A MULTILEVEL ANALYSIS OF GOVERNANCE AND PROGRAM OUTCOMES: A CASE STUDY OF PUBLIC CASH ASSISTANCE PROGRAMS

DISSERTATION

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of The Ohio State University

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2003

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ABSTRACT

The passage of the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996 created an unprecedented atmosphere for the welfare system in the United States: the entitlement to aid was abolished and much of the authority for program design and service delivery was given to the states. States have experimented with many innovative programs to move welfare recipients from dependency to self-sufficiency. This reform also created many opportunities for evaluation of the effects of these changes.

This dissertation has investigated the determinants of success of public cash assistance programs for welfare leavers during the PRWORA era. The main research question is how state welfare policies, implementation activities of state welfare agencies, the environment, and individual characteristics interact and affect the economic self-sufficiency of former welfare recipients. This dissertation also asks what are the advantages and disadvantages of using different statistical methods in estimating interaction effects among individual- and state-level variables when there is significant within-state homogeneity and between-state variation.

Most previous studies of welfare leavers are descriptive lacking an investigation of possible links between program success and its determinants.
Some explanatory studies of welfare leavers have investigated the impacts of individual, economic and environmental, policy, and other factors on welfare outcomes, mostly measured by employment levels, earnings, recidivism, and caseload size. While these studies focus on one aspect of the many factors that influence welfare outcomes, this dissertation builds an integrative model of the determinants of welfare leavers’ outcomes based on the governance framework suggested by Lynn and Heinrich (2000). As a synthesis of the earlier literature on program evaluation, this governance framework proposes that government program outcome is the function of client characteristics, environmental factors, treatments, structures, and implementation actions.

To estimate cross-level interaction or moderating effects in multilevel, nested data structures, this dissertation uses two different estimation tools: the moderated multiple regression (MMR) method and the multilevel linear model (MLM) method. The MMR method adds interaction terms and tests whether the point estimate of the terms are statistically significant or not to detect the existence of interaction effects. Alternatively, the MLM method builds sub-models of each of the multilevel variables in the data structure, representing relationships among variables within a given level and interaction effects across the levels.
Utilizing a wide range of individual- and state-level data from various sources, this dissertation has explored the determinants of success of public cash assistance programs. The major findings of the analysis are discussed below.

First, this dissertation has found that the emphasis on work-oriented activities of state welfare agencies is positively related to the outcome variable of interest across the two estimation methods. This finding suggests that the “work first approach” is helping welfare leavers to successfully transit from welfare to self-sufficiency. Also, this dissertation has found that the provision of child care services and transportation services is positively related to the earned income of welfare leavers. The estimates range from $442 to $639 for child care services and from $545 to $617 for transportation services depending on estimation methods. These results are consistent with many previous studies (Anderson, Halter, and Schuld, 2001; Julnes, Hayashi, and Anderson, 2001; Westra, 2001).

Finally, this dissertation has found that interaction between race and maximum benefit amount for family of three is estimated to exist through the MMR method, while is not through the MLM method. That is, the MMR method suggests that non-white individuals tend to make less earned income when their monthly benefits go up.

Also, methodologically, this dissertation has found that the MMR and MLM methods produce an identical estimation result if all OLS assumptions including homogeneous variances of organizations are met. This assumption
means that the variance in outcome variable unaccounted for by independent
variables is equal across higher-level units (i.e., states or organizations).
However, in the presence of heterogeneous error variances across organizations,
the MLM method conceptually and statistically produces correct standard errors
and, thus, parameter estimates. The MMR estimation method produces smaller
standard errors than the MLM method.

This dissertation can be seen as achieving three related but different
objectives pertaining to the model, the data set and the analytical tools. First, this
dissertation focuses on leavers rather than recipients since they did succeed in
getting off welfare. In the analytic model, this dissertation has included various
components that previous studies partially incorporated in their analysis. This
model allows us to examine how individual characteristics, state welfare policies,
implementation activities of state welfare agencies, and the environment interact
and affect the economic self-sufficiency of welfare leavers.

Second, this dissertation has brought together proxies of the constructs
and variables included in the analytic model. Previous studies have often
examined the effects of various state- and individual-level variables by
aggregating individual-level variables into state-level variables or disaggregating
state-level variables into individual-level variables. Also, many studies of welfare
leavers are only descriptive lacking a model that links welfare policies and other
state-level factors to the leavers’ individual well-being. By being able to merge
longitudinal data on the leavers with various state-level data, this dissertation can examine links between welfare policies and other state-level factors to the economic well-being of welfare leavers.

Finally, this dissertation has been able to estimate the effects of individual characteristics, state welfare policies and implementation activities, and the environment on the economic well-being of welfare leavers using standard statistical techniques and also multi-level methods that better reflect the model and the hierarchical structure of the programs and the data.
Dedicated to my parents,
Kyetae Lee and Soonja Hong,
and my wife,
Bok Young Kim
ACKNOWLEDGMENTS

First of all, I thank to my adviser, Anand Desai, for being a good friend of mine throughout my doctoral education. I learned a lot about how to teach and do research as a scholar and how to live as a human from him. Also, I owe special thanks to my committee members, Mary Marvel and Bert Rockman, for giving me many constructive advice on my dissertation.

With the presence and belief on me from my parents, this dissertation could be possible. I thank to my parents, KyeTae Lee and SoonJa Hong, and my parents-in-law, past ChangHwan Kim and KyungRye Lee. Also, thanks to my brothers and sisters for always being there when I need them.

I was so lucky to marry to Bok Young Kim. Her presence always makes me happy when I was tired of and her understanding always gives me a new energy to finish my doctoral degree. Thank you, Bok Young, and I love you forever.
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# TABLE OF CONTENTS

Abstract ........................................................................................................................................ ii

Dedication ...................................................................................................................................... vii

Acknowledgments ....................................................................................................................... viii

Vita ................................................................................................................................................. ix

List of Tables ................................................................................................................................... xii

List of Figures ............................................................................................................................... xiii

Chapter 1 Introduction .................................................................................................................. 1

1.1 Motivation for the Dissertation ............................................................................................. 1
1.2 Research Questions ................................................................................................................ 8
1.3 Analytic Framework of the Dissertation .............................................................................. 12
1.4 Organization of the Dissertation ......................................................................................... 17

Chapter 2 Literature Review ....................................................................................................... 20

2.1 Previous Research on Well-being of Welfare Leavers ......................................................... 20
2.1.1 Descriptive Studies of Welfare Leavers .................................................................. 21
2.1.2 Explanatory Studies of Welfare Leavers ................................................................ 29
2.2 Governance Model of Public Program Evaluation ............................................................... 41
2.2.1 Definitions of Governance ................................................................................... 41
2.2.2 Model of Governance Framework .......................................................................... 43
2.3 Redefining Dimensions and Elements of the Model in the Welfare Context .................. 46
2.3.1 Redefining Dimensions of the Governance Model ............................................... 46
2.3.2 Specifying Measures of the Dimension .................................................................. 47
2.4 Analytical Framework .......................................................................................................... 53
Chapter 3 Estimation Methods of Cross-Level Interaction Effects

3.1 Various Methods of Estimating Moderation or Interaction Effects
   3.1.1 Multilevel Data Structure and Interaction Effects
   3.1.2 Moderated Multiple Regression Models
   3.1.3 Multilevel or Hierarchical Linear Models

3.2 Simulation: Performance Comparison of MMR and MLM Methods

3.3 An Example: A Comparison of MMR and MLM Methods

Chapter 4 Empirical Analysis of the Well-being of Welfare Leavers

4.1 Data and Sample

4.2 Measures and Models

4.3 Empirical Analysis of the Economic Well-being of Welfare Leavers
   4.3.1 Basic MMR and MLM Models
   4.3.2 Effects of Individual Characteristics
   4.3.3 Effects of State-level Variables
   4.3.4 Effects of Individual- and State-level Variables

Chapter 5 Conclusions and Discussions

5.1 Policy Implications of the Findings of the Dissertation

5.2 Methodological Implications of the Dissertation

5.3 Contributions of the Dissertation

Appendix A. Evolution of Public Cash Assistance Programs in the United States

Appendix B. Mathematical Representation of Heterogeneous Error Variance Problems

Appendix C. Sub-Models of Multilevel Linear Models

Appendix D. SAS Program Generating Random Dataset for Simulation

References
LIST OF TABLES

Table 2.1 Welfare Leavers Studies Reviewed in the Dissertation........................................... 57
Table 2.2 Employment and Earnings of Welfare Leavers.......................................................... 58
Table 2.3 Major Dimensions of States’ Welfare Policies............................................................ 61
Table 3.1 A Generated Dataset ................................................................................................. 91
Table 3.2 Estimation Results of Equal Variance Models by MMR and MLM ...................... 92
Table 3.3 Simulation Results at the 99% Significance Level.................................................... 92
Table 3.4 Simulation Results at the 95% Significance Level..................................................... 93
Table 3.5 Descriptive Statistics................................................................................................ 93
Table 3.6 Results of MMR and MLM Estimation................................................................. 94
Table 4.1 Monthly Numbers of Welfare Recipients and Leavers in the SIPP ...................... 123
Table 4.2 Sources of Data Utilized in the Dissertation............................................................. 123
Table 4.3 Descriptive Statistics of the Sample ........................................................................ 124
Table 4.4 Descriptive Statistics of Program Outcome Variables ............................................. 124
Table 4.5 Correlation Matrix of Implementation Activities .................................................. 125
Table 4.6 Results of the Extraction of Component Factors..................................................... 125
Table 4.7 Rotated Component Analysis Factor Matrix ............................................................ 127
Table 4.8 Estimation Results of Basic MMR Model................................................................. 128
Table 4.9 Estimation Results of Basic Multilevel Model......................................................... 128
Table 4.10 Estimation Results of Individual-Level MMR and MLM Models ......................... 129
Table 4.11 Estimation Results of State-Level MMR and MLM Models .................................. 129
Table 4.12 Estimation Results of Full MMR and MLM Models ............................................. 130
Table 4.13 Changes in Error Variances in Full MMR and MLM Models ......................... 130

xii
LIST OF FIGURES

Figure 1.1 Analytic Framework of the Dissertation ......................................................... 19
Figure 2.1 Relationships Between Previous Study and the Governance Framework....... 59
Figure 2.2 Measures of Outcomes of Public Cash Assistance Programs ....................... 59
Figure 2.3 Measures of Individual Characteristics .......................................................... 60
Figure 2.4 Dimensions and Measures of Environment.................................................... 60
Figure 3.1 Nested Data Structure.................................................................................... 89
Figure 3.2 Graphical Representation of Heterogeneous Error Variances......................... 90
Figure 4.1 Scree Test for Component Analysis .............................................................. 126
Figure 5.1 Analytic Model of the Dissertation ............................................................... 139
CHAPTER 1
INTRODUCTION

1.1 Motivation for the Dissertation

The Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996 has aimed to “end welfare as we know it” by abolishing the entitlement to aid and by making eligibility for assistance conditional and time limited. Over the past several decades, there have been sharp increases in the number of people on welfare, in the long-term dependency of many of the welfare recipients, and in the inability of the welfare system to move them to self-sufficiency. Dissatisfaction with this state of affairs brought various reforms and changes of the public cash assistance programs in the United States. Of these remedies, the PRWORA was perhaps the broadest and wide ranging change in welfare policy during the 1990s.

