</td>
</tr>
<tr>
<td>Allard, Danziger</td>
<td>2003</td>
<td>56,887 / 41,169</td>
<td>AFDC TANF</td>
<td>IV: # of nearby jobs&lt;br&gt;DV: Employment</td>
<td>• IV &amp; DV&lt;sup&gt;+&lt;/sup&gt;</td>
<td>Detroit, MI</td>
<td>Administrative</td>
</tr>
<tr>
<td>Bania, Coulton, Leete</td>
<td>2003</td>
<td>TANF</td>
<td>TANF</td>
<td>IV: Travel time&lt;br&gt;DV: Employment</td>
<td>• No effect</td>
<td>Cuyahoga County, OH</td>
<td>Administrative; Census data</td>
</tr>
<tr>
<td>Sanchez, Qing, Peng,</td>
<td>2004</td>
<td>190,405</td>
<td>AFDC</td>
<td>IV&lt;sub&gt;1&lt;/sub&gt;: Automobile ownership&lt;br&gt;IV&lt;sub&gt;2&lt;/sub&gt;: Evening transit service&lt;br&gt;IV&lt;sub&gt;3&lt;/sub&gt;: Employment job accessibility measure&lt;br&gt;DV: TANF status</td>
<td>• No effect</td>
<td>Atlanta; Baltimore; Dallas; Denver; Milwaukee; Portland</td>
<td>Administrative; Transit authority</td>
</tr>
<tr>
<td>Gurley, Bruce</td>
<td>2005</td>
<td>1,273</td>
<td>TANF</td>
<td>IV: Automobile ownership&lt;br&gt;DV&lt;sub&gt;1&lt;/sub&gt;: Weekly hours of work&lt;br&gt;DV&lt;sub&gt;2&lt;/sub&gt;: Hourly wage</td>
<td>• IV &amp; DV&lt;sub&gt;1&lt;/sub&gt;<em>&lt;br&gt; • IV &amp; DV&lt;sub&gt;2&lt;/sub&gt;</em></td>
<td>TN</td>
<td>Survey</td>
</tr>
<tr>
<td>Gurmu, Smith</td>
<td>2006</td>
<td>25,451</td>
<td>AFDC, TANF</td>
<td>IV: Proximity to job growth&lt;br&gt;DV: Welfare recidivism</td>
<td>• IV &amp; DV&lt;sup&gt;+&lt;/sup&gt;</td>
<td>GA</td>
<td>Administrative</td>
</tr>
<tr>
<td>Gurmu, Ihlanfeldt, Smith</td>
<td>2008</td>
<td>25,451</td>
<td>AFDC, TANF</td>
<td>IV: Proximity to job growth&lt;br&gt;DV: Employment</td>
<td>• No effect</td>
<td>GA</td>
<td>Administrative</td>
</tr>
</tbody>
</table>

**Note:** *Significant correlation between Independent Variable (IV) and Dependent Variable (DV)*
2.4. Effects of neighborhood disadvantage

The second major factor affecting employment of female former welfare recipients in this study was neighborhood disadvantage. This section discusses the theoretical background and empirical literatures regarding the effect of neighborhood disadvantage on the employment success of female former welfare recipients in particular.

2.4.1. Theoretical background

Historically, urban sociologists have recognized the effect of poor neighborhoods on the lives of residents (U.S. Department of Labor, 1965; Wilson, 1987). In particular, Wilson’s two works, “The Truly Disadvantaged” (1987) and “When Work Disappears” (1996), sketched an overview of the concentrated inner-city poverty in the 1970s and 1980s (Wilson, 1987; 1996). Wilson’s works more clearly linked social problems with urban economic and social structure, including forces such as racial segregation, suburbanization and industrial structure (Wilson, 1987; 1996). Over the last two decades, numerous studies have been based on Wilson’s early works in order to examine neighborhood effects on a broad range of outcomes. As a consequence, they have identified that the specific conditions of neighborhoods influence individuals’ behaviors and their social outcomes (e.g., Austin & Lemon, 2005; Chow et al., 2005; Fauthet al., 2005; Goering & Feins, 2003; Ludwig et al., 2008; Sampson & Sharkey, 2008; Sampson et al., 1997).
According to Wilson’s analysis, the structural changes of the economy in the postindustrial era have affected changes in family and community life (Wilson, 1987). His analysis of significant economic changes in the 1970s can be summarized into three aspects: (1) a shift from goods-producing to service-producing industries, (2) increased polarization of the labor market into low-wage and high-wage sectors, and (3) the relocation of manufacturing industries outside of the central cities to suburbs, the South, and to other countries (Wilson, 1987).

As a result, the three structural changes in the postindustrial era provoked the social phenomena which yielded important consequences for poor minority families in urban areas (Wilson, 1987). Wilson (1987) asserted that poor minority families began to experience less contact with members of the middle class, withdrawing poor families not only from exposure to mainstream norms and values, but also social networks which were important assets for finding work (Granovetter, 1995; Wilson, 1987; 1996). Additionally, the structural changes during the 1970s brought progressive “deinstitutionalization” of poor communities, depriving them of public and private institutions which were crucial to economic health and social mobility (Deverteuil, 2005; Sampson et al, 1997). Therefore, poor neighborhoods have increasingly lacked both economic and social networks: (1) businesses that might offer jobs and (2) community organizations that offer employable skills and basic services (Casciano & Massey, 2008; Deverteuil, 2005; Granovetter, 1995).

Wilson’s early works powerfully contributed to developing and expanding the theoretical knowledge of the neighborhood effects as well as inspiring subsequent neighborhood studies (Wilson, 1987; 1996). Most studies on neighborhood effects
theoretically relied on Wilson’s idea in “The Truly Disadvantaged” (Wilson, 1987). Specifically, Wilson’s sociological analysis of the structural changes of the postindustrial era has provided theoretical framework regarding concentrated inner-city poverty and affluent suburbanization (Wilson, 1987; 1996). In addition, his analysis has explained how and why welfare recipients and low-income families in poor neighborhoods faced obstacles to being employed and escaping welfare dependency (Wilson, 1987; 1996).

2.4.2. Concept of neighborhood disadvantage

Wilson’s work put forward the idea that concentrated disadvantage was growing and that it had a particularly adverse effect on residents (Wilson, 1987). To translate the concept of concentrated neighborhood disadvantage into empirical measures, Sampson and his colleagues (1997) utilized 1990 Census data in order to analyze a multitude of neighborhood characteristics (Sampson et al, 1997). Although this study initially aimed to examine the relationship between neighborhood characteristics and collective efficacy, it classified the type of neighborhoods prior to the main analysis (Sampson et al., 1997). The study analyzed 343 neighborhoods that were aggregated from 847 census tracts in the city of Chicago, IL (Sampson et al., 1997). This study included 10 census indicators in its Principal Component Analysis (PCA) with oblique rotation; and the results suggested three constructs of neighborhood characteristics such as concentrated disadvantage, immigrant concentration and residential stability (Sampson et al., 1997). Specifically, the dimension of concentrated disadvantage consisted of five indicators, poverty rates, the proportion of households with public assistance, unemployment rate, the proportion of female-headed families, the proportion of people under 18 years olds, and the percent of African-American population (Sampson et al., 1997). The dimension
of immigrant concentration was comprised of percents of Latino population and foreign-born population; the dimension of residential stability included the percent of households that resided in the same place over five years and the percent of owner-occupied houses (Sampson et al., 1997). These three dimensions of neighborhood characteristics that were represented as factor scores in the analytical model were significantly correlated with collective efficacy (Sampson et al., 1997).

Differentiating from the previous study above, DeVerteuil (2005) focused on neighborhoods with a high proportion of welfare recipients (DeVerteuil, 2005). By using 2000 Census data, this study analyzed neighborhoods in New York City, NY (37 zip codes) and Los Angeles, CA (40 zip codes) (DeVerteuil, 2005). This study defined a welfare neighborhood as zip codes where the proportion of the households on public assistance was at least twice the median value for the metropolitan area (DeVertuil, 2005). The k-means cluster analysis suggested three dimensions of neighborhood characteristics: African-American welfare neighborhoods, heterogeneous welfare neighborhoods, and immigrant enclaves (DeVertuil, 2005). African-American welfare neighborhoods had relatively high levels of services, unemployment, poverty and welfare and relatively low levels of recent immigrants and foreign-born population; and they were economically and socially isolated from the mainstream, which were approximated to the concept of Wilson’s jobless ghetto or truly disadvantaged neighborhood (DeVertuil, 2005; Wilson, 1987). Heterogeneous welfare neighborhoods experienced high levels of poverty, welfare dependency, and unemployment; but were racially heterogeneous (DeVertuil, 2005). Immigrant enclaves of welfare neighborhoods subsumed a large proportion of foreign-born and recent immigrants but a lower level of
unemployment, poverty, and welfare dependency than other welfare neighborhoods (DeVertuil, 2005).

Although these two previous studies tested the relationship between neighborhood characteristics and employment of welfare recipients, their typology of neighborhood characteristics contributed to measuring the level of neighborhood disadvantage in this study. Commonly, these two previous studies suggested that neighborhood characteristics consisted of two attributes, (1) an economic attribute (named concentrated disadvantage and African-American neighborhoods by Sampson and his colleagues (1997) and DeVertuil (2008), respectively) and (2) an immigrant attribute (named by immigrant concentration and immigrant enclaves by Sampson and his colleagues (1997) and DeVertuil (2008), respectively) (DeVertuil, 2005; Sampson et al., 1997). Among these two attributes, this study employed concentrated disadvantage, which was suggested by Sampson and his colleagues (1997), in order to define and measure the level of neighborhood disadvantage (Sampson et al., 1997).

2.4.3. Previous studies

Social experiments on the random relocations of low-income families’ neighborhood can provide more evident results that clarify the effects of neighborhood disadvantage on residents’ outcomes. From the social experiments, neighborhood effects can be explicitly examined via a comparison of outcomes between previous and current neighborhoods of low-income families.

By incorporating a housing voucher program into an experimental model, the Gautreaux litigation and the Moving To Opportunity (MTO) project examined
neighborhood effects on the changes of lives among low-income families. Several studies which used the Gautreaux litigation and the MTO project analyzed neighborhood effects on various outcomes of low-income families in urban areas including welfare recipients. Due to an excellence of study design, these two housing programs have offered useful data that demonstrated the explicit relationship between neighborhoods and various outcomes including employment of welfare recipients (Feins & Shroder, 2005; Goering & Feins, 2003; Ludwig et al., 2006; Mendenhall et al., 2006; U.S. Department of Housing and Urban Development [HUD], 2003).

First of all, the Gautreaux litigation resulted from a 1976 Supreme Court authorization of an expansive desegregation housing remedy (Mendenhall et al., 2006; Rosenbaum, 1995). The Gautreaux litigation offered Section 8 vouchers to low-income families in low-income African-American neighborhoods in order to place them in a new neighborhood, under the administration of the Leadership Council for Metropolitan Open Communities (LCMOC) in Chicago (Mendenhall et al., 2006; Rosenbaum, 1995). In addition to offering Section 8 vouchers, the LCMOC provided counseling services to the participants (Mendenhall et al., 2006; Rosenbaum, 1995). From 1981 to 1988, more than 5,000 families participated in this program and more than half moved to middle-income white suburbs (Rosenbaum, 1995). The participants of the Gautreaux litigation were assigned to city or suburban locations in a quasi-random assignment (Rosenbaum, 1995). However, the random assignment of placing the participants in a new neighborhood was affected by apartment availability and the participants’ position of the waiting list (Rosenbaum, 1995).
The results of the Gautreaux litigation demonstrated that relocations to middle-income suburbs improved adults’ employment and youth’s education of the participants (Rosenbaum, 1995). Regarding a public assistance program, Mendenhall and her colleagues (2006) tested neighborhood effects on employment on welfare recipients who participated into the Gautreaux litigation (Mendenhall et al., 2006). This study estimated the long-term impacts of changing neighborhood conditions on AFDC receipt (N=793) and employment levels (N=1,258) of low-income African Americans (Mendenhall et al., 2006). With two separated time frames, this study observed the percent of time on AFDC (1990-1992) and earnings (1995-1999) of the participants by the neighborhood characteristics of the placement communities (Mendenhall et al., 2006). The various neighborhood indicators were collected by merging the Gautreaux data and other administrative data (Mendenhall et al., 2006).

This study showed that women who were initially placed in neighborhoods with few African-Americans and moderate to high neighborhood resources experienced significantly more time employed when they were compared with women placed in neighborhoods with higher concentrations of African-Americans and lower levels of resources (Mendenhall et al., 2006). In addition, women who were placed in neighborhoods with high levels of resources and low African-American populations spent significantly less time on welfare than women who were placed in highly African-American segregated areas with low levels of resources (Mendenhall et al., 2006). In sum, the results from the Gautreaux litigation suggested that the relocation to economically better neighborhoods increased employment of welfare recipients (Mendenhall et al., 2006).
The encouraging findings from the Gautreaux program, along with some concern that the lottery process was not fully random, led HUD to launch the MTO program in 1994 (HUD, 2003). The MTO program included 4,608 families living in public housing neighborhoods with high poverty rates in cities from 1994 to 1996 (HUD, 2003).

Utilizing an experimental design, the MTO program randomly assigned the participants into three groups: (1) an experimental group that received housing vouchers and counseling services to move to census tracts with less than 10 percent poverty (n=1,729), (2) a Section 8 group (n=1,209), and (3) a control group (n=1,310) (HUD, 2003). With a longitudinal scope, the MTO program compared a wide range of the changes among these three groups, such as housing, health, delinquency, education, employment (earnings), and public assistance (Goering & Feins, 2003; HUD, 2003).

As an ongoing project, the MTO project team comprehensively collected various data from the participants and other agencies (HUD, 2003). In December 1997, the MTO project team collected data from participants and their families for the baseline; in 2002, it also collected the data for an interim evaluation in the same way (HUD, 2003). Specifically, the demographic variables of participants were gathered by their self-report (HUD, 2003). However, employment status, earnings, and welfare participation were collected from states and TANF agencies (HUD, 2003). Several studies have analyzed the effectiveness of the MTO program on comprehensive issues and various populations because the MTO data contained a wide range of information about the participants. Although the evaluation of the MTO program is not over, it appears that moving to a low poverty neighborhood has significantly improved the housing, safety, and health on the families in the experimental group compared to the control group (e.g., Bermey & Norris,
Surprisingly, the previous studies on the MTO program did not discover significant neighborhood effects on employment of participants. For instance, the interim report of the MTO program tested neighborhood effects on employment and earnings of low-income adults (HUD, 2003). By analyzing respondent self-reports from adults (N=3,517), this study did not find a significant difference from the control group on the employment rates of adults in the treatment groups at the time of the survey for the interim report; the MTO program was initiated in 1997 and the interim survey was conducted in 2002 (HUD, 2003). This study merged state administrative UI data with the MTO data in order to track the employment and earnings of its participants (N=4,070) (HUD, 2003). There were no significant impacts of the experimental or Section 8 groups on adults’ employment or on their earnings after four year follow-up (HUD, 2003).

Although the overall results of the MTO program did not demonstrate significant neighborhood effects on employment and earnings of low-income adults and youth, a study on a particular area found meaningful results regarding welfare recidivism (Goering & Feins, 2003; HUD, 2003; Ludwig et al., 2005). For example, focusing on welfare recipients among the MTO participants, Ludwig and his colleagues (2005) examined the effect of the MTO program on individual self-sufficiency (Ludwig et al., 2005). This study examined the participants in Baltimore (N=638), one of five cities where the MTO program was implemented (Ludwig et al, 2005). In order to evaluate the self-sufficiency of welfare recipients, this study combined the MTO data with employment data and the AFDC records of the participants (Ludwig et al., 2005).
Afterward, this study observed significant variations of the participants’ earnings, employment, and welfare receipt from 1994 to 1997 (Ludwig et al., 2005). Specifically, this study discovered that the MTO (experimental) group, who were offered relocation counseling and housing vouchers that could only be redeemed in low-poverty areas, experienced a reduction in welfare receipt of between 11 percent and 16 percent compared to the control group (Ludwig et al., 2005). However, these effects were not accompanied by significant changes in earnings or employment rates of welfare recipients among the MTO participants (Ludwig et al., 2005).

Even though the MTO program did not demonstrate neighborhood effects on employment and earnings of its participants, it detected an encouraging finding for female youth in low-income families (HUD, 2003). Compared to female youth in the control group, female youth (aged 15-19) in the experimental group significantly reduced their idleness (neither currently employed nor enrolled in school) with 10.2 percent decrease and raised the ratio of full-time student (enrolled in school) with 22.0 percent increase (HUD, 2003). Considering that the MTO program is an on-going project, the neighborhood conditions can potentially affect employment of female youth in low-income families via enhancing human capital of them.

As discussed earlier, the Gautreaux litigation and the MTO program provided useful empirical findings for experimental implications regarding the neighborhood effects on employment (HUD, 2003; Mendenhall et al., 2006; Rosenbaum, 1995). However, these two programs failed to provide consistent evidence regarding the impact of moving to a better neighborhood on employment of low-income families including welfare recipients. Although both programs implemented residential mobility programs
as a treatment, they did not incorporate the economic concept such as job accessibility and availability on the employment issues of low-income families; rather they emphasized sociological aspects such as racial composition or poverty status of the neighborhoods (HUD, 2003; Mendenhall et al., 2006). For example, the goal of the Gautreaux program was to move families to census tracts with 10 percent or fewer African-American residents (Mendenhall et al., 2006; Rosenbaum, 1995). However, a significant number of its participants actually moved to neighborhoods with high levels of African-American residents, high crime rates, and low family income (Mendenhall et al., 2006; Rosenbaum, 1995). The MTO program also required the treatment group to move to census tracts with less than 30 percent poverty rate (HUD, 2003). Therefore, the findings of MTO studies were a relatively distant sub-set of the population in this study because they lived in distanced public housing and volunteered for a mobility experiment so the results cannot be generalized to the welfare caseload as a whole. Finally, these two experiments neither directly targeted welfare recipients nor considered the change of public assistance program from AFDC to TANF.
2. 5. Conceptual framework and research questions

2.5.1. Conceptual framework

This study was conceptualized as multi-leveled because it focused on how individual employment was affected at the individual- and neighborhood-level. The types of variables were divided into three components: (1) dependent variables, (2) independent variables, and (3) covariates. The dependent variables were the employment success of female former welfare recipients at the individual-level (Level-1). This study assumed that the independent variables affected the dependent variables at the individual (Level 1) and neighborhood-level (Level 2) (See Figure II-3).

