5-1-2011

Welfare-to-work transition in the TANF era: evidence from Mississippi

Xuhui Zeng

WELFARE-TO-WORK TRANSITION IN THE TANF ERA:

EVIDENCE FROM MISSISSIPPI

By

Zeng, Xuhui

A Dissertation
Submitted to the Faculty of
Mississippi State University
in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy
in Sociology
in the Department of Sociology

Mississippi State, Mississippi

April 2011

WELFARE-TO-WORK TRANSITION IN THE TANF ERA:

EVIDENCE FROM MISSISSIPPI

By

Zeng, Xuhui

Approved:

Domenico Parisi
Professor of Sociology
(Director of Dissertation)

Robert L. Boyd
Associate Professor of Sociology
(Committee Member)

James D. Jones
Professor of Sociology
(Committee Member)

Emory P. Morrison
Assistant Professor of Sociology
(Committee Member)

Jeralynn S. Cossman
Professor of Sociology
Graduate Coordinator
Department of Sociology

Dean Gary Myers
Professor and Dean
College of Arts & Sciences

Name: Zeng, Xuhui

Date of Degree: April 30, 2011

Institution: Mississippi State University

Major Field: Sociology

Major Professor: Dr. Domenico Parisi

Title of Study: WELFARE-TO-WORK TRANSITION IN THE TANF ERA: EVIDENCE FROM MISSISSIPPI

Pages in Study: 185

Candidate for Degree of Doctor of Philosophy

This study examines welfare dynamics in Mississippi under the newly created TANF program. Specifically, it examines welfare-to-work transition between 2001 and 2009 and tests several hypotheses regarding individual and contextual characteristics. The data come from multiple sources that include administrative records and publicly available data. Data on TANF transitions come from the Mississippi Department of Human Services. Data on TANF employment come from the Mississippi Department of Employment Security. Data on training come from the Mississippi workforce investment system. Information on both neighborhood and labor market characteristics come from the 2000 Census.

The findings clearly support the hypothesis that individual and contextual conditions influence the ability of a poor single mother to exit TANF and gain employment. On the other hand, there is weak evidence supporting the hypothesis of welfare dependence when controlling for unobserved characteristics for multiple spells within individuals. The main implication here is that TANF might have indeed addressed the longstanding concern about welfare dependency. The results, however, show that

individual and contextual factors still play a role in determining welfare dynamics across poor single mothers with different individual and contextual backgrounds.

ACKNOWLEDGEMENTS

I am very grateful to all of those who have contributed and supported me throughout this process. Writing a dissertation is very challenging and tests the character of a student. Without the help of many, I would not have been able to finish this document. I am most grateful to my major professor, Dr. Domenico Parisi, for his professional assistance and, most importantly, his great sense of humanity. The dissertation would not have been completed without his consistent and invaluable support throughout the intricacies of the doctoral program and the dissertation process. This dissertation has benefited from my work experience in the National Strategic Planning & Analysis Research Center (nSPARC) at Mississippi State University. The center provided me a unique opportunity to handle multiple sources of data and use them in the research. I appreciate my colleagues—Dr. Steven Grice and Dr. Michael Taquino—who assisted me with getting familiar with the datasets. A sincere thanks also goes to my committee members, Dr. Robert Boyd, Dr. James Jones, and Dr. Emory Morrison. Their thoughtful suggestions (e.g., Dr. Boyd's constructive scrutiny) substantially improved this research. A special thanks is extended to Jed Raney Pressgrove for editing the dissertation draft. A special thanks is also extended to Dr. Xiaohe Xu for assisting me in starting my doctoral program in the United States. Last but not least, I cannot find words that are strong enough to thank my family, especially my wife, Li Zheng.

TABLE OF CONTENTS

LIST OF TABLES

TABLE | Page

LIST OF FIGURES

CHAPTER I

INTRODUCTION

1.1 Statement of the Problem

When the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) was signed into law in 1996, welfare in the United States changed fundamentally after evolving seven decades under the Social Security Act of 1935. Temporary Assistance to Needy Families (TANF) replaced Aid to Families with Dependent Children (AFDC) as the U.S. welfare program. The goal of TANF is to end dependence on public assistance by preparing recipients for jobs through various training programs. The assumption is that recipients will eventually become self-sufficient in the labor market. Accordingly, the workforce participation rate has been highlighted by the federal government as the critical index to measure state performance in implementing TANF.

The idea of facilitating welfare-to-work transition is not new. Decades before the passage of PRWORA, policymakers debated how to move people from welfare to work and developed programs to encourage welfare-to-work transition. One of the first ideas was workfare, a combination of welfare and work in which recipients participated in work activities designated by state agency in exchange for welfare checks. Then the Work Incentive (WIN) program was created in 1967, which required recipients with children ages 6 and up to register in work and training programs. WIN also provided child-care services to participants and disregarded the first $30 of earned income and one-third of the remainder. Next, the Family Support Act of 1988 introduced the Job Opportunities and Basic Skills (JOBS) program, which provided welfare recipients with education, skills training, job search assistance, and other work activities. Additionally, there were many welfare reform proposals that were not passed by Congress, and some of them did not even make it to policy agendas.

Meanwhile, researchers from think tanks and academies debated welfare reform long before the 1996 reform occurred. Charles Murray, Lawrence Mead, Mary Jo Bane and David Ellwood were among the researchers who set the tone of the debate. Murray's *Losing Ground* featured a conservative review of social policies regarding the poor, arguing that policy incentives encourage people in poor communities to stay on welfare and out of the workplace. Murray advocated eliminating the entire federal welfare and income support structure for working-aged persons (Murray 1984:227). In *Beyond Entitlement*, Mead (1986) offered a less provocative proposal, arguing that welfare recipients are not entitled to benefits; instead, they must participate in specific work activities in exchange for benefits. On the other side, Bane and Ellwood (1983, 1994) found that a small number of extensively long-term recipients dominated the total welfare caseload at any point in time and sapped program resources. They also found that poor single mothers had to rely on public assistant programs because work did not pay for them. Meanwhile, with support from the U.S. Department and Health and Human Services, leading nonpartisan research institutions (e.g., Brookings, Manpower Demonstration Research Corporation (MDRC), and Urban Institute) evaluated experimental state and federal policy changes under federal waivers, which aimed to move welfare recipients into the labor force.

Despite these efforts, the U.S. welfare system did not work as expected. Even worse, welfare rolls increased dramatically in the early 1990s after a decade of flat rates. Both parties intended to “end welfare as we know it,” a slogan from Bill Clinton’s Presidential Campaign in 1992. The White House and a Republican-led Congress eventually made a reconciliation that emphasized, as the title of the welfare reform act shows, personal responsibility and work opportunity. The central aim of the welfare reform was to end entitlement so that state agencies could shift their focus from eligibility determination to job transition support (Mead 2001).

The 1996 welfare reform was praised for reducing caseloads, increasing the employment rate of poor single mothers, and sustaining, if not increasing, child benefits for poor families by the late 1990s. The miserable picture of disadvantaged single mothers and their children—predicted by most critiques of welfare reform—did not happen. Encouraged by a dramatic decline in caseload and a rising work participation rate of welfare recipients, the proponents of reform announced its quick success in just a few years after implementing the TANF program.

However, many welfare issues remain unaddressed. Among these issues, the evaluation of welfare reform has drawn much attention (Blank 2002). Many studies have decomposed the effects of welfare policies, other incentive policies (e.g., Earned Income Tax Credit), and economic conditions after the reform. A number of studies focus on welfare dynamics under the mandate of work requirements and the enforcement of time limits. Still, others examine the labor market performance of welfare leavers and how they retain their jobs.

The findings of these studies, however, vary widely due to differences in data sources, sampling procedures, and measurement. Furthermore, researchers with theoretical concerns usually do not consider the urgency of policy evaluation. Many studies do not test their theoretical assumptions that would result in quite different policy implications.

Many welfare studies use either national survey data (e.g., Current Population Survey, Panel Study of Income Dynamics, and National Longitudinal Survey of Youth) or experimental data collected from a few states during the period of federal waivers. Few studies use state administrative data collected after welfare reform, especially for the period covering the recent economic downturn after 2001. In addition, few studies examine welfare-to-work transition in Deep South states characterized by rural orientation, higher poverty rates, higher proportion of blacks, and lower income.

1.2 Purpose and Significance

The purpose of my study is to add to the welfare literature by addressing some of the limitations mentioned above. In particular, my study examines the dynamics of welfare-to-work transition after the 1996 welfare reform using Mississippi administrative data. In doing so, the human capital model, labor market model, neighborhood effects model, and welfare dependence model are incorporated into one conceptual framework.

The human capital model includes its classical components: education, job training, and work experience. Although there is a wide consensus on the positive effect of human capital on labor market outcomes, less is known about the extent to which these three components facilitate the transition from welfare to work. For example, there has been debate on the effects of two strategies in policy evaluation: Human Capital Development (HCD) and Labor Force Attachment (LFA). The first strategy focuses on basic achievement of formal education (e.g., the General Educational Development (GED) or high school diploma). The second strategy emphasizes work experience and on-the-job training. Thus, the strategies address different forms of human capital. The labor market model assumes that single mothers' choices in welfare-to-work dynamics are determined by rational calculation based on the costs and benefits of the choices. Empirically, my study concerns the relationship between job opportunities within the local labor market and the likelihood of welfare recipients' work participation.

The neighborhood effects model is developed from William Wilson (1987)'s hypothesis that, controlling for other individual variables, those who live in disadvantaged neighborhoods fare worse than those who live in other places. The model has been used to explain the behavioral, cultural, and structural problems faced by inner-city residents. However, similar phenomena are found in rural areas (e.g., Duncan 1999), indicating that neighborhood effects could exist outside inner-city settings. Using the concept of neighborhood, my study explores how community characteristics affect single mothers' welfare-to-work transition across various social settings.

At the individual level, my study focuses on the distribution of welfare spells and types of welfare exits. In particular, the welfare dependence model is tested, seeing if and how time spent on welfare rolls influences recipients' future behaviors. Moreover, the corresponding topic of this issue, the effects of unobserved individual characteristics, is examined to provide a complete picture of welfare dependence in the TANF era.

Empirically, my study contributes to the current debate on welfare-to-work transition in several important ways. First, it brings new patterns of welfare-to-work transition into the analytical framework. Under current welfare policy, recipients are allowed or required to combined welfare and work before they eventually exit from welfare rolls. Although a few recent studies pay attention to these new patterns of transition under specific situations, further evidence is needed to cross-check those findings. Second, my study takes into account details of structural settings, such as neighborhood characteristics and county-level labor market unemployment rate. In doing so, multilevel models for event history data are developed. Finally, my study uses administrative data with a clear time frame.[1] These data allow us to identify the target group and avoid sample selection bias (a targeting problem). The data also clearly identify the single mothers and families using TANF. Lastly, by using Unemployment Insurance and Workforce Investment Act data, the employment status and training status of recipients can be officially documented.

1.3 Organization of the Following Chapters

Chapter II provides background on welfare policy changes as well as information on the policy environment of Mississippi during the TANF era. Chapter III develops a theoretical framework that combines the human capital model, labor market model, neighborhood effects model, and welfare dependence model. Chapter IV reviews literature on welfare-to-work transition, with particular attention to the effects of human capital, local labor market conditions, neighborhood characteristics, welfare duration, and race inequality. Several theoretical hypotheses are provided thereafter. Chapter V describes data and methods that are used in the study. The three primary data sets are TANF monthly administrative data from the Mississippi Department of Human Services, Unemployment Insurance (UI) quarterly administrative data from the Mississippi Department of Employment Security (MDES), and Workforce Investment Act (WIA) administrative data from MDES. The TANF data provide information on welfare use and

[1] Administrative data have several drawbacks. For a detailed description on the merits and drawbacks of using administrative data, see Chapter V, "Methods: Data, Measures, and Analytic Strategy."

general demographic characteristics for each TANF client. The UI data are merged with TANF data in order to track employment records for each client. Similarly, training variables are merged into TANF data to provide training records for the target population. Life table method and multilevel models (or random effects models) are used to test the hypotheses based on the theoretical concerns. Chapter VI presents the findings and results. Finally, the study ends with a conclusion and discussion.

CHAPTER II

POLICY CONTEXT

2.1 Introduction

The earliest principle regarding America's policies for aiding the poor can be traced back to colonial times, when British colonies established a law similar to the Elizabethan Poor Law. The Poor Law took effect in 1601 and was a response to the threat of economic insecurity and social disorder from the late 16th century. The renowned statute had many constructive features (Trattner 1999). First, it assumed that the state had a responsibility to relieve want and suffering and insure the maintenance of life. Second, it conceded that helpless or needy people not only deserved public assistance but have a legal right to it. In doing so, the law firmly established the principle of relief locally financed and administered for local residents. Funds for the act were raised by taxing every householder in the parish, the lowest level of jurisdiction in England. The operation of the act was placed in the hands of civil authorities outside of the church. The Poor Law was observed to be effective throughout England with "a fair degree of efficiency and success" (Trattner 1999:12). Likewise, in America, the burden of public assistance had traditionally fallen upon counties or towns based on local taxation and administration.[2] Governmental involvement at the federal and state levels was slight.

---

[2] It should be noted that private charity and faith-based philanthropy had been dominant ways of helping the poor.

The principle of localized public assistance dominated American's public policies in aid of the poor until the passage of the Social Security Act in 1935 during the Great Depression. More and more people realized that there are circumstances beyond the control of individuals. Destitution was no longer regarded as a problem of individual weakness, at least in theory. The federal government was expected to take responsibility for creating a national system of social security. In a broader view, four social trends occurred during the second half of the 19th century that rendered traditional systems of economic security increasingly unworkable: the Industrial Revolution, urbanization, the disappearance of the extended family, and a longer life expectancy (U.S. Social Security Administration 2010). Eventually, as one of the legislation packages of the New Deal during Franklin D. Roosevelt's administration, the Social Security Act was enacted. The renowned statute has several components. The major components include old-age assistance and benefits, unemployment compensation, aid to dependent children, aid to the disabled, and maternal and child welfare. In this sense, as Trattner (1999:294) put it, the Social Security Act "marked the beginning of a policy of federal aid to the states upon a permanent basis for regular, recurring social work, closing the door on three centuries of the poor law and its principle of local responsibility. For the first time in American history, funds to finance all or part of the needs of selected groups in the population became a major permanent item in the federal budget, one that has continued to grow each year. … hence, the American welfare state was born."

2.2 AFDC and Its Problem

As one of the components of the Social Security Act, the Aid to Dependent Children (ADC) program was originally designed to provide monthly cash support to low-income families with poor widowed mothers who needed to stay home to care for their children.[3] Social, moral, and economic reasons justified the program. A family with a breadwinner husband and a household wife was taken for granted before World War II, and a widow was expected to stay at home and take care of her children. Moreover, the Great Depression did not welcome female labor force participation because many male breadwinners were looking for jobs. At the beginning, the ADC program was small in terms of spending and number of clients. Policymakers even expected that the ADC program could be unnecessary as long as social insurance system was fully developed (Moffitt 2003c).

The ADC program, however, did not diminish but kept growing. By the time the program was reauthorized as Aid to Families with Dependent Children (AFDC) in 1961, the total number of families amounted to approximately 845,000 (Table A.1). Even more dramatic expansion happened between the late 1960s and early 1970s (Figure 2.1). The same period also involved the creation of the Food Stamp, Medicaid, and Social Security Income programs based on Social Security amendments of 1967 (Table 2.1). This period was later called the era of the welfare explosion and built the modern framework of means-tested transfers under the movement of the Great Society and the War on Poverty (Moffitt 2002:2-4). The late 1970s and 1980s saw a steady decline in real AFDC benefits, stringent eligibility, and mandatory work requirements. The AFDC caseload was leveled during the period. However, in the early 1990s, its caseload increased again in a dramatic

[3] According to the 1935 act, dependent child is defined as "a child under the age of sixteen who has been deprived of parental support or care by reason of the death, continued absence from the home, or physical or mental incapacity of a parent, and who is living with his father, mother, grandfather, grandmother, brother, sister, stepfather, stepmother, stepbrother, stepsister, uncle, or aunt, in a place of residence maintained by one or more of such relatives as his or their own home." Aid to dependent children is defined as "money payments with respect to a dependent child or dependent children" (Social Security Act of 1935: Title IV).

way that resembled the welfare explosion. The trend peaked at 1994 before a dramatic drop in caseload that continued through the 1996 welfare reform.

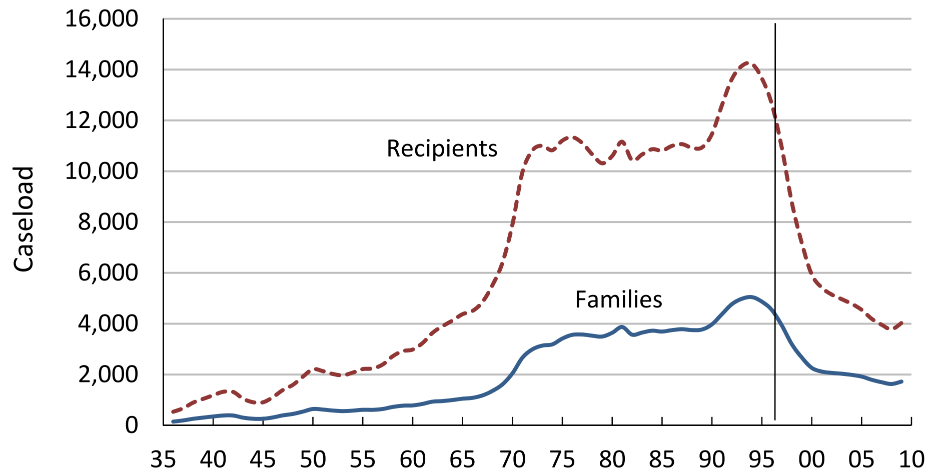


Figure 2.1 Trends in the Cash Welfare Caseload (in 1000) in the United States, by Families and Recipients, 1936-2009

Source: See Appendix Table A.1.
NOTE: The vertical line indicates the time of welfare reform in 1996.

A number of factors contributed to the welfare explosion. Some of them were recognized as noneconomic forces, including but not limited to reductions in the stigma of welfare receipt (mostly due to the welfare rights movements), the impact of court and legislative decisions, improvements in administration that facilitated the application process, and dramatic growth in the number of single mothers (e.g., Moffitt 1987; Levitan et al. 1998:71-72). The effect of economic conditions on the surge of caseloads in the late 1960s, however, is controversial. There is limited evidence that supports a relationship between welfare caseloads, female head labor supply, and changes in welfare benefits, employment rates, and economic incentives (Moffitt 1992).

Table 2.1 Major Legislation and Court in the Means-Tested Programs

Date	Title	Main Provisions
1935	Social Security Act	Created the ADC program for low-income children with only one parent present in household
1961	Amendments to the Social Security Act	Created AFDC-UP program for children in two-parent families where primary earner is unemployed (optional provision)
1964	Food Stamp Act of 1964	Food Stamp program began (and operated nationwide in 1974).
1965	Amendments to the Social Security Act	Medicaid began (and expanded its coverage for poor children in the 1980s and 1990s)
1967	Amendments to the Social Security Act	Lowered the AFDC benefit reduction rate to 2/3; created the Work Incentive (WIN) program
1968-1969	Supreme Court	Moved eligibility restriction on AFDC women living with a man; Moved welfare eligibility restriction on one year state residency requirements.
1981	Omnibus Budget Reconciliation Act of 1981	Increased the benefit reduction rate to 1; imposed a gross income limit; counted income of stepparents; allowed waiver authority.
1987	Tax Reform Act of 1986	Effective in 1987, EITC increased by over 50 percent and indexed for inflation.
1989-1990	Family Support Act of 1988	Created the JOBS program for education, skills training, job search assistance, and other work activities; created transitional child care and Medicaid programs; mandated AFDC-UP in all states;
1990	Omnibus Budget Reconciliation Act of 1990	Effective in 1991, EITC increased by over 50 percent.
1994	Omnibus Budget Reconciliation Act of 1992	Effective in 1994, EITC increased by over 50 percent.
1996	Personal Responsibility and Work Opportunity Reconciliation Act	Abolished the AFDC program and created the TANF program.
1997	Balanced Budget Act	Children's Health Insurance Program (CHIP)
1998	Workforce Investment Act	Consolidated services of many employment and training programs.
2005	Deficit Reduction Act of 2005	Tightened work participation standards; allowed to count the declined caseload as the working caseload for purposes of the participation standards.

Source: Modified from Moffitt (2008), Meyer and Rosenbaum (2001), and Murray (1993:230).

After the AFDC program expanded, it received more and more critiques from both conservative and liberal sides. Typically, conservative critics have charged that AFDC was responsible for the breakdown of the family and the devaluation of the work ethic of the poor. Liberal critics questioned the causal links between welfare and demoralization but pointed out that AFDC and other means-tested programs failed to provide support for the working poor. Thus, work did not pay for poor single mothers, making them rely on public assistant programs to survive.

Charles Murray (1984) makes perhaps the most provocative attack against American's welfare system that evolved during the 1960s. According to Murray, welfare encourages and is responsible for increasing single-mother parenting and illegitimacy and the devaluation of the poor's work ethic. Thus, he calls for eliminating many types of public assistance. Murray's proposal represents the polar extreme of conservative welfare reform. Another influential figure in the welfare reform debate is Lawrence Mead. Based on his extensive field study of the Workforce Incentives program, Mead (1986) strongly critiques the entitlement of AFDC benefits. In Mead's perspective, welfare recipients should show their commitment to work in exchange for public cash assistance.

On the liberal side, Bane and Ellwood (1983, 1994) argue that dependency on welfare can be largely explained by availability of economic opportunities and choice. Single mothers have to make a tradeoff between welfare and work. Although AFDC cash payments had declined in value since the early 1970s, a significant expansion in related programs (e.g., food stamps, subsidized housing, medical care, and social services) provided important support to the survival of single-mother families.[4] Meanwhile, the

[4] After the 1970s, AFDC benefits were not adjusted for inflation. Thus, their purchasing power declined (Moffitt 1992).

federal minimum hourly wage had declined in value in the 1980s, and few public supports were available to the working poor. According to Bane and Ellwood (1994), the AFDC program actually made a single mother favor welfare over a low-paying job.[5] For example, a single mother with three children could receive, on average, roughly the same income from AFDC and food stamps as she could earn from a full-time job at minimum wage. An AFDC mother was also automatically eligible for free medical care, which few minimum-wage employers provided. In addition, she did not face child care and other job-related costs that the working mother had to deal with. Bane and Ellwood (1994) advocate policy changes that would make work pay.

2.3 Welfare-to-Work under AFDC

In response to the rising welfare caseload in the 1960s, the early effort to enforce work requirement in the welfare system was the enacting of the WIN program in 1967, which required welfare recipients with children older than 6 to participate in a work incentive program to gain work experience and learn job search skills. Moreover, Congress offered a financial incentive for AFDC adults to work in the form of a permanent disregard of a portion of earnings. Previously, only work expenses were deducted from adult earnings, and the remainder was counted against AFDC checks (payment standard) in most states. According to WIN, states were required to disregard the first $30 earned and one-third of the remaining monthly earnings (Moffitt 2003c).

However, the effectiveness of WIN was limited due to budget constraints and administrative feasibility (Levitan et al. 1998; Mead 1986, 1988). For example, of all 11 million AFDC clients in 1986, 1.6 million were registered in the WIN program, but only

[5] Findings from ethnographic studies usually support this argument (e.g., Edin and Lein 1996).

about 220,000 received any services. Most of these services were provided by participating state welfare-to-work programs, not WIN (Bane and Ellwood 1994:20-21). In 1981, Congress repealed the permanent work incentive (disregard of one-third of every extra dollar), confining it to the first four months of a job.

Meanwhile, states were given the option of requiring the majority of recipients to participate in workfare programs. During the 1980s, 40 states set up welfare-to-work programs that provided education and training. Eventually, the federal Family Support Act of 1988 (FSA) adopted this approach, directing all states to phase in comprehensive welfare-to-work programs by 1990. Each state was to implement education, job training, and job placement programs for welfare recipients. The FSA replaced WIN with the Job Opportunities and Basic Skills program (JOBS). It required states, to the extent resources allowed, to engage most welfare recipients in education, work, and skills training and other work activities under JOBS. Those who failed to participate in work-related activities were subject to sanctions, which involved forfeiting the adult's portion of the AFDC benefit. Meanwhile, JOBS created transitional child care and Medicaid programs for 12 months to families that lost AFDC due to increased earnings.

The JOBS program was a good idea, but the implementation of the program proved to be more expensive and less efficient than lawmakers expected. First, 40% of the program's cost was supposed to be paid by states, with the federal government paying for the remaining 60%. In reality, although the federal government had set $1 billion aside for JOBS, states ended up paying 60% of the program's cost (Bane and Ellwood 1994:24). The initiative proved unsuccessful because states did not have enough money to match federal funding. Second, JOBS exempted primarily single parents with children under 3 and those working at least 30 hours a week. Other exemptions included the ill, the disabled, those over 60, those living in remote areas, those needed in the home, those in their last trimester of pregnancy, and those for whom guaranteed child care was not available. As a result, the majority of welfare mothers were still exempted. Less than half of the welfare caseload was required to participate in JOBS, and actual participation rates were much lower. The exemption rate was as high as 70 or 80 percent of the caseload for some states. Consequently, only 7 percent of all adult AFDC recipients were participating in JOBS programs in 1992 (Bane and Ellwood 1994:24-25). Moreover, those that did participate more often went into education or training than into low-paying jobs (Mead 2001).

Despite the effort to move welfare recipients to work during the 1980s, work mandates were widely perceived as too weak to push the welfare-to-work transition. Therefore, the federal administration gave some states special permission to run their welfare-to-work programs. By the early 1990s, more than 40 states were approved as federal waivers by the Department of Health and Human Services (HHS), and many of them implemented statewide reforms. These states took advantage of federal encouragement to apply for waivers of federal regulations in order to experiment with state-level reform (Levitan et al. 1998). Many states redesigned their welfare-to-work programs from basic skills and education (human capital development strategy) to job search and employment (the work-first strategy). In doing so, many states strengthened their work-related activity mandates under waivers. Common modifications included higher hour requirements, more restrictive definitions of work-related activities, and a greater restriction on the age of children. Consequently, waivers paved the way for an overhaul of the entire welfare system.

2.4 Welfare-to-Work under TANF

The most substantial moment of welfare reform occurred in 1996 when the Personal Responsibility and Work Opportunity Reconciliation Act was passed. As the act's name illustrated, new policies were required to emphasize personal responsibility of welfare recipients and strongly encourage their labor force participation.[6] TANF became the new welfare program of the United States.

The critical components of TANF are block grants, time limits, sanctions, and mandatory work. Unlike AFDC, in which federal expenditures matched state expenditures at a fixed rate, federal expenditures are fixed under TANF and, therefore, neither adjust for inflation nor rise and fall with caseload size.

TANF mandated a 24-month maximum and 60-month lifetime benefit for adult-headed families, unless they are exempted. Time limits have proven to be a crucial part of TANF's effectiveness. However, according to an annual report to Congress from the Department of Health and Human Services, few families have been affected by federal time limits. There are three major reasons (HHS 2009a: I). First, welfare reforms have proven to be effective at helping recipients move off of welfare long before reaching their time limits. As the report shows, only 1.2 percent of case closings in fiscal year 2006 were due to families meeting federal time limits. Second, more than 47% of cases are exempt from the accrual of months for a variety of reasons: (1) the case does not contain a countable head-of-household; (2) assistance is state-funded (e.g., Separate State

[6] The statute (PRWORA of 1996, §101) was designed to (1) provide temporary assistance to needy families so that children may be cared for in their own homes or in the homes of relatives; (2) end the dependence of needy parents on government benefits by promoting job preparation, work, and marriage; (3) prevent and reduce the incidence of out-of-wedlock pregnancies and establish annual numerical goals for preventing and reducing the incidence of these pregnancies; and (4) encourage the formation and maintenance of two-parent families. However, in implementing and evaluating welfare reform, the recipients' labor force participation draws far more attentions than other purpose.

Program[7]); (3) the family is exempt under an approved welfare waiver; or (4) the family lives in Indian reservation or an Alaska native village with high unemployment. Finally, most families do not receive assistance continuously.

TANF required states to increase the fraction of their caseloads participating in work-related activities.[8] Furthermore, TANF limited the extent to which education and training could be used to satisfy this requirement. The key index to welfare-to-work transition is workforce participation rates. To count toward the workforce participation rate, a family must include an adult or minor head of household who is engaged in qualified work activities for at least 30 hours per week or 20 hours per week if the head of household is a single parent with a child under 6 (HHS 2009a). In practice, workforce participation rate requirements were modified in response to sharp caseload decline and TANF's caseload reduction credit. Moreover, to further facilitate the workforce participation rate of welfare recipients, the Workforce Investment Act (WIA) of 1998 mandated that states and localities use a centralized service delivery structure—the one-stop center system—to provide most federally funded employment and training assistance. Those who fail to meet work requirements are subjected to sanctions. State

[7] States are allowed to move TANF recipients who have reached the Federal time limit to Separate State Programs (SSP). Individuals in such programs are not subject to the federal time limits or to rules about child support assignment. Until October 2006, such families were not included in calculations of the work participation rate. Expenditures on SSPs count toward the maintenance-of-effort (MOE) requirement. Under the basic MOE requirement, states must spend 80 percent of Fiscal Year 1994 spending (75 percent, if they meet work participation requirements) on qualified state expenditures to eligible families (HHS 2008; Urban Institute 2009).

[8] All activities that will satisfy an individual's obligation to participate in employment-related activities under the state policy, including unsubsidized employment, subsidized private sector employment, subsidized public sector employment, work experience, on-the-job training, job search and job readiness assistance, community service, vocational educational training, job skills training, education related to employment, and completion of high school or a General Educational Development (GED) program.

sanctioning policies vary and range from partial sanctions, which reduce the grant amount, to full-family sanctions, which terminate cash assistance to the entire family.

In addition to the push to work under TANF, other poor-relief policies would attract single mothers moving from cash welfare to work. The most significant policy change was the expansion of Earn Income Tax Credit (EITC), which provides a refundable tax credit to working poor families. Meanwhile, health insurance programs for low-income workers and their children not receiving cash welfare were expanded. The expansion enabled parents to leave welfare for work without the risk of losing their entitlement to health coverage. The significant increases in federal and state child care spending over the 1990s also encouraged low-income workers to enter and remain in the labor market. Finally, the minimum wage increased to mitigate the growing living cost in the United States. Thus, welfare reform worked by ending entitlement and making work pay at the same time (Bloom and Michalopoulos 2001; Mead 2001; Moffitt 2003b, 2008).

Considering these policy changes along with the long-term economic growth in the late 1990s, welfare reform was praised for successfully moving welfare mothers into the labor force. A tabulation of CPS data shows that the workforce participation rate increased substantially for single mothers with lower education or in poor households, the target group of welfare reform (Figure 2.2 and Figure 2.3). Overall, the welfare caseload kept dropping even when the U.S. economy suffered in the early 2000s (Figure 2.1). In addition, the poverty rate stabilized, if not declined moderately, over the late 1990s among less-skilled, single-mother families. However, not all studies celebrated welfare reform success. In-depth reviews and ethnographic studies examined cases of unrelieved single mothers struggling for survival (Anderson and Van Hoy 2006; Monroe and Tiller 2001; Scott et al. 2004).

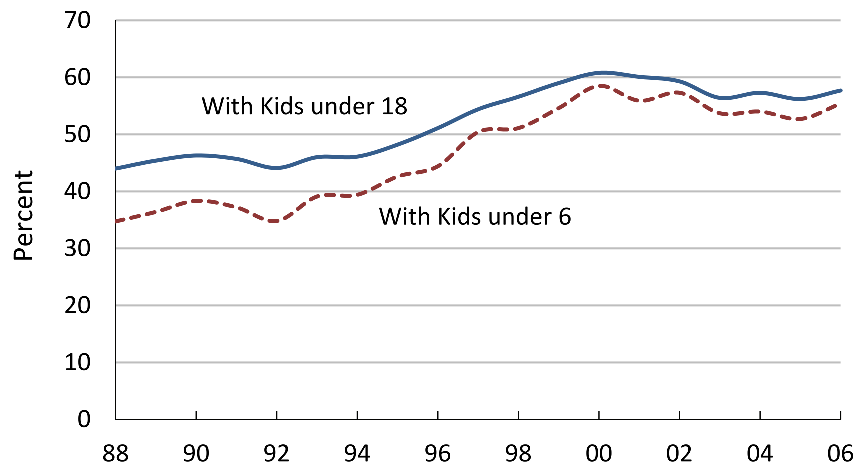


Figure 2.2 Employment Rates among Single Mothers under 200 Percent of Poverty in the United States, 1988-2006

Source: See Appendix Table A.3.

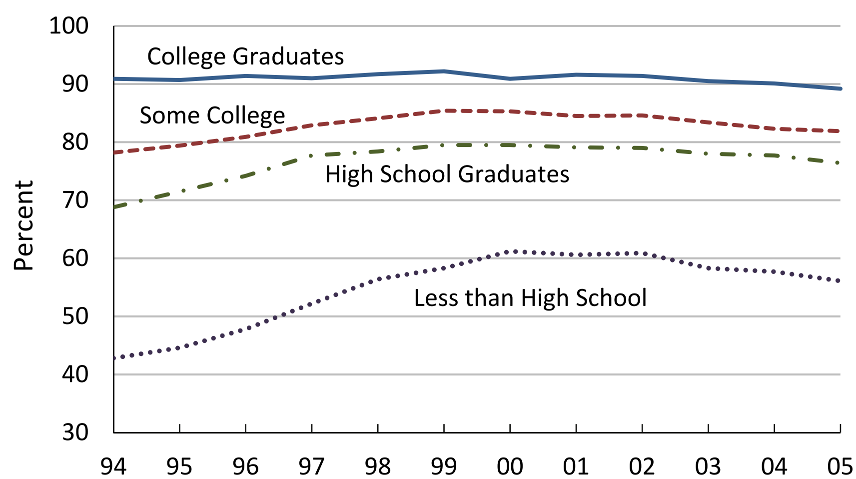


Figure 2.3 Labor Force Participation Rates of Non-Married Women with Children under 18 Years in the United States, by Educational Attainment, 1994-2005

Source: See Appendix Table A.4.

2.5 Mississippi's TANF Policy

Presumably, Mississippi plays an insignificant role in affecting the national concern of welfare reform. The simple reason is that the caseload in Mississippi only amounts to approximately 0.6% of the nation's total caseload. However, Mississippi is still relevant to the study of welfare-to-work transition for several important reasons. First, it shares characteristics with other states in terms of policy change, economic trends, and social background. Second, Mississippi represents some specific features of the Deep South, such as higher black density, more rural orientation, and lower economic development. Finally, Mississippi has distinctive social and economic characteristics, diverse local conditions, and different geographic settings. Mississippi has among the highest poverty rates in the United States[9], a large share of families with children headed by a single parent[10], and a large proportion of African Americans[11]. There are clusters of Mississippi counties with high and persistent poverty, such as those in the Delta, and counties with various socioeconomic conditions in medium-sized metropolitan areas and nonmetropolitan areas outside of the Delta. Thus, the case of Mississippi is able to provide insight into the consequences of TANF for disadvantaged families living in substantially different socioeconomic contexts.

Mississippi was one of the first states to implement the TANF welfare policy, which was implemented in October 1996 and signed into law in March 1997 (Henry et al. 2002:136; Urban Institute 2009). Caseload trends in Mississippi are similar to patterns

---

[9] Multi-sources of poverty rates by state can be found in the website of U.S. Census Bureau. http://www.census.gov/hhes/www/poverty/index.html. Accessed June 21, 2010. Meanwhile, Committee on Ways and Means published data on poverty in Green Books (e.g., Committee on Ways and Means 2008: Appendix E-Poverty, Income Distribution and Anti-Poverty Effectiveness).

[10] American Community Survey PUMS files. http://factfinder.census.gov/home/en/acs_pums_2008_3yr.html. Last revised: October 27, 2009. Or see the website of the Annie E. Casey Foundation for a quick view. http://www.aecf.org/.

[11] A recent release of population profile by state can be found in the website of U.S. Census Bureau. "Estimates of the Resident Population by Race and Hispanic Origin for the United States and States: July 1, 2009." (SC-EST2009-04). Source: U.S. Census Bureau, Population Division. Release Date: June 2010. http://www.census.gov/popest/states/asrh/SC-EST2009-04.html.

throughout the nation (Figure 2.4). The difference is that the caseload decline in the state is even sharper than the U.S. average (Figure 2.5).

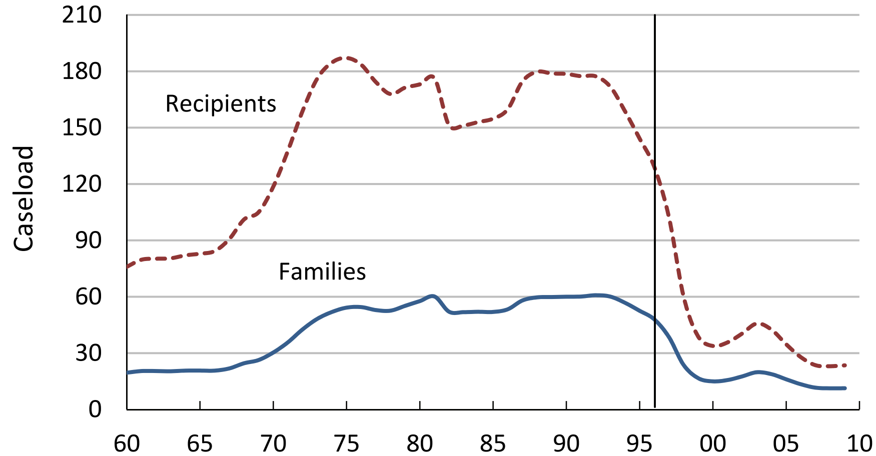


Figure 2.4 The Cash Welfare Caseload (in 1000) in Mississippi, by Families and Recipients, 1960-2009

NOTE: The vertical line indicates year 1996.
Source: See Appendix Table A.2.

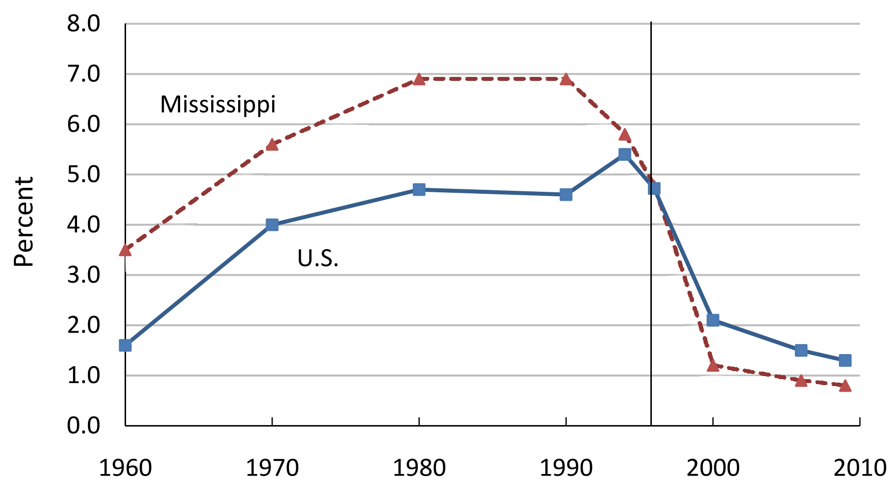


Figure 2.5 Average Monthly Number of Recipients of TANF/AFDC in Mississippi and the United States, as a Percent of Total Population, 1960-2009

NOTE: The vertical line indicates year 1996.
Source: See Appendix Table A.5.

In general, Mississippi's welfare policies are less generous than the national average. Mississippi has set stringent sanctions and moderate time limits for TANF receipt. Policy research shows that Mississippi's sanctions and time-limit policy orientation are similar to those of 24 other states, although only 10 states have policies that rank the same as Mississippi on both sanctions and time limits (Pavetti and Bloom 2001). TANF in Mississippi has the lowest payment levels, and minimal income can exclude families from eligibility. For example, maximum monthly payments for a family of three are limited to no more than $170, which ranks at the bottom nation-wide.[12] Like most states, Mississippi enforces a maximum of 24 consecutive months on TANF. Mississippi also has a 60-month lifetime limit for TANF with some hardship exemptions, which should comprise no more than 20% of all cases.[13] Mississippi also applies a family cap policy, which denies an increase in benefits for an additional child born more than 10 months after the case opens. Moreover, the cap will not be removed, even after the case closes.