In 1996, Congress passed PRWORA, which fundamentally changed the focus and the service delivery mechanism of the United States welfare system. Before the welfare reform, the Aid to Families with Dependent Children (AFDC) program was based on a perspective of entitlement and dependency. Further, states had little authority for service design and administration. Following the
passage and implementation of PRWORA, however, the focus has changed from a perspective of entitlement and dependency to an environment of economic self-sufficiency through employment. Also, much of the authority for service design and implementation now rests with the states1.

Early evaluations of the reform describe it as a “stunning success” that has led to “plunging caseloads” and “soaring employment” (Duncan and Chase-Lansdale, 2001). In terms of caseloads, the reform has been a success. For example, the number of welfare cases fell by more than half between 1996 and 2000, changing the percent of total U.S. population on welfare from 4.8% in 1996 to only 2.1% in June 2000.

However, many researchers argue that the caseload size is a narrow indicator of program success that provides little information about the well-being of people who left the welfare system (Julnes and Foster, 2001; Young, 2000). As the caseloads have fallen, what happens to the growing number of people who left the rolls? In particular, as many earlier recipients approach the 60-month lifetime limit and the strong economy of the 1990s began to fade, concern arose about the self-sufficiency of welfare recipients after their exit from the welfare system. Some of the research questions these studies have addressed include: How are former welfare recipients faring without public cash assistance? Are they working and how much do they earn? How likely are they to move out of poverty? How likely are they to return to welfare?

1 A brief description of evolution of public cash assistance programs and major changes in state TANF policies brought by PRWORA of 1996 is introduced in Appendix A.
Fortunately, we have a growing number of studies on the current status of former welfare recipients, including multi-state projects on the well-being of welfare leavers launched by the Office of the Assistant Secretary for Program Evaluation (ASPE) of the U.S. Department of Health and Human Services (USDHHS). Most of these studies have reported on earnings and employment, recidivism, the use of other governmental supportive services, their family structure and child well-being, and their hardships by former welfare recipients. While we will present a summary of these studies in Chapter 2, they are mainly descriptive, providing little information about the causal links between welfare policies, state environment, and other factors and the well-being of former welfare recipients (Isaacs, 2001).

Some efforts are made to explain what determines welfare dependency and self-sufficiency of welfare recipients and leavers. These efforts refer to various factors as the determinants of the well-being of welfare leavers and can be categorized into individual, economic and environmental, policy, and other explanations. The details of these explanations will be discussed in Chapter 2, but their main difference is in their emphasis they place on the different factors that determine welfare dependency and self-sufficiency of welfare recipients and leavers.

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2 As of April 2001, National Conference of State Legislatures reports 26 states that have released studies on the status of families who have left welfare since 1996.

3 In 1998, there were 14 multi-state projects. These project areas include Arizona, District of Columbia, Florida, Georgia, Illinois, Massachusetts, Missouri, New York, South Carolina, Washington, Wisconsin, Cuyahoga County (Ohio), Los Angeles County, and a consortium of San Mateo, Santa Clara, and Santa Cruz counties in California.
Individual explanations (Cao, 1996; Ellwood, 1986; Martinson and Friedlander, 1994; Mead, 1986; Murray, 1984; Murray and Kopel, 1995) hold that individual characteristics, such as demographics and psychosocial factors, are the main determinants of welfare dependency and self-sufficiency of welfare recipients and leavers. And economic and environmental explanations (Bell, 2001; Blank, 1997; Figlio and Ziliak, 1999; Moffitt, 1999; Wilson, 1993) emphasize the role of the economic and the societal environment in which most welfare recipients live in determining their welfare dependency and self-sufficiency, while policy explanations (CEA, 1999; Niskanen, 1996; Rector and Youssef, 1999; Schoeni and Blank, 2000; Wallace and Blank, 1999) focus on the role of devolved state welfare policies. Finally, other explanations (Heinrich and Lynn, 2000; Jennings and Ewalt, 2000; Ricco, Bloom, and Hill, 2000; Sandfort, 2000) emphasize the role of organizational characteristics and implementation activities of state welfare agencies in determining the success of welfare reform.

While each explanation provides a partial insight into welfare dependency and self-sufficiency, it is important to understand that none of them offers a complete explanation. There is a rich set of factors that ultimately influence welfare outcomes. However, most previous studies have focused on a limited number of factors and, as a result, provided relatively little explanation of welfare outcomes (Blank, 2001). Most previous studies have limitations in utilizing individual- and state-level data across states to estimate the effects of state welfare policies and implementation activities on individual outcomes. In order to have a better understanding of what determines welfare dependency and self-
sufficiency of welfare recipients and welfare leavers, we need to consider all of the above factors in a study. This argument is similar to that offered by Rossi, who suggests that to conduct a comprehensive evaluation, one has to construct a model of program inputs, causal mediating processes, and program outputs (Chen and Rossi, 1983; Rossi, Freeman, and Lipsey, 1999).

Thus, the first goal of the dissertation is to generate an integrative explanation of the determinants of welfare leavers’ outcomes.

People tend to nest within organizational settings, such as families, schools, counties, and states. In education, students are grouped within classrooms, which are in turn nested within schools, school districts, and states. Individual welfare recipients can be grouped into local welfare agencies, which in turn can be grouped into state welfare agencies. Many other organizational settings show these kinds of hierarchical structures as well.

In these situations, cross-level interaction effects refer to the ways in which attributes within the different levels influence each other in explaining variance in the outcomes of interest. For instance, suppose a researcher wants to explore the effects of state welfare policies on the earnings of welfare leavers. In such research, state welfare policies interact with individual characteristics, such as gender and education levels, to account for variations in earnings of welfare leavers. And those interactions can be unique to each state due to the fact that people in the same state tend to experience more similar policies than people from other states or people in the same state are more likely to influence each other in dealing with state welfare policies. For example, suppose state A has
strict family cap policy, which limits additional increase of benefits for newly born child when a recipient is on welfare, than state B. Then, welfare recipients in state A is more likely to not have a child than welfare recipients in state B, resulting in different patterns of behaviors by state.

When there are significant “within-group” interdependences and “between-group” variations, in hierarchical data structures, traditional analytic methods may not produce reliable estimates of the relationships among higher-(i.e., state) and lower-level (i.e., individual) attributes. One assumption of many conventional analytic techniques of estimating interaction effects, like Ordinary Least Squares (OLS) regression methods, is that observations (i.e., people, schools, and states) are independent not interdependent. If there is any evidence of the existence of within-organization homogeneity or interdependence among observations, it violates the independence assumption resulting in small standard errors and, in turn, a higher chance to reject a null hypothesis (Bryk and Raudenbush, 1992; Hanushek, Rivkin, and Taylor, 1996; Osborne, 2000).

Multilevel Linear Models (Bryk and Raudenbush, 1992, MLM) conceptually and empirically overcome this limitation of the conventional analytical methods by building at least two separate models: one model specifying the relationship among individuals within a state (individual-level

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4 Two traditional methods of dealing with hierarchical data structure are disaggregated and aggregated regression methods. In standard disaggregated (individual-level) regression models, all individuals in the sample are treated as drawn from the same population, even though they are from different states, which have different configurations of welfare policies and environment. In standard aggregated regression models, individual differences are ignored by assigning representative values (i.e., mean) for individual characteristics and outcomes by state (Bryk and Raudenbush, 1992; Hanushek, Rivkin, and Taylor, 1996; Heinrich and Lynn, 2000).
model) and the other model specifying the relationship among states (state-level model). These sub-models express relationships among variables within a given level, and specify how variables at one level influence relations occurring at another level.

For example, in an individual-level model, each state has an equation of earnings of welfare leavers as a function of individual characteristics, such as gender, race, disability status, and levels of education. And, in state-level model, each regression coefficient of the individual-level model is expressed as a function of a part or full combination of state attributes, such as state welfare policies, unemployment rate, and welfare agency structure. Thus, the basic assumption of the MLM method is that the effects of individual attributes on earnings depend on state-specific configurations of policies, environment, and organizational structure and management. In particular, this assumption is satisfied when there exist significant “between-states” variations in the outcomes of interest.

In addition to the exploration of the determinants of outcomes of welfare leavers, another motivation for this dissertation is the recognition that conventional estimation methods of cross-level interaction effects are often not appropriate for estimating person-organization interaction effects when there are significant “within-group” interdependences. This dissertation, in particular in Chapter 3, introduces and compares statistical estimation methods of interaction effects, and conducts an empirical analysis of the well-being of welfare leavers using those methods.
1.2 Research Questions

The purpose of this dissertation is to develop an integrative evaluation framework of welfare dependency and self-sufficiency of welfare leavers and to explore the determinants of the economic well-being of welfare leavers based on the framework. Many studies of the welfare outcomes of welfare leavers can broadly be categorized as:

- Descriptive studies, which present a summary or cross-tabulation of the characteristics of welfare leavers, their employment status and earnings, recidivism, use of supportive services, and hardships within a state or across states (OASPE, 2001; Brauner and Loprest, 1999; Loprest, 2001; Lower-Basch, 2000).

- Explanatory studies, which examine the determinants of welfare outcomes of welfare leavers (CEA, 1999; Figlio and Ziliak, 1999; Heinrich and Lynn, 2000; Jennings and Ewalt, 2000; Moffitt, 1999; Sandfort, 2000; Schoeni and Blank, 2000; Wallace and Blank, 1999).

These studies have found that the well-being of most leavers is better or much better than before they left the welfare system and the success of welfare leavers is attributable to individual characteristics, state welfare policies,
organizational structure and management, and environment. While these findings are valuable in molding welfare policies in the future, two issues are still noticeable.

**Substantive Research Questions** First, there is little research that examines how state welfare policies and the structure and implementation actions of state welfare agencies affect the welfare outcomes of welfare leavers in the PRWORA era. Jennings and Ewalt (2000) examined the effects of state welfare program goals and priorities and administrative actions, but the outcome of interest was welfare caseload size at the state level. Sandfort (2000) paid more attention to the structure and service technology of state welfare agencies, but utilized the caseload outcome in 82 counties in Michigan. Heinrich and Lynn (2000) explored the relationship between organizational structure and management and individual outcomes of welfare-to-work programs, but their analysis utilized data from the pre-reform era. As a result, we do not have much information about how welfare leavers after the 1996 reform fare and which aspects of policies and organizational factors contribute to better outcomes. Thus, the first research question of the dissertation is:

- How have state welfare policies and the structure and implementation activities of state welfare agencies affected the economic self-sufficiency of former welfare recipients who left the system in the PRWORA era?
In this dissertation, we explore this research question utilizing a wide range of variables measuring state welfare policies and structure and implementation actions of state welfare agencies. We measure 5 broad dimensions of state welfare policies: policies on initial eligibility, benefits, requirements, ongoing eligibility, and transitional services. Four variables that measure state implementation activities are constructed through a factor analysis on Jennings and Ewalt’s original survey (2000) data on state welfare administrators’ perceptions of the importance of implementation activities.