The dependent variables were the employment success of female former welfare recipients after exiting cash assistance and being employed. The dependent variables were measured by three attributes: (1) job retention, (2) two-year employment, and (3) average quarterly earnings. All of the dependent variables were measured with an eight-quarter window (See Figure III-4).

The independent variables consisted of two major components in order to explain the dependent variables: (1) job access measured by the distances to work at the individual-level (hereafter individual job access) and public transportation access at the neighborhood-level and (2) neighborhood disadvantage at the neighborhood-level. Individual job access was operationalized as the mean distance between a residential place and the workplaces of female former welfare recipients after exiting cash assistance; it was gauged in the post-cash assistance period. The level of public
transportation access in the neighborhood was measured by the proportion of workers’ using public transportation in the census tracts in which female former welfare recipients resided at the point of exiting cash assistance. Neighborhood disadvantage was measured as an aggregate of neighborhood characteristics based on Sampson’s indicators (Samson et al., 1997).

The effect of independent variables is grounded on different theoretical backgrounds. The effects of individual job access and neighborhood public transportation access were based upon the SMH, as suggested by Kain’s economic observations of urban labor markets (Kain, 1968). The effect of neighborhood disadvantage was suggested by Wilson’s sociological observations of urban social structure and process (Wilson, 1987). Therefore, the conceptual model of this study, explaining the effects of job access and neighborhood disadvantage on the employment success of female former welfare recipients, consisted of a theoretical perspective (economic and sociological perspectives) and a methodological perspective (analysis at the individual- and neighborhood-levels).

In addition to the independent variables, this study included several covariates such as demographic, human capital, and involuntary exit of cash assistance, which were related to the employment success of female former welfare recipients. At the individual-level, the covariates were controlled in the main analysis. Those covariates were selected based on human capital theory and the empirical literatures on welfare recipients’ employment. Controlling for all covariates, this study established four step analytical models in order to extract the effects of job access and neighborhood disadvantage on the employment of female former welfare recipients.
Figure II-3. Conceptual framework

- **Theoretical backgrounds**
  - Spatial Mismatch Hypothesis (Kain, 1968)
  - Concentrated disadvantage (Wilson, 1987)

- **Independent variables**
  - **Individual-level**
    - Demographics
    - Human capital
    - Welfare
    - Job access
  - **Neighborhood-level**
    - Neighborhood disadvantage
    - Public transportation access

- **Dependent variables**
  - Employment success of former TANF recipients
    - Job retention
    - Two-year employment
    - Average quarterly earnings
2.5.2. Research questions and hypotheses

As noted earlier, this study aimed to test the effects of job access and neighborhood disadvantage on the employment success of female former welfare recipients who were employed after exiting cash assistance. The dependent variables, the employment success of female former welfare recipients, were measured by three attributes: job retention, two-year employment, and average quarterly earnings. In order to explain the dependent variables, this study included the independent variables: individual job access (Level-1), neighborhood disadvantage (Level-2), and neighborhood public transportation access (Level-2). As well, this study controlled for several covariates (Level-1) to explain the association between the independent and dependent variables.

In order to effectively test the relationship between the individual- and neighborhood-level variables and the dependent variables, four analytical models were built by adding covariates and independent variables by a hierarchical sequence. The initial model without any covariates and independent variables observed the variance of the dependent variables among census tracts (null model); the second model only included the individual-level variables (i.e., covariates and individual job access) into the initial model (random-intercept model); the third model only took the neighborhood-level variables (i.e., neighborhood disadvantage and public transportation access) into the initial model (random-intercept regression model). The final model included both individual-neighborhood variables (random-intercept ANCOVA model).
In accordance with the research purposes and analytical models, this study established three research questions and each of that contained five hypotheses (from a to e) were organized with a hieratical modeling as follows:

Research question one: How do job access and neighborhood disadvantage influence female former welfare recipients’ job retention within eight quarters after exiting cash assistance and being employed?

H1a. There will be a significant variance in job retention of female former welfare recipients by census tracts (Model 1).

H1b. The differences of the covariates (demographic, human capital, and involuntary exit of cash assistance) will affect job retention of female former welfare recipients (Model 2 & 4).

H1c. A longer individual job access (distance) will decrease job retention of female former welfare recipients (Model 2 & 4).

H1d. A higher level of neighborhood public transportation access will increase job retention of female former welfare recipients (Model 3 & 4).

H1e. A higher level of neighborhood disadvantage will decrease job retention of female former welfare recipients (Model 3 & 4).
Research question two: How do job access and neighborhood disadvantage influence female former welfare recipients’ two-year employment within eight quarters after exiting cash assistance and being employed?

H2a. There will be a significant variance in the possibility of two year employment of former TANF recipient by census tracts (Model 5)

H2b. The differences in the covariates (i.e., demographic, human capital, and involuntary exit of cash assistance) will affect the possibility of two-year employment of female former welfare recipients (Model 6 & 8).

H2c. A longer individual job access (distance) will decrease the possibility of two-year employment of female former welfare recipients (Model 6 & 8).

H2d. A higher level of neighborhood public transportation access will increase the possibility of two-year employment of female former welfare recipients (Model 7 & 8).

H2e. A higher level of neighborhood disadvantage will decrease the possibility of two-year employment of female former welfare recipients (Model 7 & 8).
Research question three: How do job access and neighborhood disadvantage influence female former welfare recipients’ average quarterly earnings within eight quarters after exiting cash assistance and being employed?

H3a. There will be a significant variance in average quarterly earnings of female former welfare recipients by census tracts (Model 9).

H3b. The differences in the covariates (i.e., demographic, human capital, and involuntary exit of cash assistance) will affect average quarterly earnings of female former welfare recipients (Model 10 & 12).

H3c. A longer individual job access (distance) will decrease average quarterly earnings of female former welfare recipients (Model 10 & 12).

H3d. A higher level of neighborhood public transportation access will increase average quarterly earnings of female former welfare recipients (Model 11 & 12).

H3e. A higher level of neighborhood disadvantage will decrease average quarterly earnings of female former welfare recipients (Model 11 & 12).
CHAPTER THREE: METHOD

3.1. Study design

The main purpose of this study was to examine the effects of job access and neighborhood disadvantage on the employment success of female former welfare recipients who exited cash assistance after the 1996 welfare reform. Targeting female former welfare recipients who exited cash assistance in Cuyahoga County of Ohio, this study observed the three types of employment success: job retention, two-year employment, and average quarterly earnings. As a non-experimental and longitudinal design, this study merged two sets of administrative datasets with 2000 Census data. These two sets of administrative data provided individual-level variables; 2000 Census data contained neighborhood-level variables. Therefore, the statistical models of this study simultaneously examined two-levels of effects, the individual and neighborhood-levels, on the employment success of female former welfare recipients (Level-1 and 2).

3.1.1. Data manipulation

This study combined two sets of administrative data with Census 2000 data (See Figure III-1). Two sets of administrative data were provided by Cuyahoga County Employment & Family Services (EFS), Ohio. These administrative data sets were longitudinal data which consisted of (1) TANF data and (2) the Quarterly Wage Recode (QWR). These two administrative data sets have been strictly managed by the Center on Urban Poverty and Community Development (CUPCD) at Case Western Reserve
University (CWRU) in Cleveland, Ohio. Since these data sets were merged by matching the TNAF recipients’ social security number, the personal information of the TANF recipients was protected under the review and regulations of the Institutional Review Board (IRB) at CWRU. In addition to these administrative data, Census 2000 data was collected at the Census Bureau’s website (U.S. Census Bureau, 2012). Those two administrative data sets and Census 2000 data were merged by a census tract in which the welfare recipients resided at the point of exiting cash assistance.

3.1.1.1. TANF data

TANF data aimed to manage administrative information of welfare recipients in Cuyahoga County, Ohio. TANF data contained the information of TANF recipients (e.g., demographic, human capital, and welfare). The demographic information of the recipients included age, race, the number of children, and the residential address at the point of and after exiting cash assistance. By using this data, human capital variables were measured by the recipients’ educational attainment at the point of exiting cash assistance. The welfare variable was whether the welfare recipients involuntarily exited cash assistance or not.

3.1.1.2. Quarterly Wage Records

For administrative purposes, QWR was managed by Cuyahoga County EFS. The QWR contained information regarding TANF recipients’ quarterly taxable wages before and after exiting cash assistance and the address of workplaces. The QWR made it possible to measure (1) employment history before exiting cash assistance, (2)
employment success after exiting cash assistance, and (3) workplaces. This study measured the employment success of the female former welfare recipients within eight quarters after exiting cash assistance: job retention, two-year employment, and average quarterly earnings. As well, the QWR tracked the TANF recipients’ employment activities within one year before they exited cash assistance. Therefore, it was possible to measure the work-experience of former welfare recipients prior to exiting cash assistance.

After combining the QWR with TANF data, former welfare recipients’ job access was measured by the distances between a resident place and workplaces. Thus, QWR contributed to measuring variables in this study: (1) three types of the employment success, (2) work-experience before exiting cash assistance (human capital), and (3) job access which was the geographic distances (miles) between residential addresses and workplace addresses.

3.1.1.3. 2000 Census data

This study merged 2000 Census data with two administrative data sets (TANF data and OWR) in order to test the effect of neighborhood disadvantage on the employment success of female former welfare recipients. To observe the nested effect of neighborhood disadvantage, 2000 Census data was collected by census tracts where female former welfare recipients resided at the point of exiting cash assistance. Because this study focused on the female former welfare recipients who exited cash assistance between January 2000 and December 2003, it was plausible to use 2000 Census data.
**Figure III-1. Data manipulation**

**Sources**
- Cuyahoga County Employment & Family Services (EFS)

**Data**
- Quarterly Wage Records (QWR)
- TANF Data

**Merged by**
- Individual identifier

**Variables**

**Human capital**
- Employed before exiting cash assistance

**Individual job access**
- Workplace addresses

**Employment success**
- Job retention
- Two-year employment
- Average quarterly earnings

**Demographic**
- Age
- Race
- Number of children

**Human capital**
- Educational attainment

**Welfare**
- Involuntary exit of cash assistance

**Individual job access**
- Residential addresses

**Level (unit)**
- Individual (Person)

**US Census Bureau**
(www.census.gov/)

**Census 2000 data**

**Public transportation access**
- Workers' use a public transportation for commuting

**Neighborhood disadvantage**
- Poverty
- Female headed family
- People under 18 years
- African-Americans
- Unemployment
- Welfare recipient

**Neighborhood (Census tract)**

US Census Bureau
(www.census.gov/)
3.1.2. Sampling criteria

Congruent with the research purpose and data availability, this study selected its sample by establishing eight criteria: (1) gender, (2) disability, (3) the period of exiting cash assistance, (4) the event of being employed after exiting cash assistance, (5) age at the point of exiting cash assistance, (6) the number of children at the point of exiting cash assistance, (7) the residential place at the point of exiting cash assistance, and (8) the workplaces after exiting cash assistance.

This study focused on female welfare recipients because they were a majority of the cash assistance program and their employment context was different from males (Hanson et al., 1995) (Criterion 1). Further, the selected sample were those without disability because it assumed that former welfare recipients were capable of being employed (Criterion 2). Considering data availability and policy context, the sample should exit TANF cash assistance between 2000 and 2003. The time-limit of cash assistance (i.e., 36 month time limit of TANF in the State of Ohio) was effective since 1997 (ODJFS, 2001). Therefore, most of the first TANF generation in Cuyahoga County, Ohio began to exit cash assistance during the time period of this (2000-2003). Accordingly, this criterion properly reflected the time-limit regulation, which was one of the key components in 1996 welfare reform (Criterion 3). In this study, the event of being employed was prerequisite to measuring employment success and individual job access. For instance, it was unfeasible to measure job retention and individual job access of female former welfare recipients unless they were employed. Hence, the sample had to participate in taxable work-activities within one quarter from the date of exiting cash assistance.
assistance. This criterion also considered the work-requirement that was one of important regulations of 1996 welfare reform (Criterion 4). The sample should be an adult (over 18 years old) at the point of exiting cash assistance (Criterion 5). The sample also had at least one child whose age should be below 18 at the point of exiting cash assistance. Hence, all of the sample should have a minimum burden of childcare (Criterion 6). In addition, this study excluded the sample that resided outside of Cuyahoga County within two year after exiting cash assistance (See Figure III-2). The residential places were important in this study in order to observe the effect of job access and neighborhood disadvantage on the employment success of female former welfare recipients. If female former welfare recipients resided outside of Cuyahoga County during the time frame of this study (within two years after exiting cash assistance), their information regarding job access and employment success was more likely to be less reliable (Criterion 7). Finally, the sample should work in two in Metropolitan Statistical Areas (MSA), Cleveland-Elyria-Mentor MSA and Akron MSA, within eight quarters after exiting cash assistance (See Table III-1 & Figure III-3). As a key independent variable, individual job access was calculated by a distance between residential addresses and workplace addresses. If a sample worked outside of these two MSAs, it was unreasonable to measure the distance between a residential place and the workplaces of the sample. Therefore, this study excluded the sample who worked outside of these two MSAs during the time frame. Following this criterion, this study selected 66,790 job locations in these two MSAs (Criterion 8; See Table III-1, Figure III-2, & Figure III-3).
In sum, this study targeted a specific population among female welfare recipients with children, the predominant population of TANF. What was more, this study considered the important characteristics of welfare reform’ regulation as it selected those who exited cash assistance after 2000 and were employed. This study could observe the neighborhoods effect on the employment success of female former welfare recipients in an urban area. According to these criteria, this study collected 13,788 female former welfare recipients.
Figure III-2. Sample by neighborhoods

Sample size by census tracts
- 1 - 20
- 21 - 60
- 61 - 120
- 121 - 252

Source: 1. TANF data 2000-2003
2. QWR
(N=13,788; N of tracts=445)
Figure III-3. Job locations in Metropolitan Statistical Areas

Source: 1. TANF data 2000-2003
2. QWR
<table>
<thead>
<tr>
<th>Metropolitan Statistical Area</th>
<th>County</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cleveland-</td>
<td>Cuyahoga</td>
<td>61,791</td>
</tr>
<tr>
<td>Elyria-Mentor metro</td>
<td>Lorain</td>
<td>411</td>
</tr>
<tr>
<td></td>
<td>Lake</td>
<td>1725</td>
</tr>
<tr>
<td></td>
<td>Geauga</td>
<td>237</td>
</tr>
<tr>
<td></td>
<td>Medina</td>
<td>634</td>
</tr>
<tr>
<td>Akron metro</td>
<td>Summit</td>
<td>1955</td>
</tr>
<tr>
<td></td>
<td>Portage</td>
<td>217</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>66,970</td>
</tr>
</tbody>
</table>
3.2. Time frame and operational definition of variables

This study specified a time frame in order to clarify the sequences of several complicated events that were associated with the independent and dependent variables. The time frame was divided into two phases: the cash assistance period and the post-exiting cash assistance period. Following the time frame, this study organized the dependent variables and the independent variables at the individual- and neighborhood-level (See Figure III-4).

3.2.1. Time frame

This study established a time frame in order to organize the periodic sequences of each variable between before and after that female former welfare recipients exited cash assistance. Based on the periodic concept, this study observed the causal relationship between the pre-events with independent variables and the post-events with dependent variables of female former welfare recipients. Therefore, this time frame served as a guide to define the independent and dependent variables and to build statistical models. By the point of exiting cash assistance, the time frame of this study was divided into two phases: (1) the cash assistance period, and (2) the post-exiting cash assistance period (See Figure III-4).
3.2.1.1. Cash assistance period

The cash assistance period referred to the period before female former welfare recipients exited cash assistance. Most of the individual-level variables were time-invariant variables determined before they exited cash assistance. Some individual-level variables might be time-variant. For example, some of female former welfare recipients might have a child or attain educational degrees after exiting cash assistance. However, the number of children and educational attainment were regarded as time-invariant variables in this study because of data availability.

In order to measure the neighborhood-level effect, it was necessary to specify a geographic boundary. The unit of analysis on neighborhood-level variables was the 2000 Census tracts in which female former welfare recipients resided at the point of exiting cash assistance. Therefore, it was possible for the sample to move or migrate into other places during the time framework of this study. However, the census tract was also regarded as a time-invariant variable because the data of this study could not track the sample’s mobility or migration after exiting cash assistance.
3.2.1.2. Post-cash assistance period

The post-assistance period was defined as the phase within eight quarters after female former welfare recipients exited cash assistance. As mentioned previously in the sampling criteria, this study targeted female former welfare recipients who were employed in the first quarter of exiting cash assistance. After the female former welfare recipients were employed, their employment success, such as job retention, two-year employment, and average quarterly earnings, was measurable. Among the independent variables, only the sample’s job access, which was the distances between a residential place and workplaces, was collected during this period. Individual job access at the individual-level was measurable after former welfare recipients exited cash assistance and were employed. In sum, the sequence of events was organized by the time frame. The employment success of female former welfare recipients and individual job access were collected during the post-cash assistance period. Most of independent variables were measured during the cash assistance period.
Figure III-4. Time frame

<table>
<thead>
<tr>
<th>Period</th>
<th>First date of cash assistance</th>
<th>Exit date of cash assistance</th>
<th>First date of employment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level variable (Person)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demographic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of children</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Human capital</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed before exiting cash assistance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Educational attainment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Welfare</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Involuntary exit of cash assistance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neighborhood public transportation access</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Worker’s use a public transportation for commuting</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neighborhood disadvantage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poverty</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female headed family</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>People under 18 years</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>African-Americans</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Welfare recipient</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(1) Cash assistance period

(2) Post-cash assistance period

Job access
- Residential addresses
- Workplace address

Employment success
- Job retention
- Two-year employment
- Average quarterly earnings
3.2.2. Dependent variables

With an eight-quarter window, the employment success of female former welfare recipients was measured by three variables: (1) the level of job retention, (2) two-year employment, and (3) average quarterly earnings. All of the dependent variables were measured during the post-cash assistance period (See Figure III-4).