According to *Welfare Rules Databook* released by the Urban Institute (2009), Mississippi is one of the 16 states without a program for formal diversion payment. On the other hand, Mississippi is one of the 22 states that require a job search during

[12] A TANF recipient is automatically eligible for another federal program, Supplemental Nutrition Assistance Program (SNAP) (which used to be called Food Stamps). The average SNAP benefits per household in Mississippi ($268.98 in 2009) are close to the national level ($275.52 in 2009). http://www.fns.usda.gov/pd/snapmain.htm. Accessed June 21, 2010.

[13] A client may be eligible for an exemption from the 24-month time limit for the following reasons: caretaker of an ill or incapacitated person, as verified by a physician; age over 60 or under 18 years old; domestic violence - documented by a physician and law enforcement records (not to exceed 12 months); disability or temporary disability (no more than 30 days); pregnancy - third trimester (in or later than 7 months) with complications; Substance Abuse Treatment (this exemption may only be requested at the time of application, reevaluation, or change from exempt to mandatory participation status); or caring for a child under 12 months old (this exemption can only be granted for a total of 12 months in a lifetime, regardless of the number of children) (MDHS 2009; Or see the website of Mississippi Department of Human Services).

application.[14] When family members do not comply with program requirements (e.g., work and child support compliance), the entire family is sanctioned and loses eligibility. In addition, all adults in the TANF household must participate satisfactorily in the TANF Work Program (TWP) unless they meet a work exemption. TWP serves all TANF adults who must participate or who volunteer in order to receive assistance in finding and keeping a job. Support services are available. A family participating in TWP may continue to receive benefits (not cash) for a period of up to 12 months once the case is closed because of increased earnings. These benefits include transitional child care, transitional transportation services, and job retention bonus payments when needed to continue employment (MDHS 2009).

Mississippi enacts earned income disregards in favor of workforce participation (MDHS 2009). TANF recipients can have earned income totally disregarded from the TANF budget for up to six months if they work 35 hours per week and earn at or above the federal minimum wage. This disregard allows one to receive both TANF benefits and paychecks when one finds full-time employment within 30 days of the initial job readiness or job search work activity in TWP. Also, if one does not qualify for the 6-month total earned income disregard, one may be eligible for a 3-month total earned income disregard if one is employed at least 25 hours per week at or above the federal minimum wage. Mississippi allows six months of total earned income disregards for benefit computation and $90 thereafter.

[14] Specifically, applicants in Mississippi are required to make three job search contacts during the 30-day application period, or their applications will be denied, except those who are exempt from work requirements. The job search requirement suggests that participant entrance is selective in that the most employable can find jobs and do not need TANF, while the less employable cannot get jobs at the time of application and must enter into the program (MDHS 2009).

Moreover, a client is required to work with her case manager to determine her employment goal for moving her and her family to self-sufficiency. The client and her case manager will develop a work plan to help her reach her employment goal as quickly as possible. She must participate in one or more of the following TANF work activities: job readiness and job search; unsubsidized employment; work experience programs; community service programs; vocational education (not to exceed 12 months); high school or GED equivalent or education related to employment, if under age 20; job skills training; and education directly related to employment (MDHS 2009).

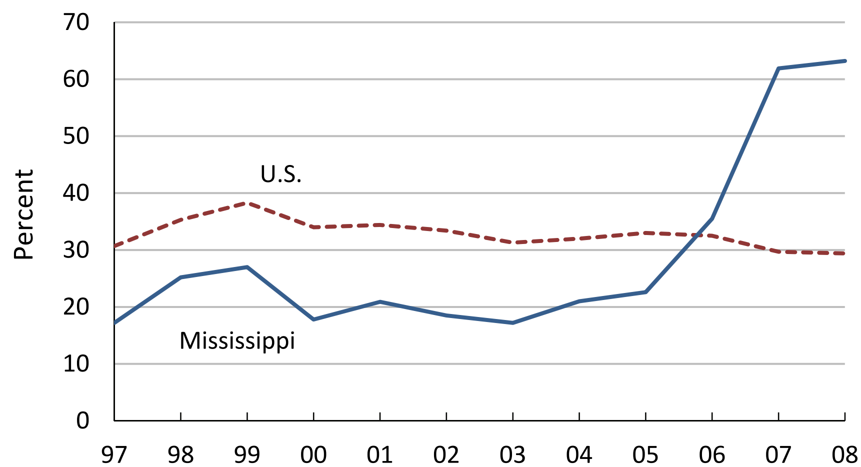


Figure 2.6 TANF All-Families Workforce Participation Rates in Mississippi and the United States, 1997-2008

NOTE: All-families rates are adjusted by State's caseload reduction credit.
Source: See Appendix Table A.6.

The state's effort to improve workforce participation for TANF recipients worked according to federal reports. As we see in Figure 2.5, the caseload in Mississippi dropped even faster than the national average. However, in spite of the mandatory work requirement, Mississippi's work participation rates had failed to match the national average level until 2006, when the rates substantially jumped to 35.5, 3 points higher than that of the nation. An even more dramatic increase was observed after 2007. The workforce participation rate doubled to 61.9 in 2007 and stayed above 60 in 2008 (Figure 2.6). There is no specific explanation of the dramatic increase in Mississippi (but not in the U.S.). As noted from the website of Department of Health and Human Services, one of the most important reasons could be the change of statutes and regulations in the families included in the rates and the countable work activities and hours.[15] We assume that Mississippi state agency took this advantage to classify far more work-related activities than before. Considering the large portion of single mothers leaving TANF in the late 1990s and the dramatic rise in workforce participation rates in recent years, one may have concerns about the mechanism that determines the transition from welfare to work. I will get back to the issue of workforce participation within the TANF program in the Chapter VI.[16]

[15] See Footnote 2 under the Table 1C "Changes in TANF and SSP-MOE Combined Work Participation Rates: From FY 2006 to FY 2007." Available at http://www.acf.hhs.gov/programs/ofa/particip/2007/tab1c.htm.
[16] See Figure 6.5 and Footnote 51.

CHAPTER III

THEORETICAL FRAMEWORK

3.1 Introduction

Like other social facts, welfare-to-work transition can be causally interpreted based on both individual approaches and structural approaches. Individual approaches attribute different welfare-to-work transition outcomes to a welfare recipient's different characteristics, such as human capital, assuming equilibrium of the socioeconomic environment. In contrast, structural approaches argue that it is social and economic inequality (e.g., inequality of opportunity) that places single mothers on welfare rolls (e.g., O'Connor 2000; Rank 2005; Sharon 2003:128-137). In other words, it is the social structure that reproduces inequality, not the irresponsibility of individuals. Typically, in the study of human behaviors, theories based on neoclassical economics take an important role in favor of individual causation, while theories proposed by sociologists focus on structural causation (Baron and Hannan 1994; Kalleberg 1995).

The underlying assumption of neoclassical economics is that individual behaviors are guided by rational calculation between cost and benefit. The explanatory power of the rationality assumption depends on what factors (e.g., monetary or non-monetary, individual or structural) are incorporated into an individual's decision making. In doing so, neoclassical economics could model all kinds of human behaviors by an individual's rational calculation and maximization of self-interest. For the sake of conceptual clarity, empirical studies treat human capital theory as the core of neoclassical economics, which provides an explanation of how education, training, and work experience affect an individual's labor market performance. Meanwhile, some structural factors are viewed as exogenous to individual calculation, such as local labor market conditions or occupational composition. Still others are partly addressed by theories such as state dependence and neighborhood effects.[17] In the study of welfare-to-work transition, the model of state dependence (or welfare dependence) predicts the likelihood of work for long-term welfare recipients, while neighborhood effects theory predicts the probability of entering welfare rolls rather than the labor force for those who reside in disadvantaged neighborhoods.

In the remainder of this chapter, I conduct a survey of these theories, beginning with human capital theory and its theoretical background—neoclassical economics and rational assumption. Then I examine alternative explanations based on neighborhood effects and state dependency hypotheses. In doing so, I include conceptual components that are consistent with previous studies (e.g., Bane and Ellwood 1994; Harris 1993, 1996; and Herbst and Stevens 2010).

3.2 A Survey of Theory

3.2.1 Human Capital, Labor Market, and Rational Choice

Due to the pioneering work of Theodore Schultz (1962), Gary Becker (1962, 1964), and Jacob Mincer (1962, 1974), the human capital model has an influential role in social science. Typically, the model is used to explain differentials in labor market outcomes in terms of investments in educational attainment, work experience, and

[17] Corcoran (1995) offers a review of theoretical models of the intergenerational transition of poverty, which includes hypotheses of welfare culture and neighborhood effects.

training. According to the human capital model, education, work experience, and training increase one's productivity. Thus, investment in human capital potentially increases one's income. The core of classical human capital theory is the concept of life cycle rewards in the labor market (Welch 1975). From this perspective, an individual's investment in human capital is a function of discounted lifetime earnings. Polachek (1981) provides a generalization of the human capital model in explaining the relation between patterns of life cycle labor force participation and occupational choice. It is hypothesized that (1) intermittent labor force participation[18] affects occupational choice and that (2) the impact of lifetime labor force participation on the probability of entering a given occupation varies with the cost of intermittent employment. Thus, the less one is expected to work in the future, the less likely one will invest one's human capital.

The explanatory power of human capital theory, however, is not limited to modeling life cycle rewards of education or training. Mostly due to the significant work of Becker (e.g., 1964, 1981), human capital theory—and the neoclassical economic approach in general—has been tied to fields that traditionally belong to other disciplines, such as sociology, demography, and political science, by incorporating exogenous factors, such as taste, preference, and uncertainty. On the other hand, sociologists have borrowed the concepts of human capital and labor market from neoclassical economics (for a review of the communication between sociology and economics, see Baron and Hannan 1994; Kalleberg 1995; and Boyer and Smith 2001). As a result, human capital theory has changed its mathematically rigorous form to a conceptual framework that is more inclusive and ready to explain most social phenomena. Human capital, as a loose concept,

[18] Intermittent labor force participation typically refers to women who interrupt their careers and leave the labor market for family responsibilities.

has served as a default explanatory model in the sociological literature on earnings inequality, discrimination, poverty, marriage and family, fertility, health, and welfare.

In a broader perspective, human capital theory is incorporated into the paradigm of rational choice (Hechter and Kanazawa 1997). The fundamental assumption is that human behaviors and their consequences can be explained by an individual's rational calculation and maximization of self-interest. There has been a persistent debate among sociologists over the rational choice approach. Some have welcomed the extension of rational choice theories in the explanation for non-economic phenomena. Others have criticized its assumptions of individualism and rational action (Kalleberg 1995; Hechter and Kanazawa 1997; see Zafirovski 2000 for a critical review). In empirical studies, the validity of a rational choice approach in general, and the human capital model in particular, heavily depends on what variables are incorporated into the theoretical framework. In the case of welfare-to-work transition, for example, the components of the model include not only wages, education, work experience, and training but also health, child care, work incentive plan, local labor market opportunity, preference for leisure, family orientation, commitment to job, welfare stigma, transportation cost, the presence of partners or relatives, and so on.

In a well-recognized study from the welfare literature, for example, Bane and Ellwood (1994) examine the efficacy of rational models as tools for explaining welfare dependency. According to Bane and Ellwood, rational models suggest that "individuals examine the options they face, evaluate them according to their tastes and preferences, and then select the option that brings them the greatest utility or satisfaction" (p. 69). Thus, patterns of welfare use are viewed as a series of rational choices based on available options that could be monetary and nonmonetary, individual or structural.

Another example in the study of welfare-to-work transition is from Harris's (1993) conceptual framework that is built on the human capital model. According to Harris, the model "specifies that welfare mothers with favorable family resources, whose early life-course path has not impeded finishing high school and attaining some work experience, and who have relatively small families are more likely to exit welfare through a high-quality job than mothers with more disadvantaged family backgrounds, larger families, and fewer investments in human capital" (24). Harris, therefore, is able to incorporate structural factors that are viewed as having causal relations with the development of human capital. Thus, urban residence is expected to improve the effect of human capital investments and facilitate welfare-to-work transition. Also, black women are less likely to exit welfare through a job because of their historical disadvantage over white women in education and training. Moreover, the greater the wages a welfare recipient can expect to earn in the labor market, the more rapidly she will exit welfare through work. Finally, structural effects of welfare benefits and the unemployment rate are expected to prolong welfare dependence. In addition, relatively high welfare grants presumably provide lower incentives to work, and high unemployment makes it especially difficult for welfare recipients to find jobs.

In an updated study, Harris (1996) models the process of welfare recidivism based on a function of the trade-offs, which incorporates economic components, family and social structural components, and contextual factors. The economic components are measured by a welfare recipient's human capital, potential wage rate, union status, potential earnings of her partner, and her maximum welfare cash assistance. A welfare mother's family and social structural components include her family background, race, age, and the number and age of her children. Contextual factors include central city residence, residence in the South, the local unemployment rate, and the length and exit route of the prior welfare spell. As we see, the trade-off model includes a wide range of variables that are assumed to affect a welfare mother's rational choice.

In conclusion, the human capital model is a benchmark in the study of labor market outcomes, predicting the differentials of labor market outcomes in terms of the variance of human capital. An important caveat is that the model can never explain all, or even the major, differentials. The key is not whether the human capital model has failed to explain labor market outcomes but to what extent the model has explanatory capacity compared to other theoretical models.[19]

3.2.2 Neighborhood Effects

If human capital theory is personally attached to Gary Becker, neighborhood effects theory is specifically attributed to William Julius Wilson. The central theme of Wilson's theory is the interaction between structure and culture in determining the experiences and life chances of inner-city residents.

According to Wilson (1987, 1996), structural causations are responsible for inner-city deterioration. By structural realities, Wilson emphasizes the shift of manufacturing employment from the cities to the suburbs[20] and the outmigration of middle class blacks

---

[19] In the challenge of mainstream neoclassical theory on labor economics, Labor Market Segmentation (LMS) theory focuses on the default of the labor market in wage inequality (e.g., Beck et al. 1978; Cain 1976; Dickens and Lang 1985; England 1982; Hudson 2007; Kalleberg and Sorensen 1979; Leontaridi 1998; Reid and Rubin 2003; Sakamoto and Chen 1991; Tolbert et al. 1980). The central concern of segmentation theory is wage inequality by gender and/or race in terms of different occupations or industries. Addressing the issue of labor market segmentation is beyond the purpose of this study. Since the group in this study is welfare recipients, a small part of labor forces that only occupies the lower end of occupations or a limited range of industries, the overall range of occupations or industries is missing. The examination of labor market segmentation theory, however, requires a sample representative of the population of labor forces and should account for all possible occupations or industries. For this reason, I do not bring LMS theory in the conceptual framework.

[20] Here Wilson borrows from spatial mismatch theory (Small and Newman 2001).

from urban poverty areas. As a result, inner cities have experienced an increase in male unemployment, weakened community supports, and the absence of role models for children (see reviews from Corcoran 1995; and Small and Newman 2001). In addition, residential segregation has worked as another important structural factor that contributes to social isolation of the inner-city black population (Massey and Denton 1993).

By cultural patterns, Wilson (1987) means the sharing of modes of behavior and outlook within a community. In this sense, "ghetto-related behaviors often represent particular cultural adaptations to the systematic blockage of opportunities in the environment of the inner city and the society as a whole" (p. 72). Wilson's cultural component has a significant difference from the culture of poverty. The culture of poverty assumes that people live in an area of concentrated deprivation that is geographically and socially isolated from mainstream society, resulting in deviant behaviors and norms (Lewis 1966). It predicts that, for those trapped by such a culture, welfare becomes a way of life and seems like a natural and legitimate alternative to either marriage or work. In contrast, Wilson's model emphasizes structural constraints, such as the loss of jobs and restraints on the social mobility of inner-city residents. Due to these differences, Ellwood classifies the culture of poverty as a conservative version of the cultural perspectives in modeling welfare dependency and Wilson's model as a liberal one (Bane and Ellwood 1994).

Wilson (1993) also emphasizes the interaction between individual causation and structural causation. He cautions that "a heavy stress on individual causation neglects the mounting evidence of the relationship between increasing joblessness and the dismal employment prospects in the inner city" (p. 3). On the other hand, "too great an emphasis on structural causation leads one to ignore the significance of culture and therefore leaves us unaware of the unique collective responses or adaptations to economic disadvantage, prejudice, and the problems of raising a family and socializing children under such conditions" (p.3).

When addressing the causation of inner-city problems, Wilson (1987) focuses on the linkage between structural realities, changing norms, and evolving cultural patterns. Structural realities diminish employment opportunities for low-skilled workers; changing norms weaken the commitment to the two-parent family and encourage short-term relationships; and evolving cultural patterns reinforce negative outlooks toward marriage and relationships between males and females in the inner city. According to Wilson, "the combination of factors has increased out-of-wedlock births, weakened the family structure, expanded the welfare rolls, and, as a result, caused poor inner-city blacks to be even more disconnected from the job market and discouraged about their role in the labor force" (1987:106). In the 1990 Presidential Address of the American Sociological Association, Wilson (1991) provides a concise illustration of the mechanism of neighborhood effects in the interaction between structural and cultural conditions at both community level and individual level (Table 3.1).

Table 3.1 The Mechanism of Neighborhood Effects in the Interaction between Structure and Culture

	Structural		Cultural (behavioral)
Neighbor-hood Level	▪ Spatial mismatch (Industrial restructuring) ▪ Racial residential isolation ▪ Outmigration of middle class blacks	⇆	▪ Lower collective efficacy ▪ Deviation of social norms
	↓		↑
Individual Level	▪ Weak labor-force attachment ▪ Lack of role models ▪ Weakened community supports	→	▪ Lower perceived self-efficacy ▪ Deviation of behaviors

In sum, the neighborhood effects model examines causal relations that result in inner-city problems, including detachment from the labor force and wide use of public assistance. The model highlights neighborhood effects that are independent of other socioeconomic factors. That is, everything else being equal, poor individuals living in disadvantaged neighborhood conditions are more likely to be worse off than those living in the absence of such conditions.

3.2.3 Welfare Dependence

Welfare dependence is a concept with many meanings.[21] In the political and public debate, welfare dependence, as Bane and Ellwood (1994) point out, often has a "pejorative connotation" (1994:67-68). That is, those who use welfare for a long time are more likely to be viewed as undeserving because they presumably lack a work ethic. Even worse, welfare is viewed as a way of life that trapped single-mother families in a cycle of welfare dependency, creating more, rather than less, poverty (Murray 1984). In this sense, welfare dependence shares some ideas with welfare culture in that both focus on behaviors and norms that deviate from the mainstream. The difference is that welfare dependence blames the individual who loses the incentive to leave welfare, while welfare culture blames the neighborhood that traps individuals and pushes them toward public cash assistance.[22] With these assumptions in mind, proposals from the conservative camp

---

[21] See Fraser and Gordon (1994) for a counterargument against the concept of welfare dependency. They question the underlying assumptions of "dependency." They argue that *dependency* is an ideological term in terms of the hegemonic discourse of *independence* that appreciates wage labor in the postindustrial society. The term, according to Fraser and Gordon, draws attention to individual problems of the recipients, as much moral or psychological as economic.

[22] Intergenerational association of welfare dependence is another perspective focusing on the role of the family as the main socializing agent (Corcoran 1995; Martin 2003). The empirical study of this issue, however, requires intergenerational data, which are not available in my study.

appealed for the end of welfare entitlement, mandatory work requirements, sanctions, and time limits (Mead 1986). Welfare policies after 1996 feature these arguments.

Welfare dependence can be a neutral definition, a synonym for long-term welfare use, which can be measured by the amount of time on the welfare roll (Gottschalk and Moffitt 1994; also see Bane and Ellwood 1994:67-68). Alternatively, HHS (2009b) provides a cross-sectional definition of welfare dependence as "the proportion of all individuals in families that receive more than half of their total family income in one year from TANF, food stamps, and/or SSI" (2009b:I-2).

The theoretical concern of welfare dependence comes from the observation that long-term welfare users have more disadvantages than short-term users in finding a way to leave welfare.[23] In statistical terms, probability of exit declines when time spent on welfare increases. There are two quite different explanations for this observation. On the one hand, as a common assumption, the experience of welfare significantly changes a single mother's behavior, making her develop a sense of "dependency" on public cash assistance and less likely to try alternatives. On the other hand, welfare experience may not have an impact on the recipients' decision making. Probability of exit could be constant, with probability changing for different recipients. For example, recipients with higher human capital may have higher exit probability than those with lower human capital. The first group is more likely to exit than the second. When time on welfare increases, the percentage of the first group declines, but the percentage of the second increases. It is exactly this change of composition in welfare population that results in the overall decline of exit probability (Figure 3.1).

[23] The classical example of the state dependence study is the estimation of unemployment spells in the labor economics literature (e.g., Heckman and Borjas 1980; Heckman 1981).

The empirical resolution of the two explanations leads to an examination of two statistical components in the longitudinal study: state dependence and unobserved heterogeneity.[24] State dependence implies that the history of a state occupied by an individual affects the individual's current status. Individuals who have experienced an event in the past are more likely to experience that event in the future; that is, a previous event induces a change in individual behavior. Unobserved heterogeneity implies that individuals differ in certain unobserved characteristics that cannot be included in the model but affect their probability of experiencing an event. Thus, controlling for unobserved heterogeneity is a critical way to predict the sequence of transitions.[25]

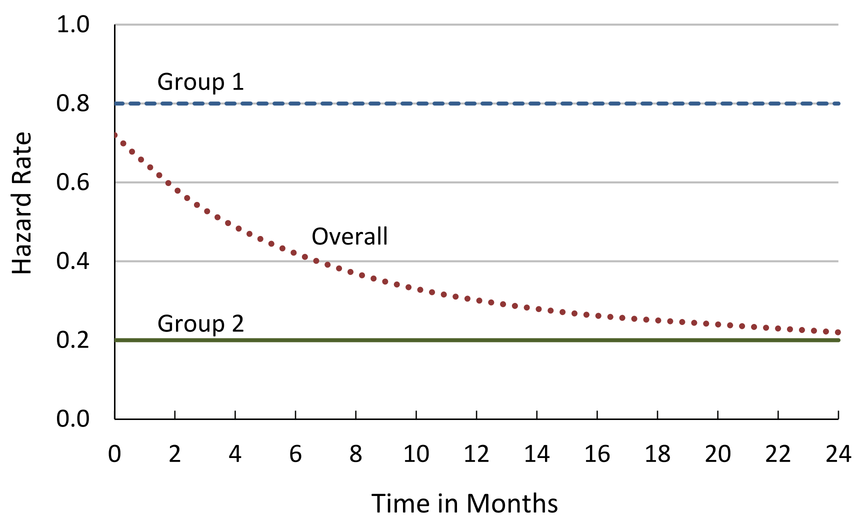


Figure 3.1 Effects of Unobserved Heterogeneity on the Observed Hazard Rate of an Event

[24] How unobserved heterogeneity influences patterns of hazard rates is a classic topic in the literature on modeling longitudinal data in social sciences, e.g., Powers and Xie (2000:178) and Allison (1995:235).

[25] In a recent study on this issue, Contini and Negri (2007:21) demonstrate that "negative duration dependence in the exit rate from welfare is not necessarily a consequence of welfare dependence, even in the absence of unobserved heterogeneity." They argue that the observed pattern of declining exit rates may be due to effects of persistent poverty or unemployment. More empirical studies, however, are needed to examine the argument.

3.2.4 Summary

In modeling welfare-to-work transition, different theories have different assumptions and hypotheses that lead to various policy implications. Human capital theory is less controversial for both the liberal and conservative sides of the welfare debate. After all, compared to dropping out of high school, getting a high school diploma is surely helpful, as are training and work experience, to single mothers needing to leave welfare and keep a job in the long run. Based on the assumptions of rational choice, a model would include exogenous variables that are explained as components of individual benefit and cost calculation. In doing so, the human capital model, and the tradeoff model in general, increases its explanatory power but loses theoretical clarification. The neighborhood effects model shows sympathy to cultural explanations but explicitly emphasizes structural causation. The balance between cultural views and structural perspectives makes the model acceptable for many liberals or conservatives, depending on which components they prefer to use. Not surprisingly, welfare dependence is at the center of welfare debate. Interestingly, the ideological debate on welfare dependence could be examined by a purely statistical method. I provide detail discussion of this issue in the chapter of data and methods.

3.3 Conceptual Framework

Based on the theories I have reviewed, a conceptual framework can be constructed by incorporating the components below.

3.3.1 Human Capital

Human capital serves as a benchmark for the study of welfare-to-work transition, given its significant theoretical and policy implications. Currently, human capital plays a unique role in the policy agenda of moving single mothers from welfare dependence to self-sufficiency in the labor market. According to human capital theory, welfare recipients have disadvantages in the labor market due to low human capital, e.g., poor educational attainment, skill deficiency, and lack of training. Thus, federal and state governments design various training programs to improve welfare recipients' human capital. It is expected that such training and schooling, as an investment of human capital, would increase welfare recipients' productivity and then increase their competition in the labor market in the long run. Since higher human capital assumes higher wages, all other things being equal, welfare recipients who received training or schooling are expected to find jobs with reasonable pay that allow them to be self-sufficient without welfare checks.

However, when applying human capital theory to the study of welfare-to-work transition, we should be aware of significant deviations from the assumptions on which the theory is based. First, investment in either public schooling or job training is primarily provided by public programs rather than individuals based on personal cost-benefit calculations. In many cases, welfare recipients participate public training programs under the guidance of case workers. Furthermore, work activities, including work-related training, are enforced by state agencies in exchange for welfare benefits. Time limits and sanctions are "sticks" to guarantee their "incentives" for participating in these training programs. Thus, work activities are not merely a personal choice as the classical human capital theory assumes.

Second, lifetime intermittent labor force participation is more difficult to predict for welfare recipients than regular workers. Moreover, foregone income is difficult to predict as well. In the case of public education, dropping out of high school will not help a teenage mother make more money than those who stay in school because many high school dropouts are not predicted to join the labor force. In the case of job training, a welfare recipient can enroll in a training program and keep receiving welfare checks. Thus foregone income of training, as a key concept of human capital theory, tends to be insignificant in determining a welfare recipient's choice.

Third, welfare recipients are single-mother household heads with very young kids. They have burdensome family duties. Thus, the conflicted dual role of household mother and breadwinner strongly influences their life cycle earning profiles. For example, some of them might prefer part-time jobs to enhance investments in their children. Given all these deviations from classical assumptions, one may wonder if the classical components of human capital could provide predictions similar to previous studies focusing on regular labor forces.

3.3.2 Labor Market Conditions

If human capital focuses on the supply side of the welfare-to-work transition, labor market conditions represent the demand side of the neoclassical economics. The labor market approach could result in different theoretical concerns. For example, proponents of labor market segmentation criticize human capital theory (and neoclassical economics in general) by emphasizing the heterogeneity and inequality of the labor market (Beck et al. 1978; Dickens and Lang 1985; Hudson 2007; Leontaridi 1998; Reid and Rubin 2003; Sakamoto and Chen 1991; Tolbert et al. 1980). On the other hand, human capital theory includes labor market conditions in its conceptual framework by explaining how different forms of human capital lead to different labor market outcomes. In the study of welfare-to-work transition, single mothers appear to be more sensitive to the change of local labor market conditions than are regular full time workers. The objective of this study is to examine the role of the labor market in determining the process of transitioning from welfare to work.

3.3.3 Neighborhood

Similar theoretical concerns exist in the application of the neighborhood effects model. When Wilson puts forward the theory of neighborhood effects, he focuses on industrial metropolises in the Northeast and Midwest (Wilson 1987, 1991). The primary structural causation is industrial restructuring since 1970, especially the shift from manufacturing to services and retail in industrial metropolises. It is this kind of restructuring and outmigration of middle-class blacks that created the disadvantaged inner-city "under class" observed in Northeast and Midwest metropolises.[26] Thus, Wilson's neighborhood effects model is a narrowly defined framework in terms of time and space.

In response to Wilson's approach, the neighborhood effects literature focuses heavily on inner-city social contexts in the Northeast. Less is known about neighborhood effects in Southern urban and rural areas.[27] For example, the Mississippi Delta has witnessed chronic poverty, persistent joblessness, and out-migration of the black middle class. Similar interest could be given to Southern cities like Jackson, Mississippi.

Another concern of this study is the connection between neighborhood effects and welfare use. The neighborhood effects literature includes a wide variety of themes, such as child development, health-related outcomes, crime, and dropping out of school. Surprisingly few studies have connected neighborhood effects to welfare use and

---

[26] In addition, Massey and Denton (1993) argue that racial residential segregation plays a significant role in the deterioration of blacks' opportunities in the inner-city.

[27] Interestingly, Wilson (1991) finds some evidence that southern cities recorded significant declines in ghetto poverty during the 1970s.

welfare-to-work transition (see Osterman 1991 for an exception). This study will contribute to the neighborhood effects literature by addressing this issue.

3.3.4 Welfare Dependence

According to Mississippi TANF rules, a recipient cannot stay on TANF more than 24 consecutive months and cannot exceed a maximum 60-month lifetime limit. Thus, this study assumes that the maximum length of a welfare spell is 24 months and that the maximum total of all spells from one case is 60 months.[28] Under these assumptions, it is reasonable to predict that post-welfare spells are less likely to last more than two years and that total time on welfare rolls tends to be less than five years. Moreover, long-term cases observed before the implementation of TANF are expected to change the distribution of these variables. Unfortunately, we have insufficient knowledge about the post-welfare reform period. One reason is that the evaluation of time limits requires longitudinal data spanning more than a few years. Indeed, it is hard to generate any findings on the effect of time limits when almost all welfare recipients have plenty of time left. Concerning the strategy of quickly moving welfare recipients to work, the question is whether relatively long-term recipients still have disadvantages that keep them on welfare rolls, net of other personal and contextual factors.

[28] States do have a maximum 20 percent of exemption for those who are classified as not suitable for work, e.g., older than 60, or disabled but not qualify for Supplemental Security Income (SSI). So far, state agencies prefer to encourage work transition and hesitate to use this exemption.

CHAPTER IV

RESEARCH CONTEXT

4.1 Introduction

Many studies have added to the body of literature on welfare for decades. A few interrelated topics dominated studies of welfare before the 1996 reform, including the demographic composition of welfare population, spell duration and spell distribution, probability of exit and/or recidivism, and types of exit (see Bane and Ellwood 1994 for a review). After TANF was enacted, central concerns of welfare studies shifted to policy evaluation. In doing so, researchers studied a variety of indicators of welfare reform at the state level, such as caseload, policy components, economic incentives, income and poverty, job training programs, labor force participation, and family formation and fertility (see Blank 2002 for a review based on the economic literature; see Lichter and Jayakody 2002 and Corcoran et al. 2000 for reviews from a sociological perspective). My current interests are in line with classic welfare topics, that is, the transition from welfare to work and the factors that affect the likelihood of the transition. I will now review findings from previous studies on the components that were addressed conceptually in the previous chapter (see table 4.1 for selected studies on welfare-to-work transition).

Table 4.1 Selected Studies on Welfare-to-Work Transition

Title	Study Period	Dependent Variable	Key Explanatory Variables	Source of Data	Sampling	Sample Size
Pre-Welfare Reform						
Bane and Ellwood (1983)	1968-1979	Exit; Recidivism	Synthesis	PSID	Recipients	676
O'Neil et al. (1987)	1968-1982	Exit	Spell duration	NLS	Recipients born between 1944 and 1954	About 2,500
Blank (1989)	1970-1976	Exit	Heterogeneity	SIME/DIME	Recipients from Seattle /Denver experiments	508
Harris (1993)	1984-1986	Exit	Human capital	PSID	Recipients	204
Pavitte (1993)	1979-1989	Exit; Recidivism	Synthesis	NLSY79	Recipients born between 1958 and 1965	1,137
Bane and Ellwood (1994)	1968-1988	Exit; Recidivism	Spell duration	PSID	Recipients	1,000 for 1st spell
Lane and Stevens (1995)	1985-1993	Recidivism	Family AFDC, work history, and firms	Maryland state agency	Leavers born in 1971	983
Fitzgerald (1995)	1983-1987	Exit	Type of exit, local area characteristics	SIPP	Recipients	4,699
Harris (1996)	1984-1988	Recidivism	Types of exit	PSID	Recipients	591
Browne (1997)	1989	Being in labor force	Human capital, region, family, and welfare use	PSID	Women heading households (age 18-54)	922
Hoynes (2000)	1987-1992	Exit; Recidivism	Alternative measures of local labor market	California state agency	Recipients (age <=54)	12,117
Waivers/Policy Transition						
Hofferth et al. (2002)	1989-1996	Exit	State policies	PSID	Recipients	928
Hofferth et al. (2005)	1989-1996	Recidivism	State policies	PSID	Recipients	1,085
Blank (2002)	1990s		Synthesis	Literature Review		

Table 4.1 (Continued)

Title	Study Period	Dependent Variable	Key Explanatory Variables	Source of Data	Sampling	Sample Size
Post-Welfare Reform						
Parisi et al. (2003)	1997	Community Participation rate	Community characteristics	Mississippi state agency	Communities	215
Bruce et al. (2004)	1996-2001	Recidivism	Synthesis	Tennessee state agency	Leavers	128,775
Nam (2005)	1997-2002	Exit; Recidivism	Types of exit	WES	WES recipients in urban Michigan county	692
Danziger et al. (2002, 2005)	1997-2001	Earnings	Types of welfare-to-work	WES	Recipients (age 18-54) in a Michigan county	632
Moffitt and Winder (2005)	1997-2002	Earnings	Types of welfare-to-work	Three-City Study	Low-income families	About 800
Parisi et al. (2006)	1996-2004	Exit	Local area characteristics	Mississippi state agency	Recipients	94,465
Dyke et al. (2006)	1997-1999	Earnings	Welfare-to-work programs	Missouri & North Carolina state agencies	Recipients (age 18-65)	134,326
Negrey et al. (2007)	1998-2001	Employment transition	Human capital	Kentucky panel survey	Leavers	503
Irving (2008)	1996-2003	Exit	Place of residence; state policies	SIPP	SIPP clients (age 15-64)	4,487 (77% attrition)
Herbst and Stevens (2010)	1996-2005	Exit	Local labor market; Types of welfare-to-work	Maryland state agency	Recipients born in 1977 (age 19-28)	1,712

NOTE: NLS = National Longitudinal Survey of Young Women
PSID = Panel Study of Income Dynamics
SIPP = Survey of Income and Program Participation
WES = Michigan Women's Employment Study
NLSY = National Longitudinal Survey of Youth
SIME/DIME = Seattle/Denver Income Maintenance Experiments
UI = Unemployment Insurance

4.2 Dynamic of Welfare and Work

The effort to estimate the dynamic of welfare and work has been well documented in previous research. Dependent variables in these studies include welfare exit and welfare recidivism. Some studies even make an effort to classify types of exits as a dependent variable.[29]

There is no consistent way of classifying welfare-to-work transition in the literature, mainly due to data limitations and different data sources. In a pioneering study, Bane and Ellwood (1983) set a criterion to classify exit types for AFDC spells based on annual PSID data. They look for events that occurred at the same time as a transition out of AFDC receipt. In particular, they look for events in the following order: getting married, no longer having an eligible child, increased earnings, and others. Bane and Ellwood (1983, 1994) note that the classification would tend to understate the significance of work exit from AFDC because changes in family formation have higher priority than changes in work status. By definition, those who experienced both family formation change and employment would not be treated as leavers with work exits. Moreover, people who worked but failed to increase their annual earnings are also excluded from this type of work exit (work exit is defined as annual earnings increased by $250).

In a later study using monthly NLSY data, Pavetti (1993) provides an extensive evaluation of Bane and Ellwood's 1983 study and other following studies. Pavetti classifies 46% of case closures as work exits, a much higher percentage than Bane and Ellwood's predictions: 32% and 25% in their 1983 and 1994 studies, respectively. Pavetti (1993:43) attributes a large part of the gap between these estimations to the difference

[29] Types of welfare exits could be used as an explanatory variable in the study of welfare recidivism (e.g., Harris 1996).

between annual data and monthly data. Harris (1993) further points out that the various definitions of work exit and welfare receipt would dramatically change the estimates. Moreover, differences in data sources also play a significant role in estimating the probability of welfare-to-work transition. For example, using PSID data, Harris (1993) is able to find that 69 percent of welfare exits happened due to employment. The percentage is much higher than Pavetti's (1993) estimation based on NLSY data. Both studies, however, cover similar time periods and adopt similar definitions of work exit.[30]

Pavetti (1993) further points out that cohort differences might be a factor in recent data showing a higher percentage of work exits. But no solid evidence supports the argument. For example, in an updated study using PSID data between 1989 and 1996, Hofferth et al. (2002) are able to identify 64% of case closures as work exits, five percent lower than Harris's (1993) similar study using PSID data between 1984 and 1986.[31] A few studies using Survey of Income and Program Participation (SIPP) data find much lower work exit rates, ranging from 41% to 53% after 1996 (Bavier 2001; Irving 2008). The considerable variance of employment rates is also observed in state welfare leaver studies funded by Congressional Research Services (CRS). Of all these studies, administrative data indicate that anywhere from 45% to 87% of leavers are employed in the first quarter after exit; survey data illustrate that between 34% and 77% are employed at the time of the survey (Devere 2001). Considering the wide range of estimated indicators of welfare-to-work transition, we need to be cautious about any general conclusion without specifying the context of a study.

[30] Both of them define work exits by examining work status during the three months before and after a welfare exit, while Bane and Ellwood (1983, 1994) define work exit based on increased earnings of single mothers.

[31] Again, the definition of work exit slightly changes in that Hofferth et al. (2002) only examine work status during one month before and one month after an AFDC exit.

Interestingly, although policies after welfare reform allow the combination of welfare and work, the pattern had been documented well before welfare reform. Given high incidence of work exits, Harris (1993) distinguishes between new job exits and work-off welfare exits using PSID data. New job exit refers to a transition from welfare to work, and work-off welfare exit refers to a combination of welfare and work right before the end of a welfare spell.[32] Harris classifies 42% of the work exits in the study as new job exits and 27% as work-off welfare exits. Harris further finds that characteristics of these two groups of women support a human capital perspective of labor market earnings. Women who do not leave welfare when they find work have more disadvantaged backgrounds, less education and job skills, and more children to support, as opposed to women who exit welfare when they begin to work.

The transition between welfare and work has been widely observed since welfare reform of 1996. As mentioned before, there are four categories of welfare-to-work transition: (1) no work, no welfare; (2) no work, welfare; (3) work, welfare; and (4) work, no welfare (e.g., Danziger et al. 2002; Herbst and Stevens 2010). Consequently, current or former welfare recipients can be grouped into wage-reliant mothers, combiners, welfare-reliant mothers, and those neither working nor receiving TANF benefits. However, there is a disagreement about the profile of these subgroups. Using panel data from the Women's Employment Study (WES), Danziger and his colleagues (2002, 2005) find that wage-reliant mothers are better off than other groups. Conversely, Moffitt and Winder (2005) find that combiners could have the same income gains as wage-reliant mothers. Thus, wage-reliant mothers are less advantaged than combiners because welfare

[32] By definition, only welfare recipients who work for more than three months before a welfare exit are eligible for a work-off welfare exit.

income is completely lost. Both studies, however, do not use random sampling and focus on particular welfare recipient groups. One study uses the WES data that are collected from an urban Michigan county, another study is based on the Three-City Study, focusing on low-income families. In addition, neither study includes human capital in its wage determinant model. Due to these limitations, one should be cautious in generalizing their findings.

Most previous studies use survey data to identify patterns of welfare-to-work transition, an approach that relies heavily on the researcher's discretion or statistical specification. Recent studies take advantage of state-level administrative data that provide a less arbitrary measure of transition patterns. For example, state TANF data provide monthly records of a recipient's welfare use status, and state UI data keep quarterly records that indicate the employment status of a recipient. Thus, patterns of welfare-to-work transition can be directly identified by merging TANF data and UI data. Taking this approach, Herbst and Stevens (2010) find economic improvements for disadvantaged groups (e.g., African American women and high school dropouts) when they are encouraged to work in conjunction with welfare. For white women and those with at least a high school degree, economic opportunities provide more powerful incentives as they move into employment without welfare. Herbst and Stevens's (2010) study, however, has a limitation in that it only focuses on a specific group of women who were born in 1977.

In sum, although the event of work exit has been well-documented in previous studies, the estimate of the incident varies from one study to another, depending on data sources, data processing, samples, definition of in and out of welfare roll, and unit of analysis. Despite the availability of administrative data that record detailed information on welfare use and work, we still have limited knowledge about transition patterns after welfare reform.