**Methodological Research Question** Second, when outcome variables are collected at the individual level and other variables at the state level, most previous studies on welfare leavers examined the relationship either by assigning state characteristics to all individuals in the state (i.e., disaggregation approach) or by aggregating individual characteristics up to the state level (i.e., aggregation approach). These approaches are problematic when there exist significant “between-states” variations and, as discussed before, may produce unreliable estimates of cross-level interactions. Thus, the second and methodological research question of this dissertation is:

- What are the advantages and disadvantages of using different statistical methods in estimating interaction effects among individual- and state-level variables when there is significant “within-state” homogeneity and “between-states” variation?
This dissertation addresses this issue by reviewing several analytical strategies including moderated multiple regression models and multilevel linear models and evaluating the situations in which each model is appropriate in estimating cross-level effects. The moderated multiple regression models explicitly include the interaction terms among individual- and state-level variables and examine whether the estimates of these terms are statistically significant to indicate interaction or moderating effects. On the other hand, the multilevel linear models build their own linear sub-models, which each of the levels in the multilevel, nested data structure is formally represented. These sub-models express relationships among variables within a given level, and specify how variables at one level influence relations occurring at another.

Comparison of the performance of these two different models in estimating interaction effects will be conducted through Chapter 3 and Chapter 4 in this dissertation. And several criteria for the comparison include: (1) conceptual aspects, that is, which modeling strategy reflects complex, hierarchical data structure more precisely, (2) generalizability of findings, (3) the efficiency of estimates, and (4) standard errors of estimates. We will in detail discuss these criteria in Chapter 3.

1.3 Analytic Framework of the Dissertation
In this dissertation, we model the outcome of interest, earnings of welfare leavers one year after they left the system, as a function of individual characteristics, state welfare policies, the structure and implementation activities of state welfare agencies, and the environment, as graphically represented in Figure 1.1.

While the outcomes of public cash assistance programs include employment, earnings, recidivism, family formation, child well-being, and use of supportive services (Julnes and Foster, 2001), the focus of this dissertation is on the economic well-being of welfare leavers. Two often-used measures of the economic self-sufficiency of former welfare recipients are employment status and earnings. Among these, this dissertation uses total family earned income of welfare leavers as a measure of individual welfare outcome. There are two reasons for using total family earned income in this dissertation. First, because the interest in this dissertation is in individual outcomes, the outcome variables need to be measured at the individual level. While information on individual employment status is dichotomous (i.e., employed/unemployed), information on individual earnings provides continuous data allowing more sophisticated opportunities for modeling the economic well-being of welfare leavers. Second, methodologically, multilevel linear models using dichotomous dependent variables are not yet available, as a consequence, limiting the use of employment
status as an outcome variable. This family earned income is measured one year after the welfare recipient left the system.\(^5\)

The independent variables are constructed through a review of welfare program evaluation literature in general and of descriptive and explanatory studies of welfare leavers in particular. First, previous studies have suggested several individual characteristics that are related to welfare outcomes. Previous studies have examined the relationships between welfare outcomes and individual demographics (Brauner and Loprest, 1999; Loprest, 2001; Lower-Basch, 2000; Parrott, 1998), participation in other governmental programs, such as Food Stamps and Medicaid (Eisinger, 1999; Peller and Shaner, 1998; Stavrianos and Nixon, 1998; Zedlewski and Brauner, 1999), and human capital factors, which include level of education, job skills, job training and education, and past work experience (Martinson and Friedlander, 1994). These factors are all assumed to be related to welfare outcomes and we will examine the relationships through empirical analyses in Chapter 4.

Second, state welfare policies began to devolve substantially across states since the implementation of PRWORA in 1996 and it is assumed that differences in states’ policies have differential effects on welfare outcomes. States’ welfare policies vary on a number of dimensions, for example, who can be a recipient, what benefits are provided, what recipients should do in order to receive such benefits, and what the penalty is if there is noncompliance to the policy. These various aspects of states’ welfare policies can be organized into 5 broad

\(^5\) According to Isaacs (2001), a common definition of welfare leavers is people “that leave cash assistance for at least two months (p.22).”
categories: initial eligibility, benefits, requirements, ongoing eligibility, and transitional services.

Many studies have examined the effects of various state welfare policies on welfare outcomes. For example, MaCurdy, Mancuso, and O’Brien-Strain (2002) have examined the effects of sanction policy on caseload size and Rector and Youssef (1999) and Ziliak et al. (1997) have explored the relationship between work requirement policy and caseload size. Many studies (Anderson, Halter, and Schuldt, 2001; Westra, 2000) have also found that the continuation of transitional services is important in helping welfare leavers to stay off welfare. Generally speaking, previous studies show conflicting results on the effects of various aspects of welfare policies. In this dissertation, we will review, in detail, the literature on the effects of welfare policies in Chapter 2 and will empirically explore the relationships in Chapter 4.

The third component of the framework is the organizational structure and implementation activities of state welfare agencies. Little research has been done on how organizational structure and implementation activities affect welfare outcomes of welfare leavers. According to Lynn, Heinrich, and Hill (2000), some examples of structural variables include organization type (i.e., public/private/non-for-profit), level of integration/coordination, centralization of control, degree of formalization and specialization, functional differentiation, task complexity, contractual arrangements, and formal control/accountability systems. Sandfort (2000) and Heinrich and Lynn (2000) incorporated organizational structure measures into their analyses and found statistically
significant relationships between structure and welfare outcomes. Stoker and Wilson (1998) have found that implementation difficulties, such as complexity and inter-organizational coordination, are related to some of the outcomes of behavioral welfare reform.

Implementation activities are very broad concepts and include such factors as organizational mission/objective priorities, leadership practices, and several aspects of management including human resource management, information management, financial management, capital management, and performance management (Ingraham and Kneedler, 2000; Lynn, Heinrich, and Hill, 2000). Jennings and Ewalt (2000) have found that some of these factors play an important role in reducing caseload size. However, little research is done on the effects of implementation activities on welfare outcomes of welfare leavers.

In this dissertation, we utilize a survey of state welfare agency administrators collected by Jennings and Ewalt (2000) and construct four dimensions of state implementation activities through a factor analysis. Through a construction of implementation activity factors, we examine the effects of these factors on the economic well-being of welfare leavers, measured by earnings.

Finally, environment in the framework can be defined as consisting of factors that influence the outcomes of a welfare system but are partly or entirely outside the control of the system. Economic conditions and the characteristics of the area in which welfare leavers live are the most often-used indicators of environment. Previous studies (Bell, 2001 Blank, 1997; CEA, 1997, 1999; Figlio and Ziliak, 1999; Moffitt, 1999; Wallace and Blank, 1999; Ziliak et al., 2000) have
generally found that favorable state economic and demographic environments are positively related to the outcomes of interest.

In sum, while previous studies focus on a limited number of the many factors that influence welfare outcomes, the framework of this dissertation focuses on the development of an integrative analysis of welfare outcomes. This framework allows research to examine how individual characteristics, states welfare policies, organizational structure and implementation actions of state welfare agencies, and environment interact and affect the economic self-sufficiency of welfare leavers. A general assumption here is that a better understanding of welfare dependency and self-sufficiency of welfare leavers would be obtained by integrating all of the foci of previous studies into a single, integrative analysis. One possible consequence of focusing one aspect of many factors is that we are not sure whether the welfare outcomes are the effects of the factor considered, the other factors not included in the analysis, or some combination of the two. Another limitation is that focusing only one aspect explains less than a more integrative model does (Blank, 2001).

In addition to the above five components, the analytic framework in Figure 1-1 recognizes two different levels of these components. Another research question of this dissertation is to explore how the state-level components interact with individual characteristics for accounting for variations in individual outcomes. Individuals in a state have similar state welfare policies, receive similar services through the state welfare agency, and share the same environment. These state-level conditions may greatly differ from state to state,
influencing welfare leavers in each state in a different way. Under this situation, traditional statistical estimation techniques, which ignore grouping of people within a state, may be inappropriate in producing reliable interaction effects. In this research, we introduce several estimation methods including moderated multiple regression models and multilevel linear models and evaluate their appropriateness to study cross-level interaction effects between individual characteristics and the state-level variables.

1.4 Organization of the Dissertation

The dissertation is in five chapters. After this introduction, Chapter 2 begins with a review of the previous studies of welfare leavers. Two strands of these studies are introduced: descriptive studies and explanatory studies. Several factors that are deemed to affect welfare outcomes are discussed in Chapter 2. The purpose of the chapter is to identify the main dimensions and elements that contribute to the success of a public cash assistance program. Chapter 3 introduces the current methods of modeling and estimating interaction effects in multilevel settings. The traditional statistical methods, such as aggregated and disaggregated ordinary least squares (OLS) methods, are introduced with a discussion of their strengths and weaknesses. Also, this chapter provides an introduction to multilevel linear models (MLM) and how we can interpret the results. An exploration of the situations in which each method is appropriate in dealing with interaction effects is discussed. Chapter 4 provides an empirical evaluation of public cash
assistance program. Utilizing individual-level data from the Survey of Income and Program Participation (SIPP) and state-level data from various sources, this dissertation analyzes the effects of individual characteristics, state welfare policies, implementation actions, environment, and other factors on the economic well-being of welfare leavers, who left the system during October 1998 and July 1999. The economic well-being of leavers are measured by total family earned income and total family income between August 1999 and February 2000. The dissertation ends with the summary of the findings and discussions on policy implications in Chapter 5.
Figure 1.1 Analytic Framework of the Dissertation
CHAPTER 2
LITERATURE REVIEW

This chapter begins with a review of the literature on well-being of welfare leavers. This literature review introduces the descriptive and explanatory studies of welfare leavers and suggests a need for building an integrative framework to explain what determines welfare dependency and self-sufficiency of welfare leavers. The governance framework suggested by Lynn and Heinrich (2000) is introduced as an example of such a framework for an evaluation of a successful governmental program. And, based on the literature review of welfare leavers and the governance framework, we suggest an analytical framework for this dissertation to study the determinants of success of public cash assistance programs.

2.1. Previous Research on Well-being of Welfare Leavers

In this section, we review recent studies of welfare leavers, which analyze the well-being of people who left public assistance programs following welfare reform in 1996. Largely, these studies have been of two types: descriptive
analyses of welfare leavers, i.e., “descriptive studies”; and analyses of factors that influence leavers’ employment, recidivism, and other welfare outcomes, i.e., “explanatory studies.” The descriptive studies provide information on how welfare leavers are faring after a certain period of time, while the explanatory studies examine the effects of policies and policy environment on the well-being of welfare leavers. In the following section, we review in turn the descriptive studies and the explanatory studies in detail.

2.1.1. Descriptive Studies of Welfare Leavers

In fiscal year 1998, the Office of the Assistance Secretary for Program Evaluation (ASPE) of the U.S. Department of Health and Human Services (USDHHS) launched multi-state project on the well-being of welfare leavers in ten states, the District of Columbia, and three large counties\(^1\). These fourteen states and counties have monitored and reported outcomes of former welfare recipients. Also, many other states, such as, Iowa, New Mexico, New Jersey, and North Carolina, have undertaken similar efforts to assess the current status of the growing number of welfare leavers.