First of all, this study measured the level of job retention within an eight-quarter window after exiting cash assistance. The unit of job retention was a quarter (range one to eight). Specifically, the scores of job retention meant the last quarter for which the sample was continuously employed since the first quarter; as stated earlier, the entire sample should be employed within the first quarter after exiting cash assistance. A higher score meant longer job retention and more successful in employment.

Two-year employment was gauged to measure employment success of the sample. The unit of this variable was also a dichotomous. If the sample was employed for two years since the first quarter of exiting cash assistance, it was coded as one; otherwise, coded as zero.

The average quarterly earnings were the mean taxable earning of the employed quarters within eight quarters after exiting cash assistance regardless of job retention. Specifically, the earnings of eight quarters were summed and divided by the number of the employed quarters. Therefore, the average quarterly earnings represented the earning during actual work activities. A higher score for this variable meant more success in employment. The unit of average quarterly earning was US dollars (See Table III-2).
3.2.3. Individual-level variables

This study examined two-level effects on the employment success of female former welfare recipients. The individual-level variables were comprised of several covariates and individual job access.

3.2.3.1. Covariates

The main analysis controls three sets of covariates were controlled at an individual level: (1) demographic, (2) human capital, and (3) involuntarily exit of cash assistance (See Table III-2). The covariates were obtained from TANF data and QWR. In terms of the time frame, they were measured during the cash-assistance period (See Figure III-4).

TANF data contained four demographic variables: age, race, and number of children at a point of exiting cash assistance. The age (year) of the sample was calculated at the time of exiting cash assistance. Considering the racial proportions of the sample, race was divided into three categories: Whites, African-Americans, and a reference (other). The sample’s number of children in the house was measured at the point of exiting cash assistance; as mentioned earlier, the sample should have one child at least at the point of exiting cash assistance.

In addition to the demographic variables, two human capital variables were included in the main analysis: (1) educational attainment at the point of exiting cash assistance and (2) work-experience before exiting cash assistance. The sample’s educational attainment was collected from TANF data. If the level of educational
attainment at the point of exiting cash assistance was higher than at high school graduation, it was coded into one; otherwise, it was coded into zero. The sample’s work-experience was measured within one quarter before exiting cash assistance. If the sample was employed one quarter before exiting cash assistance, it was coded into one; otherwise, it was coded into zero. The reasons of leaving cash assistance were coded into a dichotomous variable; if the sample involuntarily exited cash assistance is coded into one; otherwise, it was coded into zero.

3.2.3.2. Individual job access

In this study, individual job access was defined as the average distance (in miles) between a residential address at the point of exiting cash assistance and workplaces after exiting cash assistance of the female former welfare recipients. The residential address and workplace address were obtained from TANF data and QWR, respectively. First, each address of a residential address and workplaces was geo-coded by ArcGIS 10.0 in order to obtain its geographic boundaries (i.e., census tract) and coordinators (i.e., longitude and latitude). Then, the Euclidean distance, the airway distance between two points, was used to calculate the distance between a residential place and workplaces of the sample. The Euclidean distances were theoretical distances between each point. Average job distance of each quarter was measured using the basic formula for the distance between any two points:

\[
D_{i_q} = \sqrt{\frac{\sum_{j=1}^{j} (r_i - w_{ij})^2}{j}}
\]
The sample’s (i) residential location was \( r_i \); this study obtained only one residential location of the sample. Depending on the number of employments (j) in each quarter (q), the sample (i) was employed at workplaces (\( w_{ij} \)). For i’s average job distance of each quarter (\( D_{iq} \)), the sum of distances within each quarter (q) was divided by the number of employment (i). After geo-coding and measuring the average job distance, two types of average job distances between a residential place and workplaces was produced in accordance with the attributes of the dependent variables.

For the statistical model for job retention, individual job access A (\( A_i \)) was calculated by the average quarterly job distance between a residential addressee and workplaces until the quarter (\( q' \)) that the sample quitted their continuous employment since the first quarter. For example, if a sample was employed until 5\(^{th} \) quarter after the first quarter, its job access was calculated by the average distance between quarter one and quarter five.

\[
\text{Individual job access (A)} \quad A_i = \frac{\sum_{q'=1}^{q'} D_{iq'}}{q'} \quad [3.2]
\]

For the statistical model with two-year employment and average quarterly earnings, job access B (\( B_i \)) was calculated. Regardless of job retention, job access B (\( B_i \)) was calculated for the quarters in which the sample was employed. Specifically, the sample’s average job distance of each quarter (\( D_{iq} \)) was over the number of employed quarters (q).
Individual job access (B) \[ B_i = \frac{\sum_{q=1}^{q} D_{iq}}{q} \]  

3.2.4. Neighborhood-level variables

As noted earlier, TANF data contained addresses of the female former welfare recipients resided in at the point of exiting cash assistance. By using ArcGIS 10.0, the addresses were geo-coded in order to identify Census 2000 tract number (geographic boundaries) of the sample. This study was able to collect neighborhood information of female former welfare recipients as it merged TANF data and Census 2000 data. The neighborhood characteristics of female former welfare recipients was collected from decennial Census 2000 data (U.S. Census Bureau, 2012). According to Census 2000 data, Cuyahoga County consisted of 502 census tracts. From this study, the sample resided in 445 Census tracts at the point of exiting cash assistance.

3.2.4.1. Neighborhood disadvantage

The variables to measure the level of neighborhood concentrated disadvantage were collected based on the theoretical background (Wilson, 1996) and the empirical study (Sampson et al., 1997). The level of concentrated disadvantage was gauged by the factor scores of six items in each census tract. These six variables were comprised of each census tract’s ratio of poverty, race, receipt of public assistance, the labor market, age composition, and family structure (Sampson, et al., 1997). Each of these six variables was calculated by a proportion of the census tract where female former welfare recipients resided at the point of exiting cash assistance (See Table III-2).
Specifically, the six variables to measure the level of neighborhood disadvantage in 1999 were (1) poverty rate (a proportion of individuals below the federal poverty threshold), (2) a proportion of households that received public assistance, (3) a proportion of female-headed families with children, (4) unemployment rate, (5) a proportion of individuals less than 18 years old, and (6) a proportion of African-Americans (U.S. Census Bureau, 2012; See Table III-2). Similar to the previous study, this study conducted a PCA with oblique rotation in order to check the factor structure of these six variables (Sampson, et al., 1997). As an aggregated number of these six items, the regression factor score from PCA was inputted in the main analysis.

3.2.4.2. Neighborhood public transportation access

As a proxy of neighborhood job access, this study included the neighborhood-level of public transportation from 2000 Census data (U.S. Census Bureau, 2012). Specifically, it included the percentage of workers’ use of public transportation in the census tract where female former welfare recipients resided at the time of exiting cash assistance. This study assumed that this indicator was a proxy for access to public transit.
Table III-2. Composition of variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Type</th>
<th>Value</th>
<th>Timea)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Job retention: The last quarter of continuous quarters in employment</td>
<td>Numeric</td>
<td>Quarter</td>
<td>2</td>
</tr>
<tr>
<td>2. Two-year employment</td>
<td>Dummy</td>
<td>0, 1</td>
<td>2</td>
</tr>
<tr>
<td>3. Average quarterly earnings</td>
<td>Numeric</td>
<td>Dollar</td>
<td>2</td>
</tr>
</tbody>
</table>

| Individual-level variables (Level-1)           |            |             |        |
| 1. Demographic variables                      |            |             |        |
| • Age at the time                             | Numeric    | Year        | 1      |
| • Race (Other=Reference)                      | Dummy      | 0, 1        | 1      |
|   o Whites                                    | Dummy      | 0, 1        | 1      |
|   o African-Americans                         | Dummy      | 0, 1        | 1      |
| • Number of children                          | Numeric    | Number      | 1      |
| 2. Human capital variables                    |            |             |        |
| • High school diploma or more (=1)            | Dummy      | 0, 1        | 1      |
| • Employed one quarter before exiting cash assistance (=1) | Numeric    | 0, 1        | 1      |
| 3. Involuntary exit of cash assistance (=1)   | Dummy      | 0, 1        | 1      |
| 4. Individual job access                      |            |             |        |
| • Individual job access (A): Average distance between a residential address and workplace addresses before quitting job | Numeric    | Miles       | 2      |
| • Individual job access (B): Average distance between residential addresses and workplace addresses within 8 quarters | Numeric    | Miles       | 2      |

| Neighborhood-level variables (Level 2)         |            |             |        |
| 1. Neighborhood disadvantage                  | Numeric    | Score       | 1      |
| • Individuals below poverty threshold          | Numeric    | percent     | 1      |
| • Household on public assistance              | Numeric    | percent     | 1      |
| • Female-headed families                      | Numeric    | percent     | 1      |
| • Unemployed                                  | Numeric    | percent     | 1      |
| • Less than aged 18                           | Numeric    | percent     | 1      |
| • African-Americans                           | Numeric    | percent     | 1      |
| 2. Neighborhood public transportation access   | Numeric    | percent     | 1      |

*Note: a) See Figure III-4: (1) cash assistance period and (2) post-cash assistance period

*Source: 1) TANF data, 2) QWR, & 3) 2000 Census data*
3.3. Statistical analysis

This study was designed to conduct two steps of statistical analysis: (1) explanatory and (2) main analysis. The explanatory approach was comprised of descriptive analysis, spatial analysis, and PCA. After completing the explanatory analysis, this study utilized multi-level analyses such as Hierarchical Generalized Linear Model (HGLM) and Hierarchical Linear Model (HLM) in order to test the research questions (Raudenbush & Bryk, 2002; Raudenbush, Bryk, Cheong, Congdon, & Toit, 2011).

3.3.1. Explanatory analysis

The explanatory analysis consisted of descriptive analysis, spatial analysis, and PCA.

3.3.1.1. Descriptive analysis

Prior to conducting the main analysis, a descriptive analysis explored the overall distributions of each variable: means, standard deviation, frequency, range, and percentage, and so on. Especially, the variance distribution of each variable was tested prior to the main analysis. Bivariate analysis checked simple relationships among the individual-level, neighborhood-level, and dependent variables. Explicitly, the correlation analysis (e.g., $r$, eta., & phi.) were conducted in accordance to the attribute of each variable.
3.3.1.2. Spatial analysis

This study used spatial analysis with five purposes: (1) geo-coding, (2) calculating distances, (3) mapping, (4) checking spatial statistics, and (5) exporting geographic weights for the main analysis. As the first step, a residential place and workplaces of the sample were geo-coded in order to specify geographic coordinates (i.e., longitudes and latitudes) and boundaries (i.e., 2000 census tract). By using the results of the geo-coding, the distances between a residential place and workplaces were calculated. As one of important analytical tools in this study, a spatial analysis provides visual results, especially data-rich maps. This spatial analysis generated several maps to visualize the results of the main analyses. Furthermore, this study used a spatial analysis to test a spatial autocorrelation between a residential place and the dependent variables.

According to Moran’s I, the spatial autocorrelation between residential places and employment success of the sample was detected (Dormann et al., 2007; See Table IV-1). Therefore, this study used a spatial analysis tool to calculate and to produce spatial weight scores within Census 2000 tracts of Cuyahoga County, Ohio. Then, the spatial weights were inputted and adjusted in the main analyses (Raudenbush et al., 2011)
3.3.1.3. Principal component analysis

Prior to the main analysis, PCA aggregated six neighborhood-level variables for neighborhood disadvantage into one regression factor score. These six neighborhood-level variables were to be evaluated with three aims: (1) to examine the factorability, (2) to identify the latent constructs (factors structures), and (3) to reduce the current items of the six neighborhood-level variables for each census tract (i.e. data reduction). Most neighborhood variables in this study shared high communalities. Hence, it was inappropriate to input all neighborhood-level variables into the main statistical analysis. Therefore, PCA determined the factor structures of six items and reduced the number of the six items which were included in the main analysis.

Prior to PCA, it was necessary to explore whether the six neighborhood variables were factorable or not. Three indexes were tested in order to determine the factorability of the six neighborhood-level variables. First of all, Bartlett’s test of Sphericity should be significant \((p<.05)\) (Pett, Lackey, & Sullivan, 2003). Second, the Kaiser-Meyer-Olkin (KMO) score should be above .6 (Pett et al, 2003; Spicer, 2005). Finally, by using the Anti-image correlation matrix, the individual Measures of Sampling Adequacy (MSA) was tested; each value in the Anti-image correlation matrix should be above .6 (Pett et al., 2003).

Depending on the inclusion (or exclusion) of unique variance, there were two significant extraction methods in the Explanatory Factor Analyses (EFA): PCA and Principal Factors Analysis (PFA) (Bryman & Cramer, 2004; Fabrigar, Wegener, MacCallum, & Strahan, 1999; Widaman, 1993). Although both extraction methods were
conducted prior to identifying the dimensionality of the six neighborhood-level variables, the major extraction method of this study was PCA in accordance with the previous studies on the neighborhood variables of concentrated disadvantage (Sampson, et al., 1997).

This study determined the number of factors by three major criterions: an eigenvalue, total variance explained, and a scree plot. First of all, according to the Kaiser-Guttman rule, the eigenvalue should be greater than one (Bryman & Cramer, 2004; Comrey, 1988, Pett et al., 2003). Second, considering that the six neighborhood variables were included in social science, the total variance explained by extracted factors should be above 50 percent (Pett et al., 2003). The third method to determine the number of factors, the scree plot, was to plot the extracted factors against their eigenvalues in descending order of magnitude to identify distinct breaks or discontinuities in the slot of the plot (Pett et al., 2003; Ford, MacCallum, & Tait, 1986). Because it was better to overestimate rather than to underestimate the number of factors, this study examines the highest (number of factors=6) to the lowest number of factors (number of factors=1) until the most interpretable solution was found (Guertin, Guertin, & Ware, 1981; Ford et al., 1986). The choice of criterion may have depended on the size of the average communalities and the number of variables and subjects (Bryman & Cramer, 2004; Ford, et al., 1986).

Depending on the intercorrelation among factors, there are two rotation methods, orthogonal and oblique, in PCA (Bryman & Cramer, 2004; Pett et al., 2003; Spicer, 2005). Unfortunately, it was not feasible to estimate the statistical intercorrelation among factors prior to conducting PCA. However, the oblique rotation was initially run because
it could produce uncorrelated factors (Spicer, 2005). In addition, oblique rotation more accurately represented the complexity of the examined variables because constructs in the real world were seldom uncorrelated (Harman, 1976 cited in Ford et al., 1986). This study selected an oblique rotation for PCA in accordance with the previous study (Sampson, et al., 1997).

After determining the number of extracted factors by PCA with oblique rotation, factor loading of each item was observed. In general, no item that loads <.30 should be part of defining a factor because less than nice percent of that item’s variance was shared with the factor (Comrey & Lee, 1973 as cited in Pett et al., 2003). However, this analysis defined that the cut-off of the primary factor loading should be above .6 according to the previous study (Sampson, et al., 1997). Additionally, if the results recommended that the number of extracted factors was more than two, it was necessary to consider the issue of double (or multiple) loading (Pett et al., 2003). However, the results of PCA suggested one factor for the six neighborhood-level variables (See Table IV-3).

As the final step, the extracted factors were identified based on theoretical concepts. The number of factors and the composition of items in each extracted factor determined the names of the extracted factors (Ford et al., 1986; Pett et al., 2003). The labeling of the extracted factors was conceptually and theoretically judged based on previous studies (Pett et al., 2003; Sampson, et al., 1997).
3.3.2. Main analysis

By using two-level analysis, the main purpose of this study was to simultaneously test the effect of the individual- and neighborhood-level variables on the employment success of female former welfare recipients. Because this study focused on neighborhood effects, it adopted multi-level analysis to explore nested effects on the employment success of female former welfare recipients. Moreover, the data sets of this study had a hierarchical structure with individual female former welfare recipients nested within census tracts. Depending on the attribute of the dependent variables, HGLM and HM were employed to test the hypotheses and to deal with the data sets with a hierarchical structure (Raudenbush & Bryk, 2002; Raudenbush et al., 2011). The model building method was also applied to HGLM and HLM in order to observe the separated and combined effect of individual and neighborhood-level variables on the dependent variables. All of HGLM and HLM in this study were adjusted by spatial weights in order to control a spatial autocorrelation between residential places and employment success of the sample. In sum, the main analysis of this study consisted of three approaches, (1) a model building method, (2) application of multi-level analyses, and (3) adjustment of spatial autocorrelation.
3.3.2.1. Model building method

In order to systematically test the research hypotheses, this study applied a model building method on the multi-level analyses, HGLM and HLM. Raudenbush and Bryk (2002) suggested various types of HLM sub-models depending on the inclusion, exclusion, and location of individual-level (Level-1) and group-level (Level-2) variables (Raudenbush & Bryk, 2002). In accordance with the research hypotheses, this study incorporated four models: (1) null model, (2) random-intercept model, (3) random-intercept regression model, and (4) random-intercept ANCOVA model (Raudenbush & Bryk, 2002).