4.3 Human Capital

The development of human capital is the central concern of welfare reform. Previous studies have consistently provided evidence that human capital facilitates the transition from welfare to work (e.g., Bane and Ellwood 1983, 1994; Blank 1989; Harris 1993; Herbst and Stevens 2010; Hofferth et al. 2002; Nam 2005; Negrey et al. 2007; O'Neill et al. 1987; Parisi et al. 2006). Better-educated mothers and those with more work experience are more likely to leave welfare and exit due to employment.

However, there is disagreement over the extent to which formal education, job training, and work experience take effect, respectively. As far as policy is concerned, programs designed to improve formal education (e.g., high school diploma, GED, and some college) are quite different from programs aimed at placing welfare mothers in jobs. The concern relates to two strategies: human capital development (HCD) and labor force attachment (LFA) (see Blank 2002 for a review of studies that evaluate both strategies). The first strategy provides welfare mothers an opportunity to continue their in-school education, such as completing a high school diploma or going to college. The second strategy includes various programs that are designed to help welfare mothers find jobs as soon as possible. Some programs are as simple as assessment or consultation; others provide specific skills required by the local market.

A few studies try to examine the effects of HCD and LFA based on experimental programs involving random allocation of subjects to treatment and control groups. Experiments show that programs that emphasize putting welfare recipients to work in available jobs, even if they are low-paying, outperformed those programs that stressed training or education for better-paying positions (Hamilton 2002). Furthermore, in a study using administrative data from Missouri and North Carolina, Heinrich et al. (2005) find that any employment—in temporary help services or other industrial sectors—is expected to yield substantial benefits compared to no employment. They further point out that temporary jobs provide a path to other industries with higher pay and greater stability.

However, another set of studies show that, in the long run, HCD programs give many more rewards than LFA programs. Based on the same data sets used by Heinrich et al. (2005), Dyke et al. (2006) classify various work component activities into three welfare-to-work subprograms: assessment, job search/readiness training, and intensive training. The first two subprograms aim to facilitate labor force attachment as quickly as possible, while intensive training (e.g., basic education, vocational skills training, or other longer-term programs) is designed to develop human capital. Dyke et al. find that intensive training is more associated with long-term earning gains compared to other programs. They suggest that administrators should place more emphasis on programs designed to enhance participants' general human capital. Likewise, using data from California's Greater Avenues to Independence (GAIN) program, Hotz et al. (2006) find that while LFA is more effective than HCD training in the short term, HCD is relatively more effective in the long term. Using survey data that provide detailed information on types of LFA and HCD programs, Kim (2006) finds that HCD strategies can lead to higher employment rates and longer employment retention than LFA strategies.

Although HCD programs fare better than LFA in long-term evaluations, the best results occur in programs with mixed activities, that is, a combination of work first for some respondents and education for others (Blank 2002; Bloom and Michalopoulos

2001). Using a panel sample drawn from Kentucky welfare leavers between 1998 and 2001, Negrey et al. (2007) find that the strict work-first approaches may be misguided. They suggest that work experience combined with education has the greatest potential to engender self-sufficiency.

Lastly, it should be mentioned that not all studies find evidence that supports the hypothesis of human capital on welfare-to-work transition. For example, Moffitt (1987) finds that the total welfare participation rate cannot be explained by the change of female heads' education at the state level.[33] [34] Likewise, using post-welfare data, Moffitt (2003a) again finds that the effect of human capital on work exit is ambiguous. The reason is that, as Moffitt argues, higher earnings increase income for those on welfare and off of it, and the return to work may be higher for those on welfare than those off of it. In both studies, Moffitt focuses on nonfinancial factors in determining welfare participation, and thus did not give further explanation for the weakened effect of human capital observed in his studies.[35]

4.4 Labor Market Conditions

Labor market conditions or economic conditions have been extensively explored in the literature on welfare reform. Following the approach used by Herbst and Stevens (2010), I organize the literature in terms of the analytical unit of labor market conditions,

[33] The total participation rate is defined as the number of female heads of families on AFDC divided by the total number of female heads of families in the U.S. population with at least one child under 18.
[34] Moffitt (1987) does find a significant effect of education on participation rates based on a cross-sectional analysis at the individual level.
[35] In explaining the determinants of a single mother's welfare use status, Moffitt emphasizes the effects of noneconomic factors. In the previous study, Moffitt (1987) pays attention to changes in attitudes, reductions in the stigma of welfare receipt, and court and legislative decisions. In a later study, Moffitt (2003) emphasizes the importance of work requirements in the exit decisions and diversion practices upon application in the entry decisions.

measured either at the state or county level. Furthermore, the literature can be classified based on the dependent variables of interest. The dependent variable is either aggregated caseloads at the state level or individual spells. Thus, studies of labor market conditions can be grouped in a 2x2 crosstab (Table 4.2).

Table 4.2 Literature on Labor Market Conditions Grouped by the Unit of Analysis

Indicators	Caseloads	Spells*
State-Level	Blank 2001; Moffitt 1987, 2003; Ziliak et al. 2000	Hofferth et al. 2002, 2005; Irving 2008; O'Neill et al. 1987
County-Level	---	Blank 1989; Fitzgerald 1995; Herbst and Stevens 2010; Hoynes 2002; Harris 1993, 1996; Parisi et al. 2006

*The study of welfare-to-work transition is identical with the study of work exit from welfare spells.

The measure at the state level is easy to obtain when using data from large, nationally representative surveys, such as PSID or Current Population Survey (CPS). The measure is frequently used to explain the relationship between caseload changes and labor market conditions. The majority of studies use the state unemployment rate as an indicator of labor market conditions (see Blank 2002 for a review). The results from these studies are consistent: state economies have a significant effect on caseloads, and a one-point rise in the unemployment rate increases a caseload by 5 to 7 percent. This finding is not surprising, though, given that most of these studies use similar methodologies and data sets (Blank 2002). However, there is less agreement about the relative contribution of labor market conditions and welfare reform in accounting for caseload changes in the 1990s. Some (e.g., Moffitt 2003) find little evidence supporting the effects of changes in the labor market, such as the unemployment rate and potential earnings, on welfare caseloads. Others find that caseload reduction is attributable largely to favorable economic conditions and the expansion of EITC (e.g., Ziliak et al. 2000; Meyer and Rosenbaum 2001). Still, others (e.g., Blank 2001, 2002; Herbst 2008) find that caseload change is the result of economic, demographic, political, and policy changes.

Labor market conditions are expected to affect the transition from welfare to work at the individual level. Findings from these studies, however, are at best mixed. State-level economic indicators usually show insignificant effects on welfare exit (Hofferth et al. 2002; Irving 2008; O'Neill et al. 1987), as do indicators based on Metropolitan Statistical Areas (MSA) or large cities (Teitler et al. 2007). In explaining the surprising result that state unemployment rates have little effect on welfare exit, Hofferth et al. (2002) point out that annual unemployment rates may not be a good predictor of monthly individual exit rates. Likewise, state-level indicators may not catch the differentials of local labor markets within a state. In a later study of welfare reentry, however, Hofferth et al. (2005) find that the state unemployment rate is a critical variable, with welfare leavers more likely to return to welfare in states with higher levels of unemployment. They also find an unexpected positive association between average wages for production workers in manufacturing and welfare return.[36] This inconsistency means that one should be cautious in interpreting the findings.

Some studies measure unemployment at the county level but cannot identify it as a monthly time-varying indicator. Blank (1989) uses the mean for sample period and finds small or statistically insignificant effects of the unemployment rate in all models.

---

[36] Hofferth et al. (2005) use the average wages of production workers in manufacturing as an indicator of the attractiveness of employment for less-skilled workers. Hofferth et al. attribute the unexpected positive relation to increased competition for jobs in high-wage states or a geographic mismatch between jobs and workers.

Bruce et al. (2004) use administrative data from Tennessee between 1996 and 2001 to analyze welfare reentry. They calculate unemployment rate at the time of case closure. The results show that the likelihood of reentry falls when the county unemployment rate rises, quite contrary to theoretical expectation.[37] As an improvement, Harris (1993, 1996) introduces an annually based unemployment rate in her study of welfare exit and recidivism. In doing so, she finds a negative effect of unemployment rate on the probability of job exit but not on the probability of work-off exit. Likewise, in a recent study, Ribar (2005) simulates an annually based indicator, called local employment probability, and finds that it works well in predicting single mothers' welfare participation and economic success.

With more precise monthly time-varying measures at the county-level, one could expect to find a significant relation between labor market conditions and welfare-to-work transition. Among indicators of labor market conditions, the unemployment rate has been used extensively in the literature. The majority of studies find substantial effects of the unemployment rate on work exit or recidivism (Fitzgerald 1995; Herbst and Stevens 2010; Hoynes 2000; Parisi et al. 2006). In addition to the unemployment rate, a couple of studies include alternative indictors in the analysis, such as per capita retail sales (Fitzgerald 1995), total employment, and percentage of employees in manufacturing, services, or retail (Parisi et al. 2006).

Two studies contribute to the literature on the evaluation of measuring local labor market conditions. Based on administrative quarterly UI data, Hoynes (2000) constructs a

---

[37] Bruce et al. (2004) suggest that Tennessee's time limit policy might help to explain these unexpected findings. The policy permits an immediate extension if a recipient's county unemployment rate is more than twice the state average. Thus, welfare recipients in high-unemployment counties might be less likely to exit the program in the first place.

time series of county-level employment, average earnings, and employment-to-population ratios. Hoynes is in favor of alternative measures of local labor market conditions rather than the traditional unemployment rate for two reasons. First, as Hoynes argues, unemployment rates at the county level are likely to contain a high noise to signal ratio.[38] Second, unemployment rates fluctuate not only with employment but also with changes in labor force participation. Although Hoynes's study uses data before welfare reform, the measure of labor market conditions is instructive to the current study using post-welfare data. In a most recent study using data from the Census Bureau's Quarterly Workforce Indicators (QWI) series, Herbst and Stevens (2010) create county-by-quarter variables on new hires, new hires' earnings, and job flows in retail trade and accommodation/food services. In addition to the expected effect of the unemployment rate on a welfare recipient's work exit, they find that increased new hires and new hires' earnings facilitate the transition from welfare to work.

In sum, although, theoretically, labor market conditions are predicted to have effects on the transition from welfare to work, the hypothesis could be accepted or rejected partly due to the operational measures of labor market indicators. In this case, the monthly based and county-level indicators have advantages over time-fixed or state-level indicators. Still, one should be cautious with any findings that are generated from various data sets and changing measures of economic conditions.

[38] Hoynes (2000) points out that unemployment rates require household surveys that sometimes are less reliable due to small sample size of a county. The number of employment, however, can be relatively easy to get with surveys of employers.

4.5 Neighborhood Effects

Although the impact of neighborhoods on welfare use has been broadly discussed in public debate, relatively few empirical studies pay much attention to this variable for several reasons. First, neighborhood effects hypotheses assume relationships among a variety of components, including traditional topics such as joblessness, concentrated poverty, and change in family structure due to out-of-wedlock birth, teenage birth, and single motherhood (Jencks and Mayer 1990; Small and Newman 2001). Recent studies even expand the topics of neighborhood effects to violence, delinquency, depression, high-risk behavior, and health (for a review see Sampson et al. 2002). Unsurprisingly, welfare use is just one of the concerns and has received minor attention in the neighborhood effects literature. In an early review, Bane and Ellwood (1994:88-92) could find only a few studies that cover this issue. More than a decade later, literature that specifically focuses on the issue is still thin.

Second, in general it is difficult to test the causal hypothesis that an individual living in particular neighborhood conditions is worse off than an individual in the absence of such conditions, controlling for other variables (Small and Newman 2001; also see Duncan et al. 1997 for extended discussions). Even in experimental studies, one should be cautious with findings due to potential selection bias and unobservable characteristics. The most recent debate on the causal explanation of neighborhood effects comes from the evaluation of the Moving to Opportunity (MTO) intervention program (see Shroder 2001 for a brief description of the program). In the debate, we see that leading scholars in this field cannot reach consensus on a basic causal claim (Ludwig et al. 2008; Sampson 2008; Clampet-Lundquist and Massey 2008).

Finally, researchers have even less agreement on how to measure neighborhoods practically. The conventional strategy is to match a neighborhood's boundaries with a Zip Code (e.g., Osterman 1991; Hoynes 2000), census tract (e.g., Small 2007), or block groups provided by the Census Bureau (e.g., Weinberg et al. 2004). The unit of block groups is smaller than the unit of census tracts and thus offers more precise measurement. Another issue concerning the measure of neighborhood is determining the characteristics of neighborhood. There are many alternatives depending on the researcher's discretion, such as neighborhood poverty, segregation, education level, single mothers, or male joblessness. Considering that no single economic or social characteristic can fully capture the concept of neighborhood, Duncan and Aber (1997) create multivariate indices to register differences among neighborhoods. Based on 34 variables aggregated at the census-tract level, they are able to produce six factors that capture neighborhood characteristics: low SES, high SES, male joblessness, ethnic diversity, family concentration, and residential stability. Based on data from the Urban Poverty and Family Life Survey (UPFLS) of 1987, Small (2007) finds that it is the poverty, not the racial composition, of the neighborhoods that accounts for racial differences in social networks. In a most recent study, Casciano and Massey (2008) introduce a new index of concentration at the extreme (ICE) as a measure of neighborhood circumstances.

Compared to the dominant theme of inner-city neighborhoods in the welfare debate, the rural dimension of welfare use receives persistent, though much less, attention (see Coulton 2003 for a recent review in the context of metropolitan; see Weber et al. 2001 and Weber et al. 2005 for studies in the context of rural areas). The rural poverty literature has identified a rural effect that results in higher local poverty rates and higher individual odds of being poor in rural areas, even when controlling for a large number of factors at the individual and community levels (Weber et al. 2005:392-393). Methodologically, as Weber et al. (2005) argue, the study of rural effects shares the same concerns with that of inner-city neighborhood effects. In a qualitative study, Duncan (1999) observes the same social isolation in the Mississippi Delta that Wilson (1987:190-191) describes in the inner-city. Duncan argues that the haves are blamed for racial segregation, poverty of the poor, and inequality, while the have-nots are trapped in disadvantaged socioeconomic structures.

Previous studies have shown that welfare recipients in rural areas are more likely to exit from welfare than recipients in urban areas (O'Neill et al. 1987; Fitzgerald 1995; Hirschl and Rank 1991, 1999; Porterfield 1998; Rank and Hirschl 1988, 1993). Moreover, eligible households in rural areas are less likely to apply for public assistances than those in urban areas (Rank and Hirschl 1988, 1993; Hirschl and Rank 1991, 1999). According to Hirschl and Rank (1999), the reason is that urban households are more likely to possess accurate eligibility information and hold less adverse attitudes toward welfare use. In addition, community poverty level rather than population density helps explain the higher participation rate in urban areas (Hirschl and Rank 1999).

Although welfare participation rates for eligible populations are lower in rural areas than in urban areas, the percentages of aggregated caseloads are higher (HHS 2009a). A national study shows that residents of nonmetropolitan areas are significantly more likely to be poor, even after controlling for local labor market conditions (Cotter 2002). For the same reason, declines in caseloads after welfare reform have usually been smaller in rural areas (Weber et al. 2001). Moreover, using county-level data from Mississippi and South Carolina, Henry et al. (2002) find rural counties are disadvantaged in reducing welfare participation rates,[39] even when controlling for local economic conditions (e.g., unemployment rates and employment growth rates), economic incentives (e.g., EITC and ratio of minimum wage to benefits), and policy changes (TANF versus AFDC). They suggest that rural areas may experience unique problems and face additional obstacles in the transition from welfare to work. These conclusions are also confirmed by ethnographic studies (e.g., Anderson and Van Hoy 2006).

Several studies address specific characteristics of neighborhoods in determining patterns of welfare use. An early effort comes from a study using survey data on single mothers in Boston (Osterman 1991). The results support Wilson's argument that, holding personal characteristics constant, welfare receipt is influenced by neighborhood effects. First, single mothers differ by Zip Code area in their probability of receiving welfare, even after controlling for individual and family characteristics. Second, single mothers living in a Zip Code area with a higher percentage of welfare use and lower percentage of household-head employment are more likely to be on welfare, other individual factors being equal. In a post-welfare reform context, using 1997 Mississippi administrative data, Parisi et al. (2003) examine the effects of community conditions on TANF participation rates. They create local community boundaries by aggregating census block groups into a 20-minute travel time from central areas. In doing so, Parisi et al. (2003) find that TANF participation rates tend to be higher in communities with high concentrations of blacks, spatial concentration of the poor, less faith-based activity, and located in the Delta. In another study drawing upon data from the Fragile Families and Child Well-Being Study, Casciano and Massey (2008) examine the neighborhood effects on new mother's welfare

[39] Here, welfare participation rate is defined as the caseload in a county divided by the county labor force (Henry et al. 2001).

use and employment. Substantively, findings from existing literature confirm the effects of neighborhood.

4.6 Welfare Dependence

Welfare dependence has been a central concern in the welfare policy debate, especially during the 1980s and 1990s. The concern resulted in efforts to measure the length of time that single mothers remain on welfare and their probability of leaving and returning to welfare, that is, welfare dynamics. Little was known statistically until the availability of longitudinal data and the development of statistical models in the early 1980s. Since then and including the final debate of welfare reform during the 1990s, welfare dependence has been extensively explored, and various findings compared and cross-checked.

Bane and Ellwood (1983) conducted a pioneering work by drawing attention to the concept of welfare spell as a measure of welfare dependence.[40] Welfare spell is defined as a period of continuous welfare receipt. Using cumulative probability of welfare exit, Bane and Ellwood create a distribution of completed welfare spells.[41] Thus, they are able to distinguish between two groups of spells: short-term relief and long-term income maintenance. Their results indicate a large dependence on AFDC spells. They find that more than half of welfare recipients at any point in time are in the middle of a

---

[40] Gottschalk and Moffitt (1994) provide two alternatives in measuring welfare dependence in a fixed-time interval: individual's total time on measure (TTO) and total percentage of income measure (TPI). Although they argue that these two alternatives are superior to measures based on the length of single welfare spells, few studies use them.

[41] Bane and Ellwood (1983, 1994) argue that only completed welfare spells provide a useful measure of welfare duration. In contrast, the measure of uncompleted spells underestimates long-term welfare use because many of the short uncompleted spells will end with long completed spells.

spell that will last eight years or more. These recipients account for over half of the expenditures of the AFDC program.

Bane and Ellwood (1983: table 1, 1994: table 2.1) also highlight a distinction between two distributions of welfare spells. The first is the distribution of completed spells that are expected for those *beginning on welfare*. In this case, the majority of recipients have a short term spell—less than four years—and only a small portion of spells last 10 years or more. The second is the distribution of completed spells that are expected for those *on welfare at a point in time*. In this case, the welfare profile seems to be reversed. The majority stay on welfare for the long term, while a small portion are expected to end welfare after a short spell. Based on Bane and Ellwood's (1983) original methodology, Pavetti (1993:38-39) identifies three different groups of welfare use. One group of women uses welfare for relatively short periods of time, leaves it, and never returns. A second group cycles on and off the welfare rolls, some for short periods and others for longer periods. The final group stays on welfare continuously for relatively long periods of time.

Although researchers have reached a consensus on the existence of welfare dependence, empirical studies barely match each other in estimating completed spells. Based on a review of selected studies on welfare dynamics, the percentage of completed spells within one year ranges from 29 to 62; within two years from 47 to 83; and within five years from 70 to 99 (Table 4.3). Similar inconsistent findings are found in regard to the average length of spells, the percent of exit, and the rate of return to welfare (see Bruce et al. (2004: Table 1) for more details on welfare recidivism rates). For example, Blank (1989) finds that, on average, the expected length of completed spells is 3.1 years. But Bane and Ellwood (1983, 1994) find even longer spells of welfare use and more evidence of duration dependence. They estimate that 4.7 years is the average duration of welfare spells for recipients who never leave the welfare rolls.

A number of reasons account for the varied findings (for evaluations, see Bane and Ellwood 1994 and Pavetti 1993). First, early studies (e.g., Bane and Ellwood 1983; Ellwood 1986; O'Neill et al. 1987) of welfare spells had to use year as the unit of analysis due to limited data that only provided annual information on respondents. Second, sample frames vary considerably in terms of observed time period, identification of welfare recipients, and sampling procedure. Third, the definition of welfare exit is a contingent consideration based on available information from survey data. Thus, the inconsistent definitions of welfare exit make measures of spell duration less comparable.

Although there is debate about the distribution of spells, the majority of studies confirm the existence of welfare dependence in that long-term welfare use decreases the likelihood of exit or labor force participation (Blank 1989; Browne 1997; Hofferth et al. 2002; Parisi et al. 2006). Among these studies, Blank (1989) examines the effect of heterogeneity by distinguishing two groups by welfare use. One group shows a very low and constant probability of leaving welfare. The other group is more affected by time on the welfare program. However, due to unobserved characteristics, one cannot tell which group an individual belongs to in Blank's model. Hofferth et al. (2002) examine the effect of spell length on welfare exits. They find that exit rates are about 50% lower during the second year of a welfare spell. They also find that the duration of welfare spells affect work exits but not non-work exits. In contrast, Harris (1993) finds no significant effect of duration on work exits.

Table 4.3 Selected Studies on Welfare Spells Distribution

Study	Study Period	Source of Data	Percent of Spells Completed			Average Length (Year)	Percent of Work Exit	Return within One Year
			1 Year	2 Years	5 Years			
Pre-Welfare Reform								
Bane and Ellwood (1983)	1968-1979	PSID	29	48	69	4.7	32	23
Ellwood (1986)	1968-1982	PSID	-	-	-	-	-	11
O'Neill et al. (1987)	1968-1982	NLS	50	62	82	-	-	-
Blank (1989)	1970-1976	SIME/DIME	62	83	99	3.1	31	-
Harris (1993)	1984-1986	PSID	44	64	-	-	69	-
Pavetti (1993)	1979-1989	NLSY	56	70	88	2.3	46	45
Bane and Ellwood (1994)	1968-1988	PSID	31	49	75	4.7	25	17
Lane and Stevens (1995)	1985-1993	Maryland state agency	-	-	-	-	31	-
Fitzgerald (1995)	1984-1985	SIPP	52	70	-	1.0	23	-
Harris (1996)	1983-1988	PSID	-	-	-	-	60	27
Hoynes (2000)	1987-1992	California state agency	46	62	-	-	-	33
Bavier (2001)	1984-1995	SIPP	-	-	-	-	48-60	-
Hofferth et al. (2002)	1989-1996	PSID	30	47	70	2.8	64	-
Post-Welfare Reform								
Bavier (2001)	1996-1999	SIPP	-	-	-	-	45-53	-
Bruce et al. (2004)	1996-2001	Tennessee state agency	-	-	-	0.4	26	22
Nam (2005)	1997-2002	WES	-	-	-	2.7	61	39
Parisi et al. (2006)	1996-2004	Mississippi state agency	85	96	-	-	-	-
Irving (2008)	1996-2003	SIPP	-	-	-	-	41	-

NOTE: NLS(Y) = National Longitudinal Survey (of Youth)
SIME/DIME = Seattle/Denver Income Maintenance Experiments
WES = Michigan Women's Employment Study
PSID = Panel Study of Income Dynamics
SIPP = Survey of Income and Program Participation

The distribution of welfare spells and therefore welfare dependence has received less attention in recent studies. We have limited knowledge about new patterns of welfare dependence after welfare reform, when time limits were applied. Moreover, few studies of welfare-to-work transition incorporate spell duration into analytical framework. One exception comes from a Mississippi study (Parisi et al. 2006). The study finds that TANF spells have much short length, on average. Furthermore, the overall welfare exit rate within one year and two years is 85% and 96%, respectively—much higher than previous studies based on pre-welfare reform data. Finally, multivariate analysis shows that more time spent on TANF significantly reduces the odds of exit, supporting the welfare dependence hypothesis.

4.7 Race and Inequality

Race is a substantial factor in the model of labor market inequality. But with the study of welfare, it is difficult to provide a comprehensive understanding of the effects of race due to a couple of limitations. First, the population of this study is single mothers who have been on welfare rolls. We do not know if race has a differential effect on welfare-to-work transition. That is, this study cannot explain why black women are disproportionally represented in the welfare population.[42] Second, the disadvantages of blacks are consequences of accumulative and interactive social processes, such as single motherhood, dropping out of high school, peer effects, illegitimacy, male joblessness, violence, etc. It is difficult to control all these variables in order to indicate the effect of

[42] Actually, this is a very sensitive topic in that the debaters are roughly divided into liberal and conservative viewpoints. See Murray (1984) and Mead (1986) for conservative perspective; Rank (2005) and Sharon (2003) for liberal perspective.

race on patterns of welfare use. This limitation is partly the reason why findings on the effects of race on welfare use are, at best, mixed.

In empirical studies, there are three ways that race is included in an analytical model. First, race is often used as a control variable with white as a reference category. In this way, blacks are compared with whites in terms of probabilities of an event, such as the likelihood of exiting or returning to welfare rolls. A set of studies finds a significant influence of race on welfare exit (e.g., Blank 1989; Bruce et al. 2004; Grice 2005; Herbst and Stevens 2010; Hoynes 2002; O'Neill et al. 1987; Parisi et al. 2006). For example, using Mississippi administrative data, Parisi et al. (2006) find that the odds of blacks leaving TANF are 61% compared to those of whites, even after controlling for individual characteristics (e.g., human capital and family formation) and local conditions of blacks and whites. However, another set of studies finds no support for the influence of race on welfare exit. For instance, Moffitt (2003) finds no significant effect of race on exit and reentry. Similarly, a couple of studies using data from the PSID find no significant differences between races in terms of welfare exit (Harris 1993; Hofferth et al. 2002) and welfare recidivism (Harris 1996; Hofferth et al. 2005). Moreover, Browne (1997) finds an insignificant effect of race on single mothers' labor force participation after controlling for variables like dropping out of high school, having a child under the age of six, and being a long-term welfare recipient. Rank (1988) finds that the role of opportunity rather than race explains racial differences in the length of welfare use. That is, black and white single mothers with similar characteristics (e.g., education, employment status, number of children, and age) behave identically in their use of welfare.

Second, the effect of race can be estimated by running regression models based on one sample of whites and one sample of blacks, assuming that the two subsamples are different in responding to the key variables in concern. In doing so, Fitzgerald (1995) finds that black single mothers' welfare-to-work transition is more sensitive to local labor market changes compared to white single mothers' welfare-to-work transition. A recent study also shows that blacks' welfare exits are more influenced by human capital and local socioeconomic characteristics (Parisi et al. 2006). This study, however, does not specify exit patterns, particularly for work exits, which is the central concern of welfare reform.

Finally, race can be included in models in interaction with other variables, such as age, marital status, human capital, and community characteristics. In doing so, one can examine the extent to which the regression coefficients of key variables are affected by race. Few studies use this approach in models of welfare-to-work transition. In a study not directly focused on welfare users, Tomaskovic-Devey et al. (2005) find substantial interaction effects of race on the return of human capital.

4.8 Summary

After a quick reading of the literature on welfare, one may notice the considerable range of findings in estimations of welfare-to-work transition. It is interesting to summarize the factors that produce these variances.

One of the big reasons for the varied findings is the difference in data sources. In contrast to the well developed statistical methods, the data used in previous studies remain unsatisfactory. (Surely, there is no such thing as perfect data in any empirical study.) A number of widely cited studies produce findings based on relatively small samples that sometimes include only a subgroup of the total welfare population of interest. For example, Blank (1989) uses a subsample of welfare recipients extracted from the Seattle/Denver Income Maintenance Experiments (SIME/DIME) between 1971 and 1976. The representativeness of the sample is questionable due to its nonrandom sample of both SIME/DIME and the subsample generated by the researcher. In addition, the small sample size (323 completed spells and 185 right-censored spells) also weakens the explanatory power of the findings. Some researchers (e.g., O'Neill et al. 1987, Pavetti 1993) use data from the National Longitudinal Survey of Young Women (NLSYW) or NLSY. Because NLSYWM and NLSY collect information from cohorts of women born in a specific time period, the sample is not representative of the welfare population. A couple of recent studies use data from the PSID. In an influential study of welfare exit, Harris (1993) is able to identify a sample of only 204 women who experienced 116 first spells of welfare with observed beginnings during the observation period. In addition to different sources of data, the analytic period varies from one study to another. So far, numerous studies have focused on the pre-welfare reform period or the policy transition stage in the 1990s. A relatively small number of studies use data that catch the patterns of welfare use and the welfare-to-work transition in recent years, partly due to the limited availability of data.

Moreover, along with inconsistent data sources, measures of key variables differ even for studies using similar data sets, depending on available information and the conceptual preferences of researchers. For example, as a primary concept of welfare-to-work transition, work exit is one of the toughest variables to measure. Data from self-report surveys usually lack direct indicators that record the respondents' changes in employment status. Researchers have to use complex equations to distinguish job exits from other kinds of exits, such as those due to family formation changes or increased income (e.g., Bane and Ellwood 1983, 1994; Bavier 2001; Harris 1993). Instead of employing survey data, some researchers use state UI administrative data as an intuitive way to identify welfare recipients' employment statuses. UI data, however, do not cover all types of employment, such as federal government employment, employment outside of the state, informal employment, and off-the-book employment. Moreover, when using UI data, the representativeness of a study is usually confined to a target state. Because my study uses UI data from Mississippi, I will detail the merits of these data in Chapter V.

In addition to the empirical estimation of welfare-to-work transition, theoretical concerns have not been fully addressed in the welfare literature. This limitation is not surprising, though, considering that many studies are direct responses to policy needs. However, this observation does not mean theoretical modeling is secondary because the fundamental controversies of the welfare debate are rooted in different theoretical assumptions. Different models offer different predictions about welfare recipients' behaviors and therefore provide different approaches to policy implementation. Thus, it is essential to incorporate these models into one conceptual framework in order to produce a less biased picture of welfare-to-work transition,[43] which is the purpose of my study. Below, I provide several research hypotheses based on different theoretical models.

4.9 Research Hypotheses

My study contributes to the welfare literature by examining the determinants of welfare-to-work transition in the TANF era. The most important question is that if

[43] Bane and Ellwood (1994) have done an insightful job in modeling welfare dependency based on three kinds of theoretical models: choice models, expectancy models, and cultural models. Please refer to Chapter III for detailed comments on this subject.

individual characteristics and contextual factors still matter given strong policy implementation to reduce welfare rolls. Based on previous literature in this field, I try to bring together the models of human capital, local labor market, neighborhood effects, and welfare dependence. Overall, my study is about answering the three research questions:

- Are single mothers with higher human capital more likely to leave welfare and gain employment to make ends meet?
- Are single mothers under better labor market and neighborhood conditions more likely to leave welfare and move onto a path of self-sufficiency?
- Do single mothers from different racial groups have equal opportunity to leave welfare and make ends meet?

Several empirical hypotheses will be tested to answer these questions:

- Human Capital Hypotheses
  - Educational attainment facilitates welfare-to-work transition. The higher the level of education received, the easier the transition will be.
  - Training programs help welfare recipients in leaving welfare and finding a job.
  - Previous work experience helps welfare recipients in leaving welfare and finding a job.
- Labor Market Hypothesis
  - The local labor market provides job opportunities to welfare recipients and thus would affect the incidence of welfare-to-work transition.
- Neighborhood Effects Hypothesis
  - Disadvantaged neighborhoods have negative effects on welfare-to-work transition.

- Welfare Dependence Hypotheses [44]
  - Time spent on welfare rolls lowers the probability of work exit.
- Race Hypotheses
  - Blacks are disadvantaged in exiting from the TANF program in compared with their white counterparts.
  - Blacks are more sensitive to the change of human capital than whites.
  - Blacks are more sensitive to the change of contextual factors than whites.

[44] Since dependence hypothesis has loose meanings in welfare study, we can test it in a variety of ways. First we can describe the overall patterns of TANF use compared with the patterns before welfare reform. Second, we can use life table method to estimate the parameters of welfare spells. Finally, we can measure the main effect of time in the baseline discrete-time model by introducing individual specific random effects for multiple spells within a person.

CHAPTER V

METHODS: DATA, MEASURES, AND ANALYTICAL STRATEGY

In this chapter, I first provide a detailed description of the multiple data sets used in this study. Next, I break down the measurement of dependent variables and independent variables in terms of different theoretical components. Lastly, I examine the development of statistical models that are appropriate for my study. In this respect, I focus on combined approaches that include discrete-time event history analysis, competing risks models, and random effects models (or multilevel analysis).

5.1 Data

Multiple data sources are used in the study. The primary data sets are administrative data from Mississippi state agencies, including monthly welfare data, quarterly Unemployment Insurance data, and Workforce Investment Act job training accumulative data (see Table 5.1).

The monthly welfare administrative data sets are from the Mississippi Department of Human Services (MDHS). These data sets include three kinds of data that are used in my study: (1) monthly TANF (and Food Stamp) client files; (2) monthly case files with geographic information for each case; and (3) monthly TANF benefit files. The monthly TANF client data monitor TANF (and Food Stamp) participation for each client in a case. Here, "client" refers to a family member who could be in welfare programs, and "case" refers to a family. The relationship between each member is classified as primary individual, child, grandchild, etc. The primary individual (called PI client thereafter) is typically the head of a household. The monthly TANF data set also includes variables such as race, education, and date of birth. The case files can be combined with client files to produce a unique match between PI client and physical address (e.g., city, Zip Code, and county). Finally, TANF benefit files are used to double-check TANF recipients who actually received monthly payments.

The UI data set is provided by the Mississippi Department of Employment Services (MDES). These data include Base Period Files (BPF) that contain quarterly wages of employees submitted by each employer. The quarterly BPF files can be used to track one's employment status during the observed period.

Other data sources include the Workforce Investment Act (WIA) data set that is updated weekly by MDES, data from the 2000 census, and monthly county-level unemployment rates that are posted on the MDES website.[45]

[45] See "Historical Series of Unemployment Rates by Month from 1970 Forward." http://www.mdes.ms.gov (Home > Labor Market Information > Publications > Unemployment Rates). Accessed June 21, 2010.

Table 5.1 Data Sets Used in the Study

Database	File Name	Source	Data Input	Variables of Concern	Note
Welfare	Client	MDHS	1996-2010; Updated monthly	Client-based: in TANF, race, date of birth, sex, education, work code in TANF, and the relationship of each family member to household head.	Incomplete for 1997.6; duplicate for 1997.10 and 1998.1, 1998.9 and 1998.10, 2000.2 and 2000.3, and 2006.8 and 2006.9.
Welfare	Afben	MDHS	1996-2010; Updated monthly	Amount of monthly payments by case.	Missing 1997.12, between 2000.11 and 2001.6, and 2008.5; missing supplemental payments for some files.
Welfare	Case	MDHS	1996-2010; Updated monthly	County code by case.	Accumulative data.
UI	Base Period Files (BPF)	MDES	2001-2009; Updated quarterly	Quarterly wages.	
WIA	Job Training (JT) Files	MDES	Updated weekly	Training information.	Accumulative data.
UI	MS_UI	MDES	1970-2009	County-level unemployment rates.	Published on the MDES website.
County Profiles	County Profiles	Census	2000	Population distribution by block, block groups, and county; median income, and metro/non-metropolitan county.	

NOTE: MDHS = Mississippi Department of Human Services; MDES = Mississippi Department of Employment Security; WIA = Workforce Investment Act of 1998; UI = Unemployment Insurance

Before we move to the next section, I will briefly review the advantages and disadvantages of using administrative data. Compared to national survey data sets (e.g., PSID and NLSY), administrative data have several advantages. First, the sample size is large, usually containing hundreds of thousands of cases (compared to 500-1,000 cases in standard survey data sets). Second, the data contain information on county and Zip Code of residence that allows one to identify relatively small labor market areas and detailed neighborhood characteristics. Third, because the analysis is based on administrative data, welfare spells are measured in line with monthly based TANF eligibility, meaning there is no recall error and measurement error as in self-report survey data. Fourth, there is no sampling attrition or sampling error. Last but not least, administrative data sets can be matched by personal ID variables (e.g., SSN). For example, we can track a welfare recipient's employment status by merging UI wage data to welfare client data.

It should be noted that administrative data have some disadvantages in academic studies (Goerge and Lee 2002). First of all, the data are collected and saved for administrative reasons. They are not ready for the purpose of academic research. Researchers have to clean and match data by themselves. This process is difficult because of numerous sources of potential error in the data and/or lack of documentation on data collection, processing, and storage. Second, there is a lack of adequate control variables. Third, data are available only for the time periods that a client is in program. Finally, UI data sets bring about additional limitations due to their lack of documentation on self-employment and unreported jobs (Hotz and Scholz 2002).[46]

[46] Another significant drawback of UI data is the lack of work hours and average hourly wage variables. This limitation might significantly impact the study of welfare leavers' earning income because many leavers are likely to take part-time jobs. Thus, part of the variance in wages may be due to differences in work hours.

5.2 Measurement of Variables

5.2.1 Dependent Variable

Following the welfare literature, I use two dependent variables: (1) a binary variable that focuses on exits and no exits and (2) a nominal variable that estimates competing risks among work exits, non-work exits, and no exits.

The primary concern in measuring the dependent variables is identifying in-TANF status and work status. There are two set of welfare files that provide information on TANF participation. The client file contains a dichotomous variable that specifies whether a client is in TANF or not. The beneficial file provides the actual amount of payment received by each family. After matching these two sets of files, I find that the two indicators of TANF participation are not consistent.[47] I then apply a strict criterion to identify whether a PI client is in TANF. That is, *in order to be in TANF, a client must present in the TANF program based on client files, and her family must receive payment based on the beneficial files.* Finally, we need to transform the monthly based TANF participation to quarterly based TANF participation. The reason is that UI data sets, which provide employment information, are quarterly based. In this study, *a client is in TANF for a given quarter as long as she is in TANF during one of the three months of that quarter.*[48]

---

[47] There are a variety of situations. For example, in some cases, the actual payment has a one- or two-month lag behind the participation record; in other cases, a one-month participation record did not lead to payment for a family; and in other cases still, a supplemental payment, or a payment for a previous month, was received by a family.

[48] Defining quarterly TANF participation in this way could potentially fix the one-month administrative error. The one-month administrative error occurs when two spells that are divided by a one-month break (or two-month break) are actually a single spell. A common situation is that people leave the welfare roll because of failure to comply with administrative rules. These individuals could come back in one or two months once they follow the rules. Luks and Brady (2003) provide a specific estimation of how this issue affects the distribution of welfare spells.

MDHS provides two fields to track a client's employment status. One field comes from the monthly close files that record the reasons for case closures. One of these reasons is coded as "EI" ("Earnings Income Exceeds"). However, according to a national survey, the rates of closure due to employment that are reported from state agencies underestimate the real value of labor force participation (HHS 2009a). The study finds that many closures due to employment are coded as failure to cooperate or as another category because the state agency is often unaware about clients becoming employed at the point of closure. The MDHS monthly client files provide another field relevant to employment identification, defined as "Workcode," which has as many as 68 categories. Three of them are coded as follows: "WH"=work 35 hours or more, "WP"=work 20-34 hours, and "WL"=work more than 0 and less than 20 hours. However, one must be cautious when using this variable to identify employment status for the similar reason of underestimation.

Alternatively, individuals' employment information can be obtained from Base Period Files (BPF) in the state UI database. The original variables in the BPF file are quarterly wages reported by employers. An individual may be coded as employed in a quarter when he or she has a positive wage (i.e., greater than zero) presented in that quarter. It should be noted, however, that employers are allowed to skip the regular quarterly wage report occasionally.[49] As a result, the total number of employees (based on the positive wage records) drops to zero in the unreported quarter and reverts to its

[49] We do not know how this occurs. Some employers report the wages of their employees without any interruption, while a few employers occasionally skip wage reports for one or two quarters within a year. This kind of missing data could lead to significant bias in calculating quarterly job transitions by industrial sector or county if one or two of the biggest employers do not provide wage reports for a quarter.

normal level in the next quarter. It is technically difficult to identify whether a missing wage for a given employee is due to losing a job or an absent wage report.

Compared to the aforementioned measurements of employment, I find that the UI version is more reliable and can identify more labor force participations. Thus, *in order to exit due to employment, a client must leave the TANF program and have a positive wage in the UI wage files in the next quarter of exit.*

5.2.2 Independent Variables

Variable names, operational definitions, and sources of data are listed in Table 5.2. I group independent variables into five categories: controls, human capital, labor market, neighborhood, and race. Control variables include age, the age of the youngest child, and a repeated spell dummy. Variables measuring human capital include education, job training, and work experiences. Education is treated as time invariant for two reasons. First, the study interest focuses on the effect of high school graduation in contrast with high school drop-out. Precise measurement of the year of education is not needed. Moreover, since the target group is adult recipients older than 18, their educational levels are not likely to change over time. Second, in regard to changes in grade values, some are real increases during the school year, but others are obviously inconsistent due to unknown reasons. Thus, precise measure is not available. I use the most recent value of education with the assumption that it is more correct than previous records.