While each study has wide variations in terms of samples and time periods, most studies provide information on the characteristics of welfare leavers and their economic outcomes, such as employment status, earnings, and

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\(^1\) These areas include Arizona, District of Columbia, Florida, Georgia, Illinois, Massachusetts, Missouri, New York, South Carolina, Washington, Wisconsin, Cuyahoga County (Ohio), Los Angeles County, and a consortium of San Mateo, Santa Clara, and Santa Cruz counties in California.
wage rate. In this section, we synthesize these studies with their findings and limitations. The studies reviewed here are shown in Table 2-1 with their study areas, time periods, sample groups, and data.

**Research Strategy**

Most studies have used administrative data to track welfare leavers who left the system from 1997. These studies also have used telephone surveys or home visits to collect information on welfare leavers. The majority of the studies have collected information across multiple topics, including leavers’ demographics, employment, program participation, economic status, family structure, child well-being, and barriers and hardship.

Of the reviewed studies, Julnes (2000) used a stratified random sample of welfare leavers, while Rangarajan and Wood (2000) was the only study that conducted longitudinal surveys of welfare leavers. Mancuso et al. (2001), Acs and Loprest (2001), Crew et al. (2000) compared different groups, such as former/current/potential welfare recipients, leavers in two different time periods, and leavers/diverts/opt-nots\(^2\). The majority of these studies focused on the collection of the information across the entire population of leavers, although final sample size varies from less than 300 people in District of Columbia to over 3,500 people in Florida.

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\(^2\) Opt-nots are people who are eligible but opted not to use the service.
There is no study that compares before and after welfare reform outcomes mainly because relatively little information is available on welfare leavers in the pre-reform period. The time period of the studies also varies study by study from three months to 30 months after people left the public cash assistance system. Although linking state-specific policies and their environment to differences in outcomes of welfare leavers is policy-relevant, the descriptive studies did not explore the effects of changes in policies, economic conditions, and other factors on the well-being of welfare leavers. The primary purpose of these studies is to describe leavers’ demographics, outcomes in employment and earnings, recidivism, program participation, family well-being, and other information. These studies provide an excellent description of profiles of welfare leavers and their conditions. The findings from these studies are summarized by major topics in the below.

Leavers’ Demographics and Differences in Outcomes

Most welfare leavers sampled in the previous studies were single parents, African-American, and female. Also, the studies generally have found that African-Americans were less likely to leave the welfare system than Non-Hispanic Whites. According to Midwest Research Institute (2000), African-Americans were 35% of leavers during the fourth quarter of 1996, compared to 46% of all welfare cases in Missouri. The gap was even larger in Illinois and Wisconsin. In Illinois, African-Americans represented 49.5% of the leavers, as compared to 72%
of the cases from the fourth quarter of 1997. In Wisconsin, 60.8% of white recipients left the system as compared to 36.3% of African-American recipients.

The studies have generally found that some individual characteristics are positively related to the likelihood of leaving the welfare system. These include being female, having higher levels of education, being U.S. citizens, having fewer children, and having other adults in the households. Foster and Rickman (2001) argued that the education levels of the leavers are likely to be related to income after exit. Also, MAXIMUS (2001a) indicates, “In some cases, failure to complete high school may be indicative of other underlying issues, such as learning disabilities, poor work ethic, and intergenerational welfare dependency (p.ES-9).”

Some of these studies have reported the relationship between individual characteristics and welfare outcomes after exit. Generally speaking, African-American leavers are more likely to be employed than Non-Hispanic Whites after exit. For example, Georgia found that the average quarterly employment rate was 51.1% for Whites, compared to 70.6% for African-Americans. Also, African-American leavers tend to have higher median earnings. For example, in Cuyahoga county in Ohio, median earnings among those employed was $2,772 for African-Americans and $2,112 for Whites per quarter. African-American leavers are also more likely to return to the welfare system within one year. The one-year recidivism rate ranges within 20%-28% for Whites and 32%-42% for African-Americans across the studies.
Employment and Earnings After Exit

The findings on employment rates and earnings of former welfare recipients are relatively consistent across these studies. Employment rates ranged from 38%-67% in the first year after exit. And, employment rates remained fairly constant in the first year after exit in most study areas. However, there is a flux of new employment and unemployment among welfare leavers. Some leavers lost their jobs, while others found new employment in the same time period. However, most of these previous studies do not provide much information on how an individual fares after exit from welfare.

In terms of earnings, for leavers, the average monthly household earnings ranged from $1,055 in Iowa to $1,250 in North Carolina approximately one year after exit. Also, in all studies, earnings rose over the course of the year following exit. Generally speaking, a person who remained off welfare longer is more likely to be employed making more money. The findings on employment rate and average earnings of welfare leavers in major studies are shown in Table 2.2.

Recidivism

The previous studies have reported the recidivism rate for welfare leavers in various time frames. ADES (2001) found the recidivism rate for the first time since leaving is 33.8% in the first year and 9.5% in the second year, while Acs and Loprest (2001) reported that about one-quarter of leavers in D.C. returned to the system within a year. Foster and Rickman (2001) reported that 9 months after exit, 15% of adults and 19% of the children had returned to TANF. A similar result
is found in MDTA (2000), which reported that 15.9% of households in the time limit closings\(^3\) and 18.6% of households in the non-time limit closings had returned to welfare some time, on average, 10 months after exit.

From survey data, several studies have reported that at least one half of the people who returned to the welfare system did so because of a job-related reason, such as job loss or decreases in work hours or wages. Other reasons include changes in family structure, such as divorce or separation from partner and pregnancy or birth of a new child, loss of other incomes, and health or mental health problems.

Leavers in the 1996 and 1999 period can return to TANF because they did not consume the five-year federal time limits on benefit receipt. Also, because some people return to the welfare and then leave again, the proportion that ever returned after exit will be much higher than that at a certain point in time. Estimates of people who ever returned within the first year after exit ranged from 17% to 38% in these studies.

\textit{Program Participation and Family Well-being}

According to these studies, families of welfare leavers use various governmental services, such as Food Stamps, Medicaid, childcare, child protective services, and emergency and supportive services. However, many studies report that leavers tend not to take full advantage of those services mainly

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\(^3\) People may leave welfare for a variety of reasons. Time limit closings are those who left because their time limit expired. Non-time limit closings could be due to voluntary departure or involuntary exit due to noncompliance of policy regulations.
because they do not know that they are eligible or that they do not like "administrative hassles" (Kauff et al., 2000; Rangarajan and Wood, 2000).

Considering many previous studies (Anderson, Halter, and Schuldt, 2001; Julnes, Hayashi, and Anderson, 2001; Westra, 2001) that raised the importance of supportive services for welfare leavers to self-sufficiency, the education and outreach of their eligibility for such services may lead to achieve one of the goals of public cash assistance programs, that is, economic self-sufficiency of welfare recipients and leavers.

According to the previous studies, the proportion of leavers who participate in governmental support programs varies from program to program. The participation rates vary from 67.3% to 87% for free or reduced priced lunch program, from 29% to 74% for Food Stamps program, from 50% to 60% for public housing or housing assistance program, from 48% to 80.5% for Medicaid, from 23% to 33.6% for fuel assistance program, from 38.6% to 49.2% for a federal or state childcare subsidy, and from 38% to 54% for the Earned Income Tax Credits (EITC). Crew et al. (2000) report that supportive services utilization rates in Florida vary by race and ethnicity. According to them, African-Americans utilize governmental services to a greater extent than do whites, Hispanics or people from other racial/ethnic groups.

A majority of leavers report that their general family well-being is better or much better than before exit (ADES, 2000; Mancuso et al., 2001). Several experiences of hardship after exit are also reported, such as difficulties with paying rent or having utilities cut off or having to skip or reduce the size of meals
(Acs and Loprest, 2001). MAXIMUS (2001a) reports that many of the respondents who are still on welfare face significant barriers, such as no work experience in the past two years, health barriers, depression problem for older recipients, and low education level (41% less than a high school or a GED). Also, Rangarajan and Wood (2000) find that in spite of the overall economic progress, there are still substantial challenges, such as health problems, food insecurity, and “barely making it from day to day.”

In sum, studies of welfare leavers within a state provide detailed information on demographics, recidivism, employment status, earnings, use of supportive services, reasons for leaving, child welfare, and basic needs after exit. The main purpose of these studies is to describe how welfare leavers are faring after exit from the welfare system. However, these studies usually do not explore the effects of state policies and underlying economic and social conditions on individual outcomes.

Even though there are a number of studies that compare welfare leavers and their outcomes across several states (Boushey and Gunderson, 2001; Brauner and Loprest, 1999; Cherlin et al., 2001; Danziger, 2000; Garrett and Holahan, 2000; Guyer, 2000; Isaacs and Lyon, 2000; Martinson, 2000; Moffitt and Roff, 2000; Oliphant, 2000; O’Neil and Hill, 2001; Richer et al., 2001; Wertheimer, 2001; and Zedlewski and Gruber, 2001), these studies tend to be simple cross-tabulations of leavers’ characteristics, employment rates, earnings, and
percentage returning to welfare after exit by state. They often lack a model that links welfare policies and other factors to the leavers’ well-being.

In the next section, we review another strand of the studies of welfare leavers, that is, the explanatory studies of welfare dependency and self-sufficiency of welfare recipients and leavers. These studies are different from the descriptive studies in that they explore the factors that may affect outcomes of welfare recipients or leavers.

### 2.1.2. Explanatory Studies of Welfare Leavers

The main purpose of these studies is to find the factors that contribute to the success of welfare programs. In these studies, the success of the program is measured through a wide range of indicators, such as, employment, earnings, recidivism, family formation and structure, child well-being, and use of supportive services of welfare leavers. Also, these studies involve multiple sources of data and analytical methods. Their findings are often conflicting and policy recommendations also vary depending on the authors’ perspectives.

In this dissertation, we try to systematically review these explanatory studies by their main focus. The explanatory studies of what determines welfare dependency and self-sufficiency of welfare leavers can be largely categorized as individual explanations, economic and environmental explanations, policy explanations, and other explanations. In the following section, we examine each of these explanations in turn.
Individual Explanations

The first explanation holds that individual characteristics, such as demographics, ability and willingness to work, past work experience, family structure, and psychosocial factors mainly determine welfare dependency and self-sufficiency of welfare recipients and leavers. For example, Ellwood’s study (1986), which is one of the earliest studies on welfare recidivism, found that education levels, marital status, number of children, work experience, and disability status of individuals are among the most closely correlated covariates of recidivism.

According to Cao (1996), from January 1978 to December 1991, on average 57% of former AFDC recipients returned to the welfare system and having a newborn is the most important cause of recipiency and recidivism. Several scholars attribute the main cause of welfare dependency to a “defect” in the individual’s moral behavior (Mead, 1986; Murray, 1984; Murray and Kopel, 1995). They argue that welfare recipients are making rational decisions using a cost-benefit calculation and that welfare programs change the calculus of choices by reducing the costs attached to being unemployed and being on welfare.

Human capital theory assumes that each individual has a stock of human capital, such as skills, knowledge and experience, and education and training. And it is argued that higher human capital tends to lead to higher earnings. Relying on human capital theory, Martinson and Friedlander (1994) argued that welfare recipients need education and training to acquire a good job to become
self-sufficient. This may be a rationale behind policies providing education and training for welfare recipients.