**Null model** The null model, also called the unconditional model or one-way ANOVA with random effects, was a type of random-intercept model that predicted the level-1 intercept of the dependent variable as a random effect to the level-2 grouping variable, without any other predictors at level-1 or 2 in a two-level model (Raudenbush & Bryk, 2002). The null model provided useful primary information about how much variance in the outcome lies within and between census tracts and about the reliability of each census tract’s sample as an estimate its true population mean (Raudenbush & Bryk, 2002). The null model made it possible for this study to gauge the magnitude of variation among census tracts. Specifically, the null model of this study was used to calculate the Intra-class Correlation Coefficient (ICC), which was a test of the need for mixed modeling. The null model also served as a baseline model for purpose of comparison with later models of this study (Raudenbush & Bryk, 2002). It was denoted that the
dependent variable(s) of former TANF recipient $i$ in census tract $j$ as $Y_{ij}$. The dependent variable was represented as:

**Individual-level**  
\[ Y_{ij} = \beta_{0j} + r_{ij}, \]  
\[ \beta_{0j} = \gamma_{00} + u_{0j}, \]

where this model was assumed by $r_{ij} \sim N(0, \sigma^2)$ and $u_{0j} \sim N(0, \tau^2)$.

**Random-intercept model**  
The random-intercept model, also called one-way ANCOVA with random effects models, possibly had only individual-level variables and still predicted the level-1 intercept (but not the slope of the level-1 covariates) as a random effect of the level-2 grouping variable, with no other level-2 predictors (Raudenbush & Bryk, 2002). This model was compared with the null model to test the improvement of model fit (Raudenbush & Bryk, 2002). This study tested the effect of the individual-level variables (e.g., covariates and individual job access) on the employment success of female former welfare recipients. In this model, it was denoted that the dependent variable(s) of former TANF recipient $i$ in census tract $j$ as $Y_{ij}$. The dependent variables were represented as a function of covariates and the independent variable, $X_{qij}$, and model error $r_{ij}$:

**Individual-level**  
\[ Y_{ij} = \beta_{0j} + \beta_{qij} X_{qij} + r_{ij}, \]
where this level-1 model was assumed by $r_{ij} \sim N(0, \sigma^2)$. The neighborhood-level equation was not included in this model (See Equation 3.5). The regression coefficients $\beta_{qj}, q = 1..., 8$, indicated how the dependent variable was distributed in census tract $j$ as a function of the measured individual-level (Raudenbush & Bryk, 2002). Among eight individual variables, three continuous variables (age, the number of children, and individual job access) were centered by their grand-mean and inputted into the model.

**Random-intercept regression model** The random-intercept regression model has also been referred to as mean-as-outcomes regression models (Raudenbush & Bryk, 2002). This variant of the random intercept model predicted the level-1 intercept on the basis of the level-2 grouping variable and also on the basis of one or more level-2 random effect predictors (Raudenbush & Bryk, 2002). In this study, the random-intercept regression model only included two neighborhood-level variables, neighborhood disadvantage and neighborhood public transportation access. This model estimated the means from each of the groups as an outcome to be predicted by group characteristics (Raudenbush & Bryk, 2002). This submodel consisted of Equation 3.4 as the level-1 model, for the level-2 model:

\[
\text{Neighborhood-level} \quad \beta_{0j} = \gamma_{00} + \gamma_{01} \cdot W_{1j} + \gamma_{02} \cdot W_{2j} + u_{0j}, \quad [3.7]
\]
where in this case \( W_1 \) was the factor score of neighborhood disadvantage and \( W_2 \) was neighborhood public transportation. This model was assumed by \( u_{0j} \sim N(0, \tau^2) \) and only tested the effect of neighborhood-level variables on the employment success of female former welfare recipients. These two neighborhood-level variables were centered by their grand-mean and inputted into the model.

**Random-intercept ANCOVA model**  
The random-intercept ANCOVA model has also been referred to as mean-as-outcomes ANCOVA model (Raudenbush & Bryk, 2002). This type was simply a random intercept regression model in which there was also level-1 covariates treated as fixed effect (slope not predicted by level-2) (Raudenbush & Bryk, 2002). In this study, this model included both individual and neighborhood-level variables on employment of female former welfare recipients. This model consisted of Equation [3.6] and [3.7].

### 3.3.2.2. Multi-level analysis: HGLM and HLM

This study used three types of dependent variables in order to measure the employment success of female former welfare recipients: (1) job retention, (2) two-year employment, and (3) average quarterly earnings. Although these three dependent variables were commonly estimated by multi-level analyses, they had different attributes. Hence, it was necessary to establish different multi-level models following the attributes of the dependent variables (See Figure III-5).
The first two dependent variables (job retention and two-year employment) were modeled by HGLM. Unlike normally distributed data, count data could not be appropriately analyzed by the standard HLM due to the issues of normality (Raudenbush & Bryk, 2002). Therefore, HGLM provided a coherent modeling framework for multilevel data with nonlinear structural models and nonnormally distributed errors (Raudenbush & Bryk, 2002). This study used HGLM with a Poisson sampling model to estimate job retention because this dependent variable was (1) not randomly distributed and (2) exposed to the same time period (an eight-quarter window). Therefore, HGLM with a Poisson distribution was to test research question one (Research question one). As well, this study applied HGLM with a Bernoulli sampling model to the model with two-year employment because two-year employment was a dichotomous variable (Research question two).

The standard HLM was appropriate for two or three-level nested data since (1) the expected outcome at each level may be represented as a linear function of the regression coefficients and (2) the random effects at each level can reasonably assumed normally distributed (Raudenbush & Bryk, 2002). Hence, a standard HLM was used to analyze average quarterly earnings which were numeric and normally distributed. The standard HLM was conducted to test research question three of this study (Research question three).
**Figure III-5. Applications of multi-level analyses**

1. Research question: Job retention
   - Dependent variable: Count
   - Attribute: Hierarchical Generalized Linear Model (HGLM)
   - Multi-level analysis: Poisson

2. Two-year employment
   - Dependent variable: Dummy
   - Attribute: Hierarchical Linear Model (HLM)
   - Multi-level analysis: Bernoulli

3. Average quarterly earnings
   - Dependent variable: Numeric
   - Attribute: Higher Linear Model (HLM)
   - Multi-level analysis: Standard

(Raudenbush & Bryk, 2002)
Individual-level model (Level-1) for HGLM with a Poisson sampling

According to HGLM with a Poisson distribution, it was denoted that the number of events (quarters) that the female former welfare recipient $i$ in census tract $j$ was continuously employed since the first quarter as $Y_{ij}$ (range 1 to 8). The time interval $m_{ij}$ may be termed the “exposed” (Raudenbush & Bryk, 2002). It was written:

\[ Y_{ij} = \log(\lambda_{ij}) \sim P(m_{ij}, \lambda_{ij}) \tag{3.8} \]

to denote the $Y_{ij}$ had a Poisson distribution with expose $m_{ij}$ and event rate of $\lambda_{ij}$.

According to the Poisson distribution, the expected value and variance of $Y_{ij}$, given the event rate, $\lambda_{ij}$, were then:

\[ E(Y_{ij} | \lambda_{ij}) = m_{ij}\lambda_{ij}, \quad \text{Var}(Y_{ij} | \lambda_{ij}) = m_{ij}\lambda_{ij} \tag{3.9} \]

the expected number of events, $Y_{ij}$, for individual $i$ in census tract $j$ is its event rates, $\lambda_{ij}$, times its expose $m_{ij}$; and the variance equaled this mean. In this study, $m_{ij}$ was set as one because every $i$ and $j$ the exposure was the same; the exposed time was eight quarters after exiting cash assistance. According to this level-1 model, the predicted value of $Y_{ij}$ when $m_{ij}=1$ was the event rate $\lambda_{ij}$.

The dependent variable was represented as a function of covariates and the independent variable, $X_{qij}$, and model error $r_{ij}$:
Individual-level $Y_{ij} = n_{ij} = \log[\lambda_{ij}] = \beta_{0j} + \beta_{1j} \cdot X_{qij} + r_{ij}$, \[3.10\]

where this level-1 model was assumed by $r_{ij} \sim N(0, \sigma^2)$.

The regression coefficients $\beta_{qj}$, $q = 1,.., 8$, indicated how the dependent variable was distributed in census tract $j$ as a function of the measured at the individual-level (Raudenbush & Bryk, 2002). $X_q$ was a set of coefficients regarding the individual-level variables (e.g., age, African-Americans, Whites, a high school diploma, being employed one quarter before exiting cash assistance, involuntary exit of cash assistance, and mean distance between a residential place and workplaces) ($q=1,\ldots,8$). Three continuous variables (age, the number of children, and individual job access) were centered by their grand-mean and entered into the model.

**Individual-level model (Level-1) for HGLM with a Bernoulli sampling**

According to HGLM with a Bernoulli sampling, it was denoted that the probability of two-year employment of the former TANF recipient $i$ in census tract $j$ is $Y_{ij}$; zero was failure and one was success. It was written:

$$
\text{Individual-level} \quad Y_{ij} = \log[\lambda_{ij}] \sim \text{Prob} (\lambda_{ij}) \quad \text{[3.10]}
$$

to denote the $Y_{ij}$ had a Bernoulli distribution and the probability of $\lambda_{ij}$. According to the Bernoulli distribution, the expected value and variance of $Y_{ij}$, given the probability, $\lambda_{ij}$, were then:
the expected number of probability, \( Y_{ij} \), for individual \( i \) in census tract \( j \) was its probability, \( \lambda_{ij} \); and the variance equaled this mean. According to this level-1 model, the predicted value of \( Y_{ij} \) is the probability of \( \lambda_{ij} \).

The dependent variable was represented as a function of covariates and the independent variable, \( X_{qij} \), and model error \( r_{ij} \):

\[
\text{Individual-level} \quad Y_{ij} = n_{ij}=\log[\lambda_{ij}]=\beta_{0j} + \beta_{1j} \cdot X_{qij} + r_{ij},
\]  

where this level 1 model was assumed by \( r_{ij} \sim N(0, \sigma^2) \).

Like the previous model, the regression coefficients \( \beta_{qj}, q = 1, \ldots, 8 \), indicated how the dependent variable was distributed in census tract \( j \) as a function of the measured individual-level (Raudenbush & Bryk, 2002). \( X_q \) was a set of coefficients regarding the individual-level variables \( (q=1,\ldots,8) \). Three continuous variables (age, the number of children, and individual job access) were centered by their grand-mean and entered into the model.
**Individual-level model (Level-1) of HLM.** It was denoted that the average quarterly earnings of the former TANF recipient \( i \) in census tract \( j \) as \( Y_{ij} \). The dependent variable was represented as a function of covariates and the set of individual-level variables and errors (See Equation 3.6).

**Neighborhood-level model (Level-2) of HGLM and HLM.** In this study, neighborhood-level modeling was commonly applicable to the individual-level models of HGLM and HLM. The effects of each census tract, captured in the set of \( \beta_{0j} \)'s in Equation 3.5 and 3.7, were assumed to vary across units; \( \beta_{0j} \) was conceived as a dependent variable that depended on a set of neighborhood-level variables, \( W_{1j} \) and \( W_{2j} \), and a unique neighborhood effect, \( u_{qj} \). Because the final model of this study was random-intercept ANCOVA model, it only subsumed one intercept, \( \beta_{0j} \). \( \beta_{0j} \) had a model of the form with Equation 3.7.

3.3.2.3. Adjustment of spatial weights

*Moran’s I* test discovered that there was a spatial autocorrelation between residential places and each variable of employment success (See Table IV-1). By using *ArcGIS* 10.0, this study produced spatial weights with census tracts’ polygons of Cuyahoga County, Ohio. Following this, spatial weights were adjusted in the main analyses (Dormann et al., 2007; Raudenbush et al., 2011).
3.3.3. Software

This study used three software packages for data manipulation, spatial analysis, and statistical analysis: Statistical Analysis System (SAS) 9.0, ArcGIS 10.0, and HLM 7.0. SAS 9.0 was used for data management, descriptive analysis, and PCA. Spatial analysis was conducted by ArcGIS 10.0. The major analyses of this study, HGLM and HLM, were conducted by HLM 7.0 (Raudenbush et al., 2011).
CHAPTER FOUR: RESULTS

4.1. Descriptive analysis

As a preliminary analysis, this section explores the basic distribution of variables with tables, figures, and maps. Next, bivariate correlations among variables were also checked. PCA was conducted (1) to explore the factor structure of the six neighborhood-level items to measure the level of neighborhood disadvantage and (2) to export the factor score of them.

4.1.1. Dependent variables

Three types of employment success were measured such as job retention, two-year employment, and average quarterly earnings (See Table IV-1). Regarding job retention, the sample on average was continuously employed for 5.36 quarters (SD=2.77) within eight quarters after exiting cash assistance (See Figure IV-1). According to Moran’s I, the locations of the sample’s residential address and job retention were spatially correlated to each other (Moran’s I=.000, z=26.936, p<.001). As shown on Figure IV-1, the distribution of job retention was clustered in Cuyahoga County, Ohio (See Figure IV-3).

Results regarding employment showed that 45.2% of the sample was employed for two years after exiting cash assistance. Similar to job retention, the pattern of this outcome was also spatially clustered. The location of the sample’s residential address
and the possibility of two-year employment were also spatially auto-correlated ($Moran's I=.000, z=32.77, p<.001$; See Figure IV-4).

As the final outcome, average quarterly earnings were examined. The mean of average quarterly earnings were $2,656.87$ (SD=1772.09) with an eight-quarter window (See Figure IV-2). In other words, the sample earned $739.22$ per month on average. Average quarterly earnings were also spatially auto-correlated with the sample’s residential location ($Moran's I=.001, z=141.7, p<.001$; See Figure IV-5).

On average, the sample was continuously employed for 5.4 quarters (approximately 16 months); 45.2% of the sample was employed for two-years. On average, the sample earned $2,657$ per quarter. According to the $Moran's I$ test, the dependent variables showed spatial autocorrelations with the sample’s residential locations.
Table IV-1. Dependent variables: Employment success

<table>
<thead>
<tr>
<th>Dependent variables</th>
<th>Mean</th>
<th>SD</th>
<th>Range</th>
<th>Moran’s I</th>
<th>z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job retention</td>
<td>5.36</td>
<td>2.77</td>
<td>1-8</td>
<td>.000</td>
<td>26.936***</td>
</tr>
<tr>
<td>The last quarters of continual employment since the 1st quarter</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Two-year employment</td>
<td>45.2%</td>
<td>n/a</td>
<td>0 or 1</td>
<td>.000</td>
<td>32.77***</td>
</tr>
<tr>
<td>Average quarterly earnings ($)</td>
<td>2656.87</td>
<td>1772.09</td>
<td>101-28784</td>
<td>.001</td>
<td>141.7***</td>
</tr>
</tbody>
</table>

Note. N=13,788, *p<.05, **p<.01, ***p<.001
Figure IV-1. Distribution of job retention

The last quarter that the sample retained employment (N=13,788)
Figure IV-2. Distribution of average quarterly earnings

Average quarterly earnings ($) (N=13,788)
Figure IV-3. Geographic distribution of job retention

Average job retention (quarters) by census tracts

- 1.0 - 3.5
- 3.6 - 5.0
- 5.1 - 6.0
- 6.1 - 7.0
- 7.1 - 8.0

Source: 1. TANF data 2000-2003
2. QWR

Moran’s I = .000, z = 26.936 (p < .001)
Figure IV-4. Geographic distribution of two-year employment

% of two-year employment by census tracts
- 0% - 15%
- 15.1% - 40%
- 40.1% - 55%
- 55.1% - 80%
- 80.1% - 100%

Source: 1. TANF data 2000-2003
2. QWR
Moran’s I=.000, z=32.77 (p<.001)
Figure IV-5. Geographic distribution of average quarterly earnings

Average quarterly earnings by census tracts
- 214 - 2000
- 2001 - 3000
- 3001 - 4000
- 4001 - 5000
- 5001 - 7533

Source: 1. TANF data 2000-2003
2. QWR
Moran's I=.000, z=141.7 (p<.001)
4.1.2. Individual-level variables

The individual-level variables consisted of demographics, human capital variables, involuntary exit of cash assistance, and job access variable(s) (See Table IV-2). Demographic variables were age, race, and number of children at the point of exiting cash assistance. The sample’s average age was 28.9 (SD=7.39). The ethnic majority was African-Americans (76.5 percent). On average, the sample had 2.15 children (SD=1.24) at the point of exiting cash assistance.

Human capital variables were comprised of two variables, a high-school diploma and work-experience. The results showed that 56.5 percent had a high school diploma at the point of exiting cash assistance. While 60.5 percent were employed one quarter before exiting cash assistance. In other words, six of ten continued to be employed at the point of exiting cash assistance.