Table 5.2 Variable Names and Operational Definitions

Variable	Description	Time Varying	Source of Data
Dependent Variables			
Binary event	If exited from TANF.	--	TANF.client
Competing event	If exited from TANF and employed in the next quarter.	--	TANF.client UI.BPF
Independent Variables			
Race	Either black or white.	No	TANF.client
Control Variables			
Age	The age of adult clients.	Yes	TANF.client
Youngest child	The age of the youngest child presented in the household.	Yes	TANF.client
Repeated spells	If a spell is a repeated spell.	No	TANF.client
Human Capital			
Education	Grade of education.	No	TANF.client
Job training	If received job training in the last four quarters.	Yes	WIA.JT1
Work experience	If worked while in the TANF program.	Yes	UI.BPF
Labor Market			
Unemployment rates	County unemployment rates.	Yes	MDES
Neighborhood			
Dissimilarity index	Based on block groups within a county in 2000.	No	Census 2000
Percent of black	Percent of black within a county in 2000.	No	Census 2000
Median income	Median household income in 2000.	No	Census 2000
Metro/micro county	A county within a metropolitan and micropolitan statistical area in 2000.	No	Census 2000

Job training can be created from the WIA dataset. Because job training serves as human capital, individuals can retain it for a period of time. I am interested in the short-term effect of job training that leads to employment. Work experience is measured based on a recipient's previous work status in the UI data set. As with job training, I focus on work experience in TANF that leads to employment after an exit.

To test labor market hypotheses and neighborhood hypotheses, I enlist five contextual variables, including quarterly county-level unemployment rate, percent of black, dissimilarity index, median income, and metropolitan/micropolitan county versus nonmetropolitan/nonmicropolitan county. The dissimilarity index measures the extent to which whites and blacks are evenly distributed, which is calculated based on block groups in a county. The basic formula for the index of dissimilarity calculated here is:

$$\left(1/2\sum_{i=1}^{N}\left|\frac{b_i}{B}-\frac{w_i}{W}\right|\right)\times 100$$

where

b_i = the black population of the ith census block group;

B = the total black population of the county;

w_i = the white population of the ith census block group;

W = the total white population of the county.

N = the number of block groups within the county.

Percent black of a county measures the proportion of blacks relative to other ethnic groups. Given that blacks and whites comprise more than 95% of Mississippi's total population, percent black can be viewed as a measure of population weight between blacks and whites. It should be noted that counties may have the same dissimilarity index score but quite different percentages of blacks. Median household income and metropolitan/micropolitan county are based on 2000 census definitions.

5.3 Analytical Strategy

My analytical strategy includes a descriptive analysis and multivariate analysis. The descriptive analysis explores the trends of overall TANF caseload between 1996 and

2010. A life table technique is then used to examine the patterns of quarterly TANF use by adult clients between September 2001 and September 2009 in line with the time frame of the multivariate analysis. The multivariate analysis begins with a discrete-time event history analysis, with a binary outcome (e.g., exit from TANF versus no exit). Furthermore, competing risk models are created by introducing a nominal outcome that distinguishes work exits and non-work exits. Finally, individual specific random effects are estimated in both binary and nominal models to control unobserved heterogeneity for repeated spells.

5.3.1 Caseload Analysis

The caseload analysis for this study is a description of the TANF population in Mississippi between October 1996 and June 2010. I focus on five key variables that provide a profile of the TANF population, including race, type of case, age composition of adult cases, monthly in-and-out of TANF, and employment status. Type of case distinguishes adult case and child-only case. If the household head of a case received TANF benefit, then the case is adult case. If only child received benefit, then the case is child-only case. In addition, I also provide a cross-sectional analysis of work transitions indicating the quarterly caseload of adult TANF clients by employment status and exit type (e.g., work or non-work) between quarter four in 2001 and quarter three in 2009.

5.3.2 Life Table

The caseload analysis gives us a cross-sectional view of TANF use. However, we also want to know the longitudinal outcomes of TANF use. In doing so, we need to utilize the life table, a primary tool for describing the timing of events (Allison 1984; Singer and Willet 2003). The life table is especially useful in welfare studies given that duration of welfare spells is a primary concern. Typically, duration of welfare spells is estimated through three statistical summaries: the hazard function, the survivor function, and the median lifetime.

The discrete-time hazard function, p_{tij}, is the conditional probability (also called hazard rate) that individual *j* will experience an event during interval *t* of episode *i*, given no earlier occurrence. The hazard function may be denoted as:

$p_{tij} = \Pr(T = t \mid T \geq t)$, where *T* is the event time, or written as:

$p_{tij} = \Pr(y_{ij}(t) = 1 \mid y_{ij}(t-1) = 0)$

where:

$y_{ij}(t) = 1$ if event occurs to of individual *j* at time *t* in episode *i*;

$y_{ij}(t) = 0$ if event has not occurred.

The discrete-time survivor function, $\mathrm{S}_{ij}(t)$, is the probability that an event has not occurred for individual *j* before time *t* in episode *i*, written as: $\mathrm{S}_{ij}(t) = \Pr(T \geq t)$. In essence, the survivor function measures the probability of event avoidance. In the welfare literature, however, the concern is the probability of occurrence, that is, the probability of exiting welfare. Thus, we need to move to the failure function, also called the cumulative density function or cumulative percentage of occurrence. The failure function, $\mathrm{F}_{ij}(t)$, is the probability that an event occurs for individual *j* before time *t* in episode *i*: $\mathrm{F}_{ij}(t) = \Pr(T < t) = 1 - \mathrm{S}_{ij}(t)$. In the following analysis, I will use the cumulative percentage of exits from TANF.

Median lifetime is the value of the survivor function (or failure function) at the point in time when half of the sample has experienced the event. Combined with the survivor function, median lifetime gives us a quick view of the estimated duration for a target group.

The life table also allows for multiple group comparisons. In doing so, we are able to test differences in welfare use patterns between subsamples. In particular, we can compare the failure functions and hazard functions between blacks and whites, between clients with higher education and clients with lower education, and between earlier spells and later spells. An intuitive way of examining the estimated hazard functions and conditional probabilities of exit is to graph values over time. In this way, we can easily detect when the event is more likely to occur and whether and how the risks change over time.

The life table analysis requires a spell-based file to calculate spell numbers and spell lengths. The spell-based file keeps unique records of spells by individual, including indicators for right-censored spells and spell duration. For further exploratory analysis, I introduce three pairs of comparable groups as shown in the layout of the spell-based file (Table 5.3).

Table 5.3 Data Layout of Spell-Based File

Client ID	Sequence	Duration by Quarter	Right-Censored	Education	Race	Earlier or Later Spells
…001	1	2	0	0	0	1
…002	1	3	0	1	1	0
…002	2	1	0	1	1	0
…002	3	5	1	1	1	1
…003	1	4	0	1	1	1
…004	1	7	1	0	0	0

Source: Created by the author based on welfare data from MDHS.
NOTE: See Table 6.2 for variable codes.

5.3.3 Discrete-Time Event History Analysis

The analytical strategy of this study is based on event history analysis—also known as survival analysis or hazard modeling. The property of the data used in my study includes longitudinal outcomes. The event occurrence for a given individual was recorded monthly or quarterly within a period of observation (e.g., the transition between welfare and work or participation in job training). Techniques of event history analysis are appropriate to the data structure. Discrete-time event history analysis requires person-quarter data in which each individual contributes as many observations as quarters on TANF (Table 5.4). For example, client *j* has three spells. Her first spell lasts two quarters. Then she leaves TANF but returns for two more spells. The third spell lasts eight quarters and is right-censored at the end of observation. Using the discrete-time person-quarter data format, we can easily add time-varying covariates, time invariants, and contextual effects.

5.3.3.1 Binary Models

Social science event-history data are typically collected in discrete time (e.g., by month or by year). Discrete-time logistic regression models the probability of an event within a given period as a function of one or more covariates (Allison 1982, 1984; Singer and Willet 1993; Singer and Willet 2003; Powers and Xie 2008). The dependent variable for a simple discrete-time model is the binary indicator of event occurrence.

Table 5.4 Data Layout of Person-Quarter File

Client (j)	Spell (i)	Time (t)	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	…	D_q	Binary Events	Competing Events	Time Invariant	Time Varying	Contextual Effects
001	1	1	1	0	0	0	0	0	0	0	…	0	0	3	1	0	111
001	1	2	0	1	0	0	0	0	0	0	…	0	1	2	1	0	111
001	2	1	1	0	0	0	0	0	0	0	…	0	0	3	1	0	111
001	2	2	0	1	0	0	0	0	0	0	…	0	0	3	1	0	111
001	2	3	0	0	1	0	0	0	0	0	…	0	1	1	1	0	111
001	3	1	1	0	0	0	0	0	0	0	…	0	0	3	1	1	111
001	3	2	0	1	0	0	0	0	0	0	…	0	0	3	1	1	111
001	3	3	0	0	1	0	0	0	0	0	…	0	0	3	1	1	111
001	3	4	0	0	0	1	0	0	0	0	…	0	0	3	1	1	111
001	3	5	0	0	0	0	1	0	0	0	…	0	0	3	1	0	111
001	3	6	0	0	0	0	0	1	0	0	…	0	0	3	1	0	111
001	3	7	0	0	0	0	0	0	1	0	…	0	0	3	1	0	111
001	3	8	0	0	0	0	0	0	0	1	…	0	0	3	1	0	111
002	1	1	1	0	0	0	0	0	0	0	…	0	1	1	0	1	111
003	1	1	1	0	0	0	0	0	0	0	…	0	0	2	0	0	111
004	1	1	1	0	0	0	0	0	0	0	…	0	0	3	0	1	222
004	1	2	0	1	0	0	0	0	0	0	…	0	0	3	0	1	222
004	1	3	0	0	1	0	0	0	0	0	…	0	0	3	0	0	222
004	1	4	0	0	0	1	0	0	0	0	…	0	1	2	0	1	222

NOTE: See Table 6.4 for variable codes.

We have a discrete-time logit baseline model as below:

$$\text{logit}[p_{tij}] = \log\left[\frac{p_{tij}}{1 - p_{tij}}\right] = \alpha(t)$$

(Model 1)

where p_{tij} is the hazard of event in time interval *t* during spell *i* of individual *j*, and $\alpha(t)$ is some function of time, called the logit of the baseline hazard function. One general approach to estimate $\alpha(t)$ uses a a set of dummy variables as below:

$$\alpha(t) = \alpha_1 D_1 + \alpha_2 D_2 + \cdots + \alpha_q D_q$$

where D_1, D_2, ..., and D_q are dummies for time intervals *t* = 1, 2, . . ., and q. q is the maximum observed event time (here q is measured by quarter).

It is advised by Singer and Willet (2003:409-419) to test alternative specifications (e.g., linear, quadratic, and cubic) of $\alpha(t)$, or the main effect of *TIME*. The specifications are necessary under three circumstances. First, this study involves many discrete time periods due to long periods of observation and a large sample size. Second, the hazard of exits is expected to be very low in some time periods. Third, some time periods have small risk sets. Following their approach, I will evaluate the validity of alternative time specifications as a baseline model.

For repeated events, as in the study of welfare, one individual could have multiple spells. The problem with analyzing recurrent events is that we cannot assume that the spells of the same individual are independent. There may be unobserved individual-specific factors that affect the hazard of an event for *all* spells within an individual. Earlier study of welfare recidivism distinguished the first and subsequent spells and analyzed them separately. In doing so, we can simply add a dummy variable with the first spell coded as "0" and repeated spells coded as "1." Alternatively, we can introduce individual specific random effects to estimate within-person variance of repeated events. Recurrent events lead to a two-level hierarchical structure. Level two is for individuals (*j*), and level one is for spells/episodes (*i*) nested within individuals. The baseline binary two-level model for recurrent events with random coefficients follows:

$$\eta = \text{logit}[p_{tij}] = \log\left[\frac{p_{tij}}{1 - p_{tij}}\right] = \alpha(t) + u_j$$

(Model 2)

where u_j is the random effect within an individual j. Even though many TANF clients do not return, it still makes sense to introduce the random effects of spells within an individual. As Powers and Xie (2008:130) point out in an example of sibling models for first premarital birth, that "(a) sole respondent per cluster, or a cluster of size 1, does not contribute information to the estimation of cross-cluster random coefficients, which are estimated from members of clusters of two or more sister."

Multilevel methods have been addressed and developed for many years (DiPrete and Forristal 1994; Guo and Zhao 2000; Raudenbush and Bryk 2002; Singer and Willet 2003). However, literature on the extension of multilevel modeling for binary/nominal data to discrete-time analysis is relatively new and receives empirical concern in social sciences only recently (Goldstein et al. 2004; Hedeker and Gibbons 2006; Powers and Xie 2008). In an example of discrete-time models for program dropout, Powers and Xie (2008:181-183) estimate the random effect for the unobserved program-specific (level-2) factors affecting dropout. They find modest between-program variability in dropout hazard. Another study makes a direct comparison between fixed effect baseline model and program-specific random effect baseline model in estimating the hazard of doctorate completion (Wao 2010:Table 1). However, the study does not make further interpretation on the random effects between programs.

Baseline binary models can be easily expanded to full models by including time invariants and time varying covariates, $x_j(t)$, in either a fixed form (Model 3) or random form (Model 4):

$$\eta = \text{logit}[p_{tij}] = \alpha(t) + \beta x_j(t)$$

(Model 3)

$$\eta = \text{logit}[p_{tij}] = \alpha(t) + \beta x_j(t) + u_j$$

(Model 4)

For the purpose of SAS NLMIXED programming, we can rewrite the baseline and full random effect models using *eta* (η) specification (see Appendix B).

$$p_{tij} = \begin{cases} \dfrac{\exp(\eta)}{1+\exp(\eta)}, & event = 1 \\ \dfrac{1}{1+\exp(\eta)}, & event = 0 \end{cases}$$

5.3.3.2 Competing Risk Models

Competing risk models are used to estimate the probability of TANF exit (work exit or non-work exit) versus no exit. The fixed forms can be modeled as below (Allison 1995:227-230):

$$\eta^w = \text{logit}\left[p_{tij}^{(w)}\right] = \alpha(t)$$

$$\eta^o = \text{logit}\left[p_{tij}^{(o)}\right] = a(t)$$

(Model 5)

where $p_{tij}^{(w)}$ is the probability of work exit versus no exit in interval *t* of spell *i* for individual *j*, and $p_{tij}^{(o)}$ is the probability of other exit (or non-work exit) versus no exit in interval *t* of spell *i* for individual *j*.

As we have done in the binary analysis, we can introduce individual specific random effects in estimating the repeated spells within a person. There are two random effects, u_{1j} and u_{2j}, for work exits and other exits as shown below:

$$\eta^{w} = \text{logit}\left[p_{tij}^{(w)}\right] = \alpha(t) + u_j^{(1)}$$

$$\eta^{o} = \text{logit}\left[p_{tij}^{(o)}\right] = \alpha(t) + u_j^{(2)}$$

(Model 6)

assuming $u_{1j} \sim N(0,\ \sigma_{u1}^2)$, $u_{2j} \sim N(0,\ \sigma_{u2}^2)$, and $\text{Cov}(u_{1j},\ u_{2j}) = \sigma_{u12}$. σ_{u1}^2 and σ_{u2}^2 respectively refer to between-individual and between-spell (within-individual) variance. The variance and covariance matrix is as below:

$$\begin{pmatrix} u_j^{(1)} \\ u_j^{(2)} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u1}^2 & \\ \sigma_{u12} & \sigma_{u2}^2 \end{pmatrix}\right]$$

Although a couple of studies introduce multilevel analysis for nominal data, few do empirical researches that combine discrete-time analysis and multilevel competing risk models (e.g., Agresti et al. 2000; Agresti and Liu 2001; Hartzel et al. 2001; Hedeker and Gibbons 2006; Goldstein et al. 2004; Powers and Xie 2008; Steele et al. 1996; Steele et al. 2004). The approach in this study follows the Stata GLLAMM guideline provided by Rabe-Hesketh et al. (2004: Chapter 9.3) and the SAS NLMIXED procedure (e.g., Kuss and McLerran 2007).

Finally, baseline competing risks models can be easily expanded to full models by including time invariants and time-varying covariates, $x_j(t)$, in either a fixed form (Model 7) or random form (Model 8):

$$\eta^w = \text{logit}\left[p_{tij}^{(w)}\right] = \alpha(t) + \beta x_j(t)$$

$$\eta^o = \text{logit}\left[p_{tij}^{(o)}\right] = a(t) + \beta x_j(t)$$

(Model 7)

$$\eta^w = \text{logit}\left[p_{tij}^{(w)}\right] = \alpha^w(t) + \beta^w x_j(t) + u_j^{(1)}$$

$$\eta^o = \text{logit}\left[p_{tij}^{(o)}\right] = a^o(t) + \beta^o x_j(t) + u_j^{(2)}$$

(Model 8)

For the purpose of SAS NLMIXED programming, we can rewrite the competing risks random effects models as below (for syntax see Appendix B):

$$p_{tij} = \begin{cases} \dfrac{\exp(\eta^w)}{1 + \exp\,(\eta^w) + \exp\,(\eta^o)}, & \text{if work exit} \\[2ex] \dfrac{\exp(\eta^o)}{1 + \exp\,(\eta^w) + \exp\,(\eta^o)}, & \text{if other exit} \\[2ex] \dfrac{1}{1 + \exp\,(\eta^w) + \exp\,(\eta^o)}, & \text{if no exit} \end{cases}$$

5.3.3.3 Software Implementation

A particular concern of this study is how to estimate individual specific random effects for repeated events with competing risks outcomes. There are several names that refer to this kind of model, including hierarchical model, multilevel model, mixed model, growth model, and random effects model. Most standard statistical software has the capacity to fit linear mixed models. However, fitting mixed models with nominal or ordered outcomes has been a challenge. A line of specific software has been developed for this purpose, including MIXNO (Hedeker 1999), WinBUGS (Spiegelhalter et al. 2003), HLM (Raudenbush et al. 2004), and MlwiN (Rasbash et al. 2009). In addition, two standard statistical software packages also provide special commands to meet the requirement of fitting nominal mixed effect models: Sata GLLAMM (Rabe-Hesketh et al. 2004) and SAS NLMIXED (for a few examples of the SAS application, see Flom et al. 2007; Hedeker and Gibbons 2006; Kuss and McLerran 2007; Malchow-Moller and Svarer 2003; Sheu 2002; and Van Ness et al. 2004). Given the variety of software in estimating nominal mixed models, few studies provide comprehensive comparison on the efficiency and reliability of each one using real data. Powers and Xie (2008:141-156) try to fit a multilevel model for binary data using Stata's GLLAMM procedure, SAS's proc GLIMMIX procedure, and OpenBUGS program. They find that the estimates from different procedures are very similar. Another research provides a comparison of estimation via Sata, SAS, and WinBUGS in the study of nominal outcomes of employment transition (Haynes et al. 2008). The results are proved to be comparable.

This study uses both Sata and SAS commends in the analyses of random effects models (see Appendix B for syntax). One reason for these choices is that Sata and SAS are popular statistical software. Literature on the application of both commands is widely available. In addition, estimating models using both statistical packages allows me to double-check reliability of the results.

CHAPTER VI

ANALYSIS AND RESULTS

I begin my analysis with a general description of the caseload and spells of TANF clients in Mississippi after welfare reform. Here, I use a set of figures to visualize the patterns of TANF use (values can be found in Appendix A). The second part of this chapter deals with multivariate issues, testing the theoretical hypotheses that are proposed in Chapter III and Chapter IV.

6.1 Profile of TANF Caseloads

First, the trend and magnitude of overall caseload in this study are resemble to what we get from federal government sources and other academic studies. We are able to observe a sharp drop in the first two years after the 1996 welfare reform (Figure 6.1). There is a slightly increase in the TANF caseload between 2002 and 2003, probably due to an economic recession at that time. A little bit surprise is that the most recent economic downturn did not increase the TANF caseload.

Second, as always, racial composition is an important factor (Figure 6.1). The majority of the Mississippi welfare caseload can be attributed to blacks, while whites account for a much smaller part of the caseload. The large number of black TANF participation could be partly explained by the fact that Mississippi has the highest proportion of blacks for a state in this country. Blacks make up 37% of the state's population; the national rate was 12.1% in 2007 (Table 6.1). Second, blacks are more likely to be poor than are whites, and this is especially true in Mississippi. Poverty rates in Mississippi are 15.7% for whites and 44% for blacks (Table 6.1).

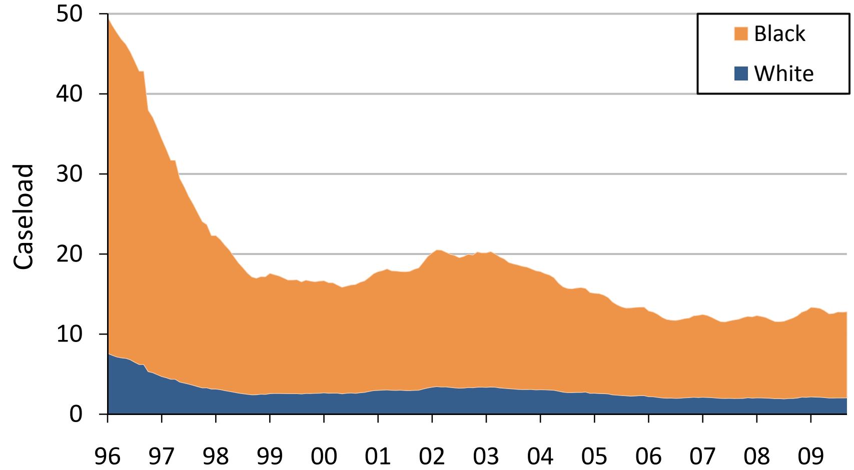


Figure 6.1 Monthly Caseload (in 1000s) of TANF Families in Mississippi, by Race, October 1996 – June 2010

Source: See Appendix Table A.7.

Table 6.1 Race Ratio in TANF Participation and Poverty, 2007

	Black	White
Mississippi:		
Client Monthly Caseload	23,056	3,965
Persons in Poverty	471,500	261,500
Poverty Rates (%)	44.0	15.7
Percent of Population (%)	37.0	57.5
U.S. Nation Wide:		
Client Monthly Caseload	1,296,990	1,068,754
Persons in Poverty	12,103,400	24,157,800
Poverty Rates (%)	33.2	12.3
Percent of Population (%)	12.1	65.4

Source: TANF client monthly caseload by race is calculated from MDHS administrative data sets. Other numbers are obtained from Kaiser Commission based on the Census Bureau's March 2008 and 2009 Current Population Survey (CPS: Annual Social and Economic Supplements), available at http://www.statehealthfacts.org.

Type of case is coded as two categories: adult case and child-only case. Consistent with previous studies, we find that the overall caseload change is highly affected by the change of adult caseload (Figure 6.2). The trend of child-only caseload is relatively flat in the past decade, except an early drop right after the welfare reform in 1996. Since my study focuses on welfare-to-work transition, only adult cases are taken into consideration. Thus, the following descriptive analyses are based on the population of adult clients.[50]

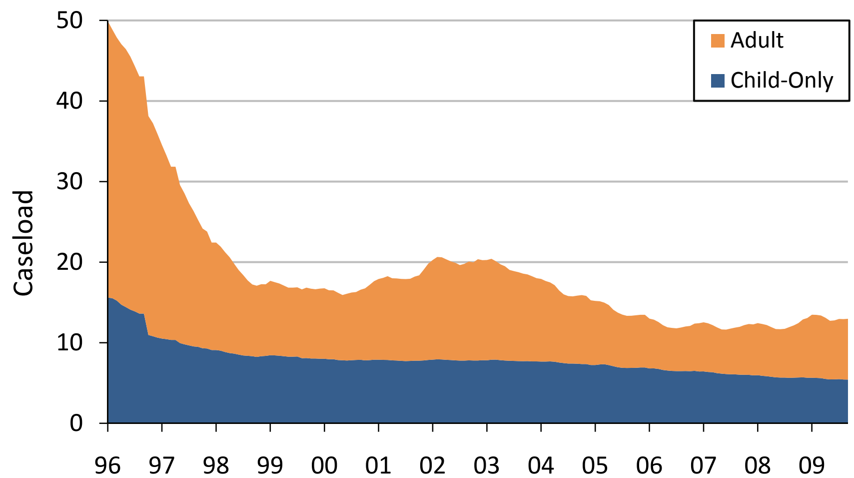


Figure 6.2 Monthly Caseload (in 1000s) of TANF Families in Mississippi, by Type of Case, October 1996 – June 2010

Source: See Appendix Table A.7.

The population of adult clients has gotten younger. The 18-24 group has made up the majority of the adult caseload since 2002 (Figure 6.3), with 57% of the current TANF adult population belonging to this group. The older-than-30 group shrank from 40% to 18% of the TANF adult population between 1996 and 2010. The younger population might entail shorter welfare use and a decline of recidivism.

[50] Racial composition of adult clients is similar to the pattern of the total TANF population.

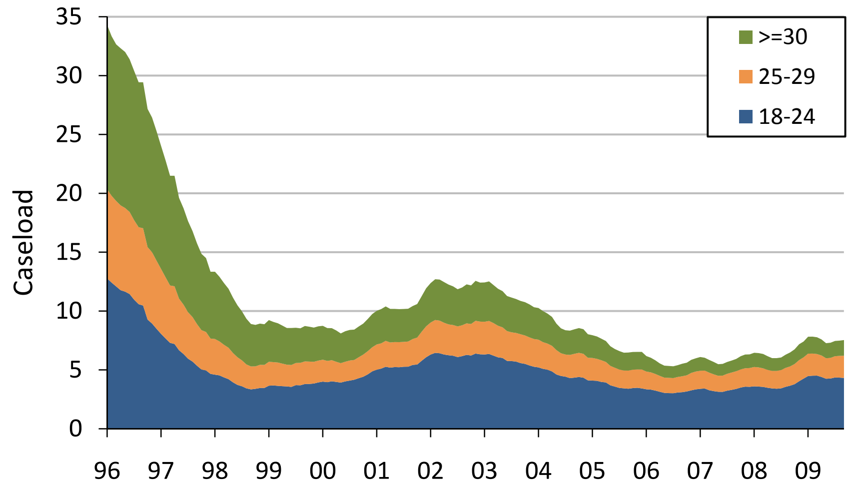


Figure 6.3 Monthly Caseload (in 1000s) of Adult TANF Clients in Mississippi, by Age, October 1996 – June 2010

Source: See Appendix Table A.7.

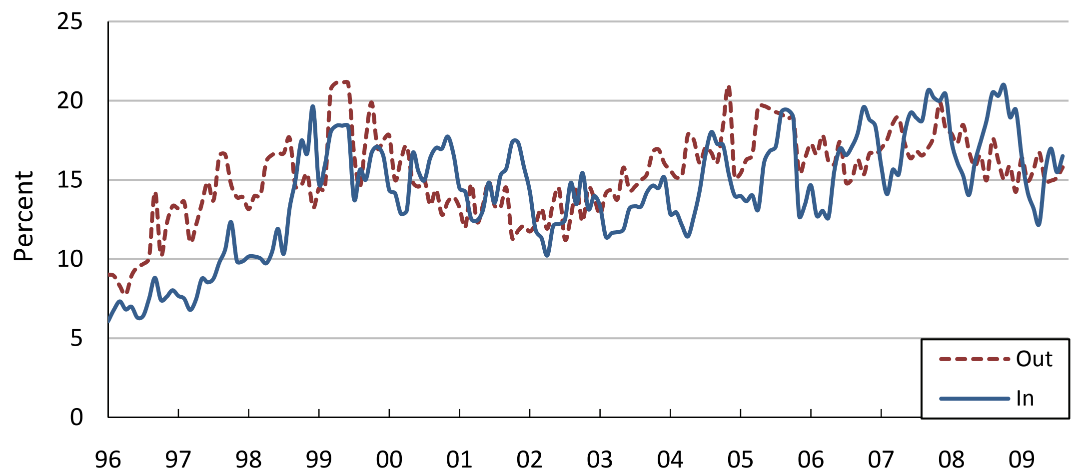


Figure 6.4 Percent of Monthly Net Change of Adult TANF Clients in Mississippi, October 1996 – June 2010

Source: See Appendix Table A.8.

The monthly net change of adult TANF clients is an interest of the welfare literature. One impression is that the in-and-out rates fluctuate continually, unlike the relatively smooth line of gross change of the total population (Figure 6.4). Overall, the percent of newly entered clients and welfare leavers increased in the first four years after welfare reform, indicating an increasing turnover of the TANF adult population. In recent years, the percent of leavers fluctuated between 15 and 20, while the percent of newly entered varied from 13 to 21.

The primary interest of this study is the work transition of TANF clients. The results from MDES UI data show that a significant part of the TANF adult population participated in work activities at the same time (Figure 6.5), and a large proportion of TANF leavers worked in the quarter after exit (Figure 6.6). The employment rates of the adult TANF clients ranged between 34% and 41% during most of the observed period, with a decline in recent quarters (e.g., 29% in the third quarter of 2009). Moreover, more than half of TANF leavers found jobs in the next quarter of exit.

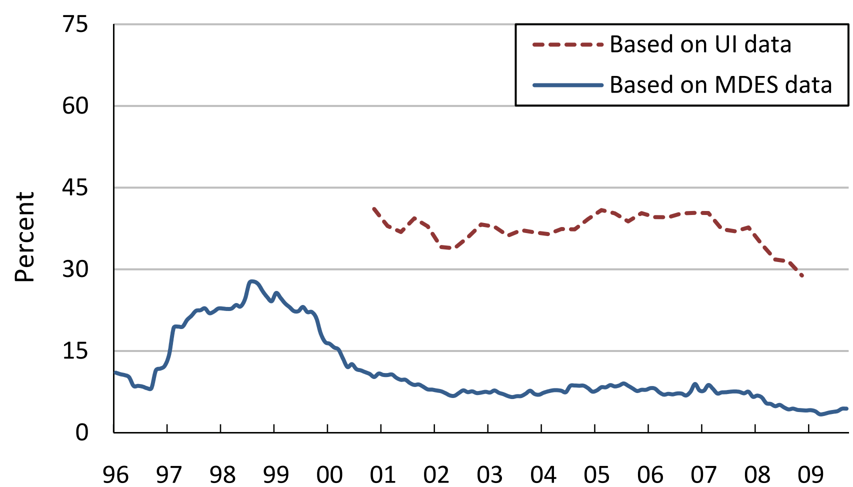


Figure 6.5 Percent of Workforce Participation in TANF for Adult TANF Clients in Mississippi, by Source of Data, October 1996 – June 2010

Source: The percentages based on MDHS data come from Appendix Table A.7; the percentages based on UI data come from Appendix Table A.9.

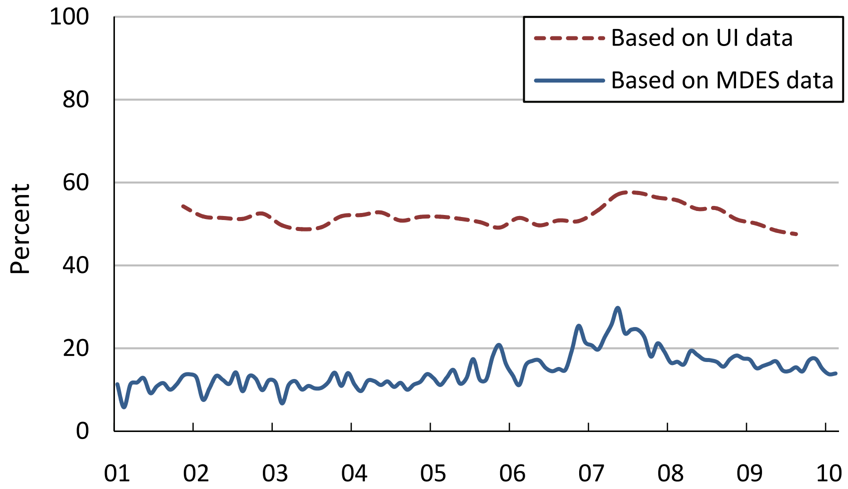


Figure 6.6 Percent of Work Exit for Adult TANF Clients in Mississippi, by Source of Data, January 2001 – June 2010

Source: The percentages based on UI data come from Appendix Table A.9; the percentages based on MDHS data come from MDHS closure files.

For comparison, I add the results from MDHS TANF data based on two fields: work code and reasons of case closure. We find that employment rates based on MDHS data are much lower than those based on UI data (Figure 6.5 and Figure 6.6), indicating a significant underestimation of work activities of TANF clients in MDHS data.[51]

6.2 Profile of TANF Spells

Using the life table, we are able to study the profile of TANF spells. I include spells between July 2001 and September 2009 and use quarter as the time interval.[52] A spell in this study is defined as a period of one or more quarters during which TANF is

[51] It would be interested to compare the Figure 6.5 to the Figure 2.6 in the trend of workforce participation rates in Mississippi. If we use the employment rates based on UI data as a baseline of workforce participation rates, we have to say that the Mississippi's workforce participation rates reported by the federal agency are definitely underestimated before 2006, and probably overestimate after then.

[52] A PI client's employment information is only available during this time period and in a quarterly based format. Since welfare-to-work transition is the primary interest of this study, I create a spell-based file consistent with the multivariate analysis in the following sections.

received continuously by a PI (adult) client. If a client is present in TANF during any month of the quarter, she is coded as in TANF for that quarter.[53] I also specify the first spells and subsequent spells in the description table, but include all spells in life table. To make sure that the first spell in the study period is the *actual* first spell, I exclude all clients that were in TANF after the 1996 welfare reform and before July 2001,[54] which reduces the total client sample by 30 percent. In doing so, we can make sure that all individuals are newly entered after July 2001.

The spell-based file includes 60,811 spells with 7,330 right-censored spells (table 6.2). There are 42,377 first spells, which is the same number of total adult clients, and 12,886 second spells, indicating that about 30% (=12,886/42,377) of adult clients returned to TANF. The majority of spells (77%) ended within one year; less than five percent of spells remain in TANF at the end of two years; and only 1% lasted beyond three years. Overall, the median lifetime of a spell is only 3.2 quarters, indicating that half of adult clients leave TANF at the time point. The characteristics of short-term spells in this study are quite different from earlier research. I will discuss this issue in the final chapter.

For each pair of groups, I produce two figures: one for cumulative percentage of exits (or failure function) and one for conditional probability of exit (or hazard function). The time interval applied in all figures is set as 12 quarters. Although the maximum

---

[53] It is possible that a PI client could be off TANF while her family (e.g., children or grandchildren) stays on the TANF roll. In this case, I count separate spells for the PI client even though her family has only one spell.

[54] In the analysis of all spells between 1996 and 2009, I find that the majority of return spells (91%) happened within three years after exits, and only 1% of recidivism happened beyond five years. Thus, it is safe to say that with a five-year screen between 1996 and 2001, those who were first present in TANF after 2001 started their first spells. It is very unlikely that a client had been in AFDC before the 1996 welfare reform and returned to TANF after 2001.

length of a spell in the study can last as long as 28 quarters (not present here), the majority (about 95%) end within eight quarters, and only about one percent of total spells last beyond 12 quarters (Table 6.2). Thus, a time period between quarter one and quarter twelve is sufficient to provide us a picture of TANF use. However, I provide the output of a life table based on a time period up to 20 quarters in Appendix Table A.10 for further interest.

Table 6.2 Descriptive Statistics for Life Table Analysis by Spell

	Number of Spells	Percent	Median Lifetime (in Quarter)
Total	60,811	100.0	3.247
Right-Censored (=1)	7,330	N.A.	N.A.
Sequence			
1st Spell (=1)	42,377	69.7	3.481
2nd Spell (=2)	12,886	21.2	2.979
3rd Spell and More (=3)	5,548	9.1	2.889
Duration (in Quarter)			
1-2	30,167	49.6	N.A.
3-4	17,227	28.3	N.A.
5-8	10,496	17.3	N.A.
9-12	2,341	3.8	N.A.
>=13	580	1.0	N.A.
Race			
White (=0)	12,180	20.0	2.828
Black (=1)	48,113	79.1	3.484
Others	518	0.9	N.A.
Education			
Less Than High School (=0)	21,911	36.0	3.117
High School and Above (=1)	36,809	60.5	3.406
Earlier or Later Spell			
Between 2001.07 and 2004.12 (=0)	23,462	38.6	3.455
Between 2005.01 and 2009.09 (=1)	37,394	61.4	3.069

Source: Created by the author based on welfare data from MDHS.

The first comparison of subgroups shows that black clients have more disadvantages to leave the TANF program than their white counterparts. The curve of all spells is identical to that of blacks because black clients dominate the TANF population (Figure 6.7).

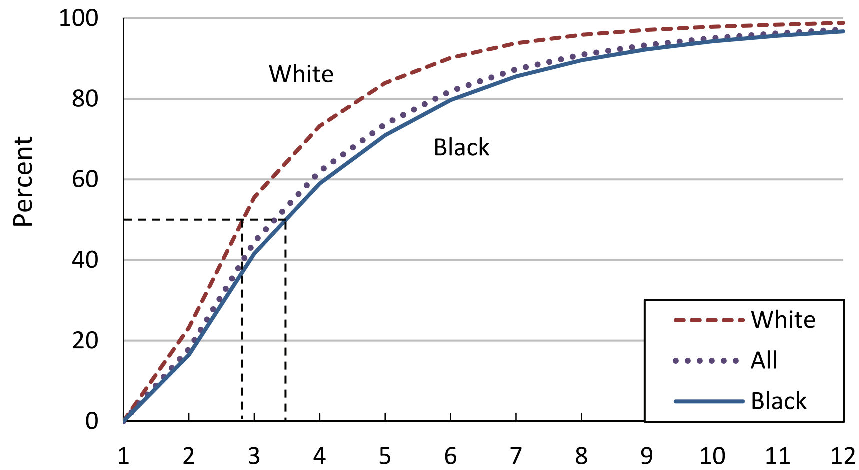


Figure 6.7 Cumulative Percent of Exit, by Race, up to 12 Quarters

Source: See Appendix Table A.10.
NOTE: The two cross points indicate median lifetime for whites (2.8 quarters) and blacks (3.5 quarters), respectively.

Overall, the conditional probabilities of exit are much lower in the initial quarter,[55] but they peak in the second quarter and then display a consistent trend of slight decline (Figure 6.8). In line with previous studies, whites have a higher exit rate than blacks. However, the hazard of exit drops faster for white clients than for black clients. As such, white clients and black clients get the same hazard rates at the tenth quarter. Although we find an increase in the hazard of exit for whites at the last observed quarter,

[55] To make more sense of the low initial exit rate, I conduct an exploration study using month as the time unit (not present here). The life table shows that the probability of exit in the first six months is 0.087, 0.161, 0.161, 0.156, 0.173, and 0.166, respectively. That is, TANF clients are much less likely to exit the program in the first month.

the estimated hazard rate is unreliable due to very few cases left. Finally, it should be noticed that the curve of all clients is almost identical with the curve of black clients because the latter dominates the TANF population.

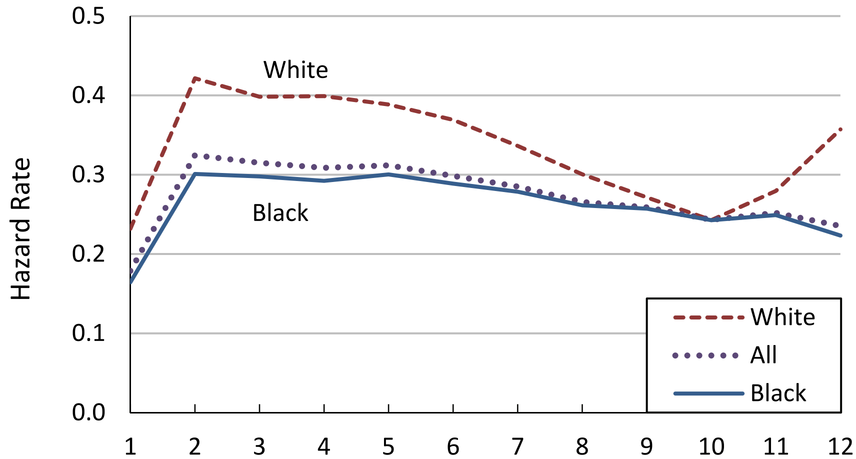


Figure 6.8 Conditional Probability of Exit, by Race, up to 12 Quarters

Source: See Appendix Table A.10.
NOTE: The sample size of white clients drops faster than that of blacks over time. By the end of the twelfth quarter, only 98 spells are that of white clients. That put instability in the estimation of white's hazard rate at the last quarter.