Other welfare policy reforms suggested by both conservatives and liberals seem to have stemmed from these explanations. Some examples of such policy reform include establishment of eligibility criteria and time limits, adjustment of welfare benefit levels, creation of work incentives, enhancement of educational and employment training programs, and enrichment of supportive services. These policy reforms are intended to make welfare less attractive than work. For example, family cap policy, which pays no or very limited extra benefits to women currently on welfare who have additional child, is designed to discourage unwed mothers from having a child out of wedlock.

While these individual based explanations provide insights on welfare dependency and policy reforms, past studies show wide variations in their findings. Blank and Ruggles (1994), using monthly data from the Survey of Income and Program Participation (SIPP), found that individual characteristics, such as age and education, provide little help in identifying potential recidivism, while ethnic origin, number of children, other non-earned income have significant effects on the probability of recidivism. The most important reason for recipiency and recidivism also varies, such as having a newborn (Cao, 1996), changes in marital status and family composition (Ellwood, 1986), and a decrease in earnings and other income (Blank, 1989). Further, most studies have found
weak relationships, for example, between welfare benefits and out of wedlock births (Duncan and Hoffman, 1990; Lundberg and Plotnick, 1995)\textsuperscript{4}.

This individual based view of welfare dependency and self-sufficiency supports some welfare policies aimed either at providing incentives and assistance such as more education and job training and more day care, or by providing disincentives by imposing time limits and limiting benefits. However, this explanation cannot be generalized to all cases of welfare recipients or may not explain a case of single individual. There are other explanations why some people remain on welfare, while others soon become self-sufficient.

\textit{Economic and Environmental Explanations}

These explanations argue that the economic and the societal environment in which most welfare recipients live play an important role in deciding welfare dependency and self-sufficiency. These explanations help us to understand how structural problems in society influence the poor in addition to individual explanations, which hold that a road to self-sufficiency exists within an individual's ability to change behavior and find a job.

Wilson (1993) argues that the primary problem of the urban poor, referred to the underclass, is “joblessness reinforced by an increasing social isolation in an impoverished neighborhood (p.20).” According to this perspective, values and attitudes of the underclass are isolated from those of the mainstream society,

\textsuperscript{4} A statistically significant and positive effect of welfare benefits on non-marital childbearing has been found in Rosenzweig (1999) and Hoffman and Foster (2001). However, the results are very sensitive with model specification and sample.
which not only result in chronic unemployment and low wages, but also act as impediments to their successful movement into the world of work. Also, they suffer from a lack of community safeguards and resources. Many governmental programs have the intention of providing resources and services to low-income areas in order to break a vicious cycle of poverty through these families and through these communities.

A conventional finding from welfare caseload studies is that economic conditions, often measured by unemployment rate, have played major role in the decline in welfare dependence for low-income families (Bell, 2001). Most studies estimate that 1% decrease in the unemployment rate leads to a lagged decline of 4% to 6% in the welfare rolls in about four years, with longer intervals producing larger effects (Blank, 1997; CEA, 1999; Wallace and Blank, 1999). Further, several studies have argued that the economy is estimated to account for the largest proportion of welfare caseload changes in many studies (CEA, 1997; Figlio and Ziliak, 1999; Moffitt, 1999; Wallace and Blank, 1999; Ziliak et al., 2000) in comparison to other factors such as individual characteristics and welfare policies.

Other studies of welfare leavers have found that earned incomes account for about 70% to 85% of leavers’ total household income (Coulton and Verma, 2001; Du, Fogarty, Hopps, and Hu, 2000; Ryan, 1999). This implies that there is a link between maintaining employment and economic self-sufficiency for welfare leavers. Whether unemployment is a result of the shortage of demand or the imperfections in the labor market (Gordon, 1972), one obvious fact is that the
economic conditions influence welfare dependence and self-sufficiency of welfare recipients and leavers.

Economic and environmental perspectives extend the scope of the study of welfare dependency and self-sufficiency to the environment in which the welfare leavers live. These explanations cast doubt on the argument that individual behaviors and characteristics determine their self-sufficiency and recognize that there are economic and social barriers with which welfare recipients and leavers have to cope in order to be self-sufficient.

*Policy Explanations*

These explanations emphasize the role of welfare policies in determining welfare dependency and self-sufficiency of welfare leavers and the views range from extremely pessimistic to extremely optimistic. On one hand, welfare is seen as a cause of several pathologic conditions, such as dependency, poverty, out-of-wedlock births, non-employment, abortion, and violent crime (Niskanen, 1996). On the other hand, public cash assistance programs in the 1990s were described as a “stunning success” (Duncan and Chase-Lansdale, 2001).

According to Niskanen (1996), an 1% increase of AFDC benefits would increase the number of welfare recipients by 3%, the number of people in poverty by 0.8%, the number of births to single mothers by 2.1%, the number of non-employed adults by 0.5%, the number of abortions by 1.2%, and the number of violent crime rate by 1.1%. According to Murray and Kopel (1995), welfare is a corrosive force, even though it is not a main cause of these phenomena. Welfare
discourages people from working, by making unemployment acceptable financially and socially and by paying more money to unwed mothers.

Several studies have argued that the size of welfare caseloads is influenced by state welfare policies (CEA, 1997, 1999; Moffitt, 1999; Rector and Youssef, 1999; Schoeni and Blank, 2000; Wallace and Blank, 1999). Majority of the researchers have found that the policies intended to increase work effort, such as time limit, limitation of work exemptions, and increase in work sanctions, were found to have significantly reduced caseloads by the majority of researchers.

According to Riccio, Friedlander, and Freedman (1994), the focus on job search and work strategies led to better employment outcomes than did education, at least in the short run. These findings supported the idea of “work first”, which required work and job search activities of welfare recipients (Pavetti, 2000). U.S. Congress (2000) confirmed that welfare outcomes vary considerably by state, depending on the formulas for allowing continuation of cash assistance along with the use of supportive services, such as the food, health, and child care, that affect economic status of welfare recipients and leavers. In terms of family formation and structure outcomes, Blank and Schmidt (2001) found that the new policies allowing eligibility to two-parent families increased the caseload size during the early 1990s.

In sum, studies of the effects of welfare policies provide conflicting results. It seems that the problem is not simply statistical or empirical analysis, but reflects real uncertainties about how these policies interact with individual
behaviors, the economy, and implementation activities of street-level bureaucrats.

*Other Explanations*

Many scholars in public administration have called attention to the roles of organizational characteristics and implementation activities in determining the success of welfare reform (Heinrich and Lynn, 2000; Jennings and Ewalt, 2000; Sandfort, 2000; Ricco, Bloom, and Hill, 2000). They generally have argued that organizational structures and characteristics and management are important influences on program outcomes and, thus, these factors need to be included in an evaluation of welfare programs.

Heinrich and Lynn (2000) explored the relationship between organizational structure and management and performance of Job Training Partnership Act (JTPA) program using multilevel analysis. Through a review of JTPA service delivery system, they confirmed three possible structural arrangements in delivering the service: contract-based arrangements, ordinary public administration arrangements, and more centralized public administration arrangements. They also included several variables describing management functions, such as performance incentive policies and service delivery and contracting strategies. They investigated the effects of these structural and management variables on participant outcomes, measured by participants’ earnings in the first post-program year. Heinrich and Lynn found that more centralized authority or control in JTPA program administration had a positive
and statistically significant impact on earnings outcomes, while the services provided directly by the administrative entity and the performance-based contracts have a negative relationship with program outcomes. Also, performance incentive variables are positively related to client outcomes, while the use of performance-based contracts was negatively related to clients’ earnings after they left the program.

Two distinguishing features of the Heinrich and Lynn study are that (1) it examines the impacts of structure and management on individual outcomes controlling for individual characteristics and environmental factors; and (2) it utilizes multilevel linear models to incorporate two different levels of data. However, by assuming the fixed relationships\(^5\) between the site-level variables and the effects of client-level predictors on earnings outcomes, it doesn’t fully explore the interactions between higher- and lower-level variables. Another limitation of this study is that it lacks complete information on program components.

Jennings and Ewalt (2000) examined the relationship among the state policy choices, the priorities and goals of state assistance programs, the actions administrators take to implement reform and welfare caseload reductions at the state level. They collected rich information on management variables including state TANF program priorities and goals, implementation strategies, and administrative activities through a survey of state government administrators.

\(^5\) The fixed modeling of hierarchical linear models is essentially same as disaggregated regression models discussed in Chapter 3. Several limitations of this method include lower explanatory power and misestimated standard errors. The details are in Chapter 3.
After specifying policy outcomes as caseload reductions, they find that state activities that emphasize client work consistently are positively related to the reductions in caseload size, while state activities that emphasize changes of the welfare office culture have smaller effects on caseload reductions.

One of the strengths of the Jennings and Ewalt study is that it utilizes a wide range of variables on program goals and management activities and links them to the outcome of interest, that is, caseload reductions. However, as they indicated, they are “less successful at capturing client or structural characteristics (p.110).” Also, aggregated analysis at the state level does not shed much light on how individuals interact with policy implementation activities, which is one of the main research questions addressed in this dissertation.

While Jennings and Ewalt (2000) focus on policy choices and management, Sandfort (2000) pays more attention to the structure and service technology and examines the impacts of environmental, client, structural, treatment, and technology factors on the proportion of a county’s caseload that moves into the workforce in 82 counties in Michigan.

Sandfort measures the service delivery structure using four variables: participation in Project Zero⁶, the number of Work First⁷ providers in a county, the frequency of nonprofit organizations, and whether special Work First contracts were given in the county to serve special client populations. She finds a positive effect of participation in the Project Zero pilot and a negative effect of the

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⁶ Project Zero is a pilot program with the goal of reducing the number of welfare cases without earned income to zero. In 1996, there were 6 pilot sites in Michigan.
⁷ Work First is the name of Michigan welfare-to-work program. This program changed its focus from education to a “quick-labor-force-attachment” since 1994.
number of Work First providers on the proportion of welfare recipients working in a county.

Although Sandfort incorporated information on environmental, service delivery structure, and service technology, the characteristics of clients and management variables are not utilized. Also, the use of aggregated data at the county level is another limitation of the study, because “micro-level data from a statewide sample of welfare recipients would be desirable in order to explore how environmental factors, client characteristics, implementation structures, and service technologies contribute to individuals' ability to find employment or leave welfare because of work (Sandfort, 2000, p.149).”

In sum, the explanatory studies of welfare leavers investigate the impacts of individual, economic and environmental, policy, and other factors on welfare outcomes, mostly measured by employment levels, earnings, recidivism, and caseload size. Also, most studies utilized aggregated single-level analysis mainly due to the lack of disaggregated data on welfare recipients.

While the above explanations focus on one aspect of the many factors that influence welfare outcomes, a better understanding of welfare dependency and self-sufficiency of welfare leavers would be obtained by integrating all of the above explanations and their foci into a single, comprehensive analysis. Rossi posits that an understanding of the theory underlying social programs is crucial to making progress in solving social problems. However, by theoretical understanding he does not mean “the global conceptual schemes of the grand

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theorists (Chen and Rossi, 1983, p.285).” He proposes theory-driven evaluation studies, which construct a theoretical model of program inputs, causal mediating processes, and program outputs (Rossi and Wright, 1984). That is, a theory-driven evaluation includes such components as how a social program is formed and delivered, how governmental organizations organized and implemented, and what outcomes are produced. In the next section, we introduce the governance framework suggested by Lynn and Heinrich (2000) as an exemplary framework for such an evaluation study. As a synthesis of the earlier literature on program evaluation, this governance framework proposes that government program outcome is the function of client characteristics, environmental factors, treatments, structures, and implementation actions. We apply this framework into the public cash assistance program context by redefining dimensions and elements of the framework.