Individual job access was defined as the distance between a residential place and workplaces of the sample. The average distance between a residential place and workplaces was measured because each sample had a different number of workplaces during the time frame. Moreover, this study measured two types of job access in accordance with the dependent variables’ attributes (See Table III-2). Job access (A) was the average distance between a residential place and all workplaces during the time the sample was continuously employed since the first quarter of exiting cash assistance. Job access (A) was used for the statistical model with job retention. The average score of job access (A) was 7.34 miles (SD=5.99). Regardless of job retention, job access (B) was measured by the average distances between a residential place and workplaces within
eight quarters after exiting cash assistance. This variable was used in the main analyses including two-year employment and average quarterly earnings. The average job access (B) was 7.36 miles (SD=5.83).
### Table IV-2. Individual-level variables

<table>
<thead>
<tr>
<th></th>
<th>Mean (%)</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age (Year)</strong></td>
<td>28.90</td>
<td>7.39</td>
<td>18</td>
<td>60</td>
</tr>
<tr>
<td><strong>Race</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>African-Amercans (Yes=1)</td>
<td>(75.5)</td>
<td>-</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Whites (Yes=1)</td>
<td>(17.2)</td>
<td>-</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Reference: Others</td>
<td>(8.3)</td>
<td>-</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>Number of children</strong></td>
<td>2.15</td>
<td>1.24</td>
<td>1</td>
<td>11.0</td>
</tr>
<tr>
<td><strong>High school diploma (Yes=1)</strong></td>
<td>(56.6)</td>
<td>-</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>Employed before exiting (Yes=1)</strong></td>
<td>(60.5)</td>
<td>-</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>Involuntary exit of cash assistance (Yes=1)</strong></td>
<td>(18.2)</td>
<td>-</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>Job access (A): Mean distance between a residential place and workplaces with continuous employment since the 1st quarter</strong></td>
<td>7.34</td>
<td>5.99</td>
<td>0.02</td>
<td>62.47</td>
</tr>
<tr>
<td><strong>Job access (B): Mean distance between a residential place and workplaces within 8 quarters</strong></td>
<td>7.36</td>
<td>5.83</td>
<td>0.02</td>
<td>62.47</td>
</tr>
</tbody>
</table>

N=13,788
4.1.3. Neighborhood-level variables

Neighborhood-level variables were comprised of two blocks, neighborhood disadvantage and neighborhood public transportation access. The unit of analysis for neighborhoods was a 2000 census tract in Cuyahoga County, Ohio. Cuyahoga County consisted of 502 census tracts in 2000 Census data (U.S Census Bureau, 2012). The sample of lived in 445 census tracts. Therefore, these 445 census tracts were used as a unit of neighborhoods in this study (See Table IV-3).

4.1.3.1. Neighborhood disadvantage

Based on a previous study, neighborhood disadvantage was operationalized through six neighborhood variables (Sampson, et al., 1997). The average neighborhood poverty rate was 17.91 percent (SD=16.191). The average proportion of households on public assistance in neighborhoods was 7.53 percent (SD=8.366). On average, the neighborhoods had 32.49 percent of female-headed families (SD=18.616). The average neighborhood unemployment rate was 4.96 percent (SD=4.033). The average proportion of young people (less than 18 years old) in neighborhoods was 25.66 percent (SD=7.576). The average proportion of African-Americans in the neighborhoods was 37.84 percent (SD=38.963).

Afterward, PCA was conducted for data reduction of these six items. The factorability of neighborhood disadvantage was examined in three ways. First of all, the results of Bartlett’s Sphericity was significant ($\chi^2(15)=2664.794$, $p<.001$) (Pett et al., 2003). The six items of neighborhood disadvantage represented a high value of KMO
measure of sampling adequacy (KMO=.797) (Pett et al., 2003). On the Anti-image correlation’s matrix, each item of neighborhood disadvantage represented a high value of MSA (the lowest value of MSA=.705). In sum, these results supported the factorability of the six items.

After checking the factorability, the dimensionality of these six items was tested (Sampson, et al., 1997). According to the eigenvalue and a scree plot, the six items for neighborhood disadvantage accepted unidimensionality (eigenvalue>1) (Pett et al., 2005). As a result of PCA, the total variance of the unidimensionality is 73.51 percent. Because PCA suggested unidimension of the six items, the rotation issue was not discussed. In sum, the six items for neighborhood disadvantage were summarized into one aggregated score which was a factor score according to the results of PCA.

Similar to the previous study, this study named one dimension of the six items as neighborhood disadvantage (Sampson et al., 1997). By aggregating the six items, the factor scores of neighborhood disadvantage were produced (Sampson et al., 1997). As a result, the average factor scores of neighborhood disadvantage was 0 (SD=1). The distribution of neighborhood disadvantage by census tracts is mapped on Figure IV-6.

4.1.3.2. Neighborhood public transportation access

As a proxy for neighborhood job access through public transportation, this study included the percent of workers’ use of public transportation from 2000 Census data. The average proportion of workers using public transportation to commute in neighborhoods was 9.7 percent (SD=9.470). The distribution of neighborhood public transportation access is visualized (See Figure IV-7).
Table IV-3. Neighborhood-level variables and PCA of Neighborhood disadvantage

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>Range</th>
<th>Factor loading&lt;sup&gt;b)&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Neighborhood disadvantage</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Factor scores)&lt;sup&gt;a)&lt;/sup&gt;</td>
<td>0</td>
<td>1</td>
<td>(-1) – 3</td>
<td>n/a</td>
</tr>
<tr>
<td>Individuals below poverty threshold (%)</td>
<td>17.91</td>
<td>16.191</td>
<td>0-100</td>
<td>.916</td>
</tr>
<tr>
<td>Household on public assistance (%)</td>
<td>7.53</td>
<td>8.366</td>
<td>0-59</td>
<td>.901</td>
</tr>
<tr>
<td>Female-headed families (%)</td>
<td>32.49</td>
<td>18.616</td>
<td>5-91</td>
<td>.958</td>
</tr>
<tr>
<td>Unemployed (%)</td>
<td>4.96</td>
<td>4.033</td>
<td>0-27</td>
<td>.847</td>
</tr>
<tr>
<td>Less than aged 18 (%)</td>
<td>25.66</td>
<td>7.576</td>
<td>1-56</td>
<td>.722</td>
</tr>
<tr>
<td>African-Americans (%)</td>
<td>37.84</td>
<td>38.963</td>
<td>0-100</td>
<td>.778</td>
</tr>
<tr>
<td><strong>Neighborhood public transportation access</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workers’ use of public transportation for commuting (%)</td>
<td>9.70</td>
<td>9.470</td>
<td>0-58</td>
<td>n/a</td>
</tr>
</tbody>
</table>

**Source:** 2000 Census data (U.S. Census Bureau, 2012; www.census.gov)

**Note.**
Number of neighborhoods=445 census tracts in Cuyahoga County, Ohio.

a) Factor loading produced by PCA with 6 items.

b) **Bartlett’s Sphericity** was significant ($\chi^2(15)=2664.794, p<.001$)
   
   KMO=.797; Eigenvalue=4.411; Total variance explained(%)=73.51
Figure IV-6. Geographic distribution of neighborhood disadvantage

Source: 2000 Census data
Figure IV-7. Geographic distribution of neighborhood public transportation access

Public transportation access by census tracts
- 0% - 7.3%
- 7.4% - 16%
- 16.1% - 30%
- 30.1% - 58.1%

Source: 2000 Census data
4.1.4. Bivariate correlations

Prior to conducting the main analysis, the bivariate correlations among all variables were tested. These results provided an overview of the basic relationships among all variables. Thus, the bivariate correlations observed the natural characteristics of the sample. The bivariate correlations among individual-level variables including the dependent variables were tested at individual-level (N=13,788; See Table IV-4).

The dependent variables were highly correlated with each other. The correlation between job retention and two-year employment was .9 \((eta=.86, p<.001)\). The correlation between two-year employment and average quarterly earnings was .5 \((eta=.49, p<.001)\). And finally, the correlation between job retention and average quarterly earnings was .5 \((r=.50, p<.001)\).

The relationship between demographic variables and other variables were also explored. Results indicated that age was highly correlated with the dependent variables \((corr\ (Job\ retention,\ age)=.08;\ corr\ (2-yr\ employment,\ age)=.08;\ corr\ (Average\ quarterly\ earnings,\ age)=.12;\ p<.001)\). In other words, the older sample tended to be more successful in employment. Average quarterly earnings of African-Americans were higher than other groups \((eta=.04, p<.001)\). Age and the number of children were positively correlated \((r=.17, p<.001)\). Additionally, African-Americans had more children than other ethnic groups in the sample \((eta=.05, p<.001)\).
Several relationships between human capital variables and other variables were identified. A high-school diploma and work-experience were positively correlated with the dependent variables (corr (Job retention, work-experience)=.15; corr (2-yr employment, work-experience)=.14; corr(Average quarterly earnings, work-experience)=.12; $p<.001$). The elder sample had a higher human capital, such as a high school diploma and work-experience (corr(work-experience, age)=.02, $p<.05$; corr(high-school diploma)=.15, $p<.001$). African-Americans had more human capital than other groups (corr(African-Americans, work-experience)=.07; corr(African-Americans, high school diploma)=.07; $p<.001$). Conversely, Whites had a lower human capital than other groups (corr(Whites, work-experience)=-.04; corr(Whites, high school diploma)=-.03; $p<.001$). The number of children and human capital variables were negatively correlated (corr(Number of children, work-experience)=-.03, $p<.01$; corr(Number of children, high school diploma)=-.08, $p<.001$) ($p<.01$).

Involuntary exit of cash assistance had significant correlations with other variables. This variable was negatively correlated with the dependent variables (corr(Involuntary exit, job retention)=-.12; corr(Involuntary exit, 2-yr employment)=-.10; corr(Involuntary exit, average quarterly earnings)=-.17; $p<.001$). It was positively correlated with age ($eta.=.05, p<.001$). Involuntary exit of cash assistance was positively correlated with African-Americans ($r=.05, p<.001$) and negatively correlated with Whites ($r=-.06, p<.001$). The number of children was positively correlated with the involuntary exit ($eta.=.23, p<.001$). The human capital variables (a high school diploma and work-experience) were negatively correlated with involuntary exit of cash assistance
(corr(Involuntary exit, high school diploma) = -0.09; corr(Involuntary exit, work-experience) = -0.08; \( p < 0.001 \)).

Individual job distance (access) was correlated with average quarterly earnings, age, Whites, and a high school diploma. Specifically, it had a negative relationship with average quarterly earnings \( (r = -0.03, p < 0.001) \). The older sample had a shorter job distance than the younger one \( (r = -0.05, p < 0.001) \). Whites had a longer job distance than other groups \( (\text{eta.} = -0.03, p < 0.05) \). The sample with a high school diploma had a shorter job distance than those who without it \( (\text{eta.} = -0.02, p < 0.001) \).

In sum, the bivariate correlations showed the simple relationships among the variables. Among individual-level variables, human capital variables, and involuntary exit of cash assistance were consistently correlated with the dependent variables.
Table IV-4. Bivariate correlations at the individual-level

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.Job retention (quarter)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.Two-year employment (Yes=1)</td>
<td>.49***</td>
<td>.08***</td>
<td>.02</td>
<td>-.00</td>
<td>-.01</td>
<td>.13***</td>
<td>.14***</td>
<td>-.10***</td>
<td>-.01</td>
<td>-.02</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.Average quarterly Earnings ($)</td>
<td>.12***</td>
<td>.04***</td>
<td>-.04***</td>
<td>-.01</td>
<td>.24***</td>
<td>.12***</td>
<td>-.17***</td>
<td>-.03**</td>
<td>-.03***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.Age (Year)</td>
<td>.01</td>
<td>.00</td>
<td>.17***</td>
<td>.15***</td>
<td>.02*</td>
<td>.05***</td>
<td>-.05***</td>
<td>-.05***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5.African-Americans (Yes=1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6.Whites (Yes=1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7.Number of children</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8.High school graduation (Yes=1)</td>
<td>.06***</td>
<td>-.09***</td>
<td>-.02*</td>
<td>-.02*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9.Work-experience (Yes=1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10.Involuntary exit (Yes=1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11.Job access (A) (Miles)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12.Job access (B) (Miles)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.96***</td>
</tr>
</tbody>
</table>

Note. N=13,788, *p<.05, **p<.01, ***p<.001
4.2. Job retention

To address the first research question, this study estimated a multi-level model for the dependent variable’s length of continuous employment within eight quarters after exiting cash assistance. Since this was a count variable with the same exposure and markedly skewed, the modeling was accomplished by HGLM with a Poisson sampling model (Raudenbush & Bryk, 2002; Raudenbush et al., 2011). This section reports the hypotheses of Research question one (See Table IV-5).

4.2.1. Model 1: Null model

As the initial model, Model 1 tested whether there was a significant difference in job retention by neighborhoods in which the sample resided at the point of exiting cash assistance (H1a). As a result, Model 1 identified that there was a significant variance of job retention among neighborhoods (Between-neighborhood variance=.005, \(\chi^2(444)=823.846, p<.001\)). Under normality of the log-event rate, most job retention was expected to be between 5.347 and 5.470, an indicator of significant variance among neighborhoods (\(\beta=1.688, \exp(\beta)=5.408, t(444)=292.199, p<.001\)). According to this model, the sample, on average, was continuously employed for 5.41 quarters since the first quarter of exiting cash assistance.

4.2.2. Model 2: Random-intercept model

As a random-intercept model, Model 2 included only individual-level variables to test the association between job retention and the individual-variables (H1b & H1c). The
residual between neighborhoods variance of this model was decreased into .003, compared to the null model (Model 1). After controlling for the individual-level variables, there was still a significant variance of job retention among neighborhoods (Between-neighborhood variance=.003, $\chi^2(444)=677.224, p<.001$).

Among these eight individual-level variables, age, education, work-experience, and involuntary exit of cash assistance were associated with job retention in the sample. Specifically, as the sample’s age at the point of exiting cash assistance increased by one year, the possibility of their job retention increased by .4 percent ($exp(.004)=1.004$, $t(13335)=6.836, p<.001$). All of the human capital variables predicted the possibility of job retention. The portion of the sample with a high school diploma was 1.12 times more likely to be continuously employed than those without it ($exp(.112)=1.118$, $t(13335)=11.847, p<.001$). The sample that had been employed one quarter before exiting cash assistance was 1.15 times more likely to retain their employment one more quarter than the sample that had not ($exp(.139)=1.149$, $t(13,335)=14.132, p<.001$). The sample who involuntarily exited cash assistance was 1.15 (=1/0.868) times less likely to retain one more employed quarter than those who did not ($exp(-.142)=.868$, $t(13,335)=-10.599, p<.001$).

4.2.3. Model 3: Random-intercept regression model

As a random-intercept regression model, Model 3 included only neighborhood-level variables (H1d & H1e). The residual between-neighborhoods variance was estimated to be .004, less than the unconditional variance of .005 (Model 1). Even after controlling for the neighborhood-level variables, a significant variation of job retention
by neighborhoods still remained to be explained (Between-neighborhood variance=.004, $\chi^2(444)=733.339, p<.001$).

This model showed a negative association between neighborhood disadvantage and job retention. A point increase in neighborhood disadvantage multiplied job retention probability by 14.1 percent decrease ($\exp(-.042)=.959, t(13,335)=-4.630, p<.001$). This result was demonstrated on a map (See Figure IV-8). However, there was no association between neighborhoods public transportation access and job retention ($p>0.05$).

4.2.4. Model 4: Random-intercept ANCOVA model

As the final model, Model 4 was the combination of Model 2 and Model 3. This model included all individual- and neighborhood-level variables (H1a to H1e). Overall, Model 4 decreased the variance of the intercept compared to the previous models (Model 1, 2, & 3); the between-neighborhood variance of this model was .002. A significant variation of job retention among neighborhoods remained even after controlling for individual- and neighborhood-level variables (Between-neighborhood variance level $2=.002, \chi^2(442)=641.654, p<.001$).

Similar to the results of Model 2, four variables were significantly associated with job retention such as age, high school diploma, work-experience, and involuntary exit of cash assistance. As the sample’s age at the point of exiting cash assistance increased by one year, the possibility of being employed one more quarter increased 1.004 times ($\exp(.004)=1.004, t(13,335)=6.701, p<.001$). All of the human capital variables predicted job retention of the sample. The sample with a high school diploma had a 1.12
times higher possibility to extend employment one more quarter than those without it \((exp(.109)=1.115, t(13,335)=11.477, p<.001)\). The sample that had been employed one quarter before exiting cash assistance was 1.15 times more likely to keep their employment one more quarter the those who had not \((exp(.138)=1.148, t(13,335)=14.100, p<.001)\). However, also of note, there was no association between the job distance and job retention \((p>.05)\).

Among the neighborhood-level variables, the level of neighborhood disadvantage negatively affected job retention of the sample. As the score of neighborhood disadvantage increased by one point, the possibility of job retention decreases approximately by 2.8 percent \((exp(-.028)=.972, t(13,335)=-3.313, p<.001)\). This result was also shown on Figure IV-8. Like the results of Model 3, neighborhood public transportation access was not associated with job retention \((p>.05)\).