In contrast to common expectation, there is barely a difference in TANF use between those with and without higher education (Figure 6.9 and 6.10). Exit rates and conditional probabilities are almost identical for the two education groups. Moreover, the lower education group are more likely to exit TANF in the first two quarters than the higher education group. In the multivariate analysis, I will show that education has somewhat positive effects on work exits but negative effects on other exits, demonstrating a mixed effect on overall patterns.

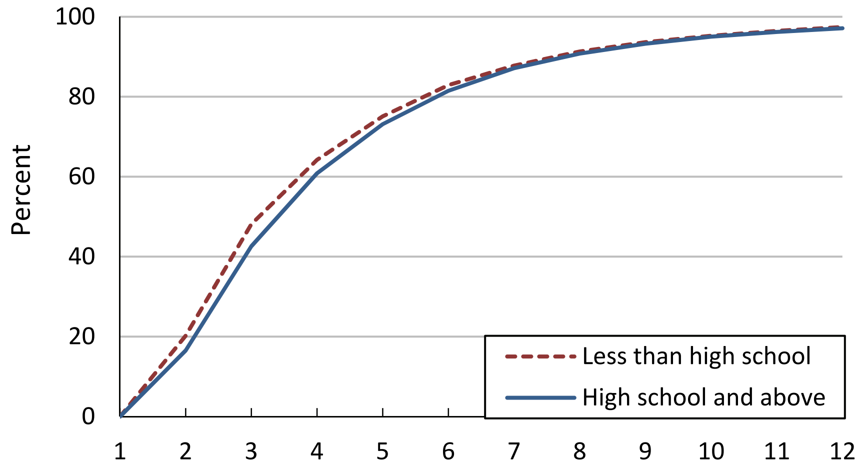


Figure 6.9 Cumulative Percent of Exit, by Educational Level, up to 12 Quarters

Source: See Appendix Table A.10.

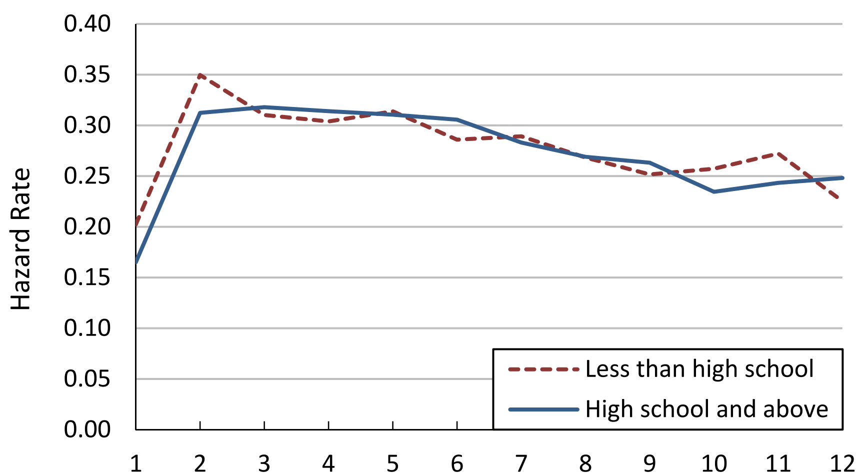


Figure 6.10 Conditional Probability of Exit, by Educational Level, up to 12 Quarters

Source: See Appendix Table A.10.

Finally, I compare TANF exit patterns between spells that began in the earlier time period and spells that began in the later time period. The later entered spells have higher rates of exit than earlier entered spells, especially from the second quarter to the sixth quarter (Figure 6.11 and 6.12).

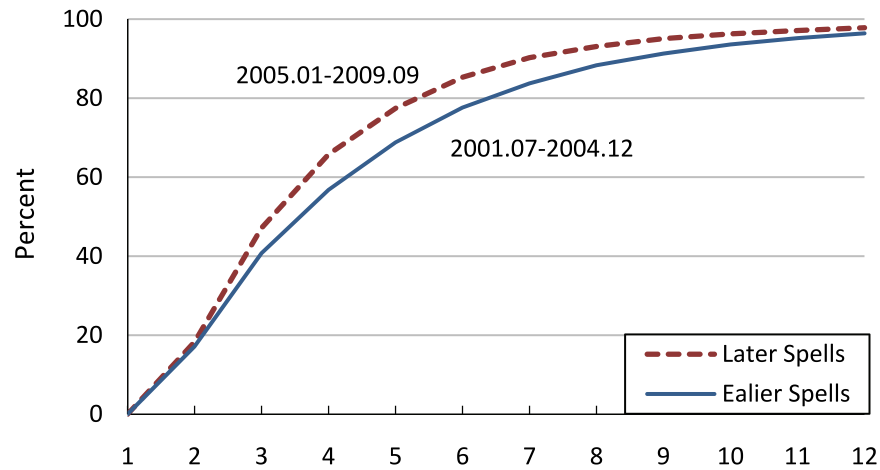


Figure 6.11 Cumulative Percent of Exit, by Time Period When a Spell Began, up to 12 Quarters

Source: See Appendix Table A.10.

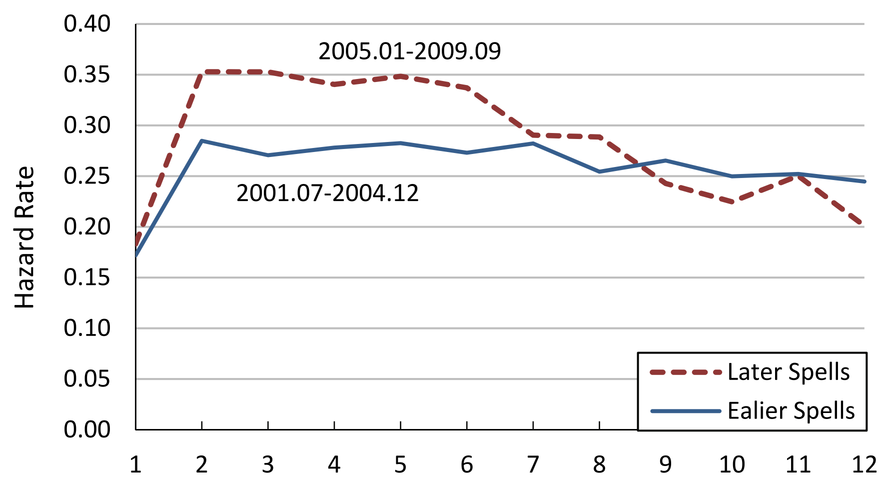


Figure 6.12 Conditional Probability of Quarterly Exit, by Time Period When a Spell Began, up to 12 Quarters

Source: See Appendix Table A.10.

At the end of this section, I pay a special attention to the effect of time-limit on the distribution of spells. Since eligibility requirements demand that spells be limited to only eight quarters, we should expect a big spike in the rate of leaving welfare at the point. However, both curve of hazard and curve of cumulative percent are smooth around the eighth quarter (see Figures 6.7 and 6.8). One simple reason of the insignificant effect of time-limit is that more than 95% of TANF clients leave the program before they reach the two-year time line. On the other hand, those who stay in the program more than eight quarters usually meet the requirement of exemption from time limit. So they do not have to leave to program due to administrative sanction. Actually, of all 2,565 spells that ended after two years (more than eight quarters), only 34% are subject to any kind of sanctions. Even for those who are sanctioned, the duration of spells are distributed in such a way that barely reflects the effect of time limits (Figure 6.13). We can only find a slight increase in the number of sanction exit by the end of five years (the twenty-first quarter) in the TANF program.

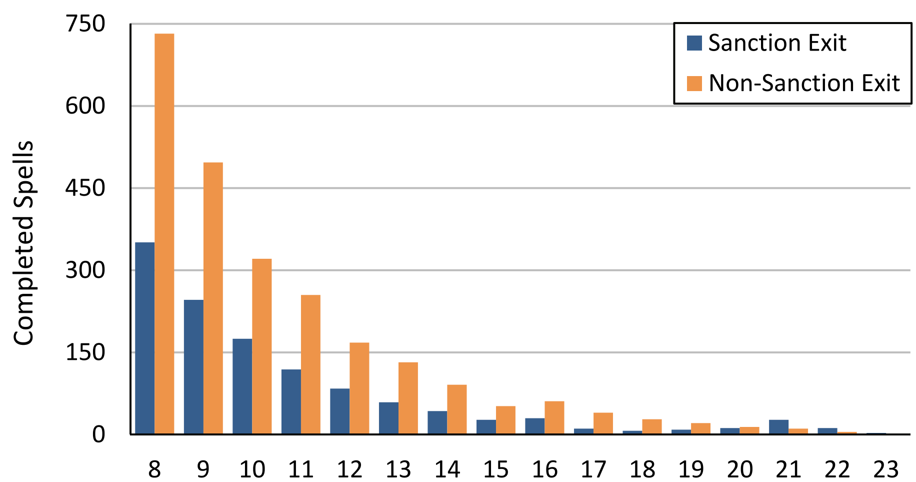


Figure 6.13 Number of Completed Spells that Last Beyond the Eighth Quarter, by Sanction or Non-Sanction

Source: MDHS welfare data.
NOTE: Three spells (one sanction exit, two non-sanction exits) last beyond the twenty-third quarter (up to quarter 28).

6.3 Discrete-Time Analysis

6.3.1 Time Specification, Variables, and Sampling

The analytic group in this study includes all female household heads, black or white, between 18 and 55.[56] In addition, to distinguish first spells and return spells, I exclude those who had been in TANF between 1996 and 2001 to ensure precise measurement of the first spells.

As a primary approach to discrete-time analysis, we need to decide which time specification is suitable for the study. The study involves 28 discrete time periods (e.g., quarters) that can lead to excessive dummy predictors. Following Singer and Willet (2003:407-419), I estimate alternative specifications for the main effect of *TIME* (see Singer and Willet 2003: Table 12.2). As expected, the deviance statistic for the constant model is the largest (=224,404), while the general specification of *TIME* has the lowest (best) deviance statistic (=220,370) (Table 6.3). Between constant model and general model, the deviance statistics drop to different values. Although quadratic model has the largest drop (1,679=223,865-222,186), the magnitude is not sufficient to warrant use of it because the deviance is still high (1,816=222,186-220,370) in compared to the general specification. Thus, alternative specifications of *TIME* do not fit better in any form.

Alternatively, I truncate the length of spells by 12 quarters (or three years) and treat truncated spells as right-censored (less than 1% of spells last beyond 13 quarters). Thus, I can create 12 dummy time variables that are reasonable for the discrete-time analysis.

[56] Less than 0.2% of total person-quarters have ages outside this range. If a client did not exit at 55, her case is treated as right-censored.

Table 6.3 Comparison of Alternative Smooth Polynomial Representations for the Main Effect of *TIME* in a Baseline Discrete-Time Hazard Model

Representation for *TIME*	*n* Parameters	AIC	Deviance (-2logL)	Difference in deviance in comparison to … Previous Model	General Model
Constant	1	224,406	224,404	.	4,034
Linear	2	223,869	223,865	539	3,495
Quadratic	3	222,192	222,186	1,679	1,816
Cubic	4	221,221	221,213	973	844
Fourth Order	5	220,762	220,752	462	382
Fifth Order	6	220,520	220,508	244	138
General	12	220,394	220,370	.	.

NOTE: See Singer and Willet (2003:411) for model specifications of polynomials.

The final sample has 188,228 person-quarters, based on 39,765 individuals and 57,398 spells. The description of variables for discrete-time analysis can be found in Table 6.4. Most of the variables are coded as either "0" (i.e., reference group) or "1," so the means indicate the percentage of observations (i.e., person-quarters) that are coded as "1." It is noticed that the values of contextual variables have wide ranges, indicating substantial differences in the characteristics of neighborhood among TANF clients.

Table 6.4 Description of Variables for Discrete-Time Analysis (N=188,228 Person-Quarters)

Variables	Coding	Means	S.D.	Min	Max
Dependent Variables					
Binary Outcome	1 = Exit; 0 = No exit.	.264	.441	0	1
Nominal Outcome	1 = Work exit; 2 = Other exit. 3 = No exit (reference).	2.598	.719	1	3
Independent Variables					
Race	1 = Black; 0 = White.	.834	.371	0	1
Age		24.4	6.0	18	55
Youngest Child	1 = Less than one year old. 0 = One year old or more.	.421	.494	0	1
Repeated Spells	1 = Repeated spells; 0 = 1st spells.	.261	.436	0	1
Education (Ref.=Less than high school):					
High School	1 = High school.	.461	.497	0	1
More Than High School	1 = More than high school.	.178	.383	0	1
Job Training	1 = Training in TANF within four quarters before exit; 0 = Others	.163	.369	0	1
Work Experience	1 = Work in TANF within four quarters before exit; 0 = Others	.467	.499	0	1
Unemployment Rates by County (%)		8.1	2.6	2.8	20.0
Racial Residential Dissimilarity Index		49.9	12.2	24.7	64.4
Percent Black (%)		47.7	19.9	3.1	86.1
Median Household Income ($1,000)		29.0	6.7	17.2	48.2
Metropolitan or Micropolitan County	1 = In metro/micro county; 0 = Not in metro/micro county	.335	.472	0	1
Time Effects					
D_1	1= In TANF; 0 = Not in TANF.	.304	.460	0	1
D_2	Same as above.	.240	.427	0	1
D_3	Same as above.	.154	.361	0	1
D_4	Same as above.	.102	.302	0	1
D_5	Same as above.	.067	.251	0	1
D_6	Same as above.	.045	.208	0	1
D_7	Same as above.	.030	.172	0	1
D_8	Same as above.	.021	.144	0	1
D_9	Same as above.	.015	.121	0	1
D_{10}	Same as above.	.010	.099	0	1
D_{11}	Same as above.	.006	.080	0	1
D_{12}	Same as above.	.005	.069	0	1

NOTE: Five continuous variables—age, dissimilarity index, percent black, median income, and county unemployment rates—are centered in the regression analyses.

6.3.2 Baseline Models

The analysis begins with baseline models. I run logistic regressions with the twelve dummy quarters for both binary outcome and competing risks. In addition, I estimate the variations by introducing individual specific random effects between repeated spells (Table 6.5). For the baseline models, raw parameter estimates, α_t's, are hard to interpret. We can convert the α_t estimates into odds, using the inverse transformation, $\exp(\alpha_t)$. However, as Singer and Willet (2003:387) suggest, it is more common to interpret the baseline models using hazard rate. In doing so, we need to take the antilogit of α_t:

$$\text{Baseline models: } p_{tij} = 1/(1 + \exp{(-\alpha_t)})$$

For baseline model, the fitted hazard rates should be identical to the sample estimates of hazard presented in life table (Singer and Willet 2003:388). The converted hazard rates are present in Table 6.6. We see that the hazard rates in the fixed binary baseline model (the second column of Table 6.6) are very close to the estimated hazard in the life table (the eighth column of Appendix Table A.10).[57]

[57] However, there are slight differences due to the small change in sample size (e.g., excluding those who are neither white nor black, focusing on ages between 18 and 55, deleting record with missing value for covariates, etc.).

Table 6.5 Estimates (Coefficients) of Main Effect of *TIME* for Discrete-Time Hazard Models - Baseline Models (N=188,228 Person-Quarters)

	Binary Outcome All Exits		Competing Risks			
			Fixed (Model 5)		Random (Model 6)	
Time Period Predicator	Fixed (Model 1)	Random (Model 2)	Work Exits	Other Exits	Work Exits	Other Exits
D_1	-1.546	-1.587	-2.391	-2.107	-2.580	-2.284
	(.011)	(.012)	(.016)	(.014)	(.020)	(.019)
D_2	-.764	-.771	-1.416	-1.499	-1.565	-1.640
	(.010)	(.010)	(.013)	(.013)	(.016)	(.016)
D_3	-.801	-.777	-1.325	-1.698	-1.424	-1.820
	(.013)	(.013)	(.015)	(.018)	(.017)	(.020)
D_4	-.831	-.778	-1.408	-1.657	-1.466	-1.759
	(.016)	(.017)	(.019)	(.022)	(.022)	(.024)
D_5	-.816	-.732	-1.454	-1.567	-1.478	-1.642
	(.019)	(.022)	(.024)	(.026)	(.028)	(.029)
D_6	-.869	-.757	-1.481	-1.651	-1.469	-1.704
	(.024)	(.028)	(.030)	(.032)	(.035)	(.037)
D_7	-.931	-.793	-1.532	-1.726	-1.487	-1.761
	(.030)	(.035)	(.037)	(.040)	(.043)	(.046)
D_8	-1.023	-.858	-1.696	-1.737	-1.623	-1.748
	(.036)	(.042)	(.047)	(.048)	(.054)	(.055)
D_9	-1.064	-.877	-1.727	-1.789	-1.626	-1.784
	(.044)	(.050)	(.057)	(.059)	(.065)	(.066)
D_{10}	-1.161	-.951	-1.844	-1.865	-1.715	-1.843
	(.053)	(.060)	(.070)	(.071)	(.078)	(.079)
D_{11}	-1.101	-.868	-1.828	-1.760	-1.678	-1.716
	(.062)	(.069)	(.083)	(.080)	(.091)	(.089)
D_{12}	-1.162	-.909	-1.868	-1.843	-1.698	-1.778
	(.073)	(.081)	(.098)	(.097)	(.107)	(.106)
Variance (σ^2)		.106			.399	.396
		(.015)			(.029)	(.030)
ICC (*rho*)		.031			.108	.107
-2LL	213,970	213,906	282,502		281,536	

NOTE: All estimates are significant at 0.001 level; Coefficients are presented, along with standard errors (in parentheses).

Table 6.6 Re-expressing Parameter Estimates as Fitted Hazard Rates for Baseline Discrete-Time Hazard Models (N=188,228 Person-Quarters)

	Binary Outcome All Exits		Competing Risks			
			Fixed (Model 5)		Random (Model 6)	
Time Period Predicator	Fixed (Model 1)	Random (Model 2)	Work Exits	Other Exits	Work Exits	Other Exits
D_1	.176	.170	.084	.108	.070	.092
D_2	.318	.316	.195	.183	.173	.162
D_3	.310	.315	.210	.155	.194	.139
D_4	.303	.315	.197	.160	.188	.147
D_5	.307	.325	.189	.173	.186	.162
D_6	.295	.319	.185	.161	.187	.154
D_7	.283	.312	.178	.151	.184	.147
D_8	.264	.298	.155	.150	.165	.148
D_9	.257	.294	.151	.143	.164	.144
D_{10}	.238	.279	.137	.134	.152	.137
D_{11}	.250	.296	.138	.147	.157	.152
D_{12}	.238	.287	.134	.137	.155	.145

NOTE: Fitted hazard rates are calculated by $p_{tij} = 1/(1 + \exp(-\alpha_t))$, where α_t denotes coefficient estimated in Table 6.5.

Based on the fitted hazard rates, we can see how individual-specific random effects affect the patterns of TANF exit. Figure 6.14 visualizes the changed patterns of all exit between quarter one and quarter twelve. We find that the hazard of all exits increases substantially from quarter one to quarter two before substantially decreasing over time. The trend, however, changes after unobserved individual characteristics are taken into account (see Model 2). We find that, controlling for individual specific effects, the hazard of exit barely decline with time spent in TANF. The intraclass correlation coefficient (ICC)[58] is estimated as 0.031. This tells us that only 3% of the variation in the odds of

[58] The intraclass correlation indicates the proportion of unexplained variance between clusters. In the case of my study, the larger the intraclass correlation coefficient, the more similar are spells within individuals. For the calculation of ICC for the logistic model, see Hedeker and Gibbons (2006:158) or Powers and Xie (2008:129): $ICC = \sigma^2/(\sigma^2 + \pi^2/3)$, where $\pi = 3.14159$.

TANF exits is due to variation between individuals. This estimate implies a weak, though significant, intra-spell correlation for an individual. In other words, the exit pattern of the first spell has a slight effect on the return spells.

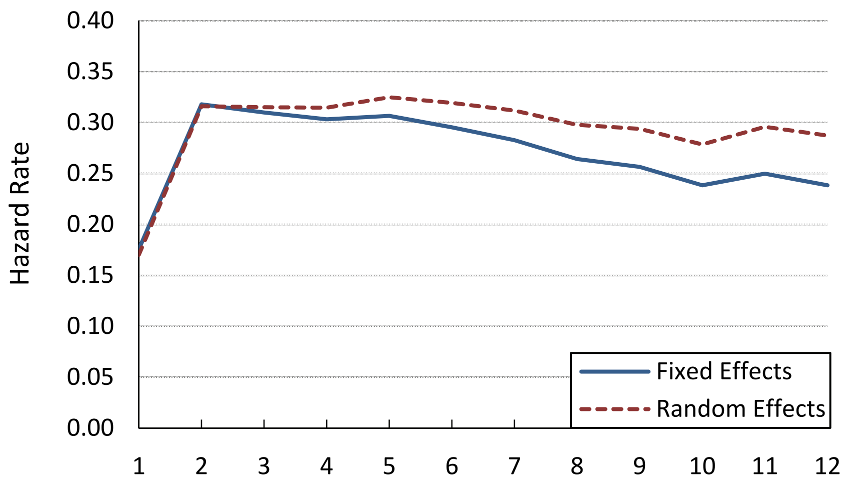


Figure 6.14 Fitted Hazard Rate of All Exit, up to 12 Quarters

Source: See Table 6.6.

I use competing risks models to estimate the likelihood of exit from TANF to work, with/without controlling for individual-specific random effects (see Model 5 and 6 in Table 6.5 and Table 6.6). We find an initial increase in the likelihood of work exit versus no exit in the first three quarters. Then the likelihood of work exit declines in the fixed model. However, the hazard rates level off for a couple of subsequent quarters (e.g., between quarter four and quarter seven) when controlling for random effects (Figure 6.15). The results indicate a significant effect of unobserved individual characteristics between spells on the overall work exit trend. The intraclass correlation (ICC) is estimated as 0.108. That means that about 11% of the variation in work exit versus no exit is due to unobserved individual characteristics. Similar to the results of work exit, unobserved individual characteristics explain about 11% of the variation in other exit versus no exit. The trend of other exits is more stable than that of work exit. The pattern of change of other exit is less substantial than that of work exit when controlling for random effects among multiple spells within individuals (Figure 6.16).

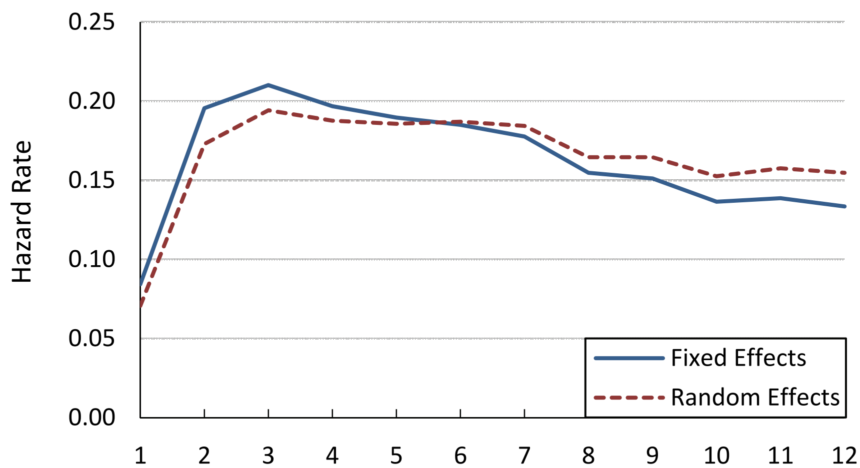


Figure 6.15 Fitted Hazard Rate of Work Exit vs. No Exit, up to 12 Quarters

Source: See Table 6.6.

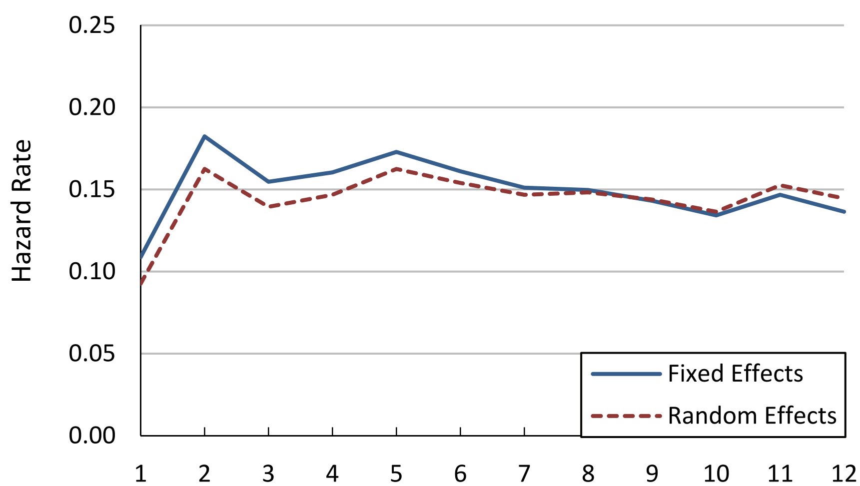


Figure 6.16 Fitted Hazard Rate of Other Exit vs. No Exit, up to 12 Quarters

Source: See Table 6.6.

6.3.3 Models with Covariates

I add covariates into the baseline models and use the same modeling strategy, estimating both fixed effects and random effects for binary outcome and competing risks (i.e., nominal outcome) (Table 6.7). For full models, the estimates of the twelve dummy time variables are specific to the baseline group—those individuals for whom all dichotomous predicators take on the value 0 and all continuous predicators assume the average values. For instance, the baseline group of all models are specified as white, single mother at average age, without any child younger than one, receiving education less than high school, without job training and work experience, living in a county with average unemployment rate, dissimilarity index, percent of blacks, and median household income, and not living in a metro/micropolitan county. Although we do not have specific interest to check the hazard of the baseline group, the estimates of the time effects are useful in simulating the effects of covariates on the exit from TANF.

The main concern of this study is to examine the effects of substantive predicators. Estimates of coefficients are not easy to interpret. Following the common approach of interpreting the data output of logistic regression, I antilog raw parameter estimates, yielding an *odds ratio*, $\exp(\beta)$. The odds ratio is the ratio of the odds of event occurrence in two groups. For dichotomous predicator, the two groups have the predicator taking on value either 0 or 1; for continuous predicator, the two groups differ by the general increment on the variable (Singer and Willet 2003:388-390). The transformed estimates of odds ratio for all covariates are present in Table 6.8.

The findings show that the three human capital indicators demonstrate different effects in determining TANF exit patterns. First, in regard to the binary outcome variable, we find that in-school education has a negative effect, while work experience in TANF has a much stronger effect on exits in general. We can more easily interpret the effects of human capital indicators in the competing risks models. There are mixed effects of in-school education and work experience according to the type of exit (e.g., work or non-work). Both indicators facilitate work exits and delay non-work exits. As we expect, when compared to less-than-high-school clients, those who graduated from high school are more likely to have a work exit and less likely to have a non-work exit. However, more-than-high-school clients have a slower exit rate than their high school counterparts. Perhaps the former group prefers to stay a bit longer in TANF while searching for better jobs. A similar mixed effect is found for work experience, which increases the odds of work exit by 7.7 times and decreases the odds of non-work exit by 32% (=1-0.677). For job training, although its effects are consistently positive for both work and other exits, the significance levels are different. Unsurprisingly, job training significantly promotes the odds of work exit.

For contextual covariates, we find that county unemployment rates exert a negative effect on work exit. A one-unit increase in the unemployment rate leads to a 6% (=1-0.941) decline in the odds of work exit versus no exit. In contrast, racial residential dissimilarity based on census block groups has a small but significant negative effect on TANF exit, especially for non-work reasons. One unit increase in the dissimilarity index decreases the odds of other exit versus no exit by 0.3% (=1-0.997). Likewise, percent black within a county slightly decreases the likelihood of exit. As we expect, higher median household income within a county increases both work exit and other exit. Finally, living in counties within metropolitan and micropolitan statistical areas significantly decreases the likelihood of exit in general and the likelihood of work exit in particular.

Table 6.7 Estimates (Coefficients) of Discrete-Time Hazard Models with Covariates (N=188,228 Person-Quarters)

	Binary Outcome – All Exits		Competing Risks			
	Fixed	Random	Fixed (Model 7)		Random (Model 8)	
Parameters	(Model 3)	(Model 4)	Work Exits	Other Exits	Work Exits	Other Exits
D_1	-1.340**	-1.346**	-3.385**	-1.245**	-3.386**	-1.290**
	(.021)	(.021)	(.032)	(.025)	(.032)	(.028)
D_2	-.565**	-.557**	-2.584**	-.483**	-2.585**	-.459**
	(.021)	(.021)	(.031)	(.026)	(.032)	(.029)
D_3	-.575**	-.556**	-2.525**	-.580**	-2.524**	-.507**
	(.023)	(.024)	(.033)	(.029)	(.034)	(.032)
D_4	-.610**	-.580**	-2.634**	-.529**	-2.633**	-.410**
	(.025)	(.027)	(.036)	(.032)	(.036)	(.035)
D_5	-.667**	-.629**	-2.714**	-.559**	-2.712**	-.403**
	(.027)	(.029)	(.038)	(.034)	(.039)	(.038)
D_6	-.730**	-.682**	-2.729**	-.669**	-2.727**	-.465**
	(.030)	(.034)	(.043)	(.040)	(.043)	(.044)
D_7	-.766**	-.708**	-2.726**	-.744**	-2.725**	-.495**
	(.035)	(.039)	(.048)	(.046)	(.048)	(.052)
D_8	-.816**	-.750**	-2.832**	-.737**	-2.830**	-.442**
	(.041)	(.046)	(.057)	(.054)	(.058)	(.059)
D_9	-.834**	-.760**	-2.829**	-.776**	-2.828**	-.444**
	(.048)	(.053)	(.066)	(.063)	(.066)	(.069)
D_{10}	-.903**	-.821**	-2.884**	-.860**	-2.883**	-.491**
	(.057)	(.062)	(.079)	(.075)	(.079)	(.081)
D_{11}	-.806**	-.715**	-2.822**	-.735**	-2.821**	-.332**
	(.066)	(.071)	(.091)	(.085)	(.091)	(.091)
D_{12}	-.850**	-.752**	-2.848**	-.795**	-2.848**	-.358**
	(.077)	(.083)	(.107)	(.101)	(.107)	(.108)

Table 6.7 (Continued)

Parameters	Binary Outcome – All Exits		Competing Risks			
	Fixed (Model 3)	Random (Model 4)	Fixed (Model 7)		Random (Model 8)	
			Work Exits	Other Exits	Work Exits	Other Exits
Human Capital						
Education (Ref.=Less than high school)						
High School	-.084**	-.087**	.098**	-.243**	.098**	-.278**
	(.012)	(.013)	(.017)	(.016)	(.017)	(.018)
More Than High School	-.161**	-.167**	.092**	-.410**	.093**	-.464**
	(.016)	(.017)	(.021)	(.022)	(.021)	(.025)
Job Training	.055**	.057**	.090**	.017	.091**	.023
	(.014)	(.015)	(.018)	(.020)	(.018)	(.021)
Work experience	.706**	.715**	2.045**	-.389**	2.046**	-.422**
	(.011)	(.012)	(.019)	(.015)	(.019)	(.017)
Local Labor Market						
Unemployment Rates (%)	-.048**	-.048**	-.061**	-.035**	-.061**	-.033**
	(.003)	(.003)	(.004)	(.004)	(.004)	(.004)
Neighborhoods						
Dissimilarity Index	-.002**	-.002**	-.002†	-.003**	-.002†	-.003**
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Percent Black (%)	-.006**	-.006**	-.005**	-.006**	-.005**	-.007**
	(.000)	(.000)	(.001)	(.001)	(.001)	(.001)
Median Income ($1,000)	.023**	.023**	.031**	.014**	.031**	.014*
	(.003)	(.003)	(.004)	(.004)	(.004)	(.004)
Squared Median Income	-.002**	-.002**	-.002**	-.001**	-.002**	-.001**
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)

Table 6.7 (Continued)

	Binary Outcome – All Exits		Competing Risks			
	Fixed (Model 3)	Random (Model 4)	Fixed (Model 7)		Random (Model 8)	
Parameters			Work Exits	Other Exits	Work Exits	Other Exits
Metro/Micropolitan County	-.118**	-.119**	-.157**	-.087**	-.158**	-.088*
	(.017)	(.018)	(.023)	(.023)	(.023)	(.026)
Control Variables						
Age	.006**	.007**	.003†	.008**	.003†	.011**
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Youngest Child under 1 Year	-.616**	-.627**	-.440**	-.802**	-.441**	-.863**
	(.012)	(.013)	(.016)	(.016)	(.016)	(.018)
Repeated Spell	.265**	.265**	.278**	.248**	.275**	.215**
	(.012)	(.013)	(.016)	(.016)	(.016)	(.018)
Race (1=black; 0=white)	-.307**	-.315**	-.099**	-.476**	-.100**	-.537**
	(.016)	(.016)	(.021)	(.019)	(.022)	(.023)
Variance (σ^2)		.039**			.000	.342**
		(.017)			(.001)	(.023)
ICC (*rho*)		.012**			.001	.094**
-2Log Likelihood	202,818	202,806	255,734		255,454	

NOTE: ** p<.001, * p<.01, † p<.05; Coefficients are presented, along with standard errors (in parentheses).

Table 6.8 Re-expressing Parameter Estimates as Odds Ratio for Discrete-Time Hazard Models with Covariates

	Binary Outcome – All Exits		Competing Risks			
			Fixed (Model 7)		Random (Model 8)	
Parameters	Fixed (Model 3)	Random (Model 4)	Work Exits	Other Exits	Work Exits	Other Exits
Race (1=black; 0=white)	.735**	.729**	.906**	.621**	.905**	.584**
Human Capital						
Education						
High School	.920**	.917**	1.103**	.784**	1.103**	.757**
More Than High School	.851**	.846**	1.096**	.663**	1.097**	.629**
Job Training	1.057**	1.058**	1.094**	1.017	1.095**	1.023
Work experience	2.026**	2.044**	7.733**	.677**	7.740**	.656**
Local Labor Market						
Unemployment Rates (%)	.954**	.953**	.941**	.966**	.941**	.967**
Neighborhoods						
Dissimilarity Index	.998**	.998**	.998†	.997**	.998†	.997**
Percent Black (%)	.994**	.994**	.995**	.994**	.995**	.993**
Median Income ($1,000)	1.023**	1.024**	1.032**	1.014**	1.031**	1.014*
Squared Median Income	.998**	.998**	.998**	.999**	.998**	.999**
Metro/Micro County	.889**	.888**	.854**	.917**	.854**	.916*
Control Variables						
Age	1.006**	1.007**	1.003†	1.008**	1.003†	1.012**
Youngest Child under 1 Year	.540**	.534**	.644**	.448**	.644**	.422**
Repeated Spell	1.303**	1.303**	1.320**	1.282**	1.316**	1.239**

NOTE: ** p<.001, * p<.01, † p<.05; Main time effects, D_1-D_{12}, are not present in the table; Fitted hazard rates are calculated by $p_{tij} = 1/(1 + \exp(-\alpha_t))$, where α_t denotes coefficient estimated in Table 6.7.

We are also interested in the effects of unobserved individual characteristics on TANF exit by introducing individual specific random effects for multiple spells within one person. We find that the ICC for work exit drops from 0.108 in the baseline model (Model 6) to 0.001 in the full model (Model 8), while the ICC for other exits changes slightly. In other words, the parameters in the full model explain much of the individual variance in work exit versus no exit. However, these parameters do not catch most of the unobserved individual characteristics in regard to other exit versus no exit.[59] We also find that the coefficients do change slightly by controlling for individual specific random effects, but the general conclusions drawn from the fixed models hold.

Overall, race is significant in all models. Black clients are less likely than white clients to exit TANF. Specifically, after controlling for covariates presented in the models, black clients are about 26% (=1-0.735) less likely to exit than their white counterparts. However, when we examine specific exit types, we find that black clients catch up with white clients in the odds of work exit versus no exit, with a less than 10% (=1-0.906) decline in the odds. In contrast, black clients are far less likely to exit TANF via non-work approaches, with a 38% (=1-0.621) lower chance of other exit versus no exit.

6.3.4 Additional Concern about Race

Given the significant effect of race in every model, we are interested in the independent patterns between whites and blacks. We can divide the sample by race and estimate the parameters via separate models. Due to our finding that the estimation of parameters holds when controlling for individual specific random effects, we can only

[59] We might assume that the change of marital status is one of the factors that affect non-work exits. Other factors could be family or community support. I will return to this topic in the final chapter.

use fixed effects models. Moreover, we add a control variable indicating whether a spell is the first spell or a repeated spell.

The description of variables by race is listed in Table 6.9. We find differences in the composition of white clients and black clients. On average, white clients are three years older with slightly lower education and have lower rates of job training and employment within TANF. However, white clients are more likely to live in a county with a lower employment rate and higher household income. Furthermore, median household income significantly promotes both work and other exits for black clients but has weak effects on the exits of white clients. Finally, black clients who live in counties within metropolitan and micropolitan statistical areas are less likely to exit TANF than their white counterparts.

The results of separate regressions for the race subgroups show that whites and blacks have different TANF exit patterns (Table 6.10 and Table 6.11). We find that, for white clients, in-school education has a weak effect on work exits and a strong negative effect on other exits. In contrast, in-school education significantly promotes work exits for black clients. The odds of work exit versus no exit increases by 11% (=1.112-1) for black high school graduates in comparison to black high school dropouts. Job training and work experience have similar effects on work exits and other exits, though the latter has an even stronger influence on the work exits of black clients.

Table 6.9 Description of Variables by Race for Discrete-Time Analysis

	White		Black			
Parameters	Means	S.D.	Means	S.D.	Min.	Max.
Youngest Child within 1 Year	.377	.485	.429	.495	0	1
Repeated Spells	.176	.380	.278	.448	0	1
Age	26.7	6.9	23.9	5.7	18	55
Education:						
Less Than High School (Ref.)						
High School	.433	.496	.467	.499	0	1
More Than High School	.152	.359	.184	.388	0	1
Job Training	.125	.331	.171	.395	0	1
Work Experience	.423	.494	.476	.450	0	1
Unemployment Rates (%)	7.0	2.3	8.3	2.6	2.8	20.0
Dissimilarity Index	47.8	11.5	50.3	12.3	24.7	64.0
Percent Black (%)	29.6	17.0	51.3	18.5	3.1	86.1
Median Income ($1,000)	32.6	6.8	28.3	6.4	17.2	48.2
Metro/Micropolitan County	.483	.500	.306	.461	0	1
Main Effects of Time:						
D_1	.364	.481	.293	.455	0	1
D_2	.269	.444	.232	.422	0	1
D_3	.150	.357	.154	.362	0	1
D_4	.087	.282	.105	.307	0	1
D_5	.051	.219	.071	.257	0	1
D_6	.030	.169	.047	.212	0	1
D_7	.018	.133	.032	.177	0	1
D_8	.012	.107	.023	.149	0	1
D_9	.008	.088	.016	.125	0	1
D_{10}	.006	.074	.011	.106	0	1
D_{11}	.004	.063	.008	.090	0	1
D_{12}	.003	.052	.006	.077	0	1
Number of Observations	31,181		157,047			

NOTE: Four variables—unemployment rate, dissimilarity index, percent black, and median income—centralized in the regression analyses.