Also, we need to consider the different types of welfare recipients and leavers who differently interact with state-level variables, such as welfare policies, economic conditions, and implementation activities. Thus, policy makers have to take into consideration the interactions among individuals and the major state-level factors that have significant effects on self-sufficiency. In particular, Chapter 3 introduces and compares various statistical methods in estimating interaction effects and their implications.
2.2. Governance Model of Public Program Evaluation

2.2.1 Definition of Governance

The term *governance* has very broad and to some extent ambiguous definitions widely used in the public and private sectors. First, the term governance seems to refer to institutional mechanism to achieve direction and control of individuals and organizations. One example is the definition from the Institute on Governance, which states governance is “the traditions, institutions and processes that determine how power is exercised, how citizens are given a voice, and how decisions are made on issues of public concern. Another example is from Wamsely (1990), who defines governance as “the use of authority in providing systemic steering and direction (p.25).”

Second, governance not only refers to institutional mechanisms of command but also arrangements or networks among individuals and institutions. Vickers (1983) refers to governing relations and to the role of authority in maintaining governing relations to maximize the values that can be realized through them. Williamson’s (1996) definition of governance is more inclusive and incorporates global and local arrangements, formal structures and informal norms and practices, spontaneous and intentional systems of control. Lynn, Heinrich, and Hill (2001) argue that these two intellectual traditions, the study of institutions and the study of networks, have contributed to the etymology of the term ‘governance’ in public administration.
In addition to the above traditions, the concept of governance also refers to the processes and implementations of decisions made by governance so defined. This concept is mainly emphasized in the field of public administration. In the context of public sector applications, Lynn, Heinrich, and Hill (2001) define governance as “regimes of laws, administrative rules, judicial rulings, and practices that constrain, prescribe, and enable government activity, where such activity is broadly defined as the production and delivery of publicly supported goods and services (p.3).” According to this definition, the term governance refers both to many different types of institutional arrangements, policies, and networks used to structure governmental activities and to governmental activities implemented to achieve the missions and goals of the government.

In sum, the concept of governance refers to institutional arrangements, relations and networks, and processes and implementations to maximize the values that the stakeholders want to achieve. In this regard, the governance definition of Lynn, Heinrich, and Hill (2001) is a compilation of the previous definitions of governance. To build an integrative model of welfare program evaluation, we first introduce the governance model suggested by Lynn, Heinrich, and Hill (2000) in detail next and then discuss how to measure the formal hierarchical or networked organizational structures, rules and policies, and processes and implementation in the context of public cash assistance program.
2.2.2 Model of Governance

Despite the increasing number of studies, one of major difficulty in studying governance comes from its broad scope and component elements (Lynn, Heinrich, and Hill, 2000). In a “full” governance model, governance may imply almost anything: laws and rules; organizational structure; managerial practices; administrative processes; missions and goals; political actors; and governmental activities. As Lynn, Heinrich, and Hill (2000) argue, “the true model may be one in which the marginal effect of many elements is zero (p.15).” Thus, in order to conduct a feasible governance research, we first have to identify a parsimonious model of governance for a specific context.

Several scholars have synthesized governance models (Heinrich and Lynn, 2000; Jennings and Ewalt, 2000; Knott and Hammond, 2000; Roderick, Jacob, and Bryk, 2000) utilizing a range of defining elements in various contexts, such as education, job training programs, and welfare programs. Acknowledging there is still much need for rigorous empirical tests, this dissertation summarizes a framework studying the impacts of governance and public management on program outcomes proposed by Lynn, Heinrich, and Hill (2000) as a base to study the relationships between governance and outcomes of welfare leavers.

According to Lynn, Heinrich, and Hill (2000), in a simple reduced-form model, government outcomes, $O$ is a function of environmental factors, $E$; client characteristics, $C$; treatments such as primary work, core processes, and technology, $T$; structures, $S$; and managerial roles and actions, $M$, as expressed in Equation (2.1).
Given the reduced-form model of governance and program outcomes, the next task is how to specify each element of the model in the context of welfare reform. Lynn, Heinrich, and Hill (2000) provide some examples of variables used in governance research for each of these model components, as briefly explained in the below.

According to them, outputs or outcomes of public programs can be measured at individual-level and/or organizational-level. If they are measures at individual-level, the variables will be precisely defined and empirically measured ones. If they are measures at the organizational-level, the variables will be broadly defined and not necessarily client-oriented ones. Thus, the implications from an analysis using different levels of outcome variables also will be different. If the purpose of a study is to explore the relationships among variables within a given level, any unit of analysis can be a logical unit. If the purpose of a research is to specify the relationships among variables in different levels, it requires data from multiple levels and an appropriate analytical technique.

The right-hand side of Equation (2.1) includes five components. First, environmental factors\(^8\) can be those that influence the outcomes of a welfare system but are partly or entirely outside the control of the system. Examples of such factors include political structures, level of external authority/ monitoring,

\[ O = f (E, C, T, S, M) \]  

---

\(^8\) These factors are often referred to as endogenous variables or control variables in other literatures.
performance of the economy, and aggregate characteristics of eligible or target population. Second, client characteristics are self-explanatory. These variables include client attributes and behaviors. The third element of the governance model is treatment, which mainly refers to organizational mission and objectives, core processes, and technology. Fourth, Lynn et al. (2000) introduced several important dimensions of organizational structure as one of main explanatory variables of successful governmental programs. These include organization type, level of integration/coordination, centralization of control, functional differentiation, contractual arrangements, and institutional culture and values. Finally, managerial role and actions are very broad concepts including leadership practices, staff-management relations, and monitoring/control/accountability mechanisms.

In sum, governance is a broad concept encompassing many sub-concepts, such as institutional mechanisms of direction and control, institutional arrangements and networks, and processes and implementation. This concept provides a basis of evaluating public programs from multiple perspectives of interests making an evaluation more complete. The governance model presented by Lynn, Heinrich, and Hill (2000) is one comprehensive example of models of governance and program outcomes including five factors that affect government program outcomes; customers’ characteristics, environment, treatment, structure, and management. However, we still need to discuss how to apply the
governance framework in the context of public cash assistance program and how to measure each component of the model. We will discuss them below.

2.3. Redefining Dimensions and Elements of the Model in the Welfare Context

The five main dimensions of Lynn et al.’s governance framework are customers’ characteristics, environment, treatment, structure, and management. The next task is to review these dimensions whether they are also applicable to the welfare program context and, if so, then, to specify measures of the dimensions.

2.3.1. Redefining Dimensions of the Governance Model

As discussed in the previous studies of welfare dependency and self-sufficiency, the descriptive and explanatory studies of welfare leavers have emphasized several factors that determine the successful outcomes of welfare leavers. They are individual characteristics, the economic and environmental characteristics, policies, and other factors, such as implementation actions of state welfare agencies. These factors are well matched with the five components of the governance model. The relationship between the determinants of the well-
being of welfare leavers in the previous study and the components in the governance model is shown in Figure 2.1.

As Figure 2.1 shows, the factors from individual explanations and the economic and environmental explanations are well matched with the clientele characteristics and environment in the governance framework. And, the state welfare policies reflect the treatment component, while state welfare agencies as implementers represent the structural and management components in the governance framework. Thus, we utilize the five dimensions of the governance framework to this dissertation, however, how to measure each dimension in the welfare context will be discussed below.

2.3.2. Specifying Measures of Each Dimension

Program Outcomes

There are multiple outcomes of interest in public cash assistance programs. Many studies of welfare reform have focused on employment and recidivism as program outcomes. Another often-used measure of welfare outcome is earnings of welfare leavers. Other measures of outcomes concern family formation, child well-being, and the use of supportive services after exit. While measures of the first two outcomes are dichotomous (employed/not and returned/not), measure for earnings are continuous allowing more sophisticated opportunities for modeling the well-being of welfare leavers.
Also, outcomes can be measured at various levels of aggregation, such as individual, local agency, and state levels. If outcome variables are measured at local agency or state agency level rather than individual level, the results from an analysis would estimate “average” effects of local- or state-level variables on “average” individuals within the local or state agency. In this case, we have very limited information on how different individuals interact with welfare policies, economic conditions, and implementation actions at the state level. Figure 2.2 presents measures of possible outcome variables mostly used in the previous studies.

**Individual Characteristics**

The characteristics of welfare recipients and leavers are also critical determinants of program outcomes. The characteristics of individuals contributing to these outcomes include age, gender, race/ethnicity, level of education, job skills, employment history, work experience, ability and willingness to work, family structure, and participation to other governmental programs. These individual characteristics can be categorized as demographics, participation in other governmental programs, and human capital factors as shown in Figure 2-3. Demographic factors include age, gender, race/ethnicity, and disability status; participation to other governmental programs capture participation to programs, such as Food Stamps, Medicaid, and Social Security; and human capital factors include those factors like education level, job skills, job training and education, and past work experience.
Some of these variables, such as age, gender, and race/ethnicity, are “fixed” in the sense that there is little room to change them in order to improve individual outcomes. However, other individual-level variables, such as level of education, job skills, and ability and willingness to work, are “flexible” in the sense that the welfare system can enhance the human capital of welfare leavers. Many policies are intended to increase this flexible side of individual characteristics.

Environment

Environmental factors can be defined as factors that influence the outcomes of a welfare system but are partly or entirely outside the control of the system. Economic conditions and the characteristics of the area in which welfare leavers live are the most often-used indicators of environment. These two environments are shown in Figure 2.4.

Some previous studies exclusively utilized unemployment rate as a measure of the economic condition (Sandfort, 2000). Other measures of the economic conditions used in the previous studies include median income, the percent of people employed in manufacturing industry, median wage, and price index. State demographic environment is also measured by a wide range of variables, including residential location (i.e., urban/suburban/rural), community demographics (fertility rate, percent of elderly, white, and the disabled), community education level, and political affiliation of state (Anderson, Halter,
and Schuldt, 2001; Bartik and Eberts, 1999; Jennings and Ewalt, 2000; Rickman, Bross, and Foster, 2001; Wallace and Blank, 1999).

_Treatment_

As discussed above, state welfare policies began to devolve substantially across states since the implementation of PRWORA in 1996 and it is assumed that differences in states’ policies have differential effects on welfare outcomes. States’ welfare policies vary on a number of dimensions, for example, who can be a recipient, what benefits are provided, what recipients should do in order to receive such benefits, and what the penalty is if there is noncompliance to the policy. These various aspects of states’ welfare policies can be organized into 5 broad categories as shown in Table 2.3 (CEA, 1997; Rowe, 2000): initial eligibility, benefits, requirements, ongoing eligibility, and transitional services. The following is a brief description of these dimensions to enhance the understanding of variations in states’ welfare policies and their potential impacts on welfare outcomes.

First, policies on initial eligibility concern key aspects of the rules imposed on families and individuals in order to determine initial eligibility for public assistance programs. These are rules related to diversion, family composition, assets, income definitions, and income tests.