In sum, there was a variation of job retention by neighborhoods (H1a). Age, human capital variables, and involuntary exit of cash assistance influenced job retention of the sample (H1b). Neighborhood disadvantage was negatively associated with the possibility of job retention (H1e). However, individual job access and neighborhood public transportation access were not associated with job retention of female former welfare recipients (H1c & H1d).
### Table IV-5. HGLM with a Poisson distribution of job retention

<table>
<thead>
<tr>
<th>Model</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed effect</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>$\beta$</td>
<td>$t$</td>
<td>$\exp(\beta)$</td>
<td>$\beta$</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.688</td>
<td>292.199***</td>
<td>5.408</td>
<td>1.532</td>
</tr>
<tr>
<td><strong>Individual-level</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (year)</td>
<td>.004</td>
<td>6.836***</td>
<td>1.004</td>
<td>.004</td>
</tr>
<tr>
<td>African-Americans (=1)</td>
<td>.023</td>
<td>1.215</td>
<td>1.023</td>
<td>.023</td>
</tr>
<tr>
<td>Whites (=1)</td>
<td>.028</td>
<td>1.501</td>
<td>1.029</td>
<td>.028</td>
</tr>
<tr>
<td># of children</td>
<td>.005</td>
<td>1.352</td>
<td>1.005</td>
<td>.005</td>
</tr>
<tr>
<td>High school diploma (=1)</td>
<td>.112</td>
<td>11.847***</td>
<td>1.118</td>
<td>.112</td>
</tr>
<tr>
<td>Employed one quarter before exit (=1)</td>
<td>.139</td>
<td>14.132***</td>
<td>1.149</td>
<td>.139</td>
</tr>
<tr>
<td>Involuntary exit (=1)</td>
<td>-.142</td>
<td>-10.599***</td>
<td>.868</td>
<td>-.142</td>
</tr>
<tr>
<td>Job distance (A) (Miles)</td>
<td>-.000</td>
<td>-.322</td>
<td>.999</td>
<td>-.000</td>
</tr>
<tr>
<td><strong>Neighborhood-level</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neighborhood disadvantage (score)</td>
<td>-0.042</td>
<td>-4.630***</td>
<td>.959</td>
<td>-0.042</td>
</tr>
<tr>
<td>% of workers’ using public transportation</td>
<td>0.001</td>
<td>1.642</td>
<td>1.001</td>
<td>0.001</td>
</tr>
<tr>
<td><strong>Model $\chi^2$</strong></td>
<td>823.846***</td>
<td></td>
<td>677.224***</td>
<td></td>
</tr>
<tr>
<td>Between-neighborhood variance</td>
<td>.005</td>
<td>.003</td>
<td>0.004</td>
<td>.004</td>
</tr>
</tbody>
</table>

**Note.** Dependent variable=The last quarter of continual employment since the 1st quarter (Range 1 to 8)  
N of individuals=13,788; N of neighborhoods=445;  $p<.05$,  $**p<.01$,  $***p<.001$
Figure IV-8. Neighborhood disadvantage and job retention

Source: 1. TANF data 2000-2003
2. QWR
3. 2000 Census data
(N=13,788; N of tracts=445)
4.3. Two-year employment

As one of the indicators to measure employment success, the success of two-year employment was tested. Two-year employment means that female former welfare recipients retain their employment for eight quarters without losing a job. Because two-year employment is a dichotomous variable, it was tested by HGLM with a Bernoulli distribution (Raudenbush & Bryk, 2002; Raudenbush et al., 2011; See Table IV-6).

4.3.1. Model 5: Null model

As the initial model, Model 5 tested whether there was a significant difference in the probability of two-year employment among neighborhoods in which the sample resided at the time of exiting cash assistance (H2a). According to the variance components, there was a significant variance of the probability of two-year employment among neighborhoods (Between-neighborhood variance=.050, $\chi^2(444)=610.866, p<.001$).

4.3.2. Model 6: Random-intercept model

As a random-intercept model, Model 6 subsumed only individual-level variables to test the association between the probability of two-year employment and the individual-variables in consideration of neighborhood variances (H2b & H2c). This model decreased its between-neighborhood variance compared to the previous model. Likewise, there was a variance of the probability of two-year employment among neighborhoods (Between-neighborhood variance=.029, $\chi^2(444)=534.320, p<.001$).
Similar to the model with job retention (specifically, Model 2), this model identified the age effect on the possibility of two-year employment. As the sample’s age at the point of exiting cash assistance increased by one year, the possibility of two-year employment increased by 1.8 percent ($exp(.018)=1.018$, $t(13,335)=7.466$, $p<.001$).

All of the human capital variables influenced the possibility of two-year employment. The sample with a high school diploma had a 1.52 times higher possibility of two-year employment than those without it ($exp(.417)=1.517$, $t(13,335)=11.652$, $p<.001$). The sample with work-experience before exiting cash assistance was 1.68 times more likely to be employed for two years than those without it ($exp(.519)=1.681$, $t(13,335)=14.312$, $p<.001$). Furthermore, the sample who involuntarily exited cash assistance was 1.64 times less likely to be employed for two years than who did not ($exp(-.496)=.608$, $t(13,335)=-9.291$, $p<.001$).

4.3.3. Model 7: Random-intercept regression model

As a random-intercept regression model, Model 7 included only the neighborhood-level variables such as neighborhood disadvantage and public transportation access (H2d & H2e). Compare to the null model (Model 5), the neighborhood-level variables contributed to decreasing the between-neighborhood variance. The amount of between-neighborhood variance in this model was .036; as well, the significant variance of between-neighborhood still remained (Between-neighborhood variance=.036, $\chi^2(44)=557.357$, $p<.001$).

Among the neighborhood-level variables, the level of neighborhood disadvantage negatively affected the probability of two-year employment. As the score of
neighborhood disadvantage increased by one point, the possibility of two-year employment decreased approximately by 14 percent \((exp(-.146)=.864, t(13,335)=-4.204, p<.001)\). This result was also mapped on Figure IV-9. However, neighborhood public transportation access was not associated with two-year employment \((p>.05)\).

4.3.4. Model 8: Random-intercept ANCOVA model

As the final model, Model 8 was the combination of Model 6 and Model 7 to test effects of all individual- and neighborhood-level variables on the probability of two-year employment. Compared to three previous models (Model 5, 6, & 7), Model 8 decreased its between-neighborhood variance. Specifically, the between-neighborhood variance of this model was .022; after controlling for individual- and neighborhood-level variables, this model showed the significant between-neighborhood variance in the probability of two-year employment \((Between-neighborhood\ variance=.021, \chi^2(442)=509.562, p<.05)\).

Among the individual-level variables, age and race influenced the probability of two-year employment of the sample. As the sample’s age at the point of exiting cash assistance increased by one year, the possibility of two-year employment increased by 1.8 percent \((exp(.018)=1.018, t(13,335)=7.380, p<.001)\). The likelihood of two-year employment among African-Americans was 1.17 times higher than the reference group \((exp(.155)=1.168, t(13,335)=2.004, p<.05)\).

All of the human capital variables affected the likelihood of two-year employment. The sample with a high school diploma had 1.49 times higher probability of two-year employment than those without it \((exp(.401)=1.493, t(13,335)=11.226, p<.001)\). The sample with work-experience before exiting cash assistance was 1.68 times
more likely to be employed for two years than those without it ($exp(.518)=1.678$, $t(13,335)=14.262, p<.001$). Moreover, the sample who involuntarily exited cash assistance was 1.63 times less likely to be employed for two years than those who did not ($exp(-.487)=.615$, $t(13,335)=-9.031, p<.001$).

Among the neighborhood-level variables, neighborhood disadvantage affected the probability of two-year employment. As the score of neighborhood disadvantage increases by one point, the sample’s likelihood of two-year employment decreased approximately by 7 percent ($exp(-.102)=.903$, $t(442)=-3.078, p<.01$) (See Figure IV-9).

In sum, there was a significant variance of two-year employment among neighborhoods (H2a). Moreover, demographic (age and African-Americans), human capital (educational attainment and work-experience), and involuntary exit of cash assistance were associated with the probability of two-year employment (H2b). Individual job access and neighborhood public transportation access were not associated with the likelihood of two-year employment (H2c & H2d). Finally, neighborhood disadvantage adversely affected the probability of two-year employment of female former welfare recipients (H2e).
Table IV-6. HGLM with a Bernoulli distribution of two-year employment

<table>
<thead>
<tr>
<th>Model</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed effect</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-.172</td>
<td>-7.553***</td>
<td>.842</td>
<td>-.757</td>
</tr>
<tr>
<td><strong>Individual-level</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (year)</td>
<td>.018</td>
<td>7.466***</td>
<td>1.018</td>
<td>.018</td>
</tr>
<tr>
<td>African-Americans (=1)</td>
<td>.118</td>
<td>1.573</td>
<td>1.125</td>
<td>.081</td>
</tr>
<tr>
<td>Whites (=1)</td>
<td>.017</td>
<td>1.251</td>
<td>1.017</td>
<td>.020</td>
</tr>
<tr>
<td># of children</td>
<td>.417</td>
<td>11.652***</td>
<td>1.517</td>
<td>.401</td>
</tr>
<tr>
<td>High school diploma (=1)</td>
<td>.519</td>
<td>14.312***</td>
<td>1.681</td>
<td>.518</td>
</tr>
<tr>
<td>Employed one quarter before exit (=1)</td>
<td>-.497</td>
<td>-9.291***</td>
<td>.608</td>
<td>-.487</td>
</tr>
<tr>
<td>Involuntary exit (=1)</td>
<td>-.004</td>
<td>-1.427</td>
<td>.996</td>
<td>-.005</td>
</tr>
<tr>
<td>Job distance (B) (Miles)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Neighborhood-level</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neighborhood disadvantage (score)</td>
<td>-.146</td>
<td>-4.204***</td>
<td>.864</td>
<td>-.102</td>
</tr>
<tr>
<td>% of workers’ using public transportation</td>
<td>.003</td>
<td>.976</td>
<td>1.003</td>
<td>.001</td>
</tr>
<tr>
<td><strong>Model χ²</strong></td>
<td>610.866***</td>
<td>534.320***</td>
<td>557.357***</td>
<td>509.562*</td>
</tr>
<tr>
<td>Between-neighborhood variance</td>
<td>.050</td>
<td>.029</td>
<td>.036</td>
<td>.021</td>
</tr>
</tbody>
</table>

**Note.** Dependent variable=Two-year employment (Yes=1)  
N of individuals=13,788; N of neighborhoods=445; *p<.05, **p<.01, ***p<.001
Figure IV-9. Neighborhood disadvantage and two-year employment

Source: 1. TANF data 2000-2003  
2. QWR  
3. 2000 Census data  
(N=13,788; N of tracts=445)
4.4. Average quarterly earnings

The third measure of the employment success of female former welfare recipients is average quarterly earnings within eight quarters after exiting cash assistance. A two-level model was established to test the effects of individual- and neighborhood-level variables on average quarterly earnings. Different from the above models, the average quarterly earnings were modeled by HLM because it was a numeric variable and normally distributed (Raudenbush & Bryk, 2002; Raudenbush et al., 2011; See Table IV-7).

4.4.1. Model 9: Null model

As the unconditional model, the analysis began with fitting a one-way random-effects ANOVA model in order to determine the total amount of variability in average quarterly earnings within and between-neighborhoods (H3a). The mean of the average quarterly earnings was estimated as $2,735.21. The pooled within-neighborhood variance was 303,358.868; the between-neighborhood variance of this model was 134,512.758. In sum, there was a significant variance of average quarterly earnings among neighborhoods ($\chi^2(444)=1022.295, p<.001$). Using these variance components, the proportion of variance between neighborhoods was estimated as 30.7 percent (ICC=.307). Around 31 percent of the variance in average quarterly earnings was due to the difference across the sample’s neighborhoods.
4.4.2. Model 10: Random-intercept model

As a random-intercept model, Model 10 tested the effect of individual-level variables on average quarterly earnings by neighborhoods (H3b & H3c). Compared to the null model (Model 9), the model fit was improved. By using the variance components, the ICC of this model was .019; approximately, 3 percent of the variance in average quarterly earnings was due to the difference across neighborhoods of the sample. Based on the null model (Model 9), the total variance explained by this model was improved to 59.2 percent. After controlling for the individual-level variables, there was a significant variance of average quarterly earnings among neighborhoods (Between-neighborhood variance=54900.214, $\chi^2$(444)=777.497, $p<.001$).

This model identified the effect of demographic, human capital, and involuntary exit of cash assistance on average quarterly earnings of the sample. Specifically, age affected average quarterly earnings. As the sample’s increased by one, its average quarterly earnings increased by $21.3 (\beta=21.332, t(13335)=10.332, p<.001)$. The average quarterly earnings for Whites was $212 less than the reference group ($\beta=-221.837, t(13335) = -3.218, p<.001$). The number of children also affected average quarterly earnings. As the number of children increased by one, the sample’s average quarterly earnings increased by $46 (\beta=46.003, t(13335)=3.697, p<.001)$.

Two human capital variables influenced average quarterly earnings. The sample with a high school diploma at the point of exiting cash assistance earned $703 per quarter more than the sample without it ($\beta=702.613, t(13335)=23.482, p<.001$). The sample having employed one quarter before exiting cash assistance earned $341 per quarter more
than its counterparts ($\beta=340.687$, $t(13335)=11.181$, $p<.001$). As well, the sample that involuntarily exited cash assistance earned $721 per quarter less than those who did not ($\beta=-721.072$, $t(13335)=-20.505$, $p<.001$).

Finally, job access affected the average quarterly earnings of the sample. As the sample’s mean distance between a residential place and workplaces increased by one mile, its average quarterly earnings decreased by $8 (\beta=-8.245$, $t(13335)=-3.321$, $p<.001$).

4.4.3. Model 11: Random-intercept regression model

As the random-intercept regression model, Model 11 only contained the neighborhood-level variables, such as neighborhood disadvantage and neighborhood public transportation access (H3d & H3e). This model was enhanced compared to the null model (Model 9). The ICC of this model was .023; that of the null model was .307. On a basis of the null model, the proportion of variance explained by this model was 45.8 percent. After controlling for the neighborhood-level variables, this model showed a significant variance of average quarterly earnings among neighborhoods ($\text{Between-neighborhood variance}=72903.019$, $\chi^2(442)=803.041$, $p<.001$).

Both neighborhood-level variables affected average quarterly earnings of the sample. As the score of neighborhood disadvantage increased by one, the sample’s average quarterly earnings decreased by $267 (\beta=-267.110$, $t(442)=-7.656$, $p<.001$). The bivariate relationship between the mean of average quarterly earnings by neighborhoods and neighborhood disadvantage is illustrated on the map (See Figure IV-10).
Furthermore, as neighborhood’s percentage of workers’ using public transportation increased by one percent, average quarterly earnings of the sample increased by $8 (\beta=-7.772, t(442)=-2.370, p<.05). The bivariate correlation between the mean of average quarterly earnings by neighborhoods and neighborhood public transportation access is also visualized on the map (See Figure IV-11).

4.4.4. Model 12: Random-intercept ANCOVA model

As the final model for average quarterly earnings, Model 12 included all individual- and neighborhood-level variables (H3a to H3e). Compared to the previous models (Model 9, 10, and 11), Model 12 was improved and obtained more explanatory power. The ICC of this model was .006, which is much smaller than that of the null model. The variance explained by this model was 87.6 percent. After including the individual- and neighborhood-level variables, there was a significant variance of average quarterly earnings among neighborhoods (Between-neighborhood variance=16686.603, \(\chi^2(442)= 631.374, p<.001\)).

Like the results of Model 10, individual-level variables influenced on average quarterly earning even after controlling for the neighborhood-level variables. As the sample’s age increased by one year, average quarterly earnings increased by $20.7 (\beta=20.730, t(13335)=10.146, p<.001). Whites earned $260 less than the reference group (\(\beta=-260.356, t(13335)=-3.395, p<.001\)). As the sample had one more child, its average quarterly earnings increased by $49 (\beta=48.594, t(13335)=3.890, p<.001).

Human capital variables significantly predicted average quarterly earnings. The sample with a high school diploma earned $684 more than its counterparts (\(\beta=684.117, t(13335)=22.581, p<.001\)). The sample that had been employed one quarter before exiting
cash assistance earned $338 more than those who had not ($β=338.333, t(13335)=11.106, $p<.001$). Average quarterly earnings of the sample that involuntarily exited cash assistance were $708 lower than those who did not ($β=-708.026, t(13335)=-19.906, p<.001$).

Different from the models with job retention and two-year employment (Model 1 to 8), this model showed that individual job access affected average quarterly earnings of the sample after controlling for neighborhood-level variables (H3c). As the mean distance between a residential place and workplaces increased by one mile, average quarterly earnings of the sample decreased by $9 ($β=-9.136, t(13335)=-3.668, p<.001$).