Table 6.10 Estimates (Coefficients) of Competing Risks Discrete-Time Hazard Models with Covariates, by Race

	Whites (Model 9)		Blacks (Model 10)	
Parameters	Work Exit	Other Exit	Work Exit	Other Exit
D_1	-3.064**	-1.177**	-3.529**	-1.712**
	(.062)	(.043)	(.031)	(.025)
D_2	-2.241**	-.245**	-2.729**	-1.004**
	(.062)	(.045)	(.030)	(.025)
D_3	-2.174**	-.427**	-2.669**	-1.069**
	(.068)	(.054)	(.032)	(.029)
D_4	-2.326**	-.327**	-2.768**	-1.028**
	(.077)	(.061)	(.034)	(.032)
D_5	-2.458**	-.496**	-2.839**	-1.025**
	(.090)	(.072)	(.037)	(.034)
D_6	-2.560**	-.595**	-2.842**	-1.136**
	(.112)	(.089)	(.042)	(.040)
D_7	-2.522**	-.874**	-2.840**	-1.176**
	(.137)	(.118)	(.048)	(.047)
D_8	-2.963**	-.766**	-2.916**	-1.187**
	(.192)	(.136)	(.057)	(.056)
D_9	-2.951**	-1.108**	-2.917**	-1.185**
	(.228)	(.180)	(.067)	(.065)
D_{10}	-3.189**	-1.148**	-2.956**	-1.273**
	(.296)	(.213)	(.080)	(.078)
D_{11}	-2.796**	-1.100**	-2.917**	-1.133**
	(.325)	(.247)	(.093)	(.088)
D_{12}	-2.118**	-.689†	-3.006**	-1.254**
	(.334)	(.272)	(.111)	(.108)
Human Capital				
Education (Ref.=Less than high school)				
High School	.091†	-.229**	.106**	-.243**
	(.039)	(.033)	(.018)	(.018)
More than High School	.030	-.324**	.110**	-.429**
	(.054)	(.047)	(.023)	(.025)
Job Training	.125†	.073	.083**	.005
	(.049)	(.046)	(.020)	(.022)
Work Experience	1.916**	-.462**	2.067**	-.380**
	(.044)	(.033)	(.022)	(.017)

Table 6.10 (Continued)

	Whites (Model 9)		Blacks (Model 10)	
Parameters	Work Exit	Other Exit	Work Exit	Other Exit
Local Labor Market				
Unemployment Rate (%)	-.025*	-.005	-.068**	-.042**
	(.009)	(.008)	(.005)	(.004)
Neighborhoods				
Dissimilarity Index	.004†	.002	-.003**	-.005**
	(.002)	(.002)	(.001)	(.001)
Percent Black (%)	-.002	-.005**	-.005**	-.006**
	(.001)	(.001)	(.001)	(.001)
Median Income ($1,000)	.022†	-.002	.031**	.016**
	(.009)	(.008)	(.004)	(.004)
Squared Median Income	-.002*	.000	-.002**	-.001**
	(.001)	(.000)	(.000)	(.000)
Metro/Micropolitan County	-.111†	-.070	-.169**	-.089**
	(.050)	(.042)	(.025)	(.027)
Control Variables				
Age	-.015**	-.003	.007**	.011**
	(.003)	(.002)	(.001)	(.001)
Youngest Child under One Year	-.651**	-.931**	-.407**	-.776**
	(.041)	(.036)	(.017)	(.019)
Repeated Spell	.071	.112*	.310**	.280**
	(.047)	(.039)	(.018)	(.018)
df	50		50	
-2Log Likelihood	48,420		207,016	
Number of Person-Quarters	31,181		157,047	

NOTE: ** p<.001, * p<.01, † p<.05; Coefficients are presented, along with standard errors (in parentheses).

Table 6.11 Re-expressing Parameter Estimates as Odds Ratio for Competing Risks Discrete-Time Hazard Models with Covariates, by Race

	Whites (Model 9)		Blacks (Model 10)	
Parameters	Work Exit	Other Exit	Work Exit	Other Exit
Human Capital				
Education (Ref.=Less than high school)				
High School	1.095†	.795**	1.112**	.784**
More than High School	1.030	.724**	1.116**	.651**
Job Training	1.133†	1.075	1.086**	1.005
Work Experience	6.795**	.630**	7.900**	.684**
Local Labor Market				
Unemployment Rate (%)	.975*	.995	.934**	.958**
Neighborhoods				
Dissimilarity Index	1.004†	1.002	.997**	.995**
Percent Black (%)	.998	.995**	.995**	.994**
Median Income ($1,000)	1.022†	.998	1.032**	1.016**
Squared Median Income	.998*	1.000	.998**	.999**
Metro/Micro County	.895†	.932	.845**	.915**
Control Variables				
Youngest Child under One Year	.522**	.394**	.666**	.460**
Repeated Spell	1.073	1.119*	1.363**	1.323**
Age	.985**	.997	1.008**	1.011**

NOTE: ** p<.001, * p<.01, † p<.05; Main time effects, D_1-D_{12}, are not present in the table; Fitted hazard rates are calculated by $p_{tij} = 1/(1 + \exp(-\alpha_t))$, where α_t denotes coefficient estimated in Table 6.10.

White clients with children less than one year old have a lower likelihood of exit compared to their black counterparts. Consistent with previous descriptive analyses, TANF recidivists are more likely to exit than are new TANF users. Moreover, racial difference is significant. The likelihood of work or other exits for black recidivists is 30% higher than that of black new users. In contrast, white recidivists have marginal increase in the likelihood of work exit and only 12% (=1.119-1) more likely to have other exits than white new users. Finally, age has mixed effects by race. Compared to their younger counterparts, older white clients are less likely to leave TANF, while older black clients are more likely to do so.

As a contextual variable, county unemployment rate has a stronger negative effect on TANF exits for black clients than for white clients. It should be noticed that high unemployment rates significantly discourage black clients (but not white clients) to leave TANF even for non-work reasons. Living in counties with higher household median income increases the odds of exits for black clients, controlling for other factors in the model. The coefficients of squared median income show that the positive effects are strong for counties with lower household median income, and weak for counties with higher household median income. Likewise, living in metro/micropolitan counties significantly lowers black clients' odds of work exit versus no exit by 15% and other exit versus no exit by 9.5%, respectively. The metro/micropolitan county indicator, however, has only mixed and less significant effects for white clients.

We find an interaction effect between racial residential dissimilarity and race. The dissimilarity index at the census block group level has a slightly positive, though less significant, effect on the exits of white clients. On the other hand, a higher dissimilarity index leads to a lower likelihood of exit for black clients. Finally, black clients are less likely to leave the TANF program if they live in counties with high percent of black, controlling other factors in the model. For example, ten percent increase in the percent of black could lower the odds of black clients' exits by 5% (=exp(-0.005*10)).

CHAPTER VII

SUMMARY, DISCUSSION, AND CONCLUSION

7.1 Summary

In 1996, President Bill Clinton signed into law the Personal Responsibility and Work Opportunity Reconciliation Act, which marked a clear break from the past. Under this act, poor single mothers are required to work and have time limits on cash assistance. Since the passage of the act, many families have left the welfare rolls, bringing the national caseload to a historic low.

The drastic decline in welfare caseload has been used to proclaim a victory in the fight to end welfare as we know it. To be sure, many scholars and researchers have shown that the policy has made a significant contribution to the welfare caseload decline. This, however, begs the question of whether poor single mothers are living under individual and contextual circumstances that favor self-sufficiency. Specifically, are single mothers with higher human capital more likely to leave welfare and gain employment to make ends meet? Similarly, are single mothers under better labor market and neighborhood conditions more likely to leave welfare and move onto a path of self-sufficiency? Do single mothers from different racial groups have equal opportunity to leave welfare and make ends meet?

Prior to the implementation of the TANF program, traditional studies on welfare use showed that investment in human capital (i.e., education, work experience, and job training) facilitates welfare-to-work transition. However, the extent to which investment in human capital influences welfare exit varies across studies. For example, Harris (1993) finds that a poor single mother with a high school diploma is two and half times more likely to leave welfare through employment than those with less than a high school degree. Another study shows that poor single mothers with high school diplomas are 41 percent more likely to leave welfare, and they are also more likely to gain employment (Herbst and Stevens 2010). Work experience and training also differentially impact welfare exit. Studies show that working while on welfare has significant impact on the likelihood of leaving the welfare roll (Hofferth et al. 2002).

Several analysts have shown that labor market conditions affect the likelihood of transitioning off welfare (Blank 2001; Moffitt 2003; Hoynes 2002; Parisi et al. 2006; Herbst and Stevens 2010). Likewise, neighborhood conditions such as level of poverty, racial concentration, and local civic engagement influence the chances of a poor single mother leaving welfare. For example, Small (2007) finds that concentration of poverty and racial minorities account for differences in local social networks and, therefore, for the level of support poor single mothers can receive from their local community organizations. Parisi et al. (2006) find that the likelihood of leaving welfare is significantly diminished when poor single mothers live in communities with high concentration of poverty, blacks, and the poor and low levels of faith-based civic engagement.

Finally, findings on the effects of race in the welfare literature are mixed. Some studies find a significant influence of race on welfare exit (e.g., Blank 1989; Bruce et al. 2004; Herbst and Stevens 2010; O'Neill et al. 1987; Parisi et al. 2006), while others find no significant differences (e.g., Harris 1993; Hofferth et al. 2002; Rank 1988). The general argument is that minorities are doubly disadvantaged. First, minorities tend to have lower investment in human capital and are thus less likely to gain employment that will secure self-sufficiency. Second, minorities tend to live in areas with a high concentration of poverty, which in turn reduces employment opportunities and social services (Parisi et al. 2006).

This study contributes to the current literature on poverty and public assistance in three important ways. First, it examines the post-1996 welfare reform period using innovative administrative data. Second, it examines welfare-to-work transition within a conceptual framework that combines human capital, labor market conditions, and racial differences. Third, it examines the extent to which time spent on welfare rolls impacts the likelihood of leaving welfare. Specifically, this study examines five main hypotheses:

- Dependence Hypothesis
  - Time spent on welfare rolls lowers the probability of exit and the probability of becoming employed.
- Human Capital Hypotheses
  - Educational attainment facilitates welfare-to-work transition.
  - Training facilitates welfare-to-work transition.
  - Previous work experience facilitates welfare-to-work transition.
- Labor Market Hypothesis
  - More advantageous local labor market conditions facilitate welfare-to-work transition.
- Neighborhood Effects Hypothesis
  - Socially disadvantaged neighborhoods undermine welfare-to-work transition.
- Race Hypothesis

- Blacks are disadvantaged in exiting the TANF program when compared to their white counterparts.
- Blacks are more sensitive to the change of human capital than whites.
- Blacks are more sensitive to the change of contextual factors than whites.

7.1.1 Data and Methods

Data for this study came from multiple sources, including administrative records and typical publicly available data. Data on TANF transitions came from the Mississippi Department of Human Services. Data on TANF employment came from the Mississippi Department of Employment Security. Data on training came from the Mississippi workforce investment system. Information on both neighborhood and labor market characteristics came from the 2000 Census.

Welfare-to-work transition was operationalized as the transition of a single mother from TANF into the labor market within the first quarter of leaving TANF. Welfare dependence was operationalized as the duration of receipt of TANF benefits and as exit hazard rates. Human capital was operationalized in three ways: (1) educational attainment, (2) job training, and (3) work experience. Labor market conditions were measured using county-level unemployment rates. Neighborhood conditions were measured by examining the extent to which racial groups were spatially separated within a county. Specifically, this was gauged using the dissimilarity index between racial groups within a county. This measure uses census block group data. Other neighborhood variables at the county level include percent black and median household income. The analysis also included a spatial measure that determined whether a county was classified as metropolitan or nonmetropolitan.

The life table technique and discrete-time event history analysis were used to estimate the determinants of welfare-to-work transition. Models with binary outcomes were used to estimate parameters that affect exits from the TANF program. Competing risks models were estimated to examine the hazard rates of job exit and other exit. In these models, individual specific random effects were introduced to control for unobserved characteristics.

7.1.2 Main Findings

The findings clearly support the hypothesis that individual and contextual conditions influence the ability of a poor single mother to exit TANF and gain employment. On the other hand, there is weak evidence supporting the hypothesis of welfare dependence when controlling for unobserved characteristics for multiple spells within individuals. The main implication here is that TANF might have indeed addressed the longstanding concern about welfare dependency. The question, however, remains whether individual and contextual factors still play a role in determining welfare dynamics across poor single mothers with different individual and contextual backgrounds.

The results show that working while on TANF increases the odds of a work exit by about seven times. A poor single mother who receives training is also more likely to gain employment. Training, however, has a much smaller effect than work. Educational attainment was found to have a positive effect on work exit. The data also show that education differentially impacts work exit for blacks and whites; that is, education has a much bigger impact on blacks than it does for whites. A plausible explanation is that blacks might be competing more than whites for low-wage jobs, and thus an increase in education among blacks increases their chances of gaining low-wage jobs.

The results show that labor market characteristics positively influence the chances of a single mother transitioning into the workforce. The results also show that neighborhood characteristics influence the likelihood of work exit. Neighborhood characteristics, however, have differential impact on racial groups; that is, higher levels of neighborhood segregation slightly increase TANF exits for whites but significantly reduce the likelihood of exit for blacks. The results also show that geographic location matters. Single mothers in nonmetropolitan counties are more likely to leave the rolls than their metropolitan counterparts. This is consistent with previous studies indicating that small places reduce anonymity and therefore increase the stigma of using welfare. Percent black was found to have a negative effect on welfare exit, and median income was found to have a positive effect on welfare exit, especially for blacks.

7.2 Discussion

7.2.1 Welfare Dependence Hypothesis

A strong assumption of the welfare dependence hypothesis is that the longer individuals use public assistance, the harder it is to become self-sufficient. Many studies prior to TANF support the dependency assumption, and they indicate that the average length of welfare spells ranges between 2.3 and 4.7 years (Bane and Ellwood 1983, 1994; Pavetti 1993). These studies also show that between 48 and 70 percent of AFDC participants left welfare within two years (Bane and Ellwood 1983, 1994; Fitzgerald 1995; Pavetti 1993). More recent studies examining TANF, however, show that poor single mothers use welfare for a much shorter period of time (Parisi et al. 2006). Results of this study also show that single mothers indeed use TANF for short-term spells. This study's results also indicate that half of all clients leave TANF before the end of one year, and less than five percent of cases exceed two years.

When hazard rates are examined, the results show that individuals who fail to leave welfare within the first few months are less likely to exit. However, when individual unobserved characteristics (or individual specific random effects) are controlled, the hazard rates of exits level off after the initial increase. These findings clearly indicate that differences in exit hazard rates are associated with differences in individual characteristics. For example, being white, having no children less than one year old, receiving job training, working while on TANF, and living in a good neighborhood increase the chances of leaving the welfare rolls. To be sure, time spent on welfare has no bearing on the likelihood of leaving welfare. On the other hand, individual and contextual characteristics dictate whether poor single mothers are ready to move into the workforce.

7.2.2 Human Capital Hypotheses

The effects of human capital have received particular attention in modeling patterns of welfare use due to policy implications. Findings from the life table analysis show a weak effect of educational attainment on the likelihood of exiting TANF. That is, patterns of TANF use are almost identical across educational levels. The results also show that those with lower education are slightly more likely to exit than those with higher levels of education. A plausible explanation is that individuals with higher levels of education might wait longer to find jobs that better fit their educational attainment. Another explanation is that those with lower education might engage in forward-looking behavior and save their eligibility for hard times. The results of discrete-time models also show that having a job while receiving welfare benefits increases the odds of work exit by about seven times. This makes work the most important factor in determining single mothers' likelihood of exit. For the same reason, single mothers with work experience are likely to wait for a job before exiting rather than quickly exiting without a job. Job training also increases the likelihood of work exit, but its effects are much weaker when compared to work.

These finding clearly show that, under TANF, investment in human capital plays a very small role in the decision to leave the welfare rolls. On the other hand, work while on TANF is the most likely strategy that poor single mothers will use to transition into the workforce. With this strategy, however, poor single mothers have to seek work opportunities at the lower end of the market queue, which in turn undermines investment in education. Therefore, TANF encourages poor single mothers to combine work and welfare as a main strategy to end welfare dependency. This does not mean that recipients are becoming self-sufficient but rather that attachment to the labor market is a potential way to leave welfare in the immediate future.

Table 7.1 Estimated Median Lifetime (in Quarter) Simulations for Changes by Education, Controlling for Work Experience and Race

	Education	Work Exits		Other Exits	
		White	Black	White	Black
Work while on TANF	Less than high school	1.81	2.19	2.37	3.68
	High school	1.74	2.03	2.80	4.46
	More than high school	1.79	2.02	2.99	5.21
No work while on TANF	Less than high school	9.26	>12.0	1.79	2.76
	High school	8.07	11.55	1.98	3.31
	More than high school	8.82	11.50	2.13	3.81

Source: See Appendix Table A.11.

Table 7.1 reports estimates on median lifetime for TANF clients with different educational attainment, controlling for work experience and race. These estimates are based on average characteristics of recipients in Mississippi. That is, they live in counties outside metropolitan or micropolitan statistical areas with average dissimilarity (=49.9), percent black (=47.7%), median household income (=$29,000), and unemployment rates (=8.1%). In addition, they have average age (=24.4), have no children under one year old, and enter into the TANF program for the first time. The statistics in Table 7.1 reveals that single mothers are much less likely to exit through jobs if they do not work while on welfare. These estimates also show that a change from high school drop-out to high school graduate increases the chances of gaining employment. The size of this effect, however, is much smaller if work experience is taken into account. For example, the median lifetime for a white client is less than two quarters if she ever worked when receiving TANF benefits, regardless of her educational level, while the median lifetime could extend to eight quarters for a white client with higher educational attainment if she does not have work experience.

To be sure, the combination of work and TANF dramatically reduces the use of welfare as an economic strategy. Single mothers who work while on TANF tend to leave the program faster and are better able to gain employment than their counterparts. Educational attainment promotes job exits but is a less effective strategy in the short run. This begs the question of whether work alone is enough for single mothers to become self-sufficient once they leave welfare. In other words, getting a job might stop a single mother from receiving training or education that could lead to better, steadier jobs.

7.2.3 Labor Market and Neighborhood Effects Hypotheses

The results clearly show that labor market conditions influence the likelihood of single mothers leaving the welfare rolls. This finding is consistent with previous studies that use time-varying county-level measurement (Fitzgerald 1995; Herbst and Stevens 2010; Hoynes 2000; Parisi et al. 2006). Table 7.2 provides estimates of median lifetime simulations for single mothers who graduate from high school in labor market conditions with different unemployment rates. All things being equal, with a change of unemployment rate by one-standard deviation (=2.6%), the likelihood of leaving welfare is clearly diminished, especially for those who do not work while on TANF.

Table 7.2 Estimated Median Lifetime (in Quarter) Simulations for Changes by Unemployment Rate, Controlling for Work Experience and Race

	Unemployment Rate	Work Exits		Other Exits	
		White	Black	White	Black
Work while on TANF	10.7	1.79	2.30	2.82	4.87
	8.1	1.74	2.03	2.80	4.46
	5.5	1.69	1.85	2.77	4.07
No work while on TANF	10.7	8.87	>12.0	2.00	3.60
	8.1	8.07	11.55	1.98	3.31
	5.5	7.32	9.63	1.97	3.03

Source: See Appendix Table A.12.

7.2.4 Race Hypothesis

The findings clearly show that race matters in explaining differential rates of exit from TANF. However, it is more an issue of individual characteristics than social and contextual factors. First, there is a racial differential in the impact of human capital. Blacks are more sensitive to the level of education or any form of human capital compared to their white counterparts (also see simulations in Table 7.1). For example, we find no significant effect of education on work exits for whites but a relatively strong positive effect on work exits for blacks. This finding is consistent with previous studies (e.g., Parisi et al. 2006), but in this study, the data show a stronger connection between education and work exit among black clients than their white counterparts.

Second, blacks are more sensitive to labor market change than whites. For example, the simulations show that a one-standard-deviation increase in unemployment rate could lead to the increase in median lifetime of job exit by 0.2 to 0.3 quarter for black clients with work experience but only 0.05 quarter for their white counterparts (Table 7.2). This result is consistent with the findings of earlier studies (e.g., Fitzgerald 1995) that local unemployment rates affect welfare exit rates, especially for blacks. Moreover, by distinguishing work exit and non-work exit, this study finds that black single mothers are disadvantaged in finding other ways of leaving the TANF program. This finding implies that back single mothers might have weak social ties or social networks to help them to leave welfare program when work opportunities are not available.

Finally, neighborhood effects have an especially pronounced impact on blacks. We find that black clients are less likely to exit the TANF program in counties with high racial residential segregation. Moreover, black clients who live in metropolitan and micropolitan statistical areas have a much lower likelihood of exit when compared to their white counterparts. This result confirms the hypothesis that blacks might face discrimination in local areas due to racial residential segregation between blacks and whites in Mississippi.

7.3 Conclusion

In conclusion, this study demonstrates that the 1996 welfare reform has changed the environment of public assistance for single mothers. Work requirements indeed might facilitate TANF exits, but they might do so at the expense of educational development, which could seriously compromise a single mother's ability to become self-sufficient. This study also shows that minorities are more likely to be disadvantaged under this current policy, especially in areas with poor socioeconomic conditions, raising serious questions about social justice.

This study is not without limitations. First, administrative data do not allow me to examine all the reasons single mothers exit TANF. Instead of exiting due to work, single mothers may leave TANF due to a change in family composition, such as getting married or having no children younger than 18 (e.g., Bane and Ellwood 1994). Moreover, support from family, communities, or charity groups could be important factors that enable single mothers to leave TANF (Parisi et al. 2006). In order to model other exits, we need additional variables, such as family formation, social network, social capital, and/or neighborhood supports. Unfortunately, these variables are not readily available in the TANF and UI administrative data in Mississippi. The use of national survey data (e.g., PSID and NLSY) could address this issue.

Giving more attention to other exits could further our understanding of different patterns of TANF use between whites and blacks. Our data show that the majority of white clients end their TANF spells due to non-work reasons, while the majority of black clients have work exits (Table 7.3). Does this mean that white single mothers have better choices than placing themselves in the low-end labor market, or are they disadvantaged in competing with their black counterparts in the labor market? Further study is needed to explore the details of other exits.

Table 7.3 Percent of TANF Spells that Ended as Work Exit and Other Exit

	Work Exit (%)	Other Exit (%)	Total Spells
White Clients	43.1	56.9	10,605
Black Clients	55.3	44.6	40,146

Source: MDHS data.

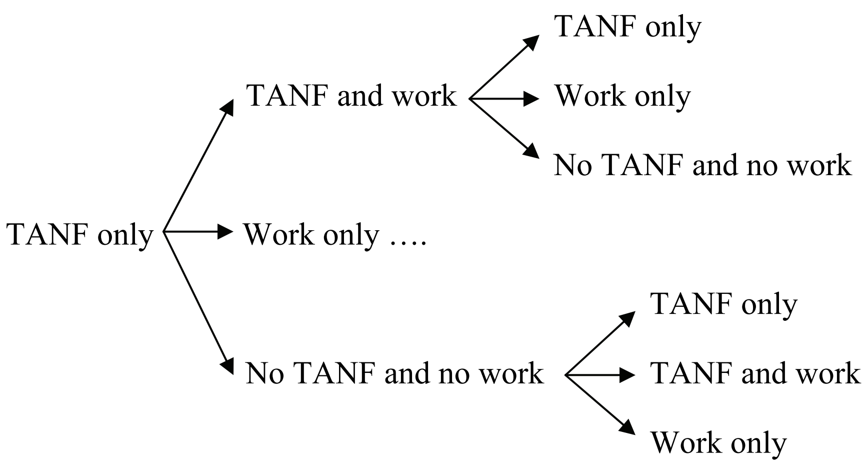
This study's narrow definition of work exit is another limitation. I focus on employment statuses in the quarter after exit. Specifically, I determine if single mothers have positive wages reported by employers in quarterly updated UI files. As I mentioned in a previous section, UI data do not catch many types of employment, such as government employment, self-employment, and some informal employment. Moreover, employment at a single point in time cannot provide a full picture of labor force participation dynamics. Earlier research shows that there is a dynamic of moving up and down in the employment transitions of young women who receive welfare (Pavetti and Acs 2001). Finally, the UI data also do not allow us to distinguish between part-time and full-time employment, though we can identify high-paying jobs and low-paying jobs or focus on wage determinants for TANF leavers.

Due to the narrow definition of work exit, we should be cautious when interpreting the efficiency of human capital. This study cannot find any significant difference in the likelihood of exit between high school education and more than high school education. At first glance, this finding supports the work-first strategy, which prefers placing TANF clients into the labor market as soon as possible, rather than the human capital development strategy, which helps TANF clients to achieve higher educational attainment for long-term rewards. However, it is highly possible that single mothers with more than high school education could spend one or two more months in TANF while searching for a better job, which could explain the racial difference in the effect of education on work exit. A study finds that high educational attainment and being white increases the odds of finding a good job (Pavetti and Acs 2001). We can assume that white clients receiving more education could have higher expectations in the labor market compared to their black counterparts. For further study, the dependent variable should be the quality of employment in the near future, which can be measured by either average wages or employment retention.

Another limitation in the evaluation of human capital is that we do not have sufficient information to detect any improvement of formal education for a given TANF recipient. The most important reason is that educational level is measured by year, but the majority of TANF spells end within one year. Thus, TANF recipients do not have enough time to document any change of educational attainment. Furthermore, as I have mentioned before, it is hard to determine whether small changes in the educational level are the results of actual achievement or administrative error.

Moreover, we also need to be cautious in interpreting the impressive influence of work experience on the likelihood of work exit. This analysis does not show how specific groups of TANF clients found jobs while in the program. We can reasonably assume that the qualities that help a single mother find a job within TANF also assist her in getting a job to exit. Thus, there is a selection effect. Further study could focus on the determinants of work transition within the TANF program.

Finally, this study has a limitation in modeling random effects between geographic units due to the challenge of computation. It is reasonable to expect that the unique aspects of a county or a block group (e.g., social capital) have unobserved effects on an individual's odds of exit. Future study could use a three-level model that takes spell, individual, and geography into account. This study also has a limitation in modeling all possibilities of welfare-to-work transition, which includes four states: (1) TANF only, (2) TANF and work, (3) work only, (4) no TANF and no work. The beginning state is in-TANF only, followed by the four possible states. In general, there may be multiple transitions as shown below:



The data layout for modeling such a multi-state transition would require time dummy variables from the first observed quarter to the last observed quarter rather than the 12 dummies used in this study (Table 7.4). We need to model the transitions from entering TANF to the end of observation, not merely the duration of a spell. In other words, attention should be diverted from work exits and directed toward the interaction of TANF spells and employment spells. Techniques and specific software have been developed to estimate the multi-state transition model (Steele et al. 1996; Steele et al. 2004). Future studies that use this model can certainly provide further insight into welfare-to-work transition.

Table 7.4 Data Layout in Discrete-Time Format with Multi-State Transition Outcomes

Client		Main Effect of Time (t)													Spell	Multi-States (k)				Time	Time	Contex-
(j)	Quarter	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	…	D_{33}	(i)	y_1	y_2	y_3	y_4	Invariant	Varying	tual ID
001	23	1	0	0	0	0	0	0	0	0	0	0	…	0	1	1	0	0	0	1	0	111
001	24	0	1	0	0	0	0	0	0	0	0	0	…	0	1	1	0	0	0	1	0	111
001	25	0	0	1	0	0	0	0	0	0	0	0	…	0	2	0	1	0	0	1	0	111
001	26	0	0	0	1	0	0	0	0	0	0	0	…	0	2	0	1	0	0	1	0	111
001	27	0	0	0	0	1	0	0	0	0	0	0	…	0	3	0	0	1	0	1	0	111
001	28	0	0	0	0	0	1	0	0	0	0	0	…	0	3	0	0	1	0	1	1	111
001	29	0	0	0	0	0	0	1	0	0	0	0	…	0	3	0	0	1	0	1	1	111
001	30	0	0	0	0	0	0	0	1	0	0	0	…	0	3	0	0	1	0	1	1	111
001	31	0	0	0	0	0	0	0	0	1	0	0	…	0	4	0	0	0	1	1	0	111
001	32	0	0	0	0	0	0	0	0	0	1	0	…	0	5	1	0	0	0	1	0	111
001	33	0	0	0	0	0	0	0	0	0	0	1	…	0	5	1	0	0	0	1	1	111
002	29	1	0	0	0	0	0	0	0	0	0	0	…	0	1	1	0	0	0	0	0	111
002	30	0	1	0	0	0	0	0	0	0	0	0	…	0	1	1	0	0	0	0	1	111
002	31	0	0	1	0	0	0	0	0	0	0	0	…	0	1	1	0	0	0	0	1	111
002	32	0	0	0	1	0	0	0	0	0	0	0	…	0	2	0	0	0	1	0	0	111
002	33	0	0	0	0	1	0	0	0	0	0	0	…	0	2	0	0	0	1	0	1	111
003	1	1	0	0	0	0	0	0	0	0	0	0	…	0	1	1	0	0	0	1	1	222
003	2	0	1	0	0	0	0	0	0	0	0	0	…	0	1	1	0	0	0	1	1	222
003	3	0	0	1	0	0	0	0	0	0	0	0	…	0	1	1	0	0	0	1	1	222
.	.	.	.	.	.	.	.	.	.	.	.	.		.	.	.	.	.	.	.	.	.
003	33	0	0	0	0	0	0	0	0	0	0	0	…	1	i	0	0	1	0	1	0	222

NOTE: (1) Multi-states are coded as: y_1=TANF only; y_2=TANF and work; y_3=work only; y_4=no TANF and no work.
(2) Spells with clients older than 55 are coded as right-censored. Thus, the maximum observed time period is 33 quarters.
(3) The observed time period for any clients begins at the first quarter of entering TANF and ends at the 33rd quarter (the last quarter of observation).

REFERENCES

Agresti, Alan, James G. Booth, James P. Hobert, and Brian Caffo. 2000. "Random-Effects Modeling of Categorical Response Data." *Sociological Methodology* 30:27-80.

Agresti, Alan, and Ivy Liu. 2001. "Strategies for Modeling a Categorical Variable Allowing Multiple Category Choices." *Sociological Methods & Research* 29:403-434.

Allison, Paul D. 1982. "Discrete-Time Methods for the Analysis of Event Histories." *Sociological Methodology* 13:61-98.

Allison, Paul D. 1984. *Event History Analysis: Regression for Longitudinal Event Data*. Sage publication.

Allison, Paul D. 1995. *Survival Analysis Using the SAS System: A Practical Guide*. NC: Cary, NC: SAS Institute Inc.

Anderson, Erin K., and Jerry Van Hoy. 2006. "Striving for Self-Sufficient Families: Urban and Rural Experiences for Women in Welfare-to-Work Program." *Journal of Poverty* 10:69-91.

Bane, Mary Jo, and David T. Ellwood. 1983. *The Dynamics of Dependence: The Routes to Self-sufficiency*. Report prepared for the U.S. Department of Health and Human Services. Cambridge, MA: Urban Systems Research and Engineering.

Bane, Mary Jo, and David T. Ellwood. 1994. *Welfare Realities: From Rhetoric to Reform*. Cambridge, MA: Harvard University Press.

Barber, Jennifer S., Susan A. Murphy, William G. Axinn, and Jerry Maples. 2000. "Discrete-Time Multilevel Hazard Analysis." *Sociological Methodology* 30:201-235.

Baron, James N., and Michael T. Hannan. 1994. "The Impact of Economics on Contemporary Sociology." *Journal of Economic Literature* 32:1111-1146.

Bavier, Richard M. 2001. "Welfare Reform Data from the Survey of Income and Program Participation." *Monthly Labor Review* 124: 13-24.

Beck, E. M., Patrick M. Horan, and Charles Tolbert. 1978. "Stratification in a Dual Economy: A Sectoral Model of Earnings Determination." *American Sociological Review* 43:704-720.

Becker, Gary. 1962. "Investment in Human Capital: A Theoretical Analysis." *Journal of Political Economy* 70:9-49.

Becker, Gary. 1964. *Human Capital*. New York: National Bureau of Economic Research.

Becker, Gary. 1981. *A Treatise on the Family*. Cambridge, MA: Harvard University Press.

Blank, Rebecca M. 1989. "Analyzing the Length of Welfare Spells." *Journal of Public Economics* 39:245-273.

Blank, Rebecca M. 2001. "What Causes Public Assistance Caseloads to Grow?" *Journal of Human Resources* 36:85-118.

Blank, Rebecca M. 2002. "Evaluating Welfare Reform in the United States." *Journal of Economic Literature* XL:1105-1166.

Bloom, Dan, and Charles Michalopoulos. 2001. *How Welfare and Work Policies Affect Employment and Income: A Synthesis of Research*. New York, NY: Manpower Demonstration Research Corporation (MDRC). http://www.mdrc.org/publications/99/overview.html. Accessed June 21, 2010.

Boyer, George R., and Robert S. Smith. 2001. "The Development of the Neoclassical Tradition in Labor Economics." *Industrial and Labor Relations Review* 54:199-223.

Browne, Irene. 1997. "Explaining the Black-White Gap in Labor Force Participation among Women Heading Households." *American Sociological Review* 62:236-252.

Bruce, Donald, Karie Barbour, and Angela Thacker. 2004. "Welfare Program Reentry among Post-Reform Leavers." *Southern Economic Journal* 70:816-836.

Cain, Glen G. 1976. "The Challenge of Segmented Labor Market Theories to Orthodox Theory: A Survey." *Journal of Economic Literature* 14:1215-1257.

Casciano, Rebecca, and Douglas S. Massey. 2008. "Neighborhoods, Employment, and Welfare Use: Assessing the Influence of Neighborhood Socioeconomic Composition." *Social Science Research* 37:544-558.

Clampet-Lundquist, Susan, and Douglas S. Massey. 2008. “Neighborhood Effects on Economic Self-Sufficiency: A Reconsideration of the Moving to Opportunity Experiment.” *American Journal of Sociology* 114:107-143.

Committee on Ways and Means. 2008. *Green Book*. Washington, DC: U.S. Government Printing Office. http://waysandmeans.house.gov/singlepages.aspx?NewsID=10490. Accessed June 21, 2010.

Contini, Dalit, and Nicola Negri. 2007. “Would Declining Exit Rates from Welfare Provide Evidence of Welfare Dependence in Homogeneous Environments?” *European Sociological Review* 23:21-33.

Corcoran, Mary. 1995. “Rags to Rags: Poverty and Mobility in the United States.” *Annual Review of Sociology* 21:237-267.

Corcoran, Mary, Sandra K. Danziger, Ariel Kalil, and Kristin S. Seefeldt. 2000. “How Welfare Reform is Affecting Women’s Work.” *Annual Review of Sociology* 26:241-269.

Cotter, David A. 2002. “Poor People in Poor Places: Local Opportunity Structures and Household Poverty.” *Rural Sociology* 67:534-555.

Coulton, Claudia J. 2003. “Metropolitan Inequities and the Ecology of Work: Implications for Welfare Reform.” *Social Service Review* 77:159-190.

Danziger, Sheldon, Colleen M. Heflin, Mary E. Corcoran, Elizabeth Oltmans, and Hui-Chen Wang. 2002. “Does It Pay to Move from Welfare to Work?” *Journal of Policy Analysis and Management* 21:671-692.

Danziger, Sheldon, and Hui-Chen Wang. 2005. “Does it Pay to Move from Welfare to Work? Reply to Robert Moffitt and Katie Winder.” *Journal of Policy Analysis and Management* 24:411-417.

Devere, Christine. 2001. *Welfare Reform Research: What Do We Know about Those Who Leave Welfare?*. Washington DC, UNT Digital Library. http://digital.library.unt.edu/ark:/67531/metacrs2069/. Accessed June 21, 2010.

Dickens, William T., and Kenvin Lang. 1985. “A Test of Dual Labor Market Theory.” *American Economic Review* 75:792-805.

DiPrete, Thomas A., and Jerry D. Forristal. 1994. “Multilevel Models: Methods and Substance.” *Annual Review of Sociology* 20:331-357.

Duncan, Cynthia M. 1999. *Worlds Apart: Why Poverty Persists in Rural America*. New Haven, CT: Yale University Press.

Duncan, Greg J., and J. Lawrence Aber. 1997. "Neighborhood Models and Measures." Pp. 62-78 in *Neighborhood Poverty: Context and Consequences for Children*, edited by Brooks-Gunn Jeanne, Greg J. Duncan, and J. Lawrence Aber. New York: Russell Sage Foundation.

Duncan, Greg J., Jame P. Connell, and Pamela K. Klebanov. 1997. "Conceptual and Methodological Issues in Estimating Causal Effects of Neighborhoods and Family Conditions on Individual Development." Pp. 219-250 in *Neighborhood Poverty: Context and Consequences for Children*, edited by Brooks-Gunn Jeanne, Greg J. Duncan, and J. Lawrence Aber. New York, NY: Russell Sage Foundation.

Dyke, Andrew, Carolyn J. Heinrich, Peter R. Mueser, Kenneth R. Troske, and Kyung-Seong Jeon. 2006. "The Effects of Welfare-to-Work Program Activities on Labor Market Outcomes." *Journal of Labor Economics* 24:567-607.

Edin, Kathryn, and Laura Lein. 1996. "Work, Welfare, and Single Mothers' Economic Survival Strategies." *American Sociological Review* 62:253-266.

Ellwood, David T. 1986. *Targeting "Would be" Long-term Recipients of AFDC*. Princeton, NJ: Mathematica Policy Research, Inc.

Enberg John, Peter Gottschalk, and Douglas Wolf. 1990. "A Random-Effects Logit Model of Work-Welfare Transitions." *Journal of Econometrics* 43:63-75.

England, Paula. 1982. "The Failure of Human Capital Theory to Expain Occupational Sex Segregation." *Journal of Human Resources* 17:358-370.

Fitzgerald, John M. 1995. "Local Labor Markets and Local Area Effects on Welfare Duration." *Journal of Policy Analysis and Management* 14:43-67.

Flom, Peter L., James M. McMahon, and Enrique R. Pouget. 2007. "Using PROC NLMIXED and PROC GLMMIX to Analyze Dyadic Data with a Dichotomous Dependent Variable." Paper 179 in *Proceedings of the SAS® Global Forum 2007 Conference*. Cary, NC: SAS Institute Inc.

Fraser, Nancy, and Linda Gordon. 1994. "A Genealogy of Dependency: Tracing a Keyword of the U.S. Welfare State." *Signs: Journal of Women in Culture and Society* 19:309-336.

Goerge, Robert M., and Bong Joo Lee. 2002. "Matching and Cleaning Administrative Data." Pp. 197-219 in *Studies of Welfare Populations: Data Collection and*

Research Issues, edited by Michele Ver Ploeg, Robert A. Moffitt, and Constance F. Citro. Washington, DC: National Academy Press.

Goldstein, Harvey, Huiqi Pan, and J. Bynner. 2004. "A Flexible Procedure for Analyzing Longitudinal Event Histories Using a Multilevel Model." *Understanding Statistics* 3:85-99.

Gottschalk, Peter, and Robert A. Moffitt. 1994. "Welfare Dependence: Concepts, Measures, and Trends." *American Economic Review* 84:38-42.

Grice, Steven Michael. 2005. "Influence of Individual and Local Conditions on Patterns of TANF Use." Ph.D. Dissertation, Mississippi State University, Starkville, MS.

Guo, Guang, and Hongxin Zhao. 2000. "Multilevel Modeling for Binary Data." *Annual Review of Sociology* 26:441-462.

Hamilton, Gayle. 2002. *Moving People from Welfare to Work: Lessons from the National Evaluation of Welfare-to-Work Strategies*. New York, NY: Manpower Demonstration Research Corporation (MDRC). http://www.mdrc.org/publications/52/summary.html. Accessed June 21, 2010.

Harris, Kathleen Mullan. 1993. "Work and Welfare among Single Mothers in Poverty." *American Journal of Sociology* 99:317-352.

Harris, Kathleen Mullan. 1996. "Life After Welfare: Women, Work, and Repeat Dependency." *American Sociological Review* 61:407-426.

Hartzel, Jonathan, Alan Agresti, and Brian Caffo. 2001. "Multinomial Logit Random Effects Models." *Statistical Modeling* 1:81-102.

Haynes, Michele, Mark Western, Laurel Yu, and Melanie Spallek. 2008. "Analysing Nominal Data from a Panel Survey: Employment Transitions of Australian Women." In *American Sociological Association 103rd Annual Meeting 2008: Worlds of Work*, MA: Boston.

Hechter, Michael, and Satoshi Kanazawa. 1997. "Sociological Rational Choice Theory." *Annual Review of Sociology* 23:191-214.

Heckman, James J., and George J. Borjas. 1980. "Does Unemployment Cause Future Unemployment? Definitions, Questions and Answers from a Continuous Time Model of Heterogeneity and State Dependence." *Economica* 47:247-283.

Heckman, James J. 1981. "Heterogeneity and State Dependence." in *Studies in Labor Markets*. edited by Sherwin Rosen. Chicago: University Chicago Press. http://www.nber.org/chapters/c8909. Accessed June 21, 2010.

Hedeker, Donald. 1999. "MIXNO: A Computer Program for Mixed-Effects Nomial Logistic Regression." *Journal of Statistical Software* 4:1-92.

Hedeker, Donald, and Robert D. Gibbons. 2006. *Longitudinal Data Analysis*. Hoboken, NJ: John Wiley & Sons.

Heinrich, Carolyn J., Peter R. Mueser, and Kenneth R. Troske. 2005. "Welfare to Temporary Work: Implications for Labor Market Outcomes." *Review of Economics and Statistics* 87:154-173.