Second, policies on benefits concern what a family would receive if it passed all eligibility tests. These policies include how much of earned income a recipient can disregard for benefit computation, the procedure by which states
compute benefits, benefit standards, and the maximum benefit for a family. There is substantial variations across states along these dimensions. For example, the maximum monthly benefit for a family of three with no income ranges from 164 dollars in Alabama to 923 dollars in Alaska with the mean of 412 dollars.

Third, states’ welfare policies on requirements concern the numerous requirements imposed on a family within an assistance unit in order to receive benefits. These requirements vary considerably by state but can include requirements for dependent children, such as immunization and school attendance, as well as requirements for the adult head of the household, such as work-related requirements. It also includes the rules on work-related exemptions, work-related activities, and work-related sanctions. There are many studies that have examined the impacts various requirement policies on caseload decline including sanction policy (MaCurdy, Mancuso, and O’Brien-Strain, 2002) and work requirement (Rector and Youssef, 1999; Ziliak et al., 1997).

Fourth, policies on ongoing eligibility concern key aspects of the rules that affect recipients’ ongoing eligibility. Recipients’ eligibility and benefits may be affected by their reproductive choices and the number of months they have received assistance. While most states have imposed a maximum 60-month lifetime time limit on benefits, there are some states that have adopted shorter lifetime limits or more generous time limits.

Finally, policies on transitional services prescribe supportive services that welfare recipients and leavers can take advantage of. These services include services regarding child care, medical care, transportation, and housing.
assistance. Many studies indicate that the continuation of these services is important in helping welfare leavers to stay off welfare (Anderson, Halter, and Schuldt, 2001; Dunton, Mosley, and Butcher, 2001; Westra, 2001).

**Structure**

Some examples of structural variables in the governance framework include organization type, level of integration/coordination, centralization of control, degree of formalization and specialization, functional differentiation, task complexity, contractual arrangements, and formal control/accountability systems (Melcher, 1976; Miller and Friesen, 1984).

There is little research on how these structural variables affect welfare outcomes of recipients and leavers. Stoker and Wilson (1998) suggest that implementation difficulties, such as complexity and inter-organizational coordination, are related to some of the supposed benefits of behavioral welfare reform. Whether other structural variables, such as program decentralization and flexibility based on recipient and local needs, are essential elements of a successful program is still a question open to empirical debate.

**Management**

Finally, managerial practices or implementation activities are very broad concepts and include organizational mission/objective priorities, leadership practices, and several aspects of management, such as human resource
management, information management, financial management, and performance management. Organizational culture is another important aspect of management in the sense that it formulates desirable managerial practices and is formulated through current managerial practices. As discussed in the review of explanatory studies, many studies indicate that these factors play an important role in determining welfare dependency and self-sufficiency of former welfare recipients.

2.4 Analytical Framework

The purpose of this dissertation is to build a comprehensive framework of public cash program evaluation and to explore the determinants of the economic well-being of welfare leavers. Through a review of descriptive and explanatory studies of welfare leavers and of the governance framework, we model the outcomes of public cash assistance programs as a function of individual characteristics, environment, treatment, structure, and management. Also, this dissertation recognizes two different levels of analysis of these factors and suggests the use of hierarchical linear modeling as a technique to estimate the interaction effects between them. Figure 1.1 (p.19) is a graphical representation of the framework for this dissertation.

Welfare program outcome for this dissertation is measured by total family earned income of welfare leavers one year after they left the system. Individual characteristics have several dimensions, such as demographic, participation in
other governmental programs, and human capital factors. Most studies suggest that being male, non-white, married, and non-disabled are positively related to the outcome variable. Thus, we hypothesize that being male, being non-white, being married, and being non-disabled are positively related to total family earned income.

Also, participation in other governmental programs, such as Food Stamps, Social Security, and Medicaid, is assumed to be negatively related to total family earned income because those programs lead to disincentives to work by providing other income in addition to income from work. Thus, the testable hypothesis would be that participation to other governmental programs, such as Social Security, Medicaid, and Food Stamps, is negatively related to total family earned income.

Finally, according to human capital theory, higher human capital factors, such as higher level of education, job skills, job training and education, and past work experience, will increase earned income. Thus, the hypothesis would be that higher the level of human capital factors, such as level of education, job skills, job training and education, and past work experience, are positively related to total family earned income.

Previous studies have generally found that favorable state economic and demographic environments are positively related to the outcomes of interest. State demographic environment can be measured by a wide variety of variables: percent of elderly, percent of never-married single female head of households, percent of immigrants, median state education level, percent of black population,
and non wedlock births per 1000 live births. And economic conditions can be measured by unemployment rate, personal income per capita, median income, and 10th and 20th percentile of usual weekly earnings. The research hypothesis related to environmental factors is that, a favorable state economic and demographic environment is related to higher total family earned income.

To estimate the effects of organizational structure on program outcomes, two structural variables are utilized: decentralization and flexibility of the program. Decentralization implies state welfare agencies that allow for local planning and implementation of the program based on local needs. And flexibility is a measure of whether states choose their programs at the local level based on local needs. While we will discuss in detail these measures in Chapter 4, it is generally assumed that these structural features are positively related to the outcomes.

As discussed before, several dimensions of state welfare policies are related to these outcomes, but previous studies often show conflicting results regarding their direction of influence and magnitude. Thus, it can be said that the effects of various aspects of welfare policies are ultimately a question of rigorous empirical tests, however, generally speaking, we assume that more restrictive, work-oriented, and work incentive policies will be positively related to higher total family earned income, while policies that are more generous, education-oriented, and offer fewer work related incentives will be negatively related to the outcome.
We utilize a survey of state welfare agency administrators collected by Jennings and Ewalt (2000) and construct four dimensions of state implementation activities through a factor analysis. These dimensions are factors related to service provision, enhancement of customers’ human capital, “work first” approach, and improvement of staff productivity. And there is no a priori expectation whether these factors have positive or negative impacts on the outcomes, that is, total family earned income.
<table>
<thead>
<tr>
<th>Author(s) (Year)</th>
<th>Area</th>
<th>Sample</th>
<th>Method/Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acs &amp; Loprest (2001)</td>
<td>D.C.</td>
<td>Leavers in the last quarter of 1997 and in the last quarter of 1998</td>
<td>Administrative data, interview</td>
</tr>
<tr>
<td>ADES (2001)</td>
<td>Arizona</td>
<td>Leavers in the first 3 months of 1998 for two years</td>
<td>Administrative data, survey data</td>
</tr>
<tr>
<td>Crew et al. (2000)</td>
<td>Florida</td>
<td>Leavers in the second quarter of 1997, diverts and “opt-nots” in the same quarter</td>
<td>Administrative data, telephone interview</td>
</tr>
<tr>
<td>Kauff et al. (2001)</td>
<td>Iowa</td>
<td>Leavers in spring 1999</td>
<td>Administrative data, survey</td>
</tr>
<tr>
<td>Mancuso et al. (2001)</td>
<td>San Mateo, Santa Clara, and Santa Cruz county, California</td>
<td>Leavers in the fourth quarter of 1998, informally diverted families in the fourth quarter of 1998, recipients of housing assistance in January 1999</td>
<td>Administrative, survey data after 6, 12, 18 months since exit or diversion</td>
</tr>
<tr>
<td>MAXIMUS (2001a)</td>
<td>New Mexico</td>
<td>Leavers between July 1998 and June 1999</td>
<td>Telephone survey</td>
</tr>
<tr>
<td>MAXIMUS (2001b)</td>
<td>North Carolina</td>
<td>Leavers between August 2000 and May 2001</td>
<td>Telephone survey</td>
</tr>
<tr>
<td>MDTA (2000)</td>
<td>Massachusetts</td>
<td>Leavers between December 1998 and April 1999</td>
<td>Interview</td>
</tr>
</tbody>
</table>

Table 2.1 Welfare Leavers Studies Reviewed in the Dissertation
<table>
<thead>
<tr>
<th>Author(s) (Year)</th>
<th>Employment rate</th>
<th>Earnings</th>
<th>Time period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acs &amp; Loprest (2001)</td>
<td>60.3%</td>
<td>$8 an hour (about $1,280/month)</td>
<td>1 year</td>
</tr>
<tr>
<td>ADES (2001)</td>
<td>57% in the first year 59% in the second year</td>
<td>$1,245 in total monthly income</td>
<td>1 or 2 year</td>
</tr>
<tr>
<td>Crew et al. (2000)</td>
<td>49.8% for diverts 53.3% for leavers</td>
<td>$10,453 for opt-nots $11,155 for leavers</td>
<td>21 months</td>
</tr>
<tr>
<td>Foster and Rickman (2001)</td>
<td>69%</td>
<td>65% below $1,000 monthly earnings</td>
<td>1 year</td>
</tr>
<tr>
<td>Julnes (2000)</td>
<td>55% at exit 37% after 6 to 8 months</td>
<td>$2,289 median quarterly earnings at exit $2,849 after 4 quarters</td>
<td>6 to 8 months</td>
</tr>
<tr>
<td>Kauff et al. (2001)</td>
<td>60%</td>
<td>$7.54 per hour $1,055 per month</td>
<td>8 to 12 months</td>
</tr>
<tr>
<td>Mancuso et al. (2001)</td>
<td></td>
<td>$1,500 monthly earned income for one-parent families $1,640 for two-parent families $1,600 for diverted families</td>
<td>18 months</td>
</tr>
<tr>
<td>MAXIMUS (2000a)</td>
<td>61.7% after one year 65.5% after two year</td>
<td>$1,082 after one year $1,196 after two year</td>
<td>1 and 2 year</td>
</tr>
<tr>
<td>MAXIMUS (2001b)</td>
<td>62%</td>
<td>58% of employed leavers: more than $1,000 per month 32%: $1,250 per month</td>
<td>3-4 months</td>
</tr>
<tr>
<td>MDTA (2000)</td>
<td>72.6% for time-limit leavers 70.5% for non-time limit leavers</td>
<td>$8.21 for time-limit leavers $8.62 for non-time limit leavers</td>
<td>6 to 16 months</td>
</tr>
<tr>
<td>NYOTDA (1999)</td>
<td>71% - 75% after one year</td>
<td>$5,034 fourth quarter earnings</td>
<td>1 year</td>
</tr>
<tr>
<td>Rangarajan and Wood (2000)</td>
<td>41% after 30 months 34% after 19 months</td>
<td>$7.30 hourly wage/ $1,084 monthly earnings after 19 months $8.15 hourly wage/ $1,271 monthly earnings after 30 months</td>
<td>19 and 30 months</td>
</tr>
</tbody>
</table>

Table 2.2 Employment and Earnings of Welfare Leavers
Figure 2.1 Relationships between the Earlier Models and the Governance Framework

Figure 2.2 Measures of Outcomes of Public Cash Assistance Programs
Figure 2.3 Measures of Individual Characteristics

- Demographics: age, gender, race/ethnicity, disability status
- Participation to other programs: Medicaid, Food Stamps, SSI
- Human capital factors: education, skills, past work experience