Similarly to Model 11, the neighborhood-level variables significantly influenced on average quarterly earnings after controlling for the individual-level variables. As the score of neighborhood disadvantage increased by one point, average quarterly earnings of the sample decreased by $229 ($β=229.634, t(442)=-7.994, p<.001$; See Figure IV-10). This result showed that female former welfare recipients in more disadvantaged neighborhoods earn less than those their counterparts (H3e). What is more, neighborhood public transportation access also influenced average quarterly earnings of the sample. As the neighborhood percentage of workers’ using public transportation increased by one, average quarterly earnings of the sample in the neighborhood increases by $6 ($β=6.661, t(442)=2.542, p<.05$; See Figure IV-11). Therefore, this result showed the association between the condition of neighborhood public transportation access and average quarterly earnings of the sample (H3d).
From Model 9 to Model 12, this section tested the effect of individual- and neighborhood-level variables on average quarterly earnings of female former welfare recipients. In sum, this section discovered that the variation of the female former welfare recipients’ earnings by neighborhoods (H3a). Similar to the previous studies on female former welfare recipients, this study identified that demographic (i.e., age, Whites, and number of children), human capital (i.e., high school diploma and work-experience), and involuntary exit of cash assistance influenced the average quarterly earnings of the female former welfare recipients (H3b). In particular, this section discovered the effects of neighborhood disadvantage and job access on average quarterly earnings. The longer job distance between a residential place and workplaces decreased average quarterly earnings of the female former welfare recipients (H3c). Female former welfare recipients in disadvantaged neighborhoods had fewer earnings (H3e). Finally, female former welfare recipients residing in a neighborhood with a higher public transportation access had more average quarterly earnings than those who reside in a neighborhood with lower public transportation access (H3d).
<table>
<thead>
<tr>
<th>Model</th>
<th>9</th>
<th></th>
<th>10</th>
<th></th>
<th>11</th>
<th></th>
<th>12</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed effect</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>2735.211</td>
<td>101.733***</td>
<td>2310.066</td>
<td>37.234***</td>
<td>2850.591</td>
<td>93.137***</td>
<td>2369.741</td>
<td>38.177***</td>
</tr>
<tr>
<td>Individual-level</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (year)</td>
<td>21.332</td>
<td>10.332***</td>
<td>20.730</td>
<td>10.146***</td>
<td>51.460</td>
<td>.773</td>
<td></td>
<td></td>
</tr>
<tr>
<td>African-Americans (=1)</td>
<td>-70.122</td>
<td>-1.042</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Whites (=1)</td>
<td>-211.837</td>
<td>-3.218***</td>
<td>-260.356</td>
<td>-3.395***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># of children</td>
<td>46.003</td>
<td>3.697***</td>
<td>48.594</td>
<td>3.890***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High school diploma (=1)</td>
<td>702.612</td>
<td>23.482***</td>
<td>684.117</td>
<td>22.581***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed one quarter before exit (=1)</td>
<td>340.687</td>
<td>11.181***</td>
<td>338.333</td>
<td>11.106***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Involuntary exit (=1)</td>
<td>-721.072</td>
<td>-20.505***</td>
<td>-708.026</td>
<td>-19.906***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Job distance (B) (Miles)</td>
<td>-8.245</td>
<td>-3.321***</td>
<td>-9.136</td>
<td>-3.668***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neighborhood-level</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neighborhood disadvantage (Score)</td>
<td></td>
<td></td>
<td>-267.110</td>
<td>-7.656***</td>
<td>-229.634</td>
<td>-7.994***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of use public transportation</td>
<td></td>
<td></td>
<td>7.772</td>
<td>2.370*</td>
<td></td>
<td></td>
<td>6.661</td>
<td>2.542*</td>
</tr>
<tr>
<td>Model $\chi^2$</td>
<td>1022.295***</td>
<td></td>
<td>777.497***</td>
<td></td>
<td>803.041***</td>
<td></td>
<td>631.374***</td>
<td></td>
</tr>
<tr>
<td>Between-neighborhood variance</td>
<td>134512.758</td>
<td></td>
<td>54900.214</td>
<td></td>
<td>72903.019</td>
<td></td>
<td>16686.507</td>
<td></td>
</tr>
<tr>
<td>Within-neighborhood variance</td>
<td>303335.868</td>
<td></td>
<td>2778557.656</td>
<td></td>
<td>3038858.725</td>
<td></td>
<td>2784241.484</td>
<td></td>
</tr>
<tr>
<td>Intra-class correlation</td>
<td>.307</td>
<td>.019</td>
<td>.023</td>
<td>.006</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>percent variance explained</td>
<td>n/a</td>
<td>59.186</td>
<td>45.802</td>
<td>87.595</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Note:** Dependent variable: Average quarterly earnings ($) within 8 quarters after exiting cash assistance
N of individuals=13,877; N of neighborhoods=445; *p<.05, **p<.01, ***p<.001
Figure IV-10. Neighborhood disadvantage and average quarterly earnings

<table>
<thead>
<tr>
<th>Neighborhood disadvantage by census tracts</th>
<th>Average quarterly earnings by census tracts</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2.5 - -0.2</td>
<td>214 - 2000</td>
</tr>
<tr>
<td>-0.1 - 0.0</td>
<td>2001 - 2500</td>
</tr>
<tr>
<td>0.1 - 1.5</td>
<td>2501 - 3000</td>
</tr>
<tr>
<td>1.6 - 2.6</td>
<td>3001 - 4000</td>
</tr>
<tr>
<td></td>
<td>4001 - 7533</td>
</tr>
</tbody>
</table>

Source: 1. TANF data 2000-2003
2. QWR
3. 2000 Census data
(N=13,788; N of tracts=445)
Figure IV-11. Neighborhood public transportation access and average quarterly earnings

Public transportation access by census tracts
- 0.0 - 7.0
- 7.1 - 15.0
- 15.1 - 30.0
- 30.1 - 58.1

Average quarterly earnings by census tracts
- 214 - 2500
- 2501 - 3000
- 3001 - 4000
- 4001 - 4500
- 4501 - 7533

Source: 1. TANF data 2000-2003
2. QWR
3. 2000 Census data
(N=13,788; N of tracts=445)
CHAPTER FIVE: DISCUSSION

5.1. Summary

This study aimed to test the effects of job access and neighborhood disadvantage on the employment success of female former welfare recipients in Cuyahoga County, Ohio. With that purpose, this study was grounded on two theoretical perspectives, (1) the SMH that explained poor employment outcomes or the barriers of distance from job opportunity and (2) Wilson’s observation that concentrated neighborhood disadvantage also undermines residents’ employment success through social processes (Kain, 1968; Wilson, 1987). By using administrative data and 2000 Census data, this study conducted multi-level statistical analyses on the employment success of female former welfare recipients (esp., HGLM and HLM). The findings of this study identified the effects of job access and neighborhood disadvantage on the employment success of female former welfare recipients as well as the effects of human capital. These effects and the contextual variables will be discussed in this chapter.

5.1.1. Background

During the policy shift from AFDC to TANF, the self-sufficiency of welfare recipients has emerged as an important issue. In actuality, losing a job or being laid-off are the most important reasons that the female former welfare recipients return to cash assistance (Loprest, 2002; Wu et al., 2006). The fact that female former welfare recipients often reside in distressed and isolated neighborhoods has been identified as a
barrier to their self-sufficiency and employment (Austin & Lemon, 2005; Allard, 2002; Allard & Danziger, 2003; Allen & Kirby, 2000; Coulton, 2005; Mendenhall et al., 2006). Nevertheless, few studies on welfare recipients have paid attention to the effects of job access and neighborhood disadvantage on the employment success of female former welfare recipients.

This study was guided by two theoretical perspectives, the SMH (Kain, 1968) and Wilson’s sociological observations on neighborhood disadvantage (Wilson, 1987). The SMH suggested that the location of jobs was an important facet of the context of work in the urban labor market, especially among low-skilled workers (Kain, 1968). According to Wilson’s sociological analysis (1987), the structural changes in the economy in the postindustrial era have adversely affected the employment prospects of families living in disadvantaged neighborhoods (Wilson, 1987). Together, these perspectives suggest that where welfare recipients live and work affects their employment success after exiting cash assistance.

5.1.2. Method

This study manipulated two administrative datasets from Cuyahoga County, Ohio (TANF data and QWR) and merged them with 2000 Census data on neighborhoods. After establishing eight criteria, 13,788 female former welfare recipients were selected who were employed after exiting cash assistance in 2000-2003. The employment success of female former welfare recipients was measured in three ways: (1) job retention, (2) two-year employment, and (3) average quarterly earnings within eight quarters after exiting cash assistance and being employed. The analytical models consisted of
individual- and neighborhood-level variables. Individual-level variables included demographics (age, race, and number of children), human capital (high school diploma and work-experience), involuntary exit of cash assistance, and job access (job distances between a residential place and workplaces). Collected from 2000 Census data, neighborhood-level variables included neighborhood disadvantage and neighborhood public transportation access (Sampson, et al., 1997). Using PCA, six items from 2000 Census data were aggregated into one factor score of neighborhood disadvantage in each census tract. As a main tool, multi-level analyses were used to test the effects of job access and neighborhood disadvantage on the employment of female former welfare recipients. In addition to the multi-level analyses, spatial analyses were used to visualize the results of the main analyses.

5.1.3. Summary of results

In accordance with the research objectives, this study established three research questions with 15 hypotheses. Multi-level analyses including HGLM and HLM tested these research hypotheses. According to the research questions and hypotheses, the results of this study are summarized as follows:
Research question one: How do job access and neighborhood disadvantage influence the female former welfare recipients’ job retention within eight quarters after exiting cash assistance and being employed?

H1a. There was a significant difference in job retention of female former welfare recipients by census tracts (Model 1).

H1b. The differences of the covariates (i.e., demographic, human capital, and involuntary exit of cash assistance) affected job retention of female former welfare recipients (Model 2 & 4). Specifically, age, educational attainment, work-experience, and involuntary exit of cash assistance affected job retention of female former welfare recipients.

H1c. Individual job distance (access) did not affect job retention of female former welfare recipients (Model 2 & 4).

H1d. The level of neighborhood public transportation access did not affect job retention of female former welfare recipients (Model 3 & 4).

H1e. A higher level of neighborhood disadvantage decreased job retention of female former welfare recipients (Model 3 & 4).
Research question two: How do job access and neighborhood disadvantage influence the female former welfare recipients’ two-year employment quarters within eight quarters after exiting cash assistance and being employed?

H2a. There was a significant difference in two-year employment of former TANF recipient by census tracts (Model 5)

H2b. The differences in the covariates (i.e., demographic, human capital, and involuntary exit of cash assistance) affected two-year of female former welfare recipients (Model 6 & 8). Specifically, age, African-Americans, high school diploma, work-experience, and involuntary exit of cash assistance affected two-year employment of female former welfare recipients.

H2c. Individual job distance (job access) did not affect two-year employment of female former welfare recipients (Model 6 & 8).

H2d. A level of neighborhood public transportation access did not affect two-year employment of female former welfare recipients (Model 7 & 8).

H2e. A higher level of neighborhood disadvantage decreased the possibility of two-year employment of female former welfare recipients (Model 7 & 8).
Research question three: How do job access and neighborhood disadvantage influence the female former welfare recipients’ average quarterly earnings within eight quarters after exiting cash assistance and being employed?

H3a. There was a significant difference in average quarterly earnings of female former welfare recipients by census tracts (Model 9).

H3b. The differences in the covariates (i.e., demographic, human capital, and involuntary exit of cash assistance) affected average quarterly earnings of female former welfare recipients (Model 10 & 12). Specifically, age, Whites, number of children, educational attainment, work-experience, and involuntary exit of cash assistance affected average quarterly earnings of female former welfare recipients.

H3c. A longer individual job distance (access) decreased average quarterly earnings of female former welfare recipients (Model 10 & 12).

H3d. A higher level of neighborhood public transportation access increased average quarterly earnings of female former welfare recipients (Model 11 & 12).

H3e. A higher level of neighborhood disadvantage decreased average quarterly earnings of female former welfare recipients (Model 11 & 12).
In sum, among the individual-level variables, age, race, human capital variables, and involuntary exit of cash assistance affected all types of the employment success of female former welfare recipients. The number of children only affected average quarterly earnings of former welfare recipients. Among the neighborhood-level variables, neighborhood disadvantage was consistently and adversely associated with all types of the employment success of female former welfare recipients. Job access at the individual-level and public transportation access at the neighborhood-level only affected average quarterly earnings of female former welfare recipients.
5.2. Discussion and implications

The results of this study can be interpreted in relation to previous studies, social work practice (especially, social programs and community development), and policy under three domains: (1) neighborhood disadvantage, (2) individual job access and neighborhood public transportation access, and (3) cash assistance program and policy

5.2.1. Effects of neighborhood disadvantage

This study focused on the association between neighborhood disadvantage and the employment success of female former welfare recipients. The multi-level analyses found a nested neighborhood effect of job access and neighborhood disadvantage on the employment success of female former welfare recipients. The null models of multilevel analyses initially discovered a variation of the employment success of female former welfare recipients by neighborhoods. Further, the final models of multi-level analyses identified that neighborhood disadvantage negatively affected the employment success of them. After controlling for the individual-level variables, female former welfare recipients who resided in more disadvantaged neighborhoods were less successful in employment than those who did not. In sum, employment success was affected by neighborhood characteristics as well as individual characteristics (Coulton, 2005; Mendenhall et al., 2003). Similar to this study, previous studies showed the importance of neighborhood effects on the employment of welfare recipients (Coulton, 2005; Mendenhall et al., 2003). Consequently, the results indicate that effects of neighborhood
disadvantage have direct implications for social policy, mobility or housing programs, and community development.

Overall, the results fundamentally supported Wilson’s explanation regarding the problems of social isolation in impoverished neighborhoods (Wilson, 1987). Wilson (1987), who initially introduced the concept of neighborhood disadvantage, asserted that this situation needed to be solved in larger environments as well as within impoverished neighborhoods (Wilson, 1996). Although neighborhood issues seem to be a local problem, they cannot be solved solely by their own local efforts. Specifically, the six items that represented the level of neighborhood disadvantage in this study (e.g., female-headed families, unemployment, poverty, etc.) may not be remedied with micro-social programs of a local government. Hence, the social investments from larger institutions should flow into disadvantaged neighborhoods and their residents.

In terms of social policy, Wilson (1987) stressed that the expansion of welfare via universal or targeted programs could help to overcome concentrated neighborhood disadvantage (Wilson, 1987). Although previous studies have emphasized the importance of the neighborhood effects which were asserted by Wilson (1987), they have rarely discussed his suggestion that the expansion of universal welfare programs could ameliorate concentrated neighborhood disadvantage (Wilson, 1987). With a broad perspective, this study suggests that the extension of welfare benefits including public assistance programs could ameliorate the adverse effects of neighborhood disadvantage by reducing the depth of poverty in these neighborhoods.

Furthermore, two types of social programs could mitigate the negative effects of neighborhood disadvantage on residents’ economic status including employment: (1)
residential mobility (or housing) programs to help residents in disadvantaged neighborhoods move to better places and (2) community development to make disadvantaged neighborhoods better.

For example, the Gautreaux program found that moving public housing residents to middle-class suburbs substantially raised the employment of the AFDC families (Mendenhall et al., 2006). Another similar mobility program, the MTO project, found that the female youth in low-income families that moved to better neighborhoods could enhance and accumulate human capital (HUD, 2003). Based on these findings, the assignment of housing vouchers should consider welfare recipients’ residential locations in order to enhance employment success (Mendenhall et al., 2006). Therefore, current housing programs (e.g., Section 8) should induce welfare recipients to relocate to better neighborhoods. Thus far, housing voucher programs have not effectively encouraged families to move to better neighborhoods because low-income families, especially minorities, have encountered numerous obstacles to mobility, such as search constraints and refusal by landlords to accept vouchers (Basolo & Nguyen, 2005; Pendall, 2000).

Consequently, it is necessary to accommodate supportive services that encourage welfare recipients to move to better places. For instance, the MTO experimental group received a housing counseling service in order to facilitate a move to low-poverty neighborhoods (HUD, 2003; Mendenhall et al., 2006). Hence, this housing counseling service can be a feasible addition to current housing program (i.e., Section 8) in order for welfare recipients to be encouraged to move to neighborhoods with better prospects (HUD, 2003). Unfortunately the current situation is that all local housing authorities have long waiting lists for services and often are forced to cap them early due to limited
resources (Quigley, 2011). Hence, the amount of public housing and housing voucher programs would need to be increased in order to enable low-income families, including welfare recipients, more chances of moving out of disadvantaged neighborhoods.

Along with residential mobility programs, community development is another approach to overcome the negative effects of neighborhood disadvantage. Community development builds up resources that can reverse the deteriorated neighborhoods while enhancing the human capital of welfare recipients in these disadvantaged neighborhoods (Austin & Lemon, 2005; Bloom et al., 2005; Bruster, 2009; Coulton, 2003). Community development agencies can implement various activities in order to revitalize inner cities via federal, state, and local supports (Coulton, 2005). Moreover, various approaches in community development can make supportive resources more available to welfare recipients and the poor in disadvantaged neighborhoods (Austin & Lemon, 2005).

For example, as a place-based program, the Jobs-Plus Community Revitalization Initiative for Public Housing Families (Job-Plus) project showed positive effects on the employment of low-income families, including welfare recipients (Bloom et al., 2005). The Job-Plus project provided three important services to public housing residents in six urban cities: (1) employment-related services and activities, (2) financial incentives to work, and (3) community supports for work (Bloom et al., 2005). Specifically, employment-related services included various types of programs such as job search assistance, education programs, vocational trainings, and supportive services (e.g., child care and transportation assistance) (Bloom et al., 2005). Moreover, the community supports for work aimed to build social ties among residents in order to promote neighbor-to-neighbor exchange of information about job opportunities or employment
services (Bloom et al., 2005). The Job-Plus project, which used community development strategies, positively impacted on residents’ earnings (Bloom et al., 2005).

As mentioned in the example above, community development strategies can build up the social resources to facilitate employment of welfare recipients in disadvantaged neighborhoods (Austin & Lemon, 2005; Bloom et al., 2005; Coulton, 2005). If the female former welfare recipients begin or continue to work, their improved economic status also contributes to enhancing their neighborhood conditions. Because welfare recipients were affected by their neighborhood’s conditions, community development programs should be broadened to address human capital and employment needs (Coulton, 2005).

With a broad perspective, the results of this study can provide insight to possible causes of neighborhood disadvantage. Wilson (1987) claimed that one of the reasons that neighborhood disadvantage increased in inner-cities was the mismatch between marriageable employed males and females (Wilson, 1987). If community development creates economic opportunities in disadvantaged neighborhoods, this can result in decreasing the overall unemployment rates of residents including young males. Ideally, the mismatch between marriageable male and female in disadvantaged neighborhoods can be mitigated (Wilson, 1987). In sum, community development is a useful approach to simultaneously better the disadvantaged residents including female former welfare recipients and their disadvantaged neighborhoods.
5.2.2. Individual job access and public transportation access

This study was the first trial to calculate actual job distances between a residential place and workplaces and to estimate the association between the job distances and the employment success of female former welfare recipients. Although job access did not influence all types of employment success, it significantly affected average quarterly earnings of female former welfare recipients. At the individual-level, the shorter job distances increased average quarterly earnings of female former welfare recipients. At the neighborhood-level, female former welfare recipients in a neighborhood with higher public transportation access tended to earn more than their counterparts.

There are more specific conclusions to be drawn regarding the result that job access (individual job access and public transportation access) only affected average quarterly earnings of female former welfare recipients. These results suggest the need for future understanding of the measurements of employment success in this study. It is important to interpret the effect of job access in the context of what is known about women’s employment, which along with job access can be discussed in relation to the skill mismatch hypothesis as well as the SMH.

To begin with, the measure of average quarterly earnings was basically different from two other measurements such as job retention and two-year employment. In this study, higher average quarterly earnings did not mean longer job duration (job retention and two-year employment). Rather, average quarterly earnings showed the employment performance of female former welfare recipients within a certain period. While job
retention and two-year employment represented employment duration, average quarterly earnings were related to job quality such as hourly wage and work-hours.