Henry, Mark, Lynn Reinschmiedt, Willis Lewis, and Darren Hudson. 2002. "Reducing Food Stamp and Welfare Caseloads in the South." Pp. 113-140 in *Rural Dimensions of Welfare Reform*, edited by Bruce A. Weber, Greg J. Duncan, and Leslie A. Whitener. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Herbst, Chris M. 2008. "Do Social Policy Reforms Have Different Impacts on Employment and Welfare Use as Economic Conditions Change?" *Journal of Policy Analysis and Management* 27:867-894.

Herbst, Chris M., and David W. Stevens. 2010. "The Impact of Local Labor Market Conditions on Work and Welfare Decisions: Revisiting an Old Question Using New Data." *Population Research and Policy Review* 29:453-479.

Hirschl, Thomas A., and Mark R. Rank. 1991. "The Effect of Population Density on Welfare Participation." *Social Forces* 70:225-235.

Hirschl, Thomas A., and Mark R. Rank. 1999. "Community Effects on Welfare Participation." *Sociological Forum* 14:115-174.

Hofferth, Sandra L., Stephen Stanhope, and Kathleen Mullan Harris. 2002. "Exiting Welfare in the 1990s: Did Public Policy Influence Recipients' Behavior?" *Population Research and Policy Review* 21:433-472.

Hofferth, Sandra L., Stephen Stanhope, and Kathleen Mullan Harris. 2005. "Remaining off Welfare in the 1990s: The Influence of Public Policy and Economic Conditions." *Social Science Research* 34:426-453.

Hotz, V. Joseph, and John Karl Scholz. 2002. "Measuring Employment and Income for Low-Income Populations with Administrative and Survey Data." Pp. 275-315 in *Studies of Welfare Populations: Data Collection and Research Issues*, edited by Michele Ver Ploeg, Robert A. Moffitt, and Constance F. Citro. Washington, DC: National Academy Press.

Hotz, V. Joseph, Guido W. Imbens, and Jacob A. Klerman. 2006. Evaluating the Differential Effects of Alternative Welfare-to-Work Training Components: A Reanalysis of the California GAIN Program." *Journal of Labor Economics* 24:521-566.

Hoynes, Hilary Williamson. 2000. "Local Labor Markets and Welfare Spells: Do Demand Conditions Matter?" *Review of Economics and Statistics* 82:351-368.

Hudson, Kenneth. 2007. "The New Labor Market Segmentation: Labor Market Dualism in the New Economy." *Social Science Research* 36:286-312.

Irving, K. Shelley. 2008. "State Welfare Rules, TANF Exits, and Geographic Context: Does Place Matter?" *Rural Sociology* 73:605-630.

Jencks, Christopher, and Susan E. Mayer. 1990. "The Social Consequences of Growing Up in a Poor Neighborhood." Chapter 4 in Laurence E. Lynn, Jr., and Michael G. H. McGeary, eds., *Inner-City Poverty in the United States*. Washington, DC: National Academy Press.

Kalleberg, Arne L. 1995. "Sociology and Economics: Crossing the Boundaries." *Social Forces* 73:1207-1218.

Kalleberg, Arne L., and Aage B. Sorensen. 1979. "The Sociology of Labor Markets." *Annual Review of Sociology* 5:351-379.

Kim, Jeounghee. 2006. "The Effects of Welfare-to-Work Strategies on TANF Recipients' Outcomes: Event History Analyses of Employment, Jobs, Welfare Use, and Economic Well-being." Ph.D. Dissertation, Washington University, Saint Louis, MO.

Kuss, Oliver, and Dale McLerran. 2007. "A Note on the Estimation of the Multinomial Logistic Model with Correlated Responses in SAS." *Computer Methods and Programs in Biomedicine* 87:262-269.

Lane, Julia, and David Stevens. 1995. "Family, Work, and Welfare History: Work and Welfare Outcomes." *American Economic Review* 85:266-270.

Leontaridi, Marianthi Rannia. 1998. "Segmented Labor Markets: Theory and Evidence." *Journal of Economic Surveys* 12:63-101.

Levitan, Sar A., Garth L. Mangum, and Stephen L. Mangum. 1998. *Programs in Aid of the Poor*. Baltimore, MD: Johns Hopkins University Press.

Lewis, Oscar. 1966. "The Culture of Poverty." *Scientific American* 215:19-25.

Lichter, Daniel T., and Rukamalie Jayakody. 2002. "Welfare Reform: How Do We Measure Success?" *Annual Review of Sociology* 28:117-141.

Ludwig, Jens, Jeffrey B. Liebman, Jeffrey R. Kling, Greg J. Duncan, Lawrence F. Katz, Ronald C. Kessler, and Lisa Sanbonmatsu. 2008. "What Can We Learn about Neighborhood Effects from the Moving to Opportunity Experiment?" *American Journal of Sociology* 114:144-188.

Luks, Samantha, and Henry E. Brady. 2003. "Defining Welfare Spells: Coping with Problems of Survey Responses and Administrative Data." *Evaluation Review* 27:395-420.

Malchow-Moller, Nikolaj, and Michael Svarer. 2003. "Estimation of the Multinomial Logit Model with Random Effects." *Applied Economics Letters* 10:389-392.

Martin, Molly. 2003. "The Role of Family Income in the Intergenerational Association of AFDC Rreceipt." *Journal of Marriage and Family* 65:326-340.

Massey, Douglas S., and Nancy A. Denton. 1993. *American Apartheid: Segregation and the Making of the Underclass*. Cambridge, MA: Harvard University Press.

Mead, Lawrence M. 1986. *Beyond Entitlement: The Social Obligations of Citizenship*. New York, NY: Free Press.

Mead, Lawrence M. 1988. "The Potential for Work Enforcement: A Study of WIN." *Journal of Policy Analysis and Management* 7:264-288.

Mead, Lawrence M. 2001. "Welfare Reform: Meaning and Effects." *Policy Currents* 11:7-13.

Meyer, Bruce D., and Dan T. Rosenbaum. 2001. "Welfare, the Earned Income Tax Credit, and the Labor Supply of Single Mothers." *Quarterly Journal of Economics* 1063-1114.

Mincer, Jacob. 1962. "On-the-Job Training: Costs, Returns, and Some Implications." *Journal of Political Economy* 70:50-79.

Mincer, Jacob. 1974. *Schooling, Experience, and Earnings*. New York, NY: Columbia University Press.

Mississippi Department of Human Services (MDHS). 2009. *Mississippi State Plan: Temporary Assistance for Needy Families*. Jackson, MS: Author.

Moffitt, Robert. 1987. "Historical Growth in Participation in Aid to Families with Dependent Children: Was There a Structural Shift?" *Journal of Post Keynesian Economics* 9:347-363.

Moffitt, Robert. 1992. "Incentive Effects of the U.S. Welfare System: A Review." *Journal of Economic Literature* 30:1-61.

Moffitt, Robert. 2002. "Experienced-Based Measures of Heterogeneity in the Welfare Caseload." Pp. 473-499 in *Studies of Welfare Populations: Data Collection and Research Issues*, edited by Michele Ver Ploeg, Robert A. Moffitt, and Constance F. Citro. Washington, DC: National Academy Press.

Moffitt, Robert. 2003a. "The Role of Nonfinancial Factors in Exit and Entry in the TANF Program." The *Journal of Human Resources* 38:1221-1254.

Moffitt, Robert. 2003b. "Introduction." Pp. 291-363 in *Means-Tested Transfer Programs in the United States*, edited by Robert Moffitt. Chicago, IL: University of Chicago Press.

Moffitt, Robert. 2003c. "The Temporary Assistance for Needy Families Program." Pp. 291-363 in *Means-Tested Transfer Programs in the United States*, edited by Robert Moffitt. Chicago, IL: University of Chicago Press.

Moffitt, Robert. 2008. "A Primer on U.S. Welfare Reform." *Focus* 26:15-25.

Moffitt, Robert, and Katie Winder. 2005. "Does it Pay to Move from Welfare to Work? A Comment on Danziger, Heflin, Corcoran, Oltmans, and Wang." *Journal of Policy Analysis and Management* 24:399-409.

Monroe, Pamela A., and Vicky V. Tiller. 2001. "Commitment to Work among Welfare-Reliant Women." *Journal of Marriage and Family* 63:816-828.

Mosisa, Abraham, and Steven Hipple. 2006. "Trends in Labor Force Participation in the United States." *Monthly Labor Review* 129:35-57.

Murray, Charles. 1984. *Losing Ground: American Social Policy, 1950-1980*. New York, NY: Basic Books.

Nam, Yunju. 2005. "The Roles of Employment Barriers in Welfare Exits and Reentries after Welfare Reform: Event History Analyses." *Social Service Review* 79:268-293.

Negrey, Cynthia, Ramona Stone, Sunhwa Lee, and Gerard M. Barber. 2007. "Mobility from Part-Time to Full-Time Employment Among Kentucky Welfare Leavers." *Journal of Poverty* 11:47-71.

O'Connor, Alice. 2000. "Poverty Research and Policy for the Post-Welfare Era." *Annual Review of Sociology* 26:547-562.

O'Neill, June A., Laurie J. Bassi, and Douglas A. Wolf. 1987. "The Duration of Welfare Spells." *Review of Economic and Statistics* 69:241-248.

Osterman, Paul. 1991. "Welfare Participation in a Full Employment Economy: The Impact of Neighborhood." *Social Problems* 38:475-491.

Parisi, Domenico, Duane A. Gill, and Michael Taquino. 2000. *Building Community Step by Step to Shoulder More Responsibility: A Procedure to Identify and Measure Community*. Starkville, MS: Mississippi State University.

Parisi, Domenico, Diane McLaughlin K., Steven Michael Grice, Michael Taquino, and Duane A. Gill. 2003. "TANF Participation Rates: Do Community Conditions Matters?" *Rural Sociology* 68:491-512.

Parisi, Domenico, Diane McLaughlin, Steven Michael Grice, and Michael Taquino. 2006. "Exiting TANF: Individual and Local Factors and Their Differential Influence across Racial Groups." *Social Science Quarterly* 87:76-90.

Pavetti, LaDonna. 1993. "The Dynamics of Welfare and Work: Exploring the Process by Which Women Work Their Way Off Welfare." Ph.D. Dissertation, Harvard University, Cambridge, MA.

Pavetti, LaDonna, and Gregory Acs. 2001. "Moving Up, Moving Out, or Going Nowhere? A Study of the Employment Patterns of Young Women and the Implications for Welfare Mothers." *Journal of Policy Analysis and Management* 20:721-736.

Pavetti, LaDonna, and Dan Bloom. 2001. "State Sanctions and Time Limits." Pp. 245-264 in *The New World of Welfare*, edited by R. Blank and R. Haskins. Washington, DC: The Brookings Institution.

Personal Responsibillity and Work Opportunity Reconciliation Act of 1996. 1996. Pub. L. No. 104-193.

Polachek, Solomon W. 1981. "Occupational Self-Selection: A Human Capital Approach to Sex Differences in Occupational Structure." *Review of Economics and Statistics* 63:60-69.

Porterfield, Shirley L. 1998. "On the Precipice of Reform: Welfare Spell Durations for Rural, Female-Headed Families." *American Journal of Agricultural Economics* 80:994-999.

Powers, Daniel A., and Yu Xie. 2008. *Statistical Methods for Categorical Data Analysis*. New York, NY: Academic Press.

Rabe-Hesketh, Sophia, Anders Skrondal, and Andrew Pickles. 2004. *GLLAMM Manual*. U.C. Berkeley Division of Biostatistics Working Paper Series. Working Paper 160. http://www.bepress.com/ucbbiostat/paper160.

Rasbash, Jon, Fiona Steele, William J. Browne, and Harvey Goldstein. 2009. *A User's Guide to MLwiN, v2.10*. Bristol, UK: Centre for Multilevel Modelling, University of Bristol.

Rank, Mark R. 1988. "Racial Differences in Length of Welfare Use." *Social Forces* 66:1080-1101.

Rank, Mark R. 2005. *One Nation, Underprivileged: Why American Poverty Affects Us All*. New York, NY: Oxford University Press.

Rank, Mark R., and Thomas A. Hirschl. 1988. "A Rural-Urban Comparison of Welfare Exits: The Importance of Population Density." *Rural Sociology* 53:190-206.

Rank, Mark R., and Thomas A. Hirschl. 1993. "The Link Between Population Density and Welfare Participation." *Demography* 30:607-622.

Raudenbush, Stephen W., and Anthony S. Bryk. 2002. *Hierarchical Linear Models: Applications and Data Analysis Methods. 2nd Edition*. Thousand Oaks, CA: Sage Publications.

Raudenbush, Stephen W., Anthony S. Bryk, Yuk Fai Cheong, and Richard T. Congdon Jr. 2004. *HLM 6: Hierarchical Linear and Nonlinear Modeling*. Lincolnwood, IL: Scientific Software International, Inc.

Reid, Lesley Williams, and Beth A. Rubin. 2003. "Integrating Economic Dualism and Labor Market Segmentation: The Effect of Race, Gender, and Structural Location on Earnings, 1974-2000." *Sociological Quarterly* 44:405-432.

Ribar, David C. 2005. "Transitions from Welfare and the Employment Prospects of Low-Skill Workers." *Southern Economic Journal* 71:514-533.

Sakamoto, Arthur, and Meichu D. Chen. 1991. "Inequality and Attainment in a Dual Labor Market." *American Sociological Review* 56:295-308.

Sampson, Robert J., Jeffrey D. Morenoff, and Thomas Gannon-Rowley. 2002. "Assessing 'Neighborhood Effects': Social Process and New Directions in Research." *Annual Review of Sociology* 28:443-478.

Sampson, Robert J. 2008. "Moving to Inequality: Neighborhood Effects and Experiments Meet Social Structure." *American Journal of Sociology* 114:189-231.

Schultz, Theodore W. 1962. "Reflections on Investment in Man." *Journal of Political Economy* 70:1-8.

Scott, Ellen K., Kathryn Edin, Andrew S. London, and Rebecca Joyce Kissane. 2004. "Unstable Work, Unstable Income: Implications for Family Well-Being in the Era of Time-Limited Welfare." *Journal of Poverty* 8:61-88.

Sharon, Hays. 2003. *Flat Broke with Children: Women in the Age of Welfare Reform*. Oxford, NY: Oxford University Press.

Sheu, Ching-Fan. 2002. "Fitting Mixed-Effect Models for Repeated Ordinal Outcomes with the NLMIXED Procedure." *Behavior Research Methods, Instruments, & Computers* 34:151-157.

Shroder, Mark. 2001. "Moving to Opportunity: An Experiment in Social and Geographic Mobility." *Cityscape: A Journal of Policy Development and Research* 5:57-67.

Singer, Judith D. 1998. "Using SAS PROC MIXED to Fit Multilevel Models, Hierarchical Models, and Individual Growth Models." *Journal of Educational and Behavioral Statistics* 24:323-355.

Singer, Judith D., and John B. Willett. 1993. "It's About Time: Using Discrete-Time Survival Analysis to Study Duration and the Timing of Events." *Journal of Education Statistics* 18:155-195.

Singer, Judith D., and John B. Willett. 2003. *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*. New York, NY: Oxford University Press.

Small, Mario Luis. 2007. "Racial Differences in Networks: Do Neighborhood Conditions Matters?" *Social Science Quarterly* 88:320-343.

Small, Mario Luis, and Katherine Newman. 2001. "Urban Poverty after The Truly Disadvantaged: The Rediscovery of the Family, the Neighborhood, and Culture." *Annual Review of Sociology* 27:23-45.

Social Security Act of 1935. 1935. Pub. L. No. 74-271.

Spiegelhalter, David, Andrew Thomas, Nicky Best, and Dave Lunn. 2003. *WinBUGS User Manual Version 1.4*. Cambridge, UK: Medical Research Council Biostatistics Unit.

Steele, Fiona, Ian Diamond, and Duolao Wang. 1996. "The Determinants of the Duration of Contraceptive Use in China: A Multilevel Multinomial Discrete-Hazards Modeling Approach." *Demography* 33:12-23.

Steele, Fiona, Harvey Goldstein, and William Browne. 2004. "A General Multilevel Multistate Competing Risks Model for Event History Data, with an Application to a Study of Contraceptive Use Dynamics." *Statistical Modeling* 4:145-159.

Teitler, Julien O., Nancy E. Reichman, and Lenna Nepomnyaschy. 2007. "Determinants of TANF Participation: A Multilevel Analysis." *Social Service Review* 81:633-656.

Tolbert, Charles, Patrick M. Horan, and E. M. Beck. 1980. "The Structure of Economic Segmentation: A Dual Economy Approach." *American Journal of Sociology* 85:1095-1116.

Tomaskovic-Devey, Donald, Melvin Thomas, and Kecia Johnson. 2005. "Race and the Accumulation of Human Capital across the Career: A Theoretical Model and Fixed-Effects Application." *American Journal of Sociology* 111:58-59.

Trattner, Walter I. 1999. *From Poor Law to Welfare State: A History of Social Welfare in America*. *Sixth Edition*. New York, NY: Free Press.

Turner, Lesley J., Sheldon Danziger, Kristin S. Seefeldt. 2006. "Failing the Transition from Welfare to Work: Women Chronically Disconnected from Employment and Cash Welfare." *Social Science Quarterly* 87:227-249.

U.S. Bureau of Labor Statistics (BLS). 2009. "A Profile of the Working Poor, 2007." *Report* 1012:1-14. U.S. Washington DC: Author. http://www.bls.gov/cps/cpswp2007.pdf. Accessed June 21, 2010.

U.S. Department of Health and Human Services (HHS). 2008. "Reauthorization of the Temporary Assistance for Needy Families (TANF) Program." *Federal Register* 73:6772-6828.

U.S. Department of Health and Human Services (HHS). 2009a. *Temporary Assistance for Needy Families (TANF) Program, Eighth Annual Report to Congress*. Washington, DC: Author. http://www.acf.hhs.gov/programs/ofa/data-reports/index.htm. Accessed June 21, 2010.

U.S. Department of Health and Human Services (HHS). 2009b. *Indicators of Welfare Dependence: Annual Report to Congress 2008*. Washington, DC: Author. http://aspe.hhs.gov/hsp/indicators-rtc/index.shtml. Accessed June 21, 2010.

U.S. Government Accountability Office (GAO). 2004. *TANF and SSI: Opportunities Exist to Help People with Impairments Become More Self-Sufficient*. Washington, DC: Author. http://www.gao.gov/new.items/d04878.pdf. Accessed June 21, 2010.

U.S. Social Security Administration. 2010. *Historical Background and Development of Social Security*. Washington, DC: Author. http://www.socialsecurity.gov/history/index.html. Accessed June 21, 2010.

Urban Institute. 2009. *Welfare Rules Databook: State TANF Polices. Between 1999 and 2008*. Washington, DC: Author. http://anfdata.urban.org/wrd/databook.cfm. Accessed June 21, 2010.

Van Ness, Peter H., John O'Leary, Amy L. Byers, Terri R. Fried, and Joel Dubin. 2004. "Fitting Longitudinal Mixed Effect Logistic Regression Models with the NLMIXED Procedure." Paper 190 in *Proceedings of the Twenty-Ninth Annual SAS Users Group International Conference*. Cary, NC: SAS Institute Inc.

Wao, Hesborn O. 2010. "Time to the Doctorate: Multilevel Discrete-Time Hazard Analysis." *Educational Assessment, Evaluation and Accountability* 22:227-247.

Weber, Bruce, Greg J. Duncan, and Leslie A. Whitener. 2001. "Welfare Reform in Rural America: What have We Learned?" *American Journal of Agricultural Economics* 83:1282-1292.

Weber, Bruce, Leif Jensen, Kathleen Miller, Jane Mosley, and Monica Fisher. 2005. "A Critical Review of Rural Poverty Literature: Is There True a Rural Effect?" *International Regional Science Review* 28:381-414.

Weinberg, Bruce A., Paricia B. Reagan, and Jeffrey J. Yankow. 2004. "Do Neighborhoods Affect Hours Worked? Evidence from Longitudinal Data." *Journal of Labor Economics* 22:891-924.

Welch, Finis. 1975. "Human Capital Theory: Education, Discrimination, and Life Cycles." *American Economic Review* 65:63-73.

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

Wilson, William Julius. 1991. "Studying Inner-City Social Dislocations: The Challenge of Public Agenda Research." *American Sociological Review* 56:1-12.

Wilson, William Julius. 1993. "The Underclass: Issues, Perspectives, and Public Policy." Pp. 1-24 in *The Ghetto Underclass: Social Science Perspectives*, edited by William Julius Wilson. Newbury Park, CA: Sage Publications.

Wilson, William Julius. 1996. *When Work Disappears: The World of the New Urban Poor*. New York, NY: Random House.

Zafirovski, Milan. 2000. "The Rational Choice Generalization of Neoclassical Economics Reconsidered: Any Theoretical Legitimation for Economic Imperialism?" *Sociological Theory* 18:448-471.

Ziliak, James P., David N. Figlio, Elizabeth E. Davis, and Laura S. Connolly. 2000. "Accounting for the Decline in AFDC Caseloads: Welfare Reform or the Economy?" *Journal of Human Resources* 35:570-586.

APPENDIX A

DATA USED TO CREATE FIGURES

Table A.1 Average Monthly AFDC/TANF Families and Recipients (in 1000) in the United States, 1936-2009

Years	Families	Recipients	Years	Families	Recipients
1936	147	534	1973	3,138	11,003
1937	194	674	1974	3,187	10,826
1938	258	895	1975	3,415	11,203
1939	305	1,042	1976	3,562	11,339
1940	349	1,182	1977	3,575	11,108
1941	387	1,319	1978	3,528	10,663
1942	387	1,317	1979	3,496	10,311
1943	304	1,050	1980	3,642	10,597
1944	260	910	1981	3,871	11,160
1945	259	907	1982	3,569	10,431
1946	312	1,112	1983	3,651	10,659
1947	393	1,394	1984	3,725	10,866
1948	449	1,595	1985	3,692	10,813
1949	541	1,918	1986	3,748	10,997
1950	644	2,205	1987	3,784	11,065
1951	621	2,134	1988	3,748	10,920
1952	583	2,022	1989	3,771	10,934
1953	560	1,970	1990	3,974	11,460
1954	580	2,076	1991	4,374	12,592
1955	612	2,214	1992	4,768	13,625
1956	611	2,239	1993	4,981	14,143
1957	645	2,395	1994	5,046	14,226
1958	724	2,719	1995	4,871	13,660
1959	774	2,920	1996	4,543	12,645
1960	785	2,982	1997	3,937	10,935
1961	845	3,241	1998	3,200	8,790
1962	933	3,642	1999	2,674	7,188
1963	957	3,903	2000	2,265	5,943
1964	996	4,125	2001	2,117	5,423
1965	1,049	4,375	2002	2,065	5,148
1966	1,083	4,501	2003	2,032	4,967
1967	1,178	4,855	2004	1,987	4,784
1968	1,355	5,516	2005	1,921	4,549
1969	1,612	6,400	2006	1,795	4,198
1970	2,045	7,898	2007	1,754	4,138
1971	2,661	9,955	2008	1,697	3,991
1972	2,990	10,815	2009	1,723	4,027

NOTE: 1936-1959 for calendar year; 1960-2009 for fiscal year.
Source: U.S. Department of Health and Human Services.

Table A.2 Average Monthly AFDC/TANF Families and Recipients in Mississippi, Fiscal Years 1960-2009

Years	Families	Recipients	Years	Families	Recipients
1960	19,586	75,925	1985	51,922	154,776
1961	20,442	79,688	1986	53,334	159,804
1962	20,466	80,225	1987	58,017	174,578
1963	20,333	80,453	1988	59,682	179,730
1964	20,680	82,024	1989	59,860	178,834
1965	20,698	82,903	1990	60,023	178,588
1966	20,673	84,305	1991	60,106	177,390
1967	21,850	90,692	1992	60,810	177,325
1968	24,583	101,092	1993	60,079	171,745
1969	26,325	105,000	1994	56,785	158,743
1970	30,325	118,583	1995	52,528	144,148
1971	35,757	137,696	1996	47,954	129,052
1972	42,634	158,851	1997	38,513	102,284
1973	48,223	176,094	1998	23,700	60,097
1974	51,881	184,622	1999	16,644	38,746
1975	54,197	187,089	2000	14,970	33,801
1976	54,504	183,490	2001	15,657	35,710
1977	52,914	174,258	2002	17,607	40,434
1978	52,598	167,860	2003	19,823	45,743
1979	55,163	171,311	2004	18,795	42,459
1980	57,691	173,052	2005	16,060	34,695
1981	60,139	176,255	2006	13,417	27,833
1982	52,015	151,088	2007	11,603	23,556
1983	51,814	151,177	2008	11,268	23,026
1984	N.A.	N.A.	2009	11,295	23,490

Source: Based on data from the U.S. Department of Health and Human Services at U.S. Social Security Administration. Available online at http://www.acf.hhs.gov/programs/ofa/data-reports/.

Table A.3 Employment Rates among Single Mothers under 200 Percent of Poverty in the United States, Fiscal Years 2002-2006

Year	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
With kids under 18	44	45.4	46.3	45.7	44.1	46	46.1	48.2	51.1	54.4
With kids under 6	34.73	36.4	38.34	37.2	34.8	39.1	39.4	42.6	44.4	50.4
Year	1998	1999	2000	2001	2002	2003	2004	2005	2006	
With kids under 18	56.6	59	60.8	60.1	59.3	56.4	57.3	56.2	57.7	
With kids under 6	51.1	54.6	58.5	55.9	57.3	53.7	54	52.7	55.4	

Source: Cited from TANF Annual Report, tabulated by ASPE using data from the CPS, U.S. Census Bureau.

Table A.4 Labor Force Participation of Non-Married Women with Children under 18 Years in the United States, by Educational Attainment, 1994-2005

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
College graduates	90.9	90.7	91.4	91.0	91.7	92.2	90.9	91.6	91.4	90.5	90.1	89.2
Some college or associate's degree	78.2	79.4	80.9	82.9	84.1	85.4	85.3	84.5	84.6	83.4	82.3	81.9
High school graduates, no college	68.8	71.5	74.2	77.7	78.4	79.5	79.5	79.1	79.0	78.0	77.7	76.4
Less than high school diploma	42.8	44.6	47.8	52.2	56.4	58.3	61.2	60.6	60.9	58.3	57.7	56.1

Source: Mosisa and Hipple (2006: Table 11).

Table A.5 Average Monthly Number of Recipients of TANF/AFDC in Mississippi and the United States, as a Percent of Total Population, Selected Fiscal Years 1960 to 2009

	1960	1970	1980	1990	1994	1996	2000	2006	2009
U.S.	1.6	4.0	4.7	4.6	5.4	4.7	2.1	1.5	1.3
Mississippi	3.5	5.6	6.9	6.9	5.8	4.8	1.2	0.9	0.8

NOTE: 1) Recipiency rates reflect the calendar year average caseloads divided by the population as enumerated by the decennial Census for 1960, 1970, 1990, and 2000.
2) Recipiency rates for 1994, 1996, 2006, and 2009 reflect fiscal year average caseloads divided by the Census estimate of the population for July 1 of each year.

Source: Table updated from *Green Book 2008* (Committee on Ways and Means 2008), Section 7 "Temporary Assistance for Needy Families" (Table 7-9), based on data from the U.S. Department of Health and Human Services (HHS) and the U.S. Census Bureau.

Table A.6 TANF Workforce Participation Rates in Mississippi and the United States, Fiscal Years 1997 to 2008

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
U.S.	30.7	35.3	38.3	34.0	34.4	33.4	31.3	32.0	33.0	32.5	29.7	29.4
Mississippi	17.2	25.2	27.0	17.8	20.9	18.5	17.2	21.0	22.6	35.5	61.9	63.2

Source: Based on data from the U.S. Department of Health and Human Services at U.S. Social Security Administration. Available online at http://www.acf.hhs.gov/programs/ofa/data-reports/ (TANF Home > Data & Reports > Work Participation Rates)

Table A.7 Profile of Monthly TANF Caseload in Mississippi, 1996-2010

	All Caseload					Adult Caseload					
Year/Month	Total	Adult	Child-Only	Black	White	White	Black	Age 18-24	Age 25-29	Age >=30	Worked
1996/10	49,925	34,309	15,616	42,006	7,599	5,287	28,809	12,773	7,585	13,951	3,783
1996/11	48,881	33,350	15,531	41,206	7,368	5,099	28,042	12,418	7,377	13,555	3,586
1996/12	47,890	32,654	15,236	40,524	7,158	4,947	27,566	12,094	7,257	13,303	3,452
1997/1	47,056	32,325	14,731	39,811	7,034	4,860	27,351	11,774	7,204	13,347	3,291
1997/2	46,446	32,013	14,433	39,228	6,983	4,864	27,017	11,650	7,107	13,256	2,751
1997/3	45,506	31,392	14,114	38,464	6,803	4,734	26,524	11,447	6,973	12,972	2,700
1997/4	44,313	30,420	13,893	37,580	6,499	4,453	25,834	10,975	6,755	12,690	2,577
1997/5	43,062	29,440	13,622	36,625	6,207	4,210	25,102	10,586	6,540	12,314	2,407
1997/6	43,062	29,440	13,622	36,625	6,207	4,210	25,102	10,470	6,563	12,407	2,407
1997/7	38,143	27,175	10,968	32,643	5,315	3,623	23,455	9,279	6,157	11,739	3,110
1997/8	37,252	26,439	10,813	31,892	5,186	3,547	22,799	8,945	6,055	11,439	3,112
1997/9	35,934	25,287	10,647	30,828	4,943	3,346	21,858	8,497	5,780	11,010	3,109
1997/10	34,546	24,021	10,525	29,672	4,713	3,134	20,808	8,063	5,508	10,450	3,467
1997/11	33,256	22,799	10,457	28,541	4,560	2,991	19,737	7,673	5,193	9,933	4,390
1997/12	31,853	21,499	10,354	27,343	4,368	2,805	18,629	7,299	4,877	9,323	4,188
1998/1	31,853	21,499	10,354	27,343	4,368	2,805	18,629	7,209	4,898	9,392	4,188
1998/2	29,582	19,626	9,956	25,424	4,016	2,511	17,043	6,673	4,386	8,567	4,063
1998/3	28,536	18,728	9,808	24,494	3,894	2,409	16,243	6,350	4,192	8,186	4,021
1998/4	27,321	17,640	9,681	23,427	3,757	2,283	15,286	5,960	3,944	7,736	3,947
1998/5	26,343	16,797	9,546	22,597	3,608	2,165	14,558	5,710	3,781	7,306	3,778
1998/6	25,254	15,753	9,501	21,667	3,446	2,019	13,655	5,362	3,536	6,855	3,598
1998/7	24,183	14,864	9,319	20,758	3,293	1,897	12,896	5,040	3,339	6,485	3,263
1998/8	23,798	14,504	9,294	20,374	3,300	1,921	12,518	4,957	3,270	6,277	3,225
1998/9	22,444	13,341	9,103	19,160	3,146	1,801	11,464	4,669	2,997	5,675	3,042

Table A.7 (Continued)

	All Caseload					Adult Caseload					
Year/Month	Total	Adult	Child-Only	Black	White	White	Black	Age 18-24	Age 25-29	Age >=30	Worked
1998/10	22,444	13,341	9,103	19,160	3,146	1,801	11,464	4,602	3,028	5,711	3,042
1998/11	21,937	12,914	9,023	18,733	3,072	1,752	11,094	4,539	2,883	5,492	2,934
1998/12	21,241	12,389	8,852	18,168	2,950	1,651	10,676	4,367	2,774	5,248	2,825
1999/1	20,624	11,897	8,727	17,656	2,849	1,574	10,263	4,222	2,664	5,011	2,789
1999/2	19,803	11,144	8,659	16,933	2,749	1,468	9,614	3,950	2,486	4,708	2,583
1999/3	19,027	10,492	8,535	16,258	2,647	1,406	9,023	3,731	2,347	4,414	2,572
1999/4	18,404	9,982	8,422	15,731	2,563	1,365	8,557	3,617	2,198	4,167	2,748
1999/5	17,742	9,354	8,388	15,141	2,491	1,290	8,005	3,437	2,030	3,887	2,596
1999/6	17,238	8,903	8,335	14,707	2,426	1,238	7,611	3,353	1,942	3,608	2,426
1999/7	17,082	8,830	8,252	14,541	2,436	1,243	7,529	3,400	1,906	3,524	2,291
1999/8	17,271	8,939	8,332	14,678	2,502	1,276	7,616	3,465	1,971	3,503	2,224
1999/9	17,258	8,882	8,376	14,680	2,480	1,245	7,584	3,471	1,955	3,456	2,145
1999/10	17,693	9,236	8,457	15,013	2,577	1,316	7,866	3,663	2,031	3,542	2,370
1999/11	17,517	9,078	8,439	14,819	2,592	1,324	7,694	3,683	1,981	3,414	2,246
1999/12	17,364	8,966	8,398	14,671	2,596	1,330	7,582	3,647	1,985	3,334	2,129
2000/1	17,104	8,765	8,340	14,427	2,584	1,328	7,382	3,623	1,916	3,226	2,021
2000/2	16,844	8,563	8,281	14,182	2,571	1,326	7,182	3,598	1,847	3,118	1,912
2000/3	16,844	8,563	8,281	14,182	2,571	1,326	7,182	3,558	1,862	3,143	1,912
2000/4	16,881	8,581	8,300	14,215	2,572	1,314	7,211	3,713	1,875	2,993	1,981
2000/5	16,622	8,536	8,086	13,989	2,534	1,322	7,152	3,697	1,908	2,931	1,891
2000/6	16,840	8,736	8,104	14,149	2,592	1,370	7,302	3,806	1,922	3,008	1,936
2000/7	16,719	8,672	8,047	14,035	2,583	1,359	7,248	3,811	1,903	2,958	1,827
2000/8	16,642	8,595	8,047	13,929	2,612	1,395	7,134	3,846	1,849	2,900	1,566
2000/9	16,721	8,703	8,018	14,001	2,620	1,398	7,240	3,943	1,853	2,907	1,449

Table A.7 (Continued)

	All Caseload					Adult Caseload					
Year/Month	Total	Adult	Child-Only	Black	White	White	Black	Age 18-24	Age 25-29	Age >=30	Worked
2000/10	16,765	8,750	8,015	13,990	2,673	1,427	7,257	4,010	1,860	2,880	1,429
2000/11	16,517	8,556	7,961	13,796	2,626	1,388	7,108	3,960	1,806	2,790	1,340
2000/12	16,507	8,550	7,957	13,777	2,629	1,364	7,124	4,033	1,795	2,722	1,304
2001/1	16,208	8,353	7,855	13,477	2,633	1,384	6,907	3,980	1,710	2,663	1,136
2001/2	15,934	8,100	7,834	13,286	2,557	1,310	6,735	3,928	1,651	2,521	977
2001/3	16,093	8,294	7,799	13,368	2,625	1,383	6,848	4,032	1,665	2,597	1,044
2001/4	16,243	8,399	7,844	13,488	2,650	1,395	6,938	4,096	1,703	2,600	981
2001/5	16,295	8,430	7,865	13,585	2,613	1,356	7,016	4,170	1,676	2,584	965
2001/6	16,584	8,692	7,892	13,789	2,686	1,415	7,207	4,300	1,781	2,611	966
2001/7	16,758	8,938	7,820	13,919	2,731	1,465	7,402	4,425	1,876	2,637	964
2001/8	17,184	9,333	7,851	14,221	2,850	1,576	7,686	4,627	1,970	2,736	955
2001/9	17,653	9,751	7,902	14,595	2,949	1,640	8,046	4,882	2,048	2,821	1,059
2001/10	17,918	10,021	7,897	14,814	2,986	1,665	8,286	5,021	2,146	2,854	1,064
2001/11	18,056	10,172	7,884	14,929	3,009	1,692	8,412	5,114	2,149	2,909	1,077
2001/12	18,268	10,398	7,870	15,116	3,031	1,729	8,597	5,270	2,199	2,929	1,111
2002/1	18,007	10,183	7,824	14,900	2,993	1,686	8,432	5,196	2,139	2,848	1,025
2002/2	17,983	10,185	7,798	14,882	2,987	1,683	8,438	5,245	2,127	2,813	989
2002/3	17,927	10,168	7,759	14,801	3,004	1,697	8,400	5,230	2,134	2,804	989
2002/4	17,910	10,177	7,733	14,824	2,965	1,655	8,453	5,272	2,111	2,794	929
2002/5	17,949	10,203	7,746	14,881	2,954	1,632	8,505	5,276	2,138	2,789	895
2002/6	18,213	10,433	7,780	15,107	2,983	1,650	8,708	5,428	2,198	2,807	924
2002/7	18,374	10,598	7,776	15,263	3,003	1,665	8,867	5,460	2,291	2,847	895
2002/8	19,078	11,267	7,811	15,808	3,154	1,814	9,384	5,783	2,460	3,024	897
2002/9	19,812	11,940	7,872	16,398	3,287	1,930	9,931	6,081	2,627	3,232	945

Table A.7 (Continued)

	All Caseload					Adult Caseload					
Year/Month	Total	Adult	Child-Only	Black	White	White	Black	Age 18-24	Age 25-29	Age >=30	Worked
2002/10	20,285	12,376	7,909	16,775	3,380	2,017	10,280	6,309	2,715	3,352	960
2002/11	20,652	12,707	7,945	17,071	3,453	2,078	10,558	6,455	2,790	3,462	967
2002/12	20,607	12,680	7,927	17,081	3,404	2,032	10,580	6,417	2,769	3,494	920
2003/1	20,352	12,459	7,893	16,825	3,410	2,038	10,355	6,309	2,697	3,453	853
2003/2	20,107	12,249	7,858	16,629	3,356	1,973	10,208	6,248	2,621	3,380	830
2003/3	19,926	12,103	7,823	16,518	3,292	1,921	10,122	6,211	2,603	3,289	882
2003/4	19,650	11,855	7,795	16,286	3,254	1,885	9,911	6,095	2,602	3,158	922
2003/5	19,799	12,007	7,792	16,425	3,274	1,901	10,054	6,177	2,615	3,215	894
2003/6	20,085	12,267	7,818	16,649	3,332	1,932	10,277	6,280	2,677	3,310	932
2003/7	19,981	12,181	7,800	16,568	3,310	1,904	10,221	6,228	2,673	3,280	887
2003/8	20,372	12,571	7,801	16,891	3,376	1,966	10,543	6,391	2,787	3,393	926
2003/9	20,258	12,419	7,839	16,765	3,380	1,952	10,401	6,333	2,772	3,314	933
2003/10	20,269	12,436	7,833	16,792	3,361	1,934	10,435	6,318	2,772	3,346	918
2003/11	20,424	12,520	7,904	16,912	3,395	1,932	10,521	6,358	2,803	3,359	971
2003/12	20,117	12,208	7,909	16,636	3,370	1,915	10,227	6,214	2,763	3,231	894
2004/1	19,741	11,900	7,841	16,343	3,287	1,839	9,994	6,073	2,683	3,144	842
2004/2	19,495	11,692	7,803	16,130	3,244	1,802	9,814	6,018	2,603	3,071	788
2004/3	19,046	11,277	7,769	15,734	3,197	1,764	9,445	5,769	2,532	2,976	738
2004/4	18,896	11,148	7,748	15,623	3,150	1,725	9,350	5,755	2,440	2,953	748
2004/5	18,760	11,029	7,731	15,525	3,106	1,680	9,271	5,710	2,436	2,883	743
2004/6	18,585	10,865	7,720	15,385	3,079	1,664	9,131	5,584	2,448	2,833	779
2004/7	18,483	10,757	7,726	15,281	3,086	1,653	9,036	5,513	2,414	2,830	829
2004/8	18,261	10,568	7,693	15,047	3,093	1,651	8,849	5,378	2,387	2,803	751
2004/9	18,014	10,328	7,686	14,859	3,044	1,595	8,672	5,270	2,356	2,702	721

Table A.7 (Continued)

Year/Month	All Caseload Total	All Caseload Adult	All Caseload Child-Only	All Caseload Black	All Caseload White	Adult Caseload White	Adult Caseload Black	Adult Caseload Age 18-24	Adult Caseload Age 25-29	Adult Caseload Age >=30	Adult Caseload Worked
2004/10	17,926	10,259	7,667	14,746	3,063	1,604	8,589	5,216	2,355	2,688	752
2004/11	17,670	10,004	7,666	14,503	3,052	1,582	8,364	5,096	2,265	2,643	759
2004/12	17,488	9,793	7,695	14,361	3,018	1,532	8,208	5,023	2,219	2,551	761
2005/1	17,154	9,504	7,650	14,053	2,990	1,506	7,943	4,880	2,169	2,455	743
2005/2	16,484	8,933	7,551	13,494	2,878	1,401	7,477	4,613	2,073	2,247	688
2005/3	16,013	8,534	7,479	13,137	2,767	1,316	7,165	4,488	1,929	2,117	635
2005/4	15,800	8,376	7,424	12,997	2,700	1,278	7,051	4,429	1,878	2,069	720
2005/5	15,763	8,340	7,423	12,954	2,706	1,278	7,015	4,305	1,971	2,064	723
2005/6	15,853	8,454	7,399	13,024	2,727	1,300	7,113	4,350	2,019	2,085	729
2005/7	15,920	8,557	7,363	13,093	2,723	1,311	7,203	4,399	2,054	2,104	739
2005/8	15,819	8,460	7,359	12,940	2,771	1,344	7,070	4,338	2,035	2,087	691
2005/9	15,277	8,036	7,241	12,569	2,615	1,212	6,791	4,117	1,917	2,002	606
2005/10	15,193	7,952	7,241	12,469	2,628	1,217	6,700	4,094	1,922	1,936	619
2005/11	15,158	7,843	7,315	12,467	2,588	1,154	6,647	4,075	1,867	1,901	655
2005/12	14,990	7,652	7,338	12,305	2,576	1,130	6,478	3,979	1,839	1,834	638
2006/1	14,687	7,458	7,229	12,029	2,546	1,125	6,288	3,938	1,741	1,779	652
2006/2	14,105	7,014	7,091	11,578	2,425	1,035	5,938	3,695	1,652	1,667	596
2006/3	13,748	6,779	6,969	11,265	2,385	1,019	5,720	3,586	1,595	1,598	588
2006/4	13,495	6,603	6,892	11,067	2,331	982	5,578	3,470	1,561	1,572	597
2006/5	13,345	6,467	6,878	10,948	2,306	954	5,479	3,441	1,511	1,515	557
2006/6	13,360	6,479	6,881	11,016	2,257	912	5,534	3,407	1,538	1,534	527
2006/7	13,420	6,525	6,895	11,043	2,288	947	5,547	3,456	1,563	1,506	500
2006/8	13,476	6,536	6,940	11,044	2,326	988	5,500	3,486	1,559	1,491	515
2006/9	13,476	6,536	6,940	11,044	2,326	988	5,500	3,431	1,607	1,498	515

Table A.7 (Continued)

	All Caseload					Adult Caseload					
Year/Month	Total	Adult	Child-Only	Black	White	White	Black	Age 18-24	Age 25-29	Age >=30	Worked
2006/10	13,002	6,184	6,818	10,705	2,189	869	5,264	3,359	1,502	1,323	506
2006/11	12,866	6,037	6,829	10,576	2,183	841	5,142	3,332	1,467	1,238	489
2006/12	12,579	5,818	6,761	10,374	2,104	775	4,993	3,251	1,407	1,160	431
2007/1	12,186	5,555	6,631	10,053	2,034	725	4,779	3,144	1,353	1,058	388
2007/2	11,922	5,365	6,557	9,819	2,009	713	4,611	3,050	1,295	1,020	383
2007/3	11,847	5,340	6,507	9,735	2,011	731	4,562	3,031	1,297	1,012	376
2007/4	11,799	5,313	6,486	9,725	1,982	708	4,568	3,025	1,282	1,006	383
2007/5	11,894	5,405	6,489	9,806	2,001	725	4,647	3,088	1,316	1,001	388
2007/6	12,026	5,527	6,499	9,892	2,050	752	4,741	3,109	1,351	1,067	378
2007/7	12,093	5,615	6,478	9,941	2,070	758	4,827	3,175	1,371	1,069	423
2007/8	12,379	5,860	6,519	10,171	2,120	793	5,042	3,271	1,474	1,115	524
2007/9	12,429	5,989	6,440	10,256	2,084	787	5,171	3,351	1,515	1,123	466
2007/10	12,546	6,097	6,449	10,330	2,121	813	5,251	3,399	1,535	1,163	471
2007/11	12,420	6,041	6,379	10,233	2,093	794	5,218	3,422	1,522	1,097	529
2007/12	12,192	5,845	6,347	10,015	2,075	784	5,034	3,275	1,493	1,077	472
2008/1	11,904	5,676	6,228	9,778	2,019	752	4,888	3,198	1,426	1,052	409
2008/2	11,658	5,485	6,173	9,570	1,981	714	4,739	3,149	1,358	978	406
2008/3	11,632	5,513	6,119	9,546	1,979	729	4,751	3,142	1,374	997	410
2008/4	11,767	5,677	6,090	9,675	1,984	738	4,906	3,242	1,433	1,002	428
2008/5	11,881	5,804	6,077	9,803	1,965	733	5,034	3,308	1,477	1,019	440
2008/6	11,981	5,938	6,043	9,891	1,972	747	5,152	3,393	1,496	1,049	445
2008/7	12,198	6,166	6,032	10,084	1,988	792	5,327	3,505	1,539	1,122	446
2008/8	12,335	6,311	6,024	10,149	2,059	854	5,412	3,578	1,563	1,170	475
2008/9	12,283	6,322	5,961	10,149	2,015	840	5,443	3,567	1,594	1,161	417

Table A.7 (Continued)

	All Caseload					Adult Caseload					
Year/Month	Total	Adult	Child-Only	Black	White	White	Black	Age 18-24	Age 25-29	Age >=30	Worked
2008/10	12,442	6,458	5,984	10,270	2,045	848	5,567	3,607	1,647	1,204	440
2008/11	12,335	6,431	5,904	10,175	2,031	849	5,533	3,587	1,627	1,217	416
2008/12	12,202	6,354	5,848	10,061	2,012	839	5,464	3,557	1,577	1,220	345
2009/1	11,947	6,166	5,781	9,813	1,998	831	5,284	3,484	1,524	1,158	326
2009/2	11,711	6,001	5,710	9,628	1,942	792	5,162	3,431	1,485	1,085	292
2009/3	11,684	6,005	5,679	9,593	1,957	809	5,156	3,401	1,517	1,087	307
2009/4	11,738	6,058	5,680	9,686	1,915	773	5,246	3,441	1,553	1,064	281
2009/5	11,952	6,298	5,654	9,847	1,962	803	5,451	3,567	1,609	1,122	270
2009/6	12,159	6,484	5,675	10,028	1,978	823	5,614	3,661	1,637	1,186	287
2009/7	12,446	6,752	5,694	10,271	2,028	857	5,849	3,792	1,710	1,250	283
2009/8	12,895	7,186	5,709	10,623	2,131	931	6,205	4,044	1,788	1,354	297
2009/9	13,082	7,417	5,665	10,821	2,116	929	6,443	4,263	1,808	1,346	303
2009/10	13,488	7,821	5,667	11,174	2,164	983	6,790	4,484	1,901	1,436	324
2009/11	13,470	7,830	5,640	11,169	2,137	957	6,818	4,508	1,886	1,436	308
2009/12	13,386	7,773	5,613	11,085	2,128	951	6,766	4,519	1,834	1,420	263
2010/1	13,106	7,593	5,513	10,843	2,086	912	6,623	4,399	1,826	1,368	263
2010/2	12,726	7,275	5,451	10,510	2,025	870	6,345	4,254	1,737	1,284	268
2010/3	12,778	7,312	5,466	10,559	2,023	861	6,393	4,270	1,752	1,290	282
2010/4	12,954	7,464	5,490	10,735	2,031	863	6,544	4,359	1,806	1,299	296
2010/5	12,934	7,489	5,445	10,710	2,036	865	6,572	4,346	1,845	1,298	330
2010/6	12,974	7,541	5,433	10,741	2,044	874	6,611	4,318	1,893	1,330	333

Source: MDHS welfare data sets.
NOTE: Five pair of months have the same data input, including 1997/5 and 1997/6, 1997/12 and 1998/1, 1998/9 and 1998/10, 2000/2 and 2000/3, and 2006/8 and 2006/9.

Table A.8 Monthly Net Change of Adult TANF Clients in Mississippi, 1996-2010

Year/ Month	Newly Entered	Drop Out	Year/ Month	Newly Entered	Drop Out	Year/ Month	Newly Entered	Drop Out
1996/11	2,026	3,010	2000/1	1,577	1,810	2003/3	1,463	1,645
1996/12	2,222	2,917	2000/2	1,577	1,810	2003/4	1,448	1,711
1997/1	2,369	2,683	2000/3	1,577	1,810	2003/5	1,497	1,350
1997/2	2,184	2,483	2000/4	1,577	1,810	2003/6	1,817	1,552
1997/3	2,194	2,809	2000/5	1,175	1,421	2003/7	1,641	1,760
1997/4	1,918	2,887	2000/6	1,366	1,272	2003/8	1,941	1,555
1997/5	1,890	2,854	2000/7	1,302	1,525	2003/9	1,634	1,798
1997/6	2,210	2,964	2000/8	1,436	1,709	2003/10	1,739	1,722
1997/7	2,397	3,875	2000/9	1,488	1,480	2003/11	1,669	1,606
1997/8	1,964	2,711	2000/10	1,444	1,532	2003/12	1,392	1,728
1997/9	1,927	3,089	2000/11	1,229	1,523	2004/1	1,385	1,706
1997/10	1,929	3,204	2000/12	1,210	1,282	2004/2	1,369	1,612
1997/11	1,750	3,012	2001/1	1,074	1,360	2004/3	1,339	1,779
1997/12	1,612	2,924	2001/2	1,059	1,387	2004/4	1,469	1,601
1998/1	1,460	2,381	2001/3	1,382	1,235	2004/5	1,471	1,609
1998/2	1,460	2,381	2001/4	1,304	1,224	2004/6	1,448	1,629
1998/3	1,639	2,528	2001/5	1,262	1,265	2004/7	1,529	1,652
1998/4	1,505	2,623	2001/6	1,424	1,166	2004/8	1,547	1,770
1998/5	1,473	2,304	2001/7	1,521	1,285	2004/9	1,497	1,747
1998/6	1,542	2,603	2001/8	1,584	1,195	2004/10	1,553	1,645
1998/7	1,578	2,467	2001/9	1,729	1,328	2004/11	1,285	1,562
1998/8	1,789	2,133	2001/10	1,661	1,393	2004/12	1,269	1,484
1998/9	1,316	1,855	2001/11	1,473	1,348	2005/1	1,151	1,450
1998/10	1,316	1,855	2001/12	1,480	1,250	2005/2	1,021	1,594
1998/11	1,312	1,698	2002/1	1,277	1,501	2005/3	1,080	1,496
1998/12	1,259	1,733	2002/2	1,266	1,257	2005/4	1,197	1,346
1999/1	1,195	1,666	2002/3	1,330	1,363	2005/5	1,383	1,421
1999/2	1,085	1,799	2002/4	1,509	1,518	2005/6	1,523	1,413
1999/3	1,097	1,739	2002/5	1,383	1,365	2005/7	1,478	1,378
1999/4	1,189	1,668	2002/6	1,593	1,383	2005/8	1,455	1,558
1999/5	967	1,561	2002/7	1,667	1,535	2005/9	1,232	1,679
1999/6	1,177	1,570	2002/8	1,958	1,277	2005/10	1,113	1,203
1999/7	1,325	1,287	2002/9	2,073	1,408	2005/11	1,097	1,209
1999/8	1,561	1,310	2002/10	1,958	1,497	2005/12	1,045	1,246
1999/9	1,481	1,365	2002/11	1,815	1,492	2006/1	1,046	1,235
1999/10	1,812	1,223	2002/12	1,501	1,551	2006/2	921	1,377
1999/11	1,342	1,314	2003/1	1,412	1,645	2006/3	1,089	1,333
1999/12	1,425	1,291	2003/2	1,253	1,460	2006/4	1,111	1,287

Table A.8 (Continued)

Year/ Month	Newly Entered	Drop Out	Year/ Month	Newly Entered	Drop Out	Year/ Month	Newly Entered	Drop Out
2006/5	1,106	1,247	2007/10	1,122	1,012	2009/3	966	953
2006/6	1,250	1,241	2007/11	961	1,026	2009/4	1,056	1,002
2006/7	1,267	1,229	2007/12	824	1,025	2009/5	1,181	943
2006/8	1,236	1,236	2008/1	888	1,054	2009/6	1,329	1,140
2006/9	832	1,013	2008/2	842	1,037	2009/7	1,371	1,095
2006/10	832	1,013	2008/3	986	956	2009/8	1,507	1,079
2006/11	885	1,043	2008/4	1,091	929	2009/9	1,406	1,178
2006/12	741	967	2008/5	1,098	975	2009/10	1,519	1,114
2007/1	725	990	2008/6	1,113	982	2009/11	1,289	1,282
2007/2	677	868	2008/7	1,272	1,049	2009/12	1,108	1,162
2007/3	830	854	2008/8	1,274	1,122	2010/1	1,004	1,186
2007/4	902	924	2008/9	1,264	1,257	2010/2	890	1,217
2007/5	895	802	2008/10	1,318	1,178	2010/3	1,132	1,093
2007/6	945	832	2008/11	1,123	1,153	2010/4	1,267	1,116
2007/7	1,008	914	2008/12	1,024	1,100	2010/5	1,160	1,134
2007/8	1,148	898	2009/1	941	1,139	2010/6	1,244	1,191
2007/9	1,126	998	2009/2	843	1,009			

Source: MDHS welfare data sets.
NOTE: The data of January 2000 is incomplete; Five pair of months have the same data input, including 05/1997 and 06/1997, 12/1997 and 01/1998, 09/1998 and 10/1998, 02/2000 and 03/2000, and 08/2006 and 09/2006. Thus the monthly in-and-out is zero. I smooth the trend line by using average values.

Table A.9 Employment Status of Adult TANF Clients and Adult TANF Leavers in Mississippi, 2001Q3-2009Q3

	In-TANF		Work and Non-Work Exit			
Year/Quarter	In TANF Only	In TANF and Worked	Non-Work Exit	Work Exit	Job Retain in the 1st Quarter	Job Retain in the 2nd Quarter
2001Q3	5,535	3,858	--	--	--	--
2001Q4	6,397	3,914	987	1,171	941	881
2002Q1	6,471	3,778	1,160	1,248	1,021	943
2002Q2	6,326	4,108	1,253	1,329	1,055	929
2002Q3	7,368	4,497	1,182	1,242	1,001	906
2002Q4	8,606	4,452	1,149	1,271	1,018	923
2003Q1	8,437	4,319	1,494	1,475	1,187	1,109
2003Q2	8,197	4,581	1,557	1,481	1,198	1,095
2003Q3	8,221	5,090	1,478	1,434	1,162	1,020
2003Q4	8,405	5,112	1,551	1,672	1,368	1,292
2004Q1	8,130	4,609	1,587	1,730	1,433	1,275
2004Q2	7,735	4,581	1,599	1,788	1,454	1,335
2004Q3	7,732	4,498	1,628	1,683	1,376	1,228
2004Q4	7,411	4,254	1,701	1,822	1,460	1,344
2005Q1	6,702	4,005	1,588	1,704	1,416	1,284
2005Q2	6,384	3,804	1,622	1,706	1,353	1,207
2005Q3	6,210	4,010	1,483	1,511	1,162	1,070
2005Q4	5,436	3,760	1,673	1,616	1,277	1,144
2006Q1	5,054	3,409	1,317	1,397	1,109	1,031
2006Q2	4,733	3,000	1,488	1,469	1,195	1,079
2006Q3	4,226	2,856	1,298	1,344	1,065	975
2006Q4	4,206	2,756	1,201	1,235	1,005	924
2007Q1	3,753	2,457	1,023	1,171	961	871
2007Q2	3,677	2,480	819	1,093	879	786
2007Q3	3,992	2,702	729	987	807	729
2007Q4	4,119	2,785	838	1,083	874	798
2008Q1	3,976	2,373	970	1,220	972	867
2008Q2	4,115	2,416	903	1,045	842	739
2008Q3	4,449	2,691	859	999	787	678
2008Q4	4,813	2,544	1,099	1,149	918	806
2009Q1	4,638	2,163	1,127	1,131	920	800
2009Q2	4,853	2,226	1,037	973	784	
2009Q3	5,746	2,331	1,044	947		

Source: MDHS welfare data sets and UI data sets.

Table A.10 Life Table - All Spells, Race, Educational Level, and Time of Spell Beginning (N=60,811 Spells)

		All Spells								
[Lower,	Upper)	Number Failed	Number Censored	Effective Sample Size	Conditional Probability	Standard Error	Hazard	Standard Error	Survival	Failure
1	2	10,624	2,690	59,466	0.179	0.002	0.175	0.002	1.000	0.000
2	3	15,135	1,718	46,638	0.325	0.002	0.319	0.003	0.821	0.179
3	4	9,526	813	30,238	0.315	0.003	0.311	0.003	0.555	0.445
4	5	6,155	733	19,939	0.309	0.003	0.303	0.004	0.380	0.620
5	6	4,109	476	13,179	0.312	0.004	0.306	0.005	0.263	0.737
6	7	2,599	248	8,708	0.299	0.005	0.294	0.006	0.181	0.819
7	8	1,685	149	5,911	0.285	0.006	0.282	0.007	0.127	0.873
8	9	1,083	147	4,078	0.266	0.007	0.261	0.008	0.091	0.909
9	10	743	100	2,871	0.259	0.008	0.254	0.009	0.067	0.933
10	11	496	77	2,040	0.243	0.010	0.239	0.011	0.049	0.951
11	12	374	39	1,486	0.252	0.011	0.249	0.013	0.037	0.963
12	13	252	42	1,071	0.235	0.013	0.231	0.015	0.028	0.972
13	14	191	27	785	0.244	0.015	0.239	0.017	0.021	0.979
14	15	134	10	575	0.233	0.018	0.231	0.020	0.016	0.984
15	16	79	15	429	0.184	0.019	0.181	0.020	0.012	0.988
16	17	91	11	337	0.270	0.024	0.266	0.028	0.010	0.990
17	18	51	11	235	0.218	0.027	0.213	0.030	0.007	0.993
18	19	35	6	175	0.200	0.030	0.197	0.033	0.006	0.994
19	20	30	6	134	0.224	0.036	0.219	0.040	0.005	0.995
20	.	89	12	95	0.937	0.025	.	.	0.004	0.996

Table A.10 (Continued)

		Race				Level of Education			
		Black		White		Less than High School		High School and Above	
[Lower,	Upper)	Conditional Probability	Failure	Conditional Probability	Failure	Conditional Probability	Failure	Conditional Probability	Failure
1	2	0.164	0.000	0.232	0.000	0.202	0.000	0.165	0.000
2	3	0.301	0.164	0.422	0.232	0.350	0.202	0.312	0.165
3	4	0.298	0.416	0.398	0.556	0.310	0.481	0.318	0.426
4	5	0.292	0.590	0.399	0.733	0.304	0.642	0.314	0.608
5	6	0.300	0.710	0.389	0.839	0.314	0.751	0.311	0.731
6	7	0.289	0.797	0.369	0.902	0.286	0.829	0.306	0.815
7	8	0.279	0.856	0.336	0.938	0.289	0.878	0.283	0.871
8	9	0.261	0.896	0.301	0.959	0.268	0.913	0.269	0.908
9	10	0.257	0.923	0.271	0.971	0.252	0.937	0.263	0.933
10	11	0.243	0.943	0.243	0.979	0.257	0.953	0.235	0.950
11	12	0.249	0.957	0.280	0.984	0.272	0.965	0.243	0.962
12	13	0.223	0.968	0.357	0.989	0.225	0.974	0.248	0.971
13	14	0.233	0.975	0.361	0.993	0.236	0.980	0.246	0.978
14	15	0.237	0.981	0.184	0.995	0.194	0.985	0.255	0.984
15	16	0.171	0.985	0.367	0.996	0.199	0.988	0.177	0.988
16	17	0.276	0.988	0.167	0.998	0.254	0.990	0.286	0.990
17	18	0.210	0.991	0.333	0.998	0.195	0.993	0.243	0.993
18	19	0.200	0.993	0.200	0.999	0.207	0.994	0.185	0.995
19	20	0.229	0.994	0.133	0.999	0.198	0.995	0.235	0.996
20	.	0.933	0.996	1.000	0.999	0.917	0.996	0.954	0.997
		-2Log(LR) = 684; Wilcoxon = 1063				-2Log(LR) = 39; Wilcoxon = 149			

Table A.10 (Continued)

		Time Period When a Spell Began			
		Jul. 2001 – Dec. 2004		Jan. 2005 – Sep. 2009	
[Lower,	Upper)	Conditional Probability	Failure	Conditional Probability	Failure
0	1	0.000	0.000	0.000	0.000
1	2	0.172	0.000	0.183	0.000
2	3	0.285	0.172	0.353	0.183
3	4	0.271	0.408	0.353	0.471
4	5	0.278	0.568	0.340	0.658
5	6	0.283	0.688	0.348	0.774
6	7	0.273	0.776	0.337	0.853
7	8	0.282	0.837	0.290	0.903
8	9	0.254	0.883	0.289	0.931
9	10	0.265	0.913	0.243	0.951
10	11	0.250	0.936	0.225	0.963
11	12	0.252	0.952	0.250	0.971
12	13	0.245	0.964	0.201	0.978
13	14	0.258	0.973	0.182	0.983
14	15	0.250	0.980	0.155	0.986
15	16	0.192	0.985	0.148	0.988
16	17	0.290	0.988	0.158	0.990
17	18	0.241	0.991	0.064	0.991
18	19	0.195	0.993	0.238	0.992
19	20	0.234	0.995	0.100	0.994
20	.	0.967	0.996	0.000	0.995
		-2Log(LR) = 151; Wilcoxon = 240			

Source: MDHS welfare data sets.

NOTE: 1) Life table is based on adult TANF clients who began their first spells after July 2001.

2) Hazard is calculated as number of failed divided by total number of survived at the beginning of the interval, e.g., 0.175=10624/60811; 0.319=15135/(60811-10624-2690). In contrast, conditional probability is calculated by considering the adjusted number at risk at the start of the interval to be total at the start minus (the number failed or censored)/2, e.g., 0.179=10624/(60811-2690/2); 0.325=15135/(60811-10624-2690-1717/2)

Table A.11 Fitted Survival Probabilities from Model 9 and Model 10 for the Simulations of Educational Attainment, Controlling for Work Experience and Race

Time Period Predicator	Work Exits						Other Exits					
	White			Black			White			Black		
	Less than High School	High School	More than High School	Less than High School	High School	More than High School	Less than High School	High School	More than High School	Less than High School	High School	More than High School
Without Work Experience												
D_1	0.955	0.951	0.954	0.972	0.968	0.968	0.764	0.803	0.818	0.847	0.876	0.895
D_2	0.864	0.852	0.860	0.912	0.903	0.903	0.429	0.495	0.522	0.620	0.680	0.722
D_3	0.775	0.758	0.770	0.853	0.838	0.838	0.259	0.326	0.355	0.461	0.536	0.590
D_4	0.706	0.684	0.699	0.802	0.784	0.783	0.151	0.207	0.233	0.340	0.419	0.479
D_5	0.651	0.626	0.643	0.758	0.736	0.735	0.094	0.140	0.162	0.250	0.327	0.388
D_6	0.604	0.577	0.595	0.716	0.691	0.690	0.060	0.097	0.116	0.189	0.261	0.321
D_7	0.559	0.530	0.550	0.677	0.649	0.648	0.043	0.073	0.089	0.145	0.210	0.267
D_8	0.532	0.502	0.522	0.642	0.612	0.611	0.029	0.053	0.067	0.111	0.170	0.223
D_9	0.505	0.475	0.495	0.609	0.577	0.576	0.022	0.042	0.054	0.085	0.137	0.186
D_{10}	0.485	0.454	0.475	0.579	0.546	0.544	0.017	0.034	0.044	0.066	0.112	0.157
D_{11}	0.457	0.426	0.447	0.549	0.515	0.513	0.012	0.027	0.035	0.050	0.090	0.130
D_{12}	0.408	0.376	0.398	0.523	0.488	0.487	0.008	0.019	0.026	0.039	0.073	0.110
Median Lifetime (in Quarter)	9.260	8.070	8.821	>12.0	11.548	11.498	1.788	1.984	2.132	2.757	3.307	3.811
With Work Experience												
D_1	0.759	0.742	0.754	0.812	0.795	0.794	0.837	0.866	0.877	0.890	0.912	0.926
D_2	0.441	0.414	0.432	0.536	0.505	0.504	0.561	0.622	0.646	0.712	0.762	0.796
D_3	0.249	0.224	0.241	0.346	0.314	0.313	0.397	0.469	0.498	0.576	0.643	0.690
D_4	0.149	0.130	0.143	0.231	0.202	0.201	0.273	0.344	0.375	0.463	0.540	0.595

Table A.11 (Continued)

Time Period Predicator	Work Exits						Other Exits					
	White			Black			White			Black		
	Less than High School	High School	More than High School	Less than High School	High School	More than High School	Less than High School	High School	More than High School	Less than High School	High School	More than High School
D_5	0.094	0.079	0.089	0.158	0.134	0.133	0.198	0.264	0.294	0.372	0.453	0.513
D_6	0.062	0.050	0.058	0.108	0.088	0.088	0.147	0.207	0.235	0.305	0.386	0.449
D_7	0.040	0.032	0.037	0.074	0.058	0.058	0.116	0.171	0.197	0.252	0.331	0.395
D_8	0.030	0.023	0.027	0.052	0.040	0.039	0.090	0.139	0.163	0.208	0.285	0.348
D_9	0.022	0.016	0.020	0.036	0.027	0.027	0.074	0.119	0.141	0.172	0.245	0.306
D_{10}	0.017	0.013	0.015	0.026	0.018	0.018	0.062	0.103	0.124	0.145	0.213	0.272
D_{11}	0.012	0.009	0.011	0.018	0.012	0.012	0.051	0.088	0.107	0.119	0.181	0.238
D_{12}	0.007	0.005	0.006	0.013	0.009	0.009	0.039	0.070	0.087	0.099	0.157	0.211
Median Lifetime (in Quarter)	1.814	1.739	1.789	2.188	2.028	2.022	2.372	2.797	2.988	3.675	4.458	5.208

NOTE: 1) Fitted survival probabilities are calculated by $S_t = S_{t-1}(1 - h_t)$, where h_t rates are fitted hazard rates, which can be calculated by $h_t = 1/(1 + \exp(-(\alpha_t + \beta_t))$, where α_t and β_t denotes coefficients estimated in Table 6.10.
2) The estimated median lifetime is the value of time for which the value of the estimated survival function is 0.5. It can be calculated by $T_m = m + (S_{t_m} - 0.5)/(S_{t_m} - S_{t_{m+1}})$, where m represent the time interval when the survival function is just above 0.5, S_{t_m} represent the value of the survival function in that interval, and $S_{t_{m+1}}$ represent the value for the subsequent interval (see Singer and Willett 2003:334-339 for details).
3) Simulations are based on the TANF clients who have different level of educational attainment, controlling for work experience and race, with other individual and contextual variables set at the mean values.

Table A.12 Fitted Survival Probabilities from Model 9 and Model 10 for the Simulations of Unemployment Rates, Controlling for Work Experience and Race

Time Period	Work Exits						Other Exits					
	White			Black			White			Black		
Predicator	5.5%	8.1%	10.7%	5.5%	8.1%	10.7%	5.5%	8.1%	10.7%	5.5%	8.1%	10.7%
Without Work Experience												
D_1	0.948	0.951	0.954	0.963	0.968	0.973	0.801	0.803	0.805	0.864	0.876	0.887
D_2	0.843	0.852	0.860	0.886	0.903	0.918	0.491	0.495	0.499	0.654	0.680	0.706
D_3	0.744	0.758	0.770	0.811	0.838	0.862	0.322	0.326	0.330	0.503	0.536	0.568
D_4	0.668	0.684	0.700	0.749	0.784	0.814	0.204	0.207	0.211	0.383	0.419	0.454
D_5	0.607	0.626	0.644	0.695	0.736	0.772	0.137	0.140	0.142	0.292	0.327	0.363
D_6	0.557	0.577	0.596	0.645	0.691	0.732	0.095	0.097	0.099	0.228	0.261	0.296
D_7	0.509	0.530	0.551	0.599	0.649	0.695	0.071	0.073	0.075	0.179	0.210	0.243
D_8	0.480	0.502	0.523	0.558	0.612	0.661	0.051	0.053	0.055	0.141	0.170	0.200
D_9	0.453	0.475	0.497	0.521	0.577	0.630	0.041	0.042	0.044	0.112	0.137	0.165
D_{10}	0.432	0.454	0.476	0.487	0.546	0.600	0.032	0.034	0.035	0.090	0.112	0.138
D_{11}	0.403	0.426	0.448	0.455	0.515	0.572	0.026	0.027	0.028	0.070	0.090	0.112
D_{12}	0.353	0.376	0.399	0.427	0.488	0.546	0.018	0.019	0.020	0.056	0.073	0.093
Median Lifetime (in Quarter)	7.319	8.070	8.871	9.626	11.548	>12.0	1.972	1.984	1.996	3.025	3.307	3.599

Table A.12 (Continued)

Time Period	Work Exits						Other Exits					
	White			Black			White			Black		
Predicator	5.5%	8.1%	10.7%	5.5%	8.1%	10.7%	5.5%	8.1%	10.7%	5.5%	8.1%	10.7%
With Work Experience												
D_1	0.759	0.742	0.754	0.812	0.795	0.794	0.837	0.866	0.877	0.890	0.912	0.926
D_2	0.441	0.414	0.432	0.536	0.505	0.504	0.561	0.622	0.646	0.712	0.762	0.796
D_3	0.249	0.224	0.241	0.346	0.314	0.313	0.397	0.469	0.498	0.576	0.643	0.690
D_4	0.149	0.130	0.143	0.231	0.202	0.201	0.273	0.344	0.375	0.463	0.540	0.595
D_5	0.094	0.079	0.089	0.158	0.134	0.133	0.198	0.264	0.294	0.372	0.453	0.513
D_6	0.062	0.050	0.058	0.108	0.088	0.088	0.147	0.207	0.235	0.305	0.386	0.449
D_7	0.040	0.032	0.037	0.074	0.058	0.058	0.116	0.171	0.197	0.252	0.331	0.395
D_8	0.030	0.023	0.027	0.052	0.040	0.039	0.090	0.139	0.163	0.208	0.285	0.348
D_9	0.022	0.016	0.020	0.036	0.027	0.027	0.074	0.119	0.141	0.172	0.245	0.306
D_{10}	0.017	0.013	0.015	0.026	0.018	0.018	0.062	0.103	0.124	0.145	0.213	0.272
D_{11}	0.012	0.009	0.011	0.018	0.012	0.012	0.051	0.088	0.107	0.119	0.181	0.238
D_{12}	0.007	0.005	0.006	0.013	0.009	0.009	0.039	0.070	0.087	0.099	0.157	0.211
Median Lifetime (in Quarter)	1.814	1.739	1.789	2.188	2.028	2.022	2.372	2.797	2.988	3.675	4.458	5.208

NOTE: 1) See the note from Table A.11 from the calculations.
2) Simulations are based on the TANF clients who are high school graduate and live in counties with unemployment rates changed by one-standard-deviation, controlling for work experience and race, with other individual and contextual variables set at the mean values.

APPENDIX B

SAS AND SATA PROGRAMING

```
**********************
* Life Table Analyses *
**********************

*NOTE: see table 5.3 for data layout of the "spell" file that is used
for the life table analyses;

*Variables;
------------------------------------------------------------------------
Name                Code
------------------------------------------------------------------------
dur                 length of a spell by quarter
status              1=right-censored
race                0=white; 1=black
episode             0=spells began before 2001; 1=spells began after 2001
education           0=less than high school; 1=high school or above
------------------------------------------------------------------------

*Calculate cumulative probability;
proc lifetest data=spell
   intervals=(0 to 20 by 1) method=LT;
   time dur*status(0);
/* strata race;          Compare race groups                  */
/* strata episode;       Compare early and later spells       */
/* strata education;     Compare groups by educational level */
   survival;
run;

*Calculate hazard of all exit in SAS
*NOTE: Edited based on computer programs that are posted on UCLA by
Singer and Willet (2003): Academic Technology Services.
http://www.ats.ucla.edu/stat/sas/examples/alda/chapter11/chapter11.htm

proc lifetest data = tf2.spell;
  time dur*status(0);
  ods output ProductLimitEstimates = tall;
run;
data table11_1all;
  set tall (where=(survival~=.));
  format left 4.0;
  myleft=lag(left);
  myfail=lag(failed);
  lags=lag(survival);
  failed=failed-myfail;
  censored=myleft-failed-left;
  hazard=1-survival/lags;
  keep survival hazard dur myleft failed censored;
run;
```

```
proc print data=table11_1all noobs;
  where hazard~=.;
  format dur 3.0;
  var dur myleft failed censored hazard survival;
run;

*Calculate hazard of all exit in SATA;
. ltable dur status, hazard noadjust interval(1(1)20)


*************************
* Discrete-Time Analyses *
*************************

*NOTE: see table 5.4 for data layout of the "sample" file that is used
for the discrete-time analyses; see table 6.4 for variable coding.
*Variables;
-----------------------------------------------------------------
Name in Analysis   Name in Variable Description (Table 6.4)
-----------------------------------------------------------------
event              binary outcome
event2             nominal outcome
d1-d12             time effects D1-D12
age                age (of the adult clients)
race               race
ych                youngest child
edu1               high school (dummy)
edu2               more than high school (dummy)
jt                 job training
wkexp              work experience
unemp              unemployment rates by county
diss               racial residential dissimilarity index
pbl                percent black
inc                median household income
metro              metropolitan or micropolitan county
sp                 repeated spells
----------------------------------------------------------------

*NOTE: Models from 1 to 11 are organized as below:
-----------------------------------------------------------------------
Name              Binary/Competing    Baseline/Full       Fixed/Random
-----------------------------------------------------------------------
Model_1           Binary              Baseline            Fixed
Model_2           Binary              Baseline            Random
Model_3           Binary              Full                Fixed
Model_4           Binary              Full                Random
Model_5           Competing           Baseline            Fixed
Model_6           Competing           Baseline            Random
```

```
Model_7            Competing          Full               Fixed
Model_8            Competing          Full               Random
Model_9            Competing          Full               Fixed
Model_10           Competing          Full               Fixed
-----------------------------------------------------------------------
```

```
***********
* Model 1 *
***********

*STATA;
. logit event d1-d12, or nocons

*SAS;
proc logistic data=sample descending;
   model event=d1-d12 /noint; run;
*or;
proc catmod data=sample;
   direct d1-d12;
   model event=d1-d12 /noprofile noiter noint; run;


***********
* Model 2 *
***********

*STATA;
. xtlogit event d1-d12, or nocons i(ssn)
*or;
. xtmelogit event d1-d12 ||ssn:, or variance

*SAS;
proc nlmixed data=sample;
   parms a1=-1.60 a2=-0.75 a3=-0.78 a4=-0.86 a5=-0.85 a6=-0.88 a7=-0.98
      a8=-1.01 a9=-0.87 a10=-0.83 a11=-1.17 a12=-1.27 sd=0.5;
   eta=a1*d1 + a2*d2 + a3*d3 + a4*d4 + a5*d5 + a6*d6 +
      a7*d7 + a8*d8 + a9*d9 + a10*d10 + a11*d11 + a12*d12 + u;
   if (event=1) then p=1/(1+exp(-eta));
   else p=1-(1/(1+exp(-eta)));
   ll=log(p);
   model event ~ general(ll);
   random u ~ normal(0,sd*sd) subject=ssn;
   estimate 'icc/rho' sd*sd/(3.29+sd*sd);
run;
*Note: there are slightly differences between the result of SATA and
that of SAS. However, if we use default ‘parms’ in SAS, the results are
exactly identical.
```

```
***********
* Model 3 *
***********

*STATA;
. logit event d1-d12 race age sp ych edu1 edu2 jt wkexp unemp diss pbl
  inc inc2 metro, or nocons

*SAS;
proc logistic data=sample descending;
   model event=d1-d12 race age sp ych edu1 edu2 jt wkexp unemp diss pbl
      inc inc2 metro /noint;
run;

***********
* Model 4 *
***********

*STATA;
. xtlogit event d1-d12 race age sp ych edu1 edu2 jt wkexp unemp diss
  pbl inc inc2 metro, or nocons i(ssn)

*SAS;
proc sort data=sample; by ssn; run;
proc nlmixed data=sample;
   parms … ;
      /*NOTE: the initial values of parameters are estimated from fixed
      model*/
   eta=a1*d1 + a2*d2 + a3*d3 + a4*d4 + a5*d5 + a6*d6 +
      a7*d7 + a8*d8 + a9*d9 + a10*d10 + a11*d11 + a12*d12 +
      b1*race + b2*ych + b3*edu1 + b4*edu2 + b5*jt + b6*wkexp +
      b7*unemp + b8*diss + b9*pbl + b10*age + b11*inc + b12*inc2 +
      b13*metro + b14*sp + u;
   if event=1 then p=exp(eta)/(1+exp(eta));
   else p=1/(1+exp(eta));
   ll=log(p);
   model event ~ general(ll);
   random u ~ normal(0,sd*sd) subject=ssn;
   estimate 'icc/rho' sd*sd/(3.29+sd*sd);
run;
*The results are identical with the results produced by SATA;

***********
* Model 5 *
***********

*STATA;
. mlogit event2 d1-d12, base(3) nocons nolog, rrr
```

```
*SAS;
proc catmod data=sample;
   direct d1-d12;
   model event2=d1-d12 /noprofile noint; run;
*or;
proc logistic data=sample;
   model event2=d1-d12 /link=glogit noint; run;

***********
* Model 6 *
***********

*STATA;
. sort ssn d1-d12 wtw
. gen patt=_n
. expand 3
. sort patt
. qui by patt: gen alt=_n
. sort patt alt
. gen chosen=alt==wtw
. tab alt, gen(a)
. eq a2: a2
. eq a3: a3
. gllamm alt d1-d12, expand(patt chosen m) i(ssn) link(mlogit) nrf(2)
  eqs(a2 a3) nip(4) nocons
*NOTE: data preparation for gllamm follows the gllamm manual (Rabe-
Hesketh et al. 2004);

*SAS;
proc sort data=tf2.sample; by ssn; run;
proc nlmixed data=tf2.sample;
   parms … ;
      /*NOTE: the initial values of parameters are estimated from fixed
      model*/
   eta1 = a11*d1 + a21*d2 + a31*d3 + a41*d4 + a51*d5 + a61*d6 +
      a71*d7 + a81*d8 + a91*d9 + a101*d10 + a111*d11 + a121*d12 + u1;
   eta2 = a12*d1 + a22*d2 + a32*d3 + a42*d4 + a52*d5 + a62*d6 +
      a72*d7 + a82*d8 + a92*d9 + a102*d10 + a112*d11 + a122*d12 + u2;
   p1 = exp(eta1) / (1+exp(eta1)+exp(eta2));
   p2 = exp(eta2) / (1+exp(eta1)+exp(eta2));
   p3 = 1 / (1+exp(eta1)+exp(eta2));
   if event2=1 then ll=log(p1);
   else if event2=2 then ll=log(p2);
   else if event2=3 then ll=log(p3);
   model event2 ~ general(ll);
   random u1 u2 ~ normal([0,0], [s11, s12, s22]) subject=ssn;
run;
*NOTE: The results are identical with the results produced by SATA;
```

```
***********
* Model 7 *
***********

*STATA;
. mlogit event2 d1-d12 race age sp ych edu1 edu2 jt wkexp unemp diss
  pbl inc inc2 metro, base(3) nocons nolog, rrr

*SAS;
proc logistic data=sample;
   model event2=d1-d12 race age sp ych edu1 edu2 jt wkexp unemp
   diss pbl inc inc2 metro /link=glogit noint;
run;

***********
* Model 8 *
***********

*STATA;
. gllamm alt d1-d12 race age sp ych edu1 edu2 jt wkexp unemp diss pbl
  inc inc2 metro, expand(patt chosen m) i(ssn) link(mlogit)
  family(binom) nrf(2) eqs(a2 a3) nip(4) nocons
*NOTE: see model 7 for data preparation for gllamm;

*SAS;
*NOTE: The program stopped due to the error "Optimization cannot be
completed".

************
* Model 9 *
************

. mlogit event2 d1-d12 age sp ych edu1 edu2 jt wkexp unemp diss pbl inc
  inc2 metro if race==0, base(3) nocons rrr

************
* Model 10 *
************

. mlogit event2 d1-d12 age sp ych edu1 edu2 jt wkexp unemp diss pbl inc
  inc2 metro if race==1, base(3) nocons rrr
```