Similar to the results of this study, previous studies showed that the job access effect varied by the measures of employment. For example, previous studies found an association between job access and the quality of employment (e.g., work-hours, earnings, and hourly wage) (Gurley & Bruce, 2005; Ong, 1996). However, other studies did not show a relationship between job access and employment rates among welfare recipients (Bania et al., 2003; Gurmu et al., 2008; Sanchez et al., 2004). Therefore, the results regarding job access in this study implied that job access did not have an influence on employment duration but rather, affected the employment quality of welfare recipients.

Furthermore, the result of job access effect in this study should be interpreted in the context of women’s employment. Studies have shown that access to appropriate jobs have an influence on the level of female employment (Hanson et al., 1995). Localized job-network and juggling domestic tasks (e.g., childcare) make it difficult for females to find a job located far from home (Blumemberg & Manville, 2004; Hanson et al., 1995). Because welfare recipients mainly depend on public transportation, far fewer jobs are manageable for them as opposed to individuals who can travel by automobiles (Blumemberg & Manville, 2004; Blumemberg & Ong, 1998; Hanson et al., 1995). As a trade-off with job distances, this context of women’s employment points to the important role that job distances may play on the equality of work for low-income females including welfare recipients.
In actuality, the results of this study indicated that female former welfare recipients in this study commuted a shorter distance than the average worker in the U.S. Although the measures differed, the average job distance of the sample (7.3 miles) was less than the national average (16 miles) (Lnager, 2005). This study found that a shorter job distance and a higher neighborhood public transportation access contributed to an increase of average quarterly earnings among female former welfare recipients. Considering that most welfare recipients are employed with low-wage and a part-time job, their job access is probably affecting their work-hours and, therefore, their earnings (Hanson et al., 1995; Mendenhall et al., 2006).

The previous studies mentioned above and the results of this study together suggest that female welfare recipients would prefer jobs that are located nearby their residence and ones that are accessible with public transportation. In other words, if female former welfare recipients find more accessible jobs nearby their residence, their job quality (e.g., hourly wage or work hours) can be increased.

Given these findings, this result largely supports the SMH which found a significant relationship between a job location and employment, although previous studies based on the SMH showed an inconsistent effect of job access on employment (Kain, 1968). However, the results regarding job access should be carefully interpreted with the SMH. The SMH essentially assumed that job suburbanization provoked unemployment in inner cities (Kain, 1968). If workers have an ability to reach suburbanized jobs (e.g., via moving residency or driving a car), they can overcome geographic job barriers (Blumenberg & Ong, 1998; Ong, 1996). In cases in which males with a vehicle can access the suburbanized jobs, a longer job distance may increase their
employment performance. However, a longer job distance can decrease female welfare recipients’ employment in the context of women’s employment mentioned above. Therefore, the effect directions of job access need to be carefully applied and interpreted depending on the employment context of gender and mode of transportation.

Moreover, the effect of job distance in this study and the context of female welfare recipients can expand the discussion from the SMH to skill mismatch hypothesis. Because the SMH mainly focused on male employment and paid little attention to the effect of economic restructuring on African-American women, who traditionally work in low-wage jobs, it has seldom showed job access effect on welfare recipients (Hanson et al., 1995; Mendenhall et al., 2006). If the SMH considers the context of female welfare recipients, it can be more persuasive in explaining the relationship of job distance and employment. The combination of the skill mismatch perspective and the SMH can enhance the explanatory power of job access on welfare recipients’ employment in poor urban areas. For example, the geographic concept of the SMH (e.g., job accessibility or availability) can be measured with that of the skill mismatch perspective (e.g., labor market segments of female welfare recipients) (Kain, 1968; Handel, 2003; Houston, 2005).

In sum, this study found that individual job access and neighborhood public transportation access affected earnings of female former welfare recipients. This result suggested that job access was one of the important barriers to welfare recipients’ employment, especially job quality (Allard & Danziger, 2003; Gurley & Bruce, 2005, Gurmu & Smith, 2006; Ong, 1996). For that reason, programs to enhance job access should be implemented in order to raise the earnings of female former welfare recipients.
As an individual based program, car ownership assistance can be developed to decrease the burden of commuting to work among welfare recipients (Blumenberg & Ong, 1998). Specifically, Hayden and Mauldin (2005) interviewed seven car ownership programs and suggested best practices to enhance car ownership among low-income people including welfare recipients (Hayden & Mauldin, 2005). They outlined nine practical approaches for car ownership assistance programs: (1) case management, (2) training and education, (3) structuring payments regarding car ownership cost, (4) insurance assistance, (5) partnership with banks and credit unions, (6) recruiting staff with industry-related experience, (7) tracking success, (8) car acquisition, and (9) car disposition (Hayden & Mauldin, 2005). In terms of social work practice, community development strategies, which organize various social resources, can apply to the best practice for car ownership programs. It is important to note however, that car-subsidy programs for welfare recipients are a politically controversial issue (Ong, 1996).

In addition to car ownership programs, it is possible to provide assistance programs to welfare recipients who currently own a car. For example, local government can give tax exemption to employed welfare recipients with an automobile (e.g., a registration fee, driver license fee, etc.). Another possibility is that car-related expenses for commuting can be made tax-deductible. For example, welfare recipients who commute by car can have some amount of tax return from gas, auto insurance, and repair expenses. Further, local agencies could provide car-repair services to welfare recipients (Hayden & Maudlin, 2005).

In addition to the individual-based programs, group-based transportation programs can be provided in order to decrease the burden of welfare recipients’
commutes. For instance, various transportation services such as extended transit service, vanpool, or rideshare can relieve welfare recipients from the hardship of commutes (Blumenberg & Ong, 1998; Ong, 1996). Public agencies can support these group-based transportation programs to welfare recipients (Ong, 1996). For example, public agencies can provide expense support to a carpooling program among female former welfare recipients or low-skilled workers (e.g., gas expense, auto insurance, etc.).

Moreover, a shuttle service to workplaces or nearby mass transit stations can increase the job accessibility of welfare recipients (Ong, 1996). For example, as a response to the TANF program, Cuyahoga County has implemented shuttle services for employees in the City of Cleveland since 1998 (Cuyahoga County Planning Commission, 2012). In collaboration with the Great Cleveland Regional Transit Authority (GCRTA) and local agencies, Cuyahoga County has operated the Work Access & Transportation Program (WATP), which is a customized shuttle service, in order to enhance job access of eligible employees in the City of Cleveland (Cuyahoga County Planning Commission, 2012). Because the WATP is funded by the federal TANF fund, its benefits can be expanded to former welfare recipients who are looking for a job or are employed (Cuyahoga County Planning Commission, 2012).

At the neighborhood level, this study discovered that the female former welfare recipients in neighborhoods with a high rate of public transportation access earned more than their counterparts. Therefore, public transportation in inner cities should be enhanced and expanded in order to facilitate employment of welfare recipients (Blumenberg & Shiki, 2003; Gurmu et al., 2008). Transit authorities must develop and adjust the daily routes and schedules of their services in accordance with the job access of
welfare recipients or the poor in inner cities. More directly, transit authorities and TANF agencies can provide a subsidy of public transportation (e.g., free-pass or discount fare) to employed welfare recipients.

In conclusion, community development is a useful approach in order to build up car-ownership, group-based transportation services or enhanced public transportation for welfare recipients’ job accessibility. Community needs assessment can be conducted to evaluate the needs of transportation access among female former welfare recipients in targeted neighborhoods. Then, community development skills can establish transportation resources that were mentioned above (e.g., car-ownership, group-based transportation, and public transportation).

5.2.3. Public assistance program and policy

This study selected its dependent variables as the employment success of female former welfare recipients who exited cash assistance. Two main components of TANF program affecting welfare recipients are a time-limit on cash assistance and work-requirements. Under these policies, this study found that the employment success of female former welfare recipients was not promising. They earned an average of $2,657 per quarter. On average, the job retention of this sample was 5.36 quarters. Furthermore, only 45.2 percent of the sample was employed for two years.

Similar to previous studies on welfare recipients, this study also identified human capital variables as a barrier to employment of welfare recipients (e.g., Allad & Danziger, 2003; Austin & Lemon, 2005; Blank & Blum, 1997; Gurley & Bruce, 2005; Ong, 1996). The results showed that female former welfare recipients with a high school diploma
were more likely to achieve employment success than their counterparts. This study reconfirmed that the current cash assistance program should empower human capitals of current and former welfare recipients, especially prior to exiting cash assistance (Austin & Lemon, 2005; Blank & Blum, 1997). Therefore, as TANF is a major cash assistance program, it must be more cohesively connected to educational programs for its recipients (Austin & Lemon, 2005).

This study also found that the employment success of female former welfare recipients was worse for those who involuntarily exited cash assistance than others. This suggests that the TANF program should modify the policy of a time-limit on cash assistance to all recipients. Several individual-level variables, which were determined before exiting cash assistance, may be associated with welfare recipients’ readiness to work. Specifically, this study found that younger female former welfare recipients were less successful in employment than their counterparts. Female former welfare recipients with work-experience before exiting cash assistance were more successful in employment than those without it. Nevertheless, TANF imposes a fixed time-limit on cash assistance regardless of its recipients’ readiness to work. With regards to these results, the time-limit regulation of the current TANF program should be revisited.

Furthermore, these results suggested that more flexible and generous regulation on cash assistance could make the female welfare recipients more successful in the labor market. As one of the solutions, TANF program can extend or adjust its period of cash assistance benefits so that TANF recipients can be more ready to work. Considering the effect of human capital variables and welfare recipient’s age, the extended period of cash assistance should result in improving the human capital of welfare recipients. For
example, young welfare recipients can have a longer period of cash assistance benefits so that they are able to complete the General Educational Development (GED) test or high school and have more work-experience before exiting cash assistance. This generous time-limit regulation can enhance the employment success of TANF recipients even after exiting cash assistance. In turn, this can prevent or delay the recidivism of cash assistance. Finally, if the current TANF program reconsiders barriers to employment with time limit pressure, its recipients may be more successful in overcoming the context of neighborhood disadvantage and geographic job access prior to exiting cash assistance.
5.3. Limitations and future study

This section discussed the limitations of this study and the directions of future studies regarding the effects of job access and neighborhood disadvantage on former welfare recipients’ employment.

5.3.1. Limitations

This study had constellations of limitations mostly due to methodological reasons, data sets, and measurements. These limitations may raise the threats to internal, statistical conclusion, and external validities.

First of all, the biggest issue for any neighborhood study is selection bias, which is one of the threats to internal validity (Ludwig et al., 2008; Sampson, Morenoffe, & Ganno-Rowley, 2002). The unobserved effect that welfare recipients choose their neighborhoods can affect their employment success. Because the study was modeled as a non-experimental design, it could not control for neighborhood selection of the sample. In other words, this study could not accurately differentiate the effects of neighborhood characteristics and neighborhood selection on the employment success of female former welfare recipients (Gurmu et al., 2008). There might be numerous unobserved factors for which welfare recipients chose their neighborhoods (Gurmu et al., 2008). For example, female welfare recipients may prefer to select poor neighborhoods with affordable housing or available public housing (Gurmu et al., 2008; Xaiver, Ferryman, Popkin, & Rendon, 2008). On the other hand, female welfare recipients may consider neighborhood characteristics related to their children (e.g., safety, crime, or school district) (Xaiver et
al, 2008). They also may select ethnically homogenous neighborhoods to avoid racial segregation. Furthermore, low-income families may prefer to stay in their current neighborhood in order to preserve their family and social support or job-network (Gurmu et al., 2008; Ludwig et al., 2008). Nevertheless, non-experimental studies typically face a difficulty in measuring the unobserved effects of selection bias and correlating with outcomes (Ludwig et al., 2008; Sampson et al., 2002). Although this study included human capital variables (educational level and work-experience) as controlled in the analytical models, it did not do enough to adjust the selection bias of the sample’s choosing neighborhoods.

In addition to the selection bias issue, this study did not track the housing mobility or migration of the sample. The residential place of the sample was measurable only at the point of exiting cash assistance. Hence, it was impossible to track mobility or immigration of the sample after exiting cash assistance. Due to the data availability, this study assumed that there was no mobility or migration of the sample within eight quarters after exiting cash assistance. Accordingly, this issue might affect measurement issues of individual job access and the neighborhood-level variables which were measured on the basis of the sample’s residential place.

Furthermore, these administrative data sets in this study had a limited number of variables and measurement issues regarding dependent variables, independent variables, and covariates. The limited number of variables may yield threats to statistical conclusion validity; the measurements issues may construct threats to external validity (Shadish, Cook, & Campbell, 2002).
The dependent variables of this study were collected from the QWR of an administrative agency. The QWR collected only taxable earnings. It did not include detailed employment information regarding government jobs or self-employment. Therefore, this study could not measure more detailed information of female former welfare recipients’ employments such as sequences of job, types of workplaces and job positions, work hours, hourly wage, job benefits, and even unreported earnings.

Moreover, the measurement issues of job access, which was one of the key independent variables in this study, may provoke the issue of external validity. Individual job access was measured by airways between a residential place and workplaces. Thus, it did not consider more realistic job accessibility such as travel time, traffic distance, and a mode of transportation. Further, this study did not measure car-ownership or driver licenses of the sample that might provide more complete measurements for transportation access (Blumenburg & Ong, 1998; Ong, 1996). What was more, this study only dealt with workers’ use of public transportation from 2000 Census data in order to measure neighborhood-level job access. Moreover, this study could not consider some information in regards to public transportation access (e.g., schedules, route, and access to transit stations).

Furthermore, this study did not include job supply in neighborhoods where welfare recipients resided. In terms of the SMH, this study did not take account of the number of jobs located in or near the neighborhoods. As mentioned earlier in the literature review, neighborhood job availability might also be an important predictor of employment success of welfare recipients (Allard & Danziger, 2003; Gurmu & Smith,
In terms of the skill mismatch perspective, this study did not identify the supply of jobs that were relevant with welfare recipients’ human capitals (Hansen, 2003).

In regard to covariates, a number of variables related to employment of welfare recipients were not addressed. Although this study considered two human-capital variables, it could not collect the variables related to human capital (e.g., vocational training, job search service, or GED program) (Dolgoff & Feldstein 2000). Moreover, this study could not rule out the effects of the childcare relevant variables (e.g., childcare voucher and family support) in the analytical models (Dolgoff & Feldstein 2000).

Finally, this study used administrative data. Because this administrative data only included the specific population of female former welfare recipients who resided and were employed in a particular local area, its results could not necessarily be generalized to TANF recipients in the U.S.

5.3.2. Future study

Future studies should take advantage of more advanced research models, more accurate data sets, and better measurements. In particular, future studies should address the limitations of this study mentioned above.

First of all, future studies could address the problem of selection bias by capitalizing on a natural experiment of policy. In particular, future studies with an experimental design can not only control for a selection bias but also can access a more accurate relationship between neighborhood disadvantage and employment of welfare recipients (Gurmu et al., 2008). For example, data on job access and transportation access could be combined with the data from the MTO that has tested neighborhood
effects by using a social experimental model and mobility programs (HUD, 2003). This study will not only test the impacts of moving to non-poor neighborhoods but also the effects of job access on female former welfare recipients in a simultaneous manner.

Along with the experimental design, non-experimental model with administrative data that statically controls for selection bias is applicable to neighborhood studies on welfare recipients. For example, propensity score matching analysis or Heckman modeling can capture the unobserved effects of selecting neighborhoods on employment success (Guo & Fraser, 2009). Prior to applying these advanced models, it is requisite to conduct studies on developing instrumental variables that explain the unobserved effects of selecting neighborhoods among welfare recipients.

Another possibility can be intervention research that targets disadvantaged neighborhoods for improvements. In a consideration of this study, the intervention research might include better transportation, community supports for work and human capital investments. The selected neighborhoods could be randomly assigned into a treatment (with community development programs such as job training, education, public transportation, childcare, etc.) and a control group. This type of research will contribute to discovering more accurate neighborhood effects and provide a rational for community development in disadvantaged neighborhoods.

Beside intervention study, future studies should develop various tools to gauge the level of neighborhood conditions, including disadvantage. Following previous research, this study used six items to measure the level of neighborhood disadvantage in an urban area (Deverteui, 2005; Sampson et al., 1997). However, the items that construct neighborhood disadvantage can differ by regional neighborhood characteristics.
Therefore, future studies need to develop various measures that can explain neighborhood characteristics.

In addition to neighborhood measurements, various measures of job access such as travel time and a mode of transportation should be considered to examine the more accurate effect of job access on employment of welfare recipients. Because women’s job access pattern is different from males, future studies should differentiate the pattern of job access between welfare recipients (or low-income females) and other groups (Hanson et al., 1995).

In addition to job access, future studies should try to test more recent and national data on TANF recipients. Thus, future studies can evaluate the contemporary trend of employment among TANF recipients as well as the long-term effect since 1996 welfare reform. Furthermore, future studies should explore employment of TANF recipients with more accurate and specific measurements. For example, these studies should obtain more specific information of TANF recipients’ employment such as work-hours, hourly wage, types of workplace and job position, unreported earnings, and benefits.

Finally, this study, which documented the negative effects of neighborhood disadvantage and job access on employment, was important for what it reveals about the role of structural factors, over and above individual characteristics. Beyond this research purpose, it is important to increase social awareness in order to enhance residents’ lives in poor neighborhoods. Therefore, future studies need to go beyond this to demonstrate various solutions to attenuate the negative effect of neighborhood disadvantage and the social welfare problems.
References


Ohio Department of Job and Family Services (ODJFS) (2001). *Temporary Assistance to Needy Families (TANF) program state title IV-A plan*. Columbus, OH: Author.


Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA; P.L. 104-193)