Figure 2.4 Dimensions and Measures of Environment

- Economic Conditions
  - Unemployment rate
  - Median income
- Demographic Conditions
  - State median education level
  - A percent of black population
  - State non-wedlock birth rate
<table>
<thead>
<tr>
<th>Broad categories</th>
<th>Sub-categories</th>
<th>Related Questions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diversion program</td>
<td>Does the state try to divert some families from becoming recipients?</td>
<td></td>
</tr>
<tr>
<td>Family composition and eligibility</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eligibility by number/type of parents</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eligibility of units headed by a minor parent</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eligibility of pregnant women</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment-related eligibility of two-parent families</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eligibility of individual family members</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inclusion of non-citizens in the unit</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asset test</td>
<td>What level of assets can a family have and still be eligible?</td>
<td></td>
</tr>
<tr>
<td>Income and Eligibility</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Countable income</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income and assets of children</td>
<td>How is income counted in determining eligibility?</td>
<td></td>
</tr>
<tr>
<td>In-kind income</td>
<td></td>
<td></td>
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<tr>
<td>Deemed income</td>
<td></td>
<td></td>
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<tr>
<td>Child support</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Earned income disregards</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income eligibility tests</td>
<td>How much income can a family have and still be eligible?</td>
<td></td>
</tr>
<tr>
<td>Dollar amounts</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Benefit computation</td>
<td>If a family passes all eligibility tests, what is received?</td>
<td></td>
</tr>
<tr>
<td>Contracts and Agreements</td>
<td>Once determined to be eligible, what must a recipient family do to maintain benefits?</td>
<td></td>
</tr>
<tr>
<td>School policies for dependent children</td>
<td></td>
<td></td>
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<tr>
<td>Immunization and health screening requirements</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Child support sanctions</td>
<td></td>
<td></td>
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<tr>
<td>Work activities</td>
<td></td>
<td></td>
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<tr>
<td>Activities exemptions</td>
<td></td>
<td></td>
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<tr>
<td>Activities requirements</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Activities sanctions</td>
<td>What work activities are required?</td>
<td></td>
</tr>
<tr>
<td>Minor parent activities requirements and bonuses</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Components</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time limits</td>
<td>How long can a family receive benefits?</td>
<td></td>
</tr>
<tr>
<td>Family cap</td>
<td>Are children eligible if born while the family receives benefits?</td>
<td></td>
</tr>
</tbody>
</table>

**Table 2.3** Major Dimensions of States’ Welfare Policies
CHAPTER 3

ESTIMATION METHODS OF CROSS-LEVEL INTERACTION EFFECTS

After the definition of cross-level interaction effects, this chapter introduces several statistical techniques of modeling and estimating cross-level interaction effects in multilevel settings. These techniques are moderated multiple regression (MMR) method and multilevel (or hierarchical) linear model (MLM or HLM) method. Also, this chapter provides a detailed introduction to MLM, the main empirical method used in this dissertation to explore the determinants of the economic outcomes of welfare leavers. In the last section of this chapter, we provide a comparison of the estimation results from MMR and MLM methods and discuss their appropriateness depending on the context.

3.1 Various Methods of Estimating Moderation or Interaction Effects

3.1.1 Multilevel Data Structure and Interaction Effects

*Multilevel, Nested Data Structure*

Social and behavioral data often have a nested structure. For example, in the field of education, students are nested within classrooms, which are nested
within schools, and in turn are nested within school districts, states, and countries. In organizational studies, workers are grouped into teams or departments, which are grouped into firms or organizations. Suppose researchers want to explore how state child support programs affect the likelihood of leaving and re-entering the welfare system (Huang, Kunz, and Garfinkel, 2002). The data structure for such study is multilevel because there are two different levels of attributes: one at the state level (i.e., state child support programs) and the other at the individual level (i.e., probability of exit and recidivism of individuals). Also, it is nested: individuals are grouped into each state. This multilevel, nested data structure is graphically represented in Figure 3.1.

**Cross-Level Interaction or Moderating Effects**

Cross-level interaction or moderation effects in multilevel, nested data structure are used to explain how variables within the different levels influence each other in accounting for variation in the outcomes of interest. For instance, in the above example of the likelihood of welfare exit and recidivism, cross-level interaction effects imply how state child support programs interact with individual attributes, such as gender and educational level, to influence the probability of exit and recidivism of the individual. As Rogers (2002) expresses, interaction or moderating effects mean “the effects of a third variable (Z) on the relationship between two variables (X and Y), the explanation of variance in a dependent variable (Y) by the interaction of two independent variables (X and Z),
or a situation in which the effect of one independent variable (X) on a dependent variable (Y) depends on the level of another independent variable (Z)” (p.212).

Scholars in applied social sciences including public administration have had a long-standing interest in searching for cross-level interaction or moderating effects. Also, various empirical approaches have been employed to estimate these cross-level interaction or moderation effects in multilevel, nested data structures. These applications include moderated multiple regression (MMR) methods using disaggregated or aggregated data and multilevel linear model (MLM) methods. The following introduces these methods with a discussion of their strengths and weaknesses.

### 3.1.2 Moderated Multiple Regression Models

A conventional statistical technique used to deal with interaction effects between different units of analysis is moderated multiple regression (MMR) models. One way to assess the existence of the interaction or moderation effects based on MMR models involves a comparison of the following two equations: additive (A) and additive-multiplicative (AM) models.

**A model:**  
\[ Y_{ij} = B_0 + B_1X_{ij} + B_2Z_{ij} + \varepsilon_{ij} \]  
\[ (3.1) \]

**AM model:**  
\[ Y_{ij} = B_0 + B_1X_{ij} + B_2Z_{ij} + B_3X_{ij}Z_{ij} + \varepsilon_{ij} \]  
\[ (3.2) \]
where a dependent variable, Y, is a linear function of two independent variables, X and Z, and their interaction, XZ, in AM model\(^1\) and \(i\) denotes individuals \((i = 1, 2, \ldots, n)\) in organization \(j\) \((j = 1, 2, \ldots, m)\). The error term, \(e_{ij}\), is assumed to be normally distributed. In multilevel, nested data structure, X denotes individual-level independent variables and Z denotes organizational-level independent variables throughout this chapter. The statistical tests regarding the existence of interaction or moderation effects are obtained either by the point estimate of population parameter \(B_3\) in Equation (3.2) or by the improvement in the predictability \((P^2)\) of the AM model over the A model. If there is no interaction effect, then \(B_3 = 0\) and the predictability of the two models will be same \((P_{AM^2} = P_{A^2})\). These hypotheses can be tested by a \(t\) test on parameter \(B_3\), or a \(F\) test of differences in predictability \((\Delta P^2 = P_{AM^2} - P_{A^2}\), estimated by \(\Delta R^2\)).

One assumption of the AM model to detect interaction effects is that errors are independently and identically distributed within and across organizations\(^2\) (Kendall and Stuart, 1979). This assumption may make the AM method elusive in detecting interaction or moderation effects because the magnitudes of the predictability change between two models hardly correspond to the substantial moderator effects (Aguinis and Pierce, 1998; Rogers, 2002; Stone-Romero, Alliger, and Aguinis, 1994). Because a multilevel, nested data structure often has heterogeneous error variances with different sample sizes across organizations, we here focus on the violation of the homogeneous error variance assumption.

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1 Throughout this chapter, \(B\) denotes population parameters to be estimated.

2 As shown in Equation (3.2), the AM model has the same intercept \((B_0)\), slopes \((B_1 - B_3)\) and single error term \((e_{ij})\) for every organization \(j\).
with the unequal sample size and their effects on the estimation of interaction
effects.

The statistical assumptions of ordinary least squares (OLS) regression
include interdependence of observations, normal distribution of population, and
homoskedasticity. Another assumption for the use of MMR models is
homogeneity of error variances across organizations (Kendall and Stuart, 1979).
Homogeneity of error variances across organizations means that the variance in
outcome variable (Y) unaccounted for by independent variables (X) is equal
across organizations. For example, suppose a researcher would test whether a
state-level dichotomous variable (Z; Z = 1 when policy A exists in a state, Z = 0
otherwise) moderates the relationship between X and Y. In such situation,
homogeneous error variances across organizations mean that variances in Y after
controlling for X are equal across states with policy A (Z = 1) and states without
policy A (Z=0). A graphical example of the violation of this assumption is shown
in Figure 3.2 below.

Figure 3.2(a) is a hypothetical relationship between X and Y. And Figure
3.2(b) and 3.2(c) are hypothetical relationships between X and Y moderated by a
state-level variable (Z). They all satisfy OLS assumptions discussed above, except
for the violation of homogeneous error variances across organizations. Figure
3.2(b) and 3.2(c) show that after controlling for X, states with Policy A (Z = 1)
have smaller variances in Y than states without Policy A (Z = 0) do.

The violation of this assumption in using MMR to estimate interaction
effects leads to two erroneous conclusions (Aguinis and Pierce, 1998; Dretzke et
al. 1982; DeShon and Alexander, 1996). First, “Type I error rates are likely to be artificially inflated when sample sizes are unequal across organizations, while Type I error rates become overly conservative when the X variance is dissimilar across organizations even when the sample sizes are equal across organizations (Aguinis and Pierce, 1998, p.306).” And, second, “with respect to Type II errors, researchers are more likely to erroneously dismiss moderating effects when the larger subgroup sample size is paired with the larger residual variance (Aguinis and Pierce, 1998, p.307).”

If the hypothesis of interaction effects is true ($B_3 = 0$, $\Delta P^2 = P_{AM}^2 - P_A^2 = 0$), then the failure to reject the null hypothesis results in a correct inference and we can conclude no interaction effects. On the other hand, if the null hypothesis is false ($B_3 \neq 0$, $\Delta P^2 > 0$) and we fail to reject the hypothesis, it is a Type II error. Several factors other than heterogeneity of error variance (Aguinis and Pierce, 1998) and unequal sample sizes across moderator-based subgroups (Stone-Romero, Alliger, and Aguinis, 1994) contribute to higher chance of committing Type II errors include small sample size (Alexander and DeShon, 1994) and measurement error (Busemeyer and Jones, 1983) as well.

Another way (Maxwell and Delaney, 1990) to build a MMR model to detect moderation or interaction effects begins with the relaxation of the same intercept and slope assumption for every organization $j$ in the AM model. The basic idea of this method is to build a separate MMR model for each organization so that the

---

3 A mathematical explanation of these conclusions is well written in Aguinis and Pierce (1998) and summarized in Appendix B at the end of this dissertation.
intercept and slope coefficients vary across organizations. This can be achieved by using dummy variables that code each organization \( j \).

\[
Y_{ij} = B_{0j} + B_1X_{ij} + B_2Z_j + B_3X_{ij}Z_j + B_4D_j + B_5D_jX_{ij} + \varepsilon_{ij}\] (3.3)

where \( D_j (j = 1, 2, \ldots, m) = 1 \) for the \( j \)th organization and \( D_j = 0 \) otherwise. The first part \( (Y_{ij} = B_{0j} + B_1X_{ij} + B_2Z_j + B_3X_{ij}Z_j) \) of the equation is the same as the AM model in Equation (3.2). However, there are three noticeable differences in this modeling strategy from the AM model. First, we relaxed the homogeneity assumption of the intercept coefficients across organization. Now a separate intercept for each organization \( (B_{0j} + B_4D_j) \) represents a unique intercept for each organization. Second, similarly, we relaxed the homogeneity assumption of the slope coefficients across organization. Now a separate slope for each organization \( (B_1X_{ij} + B_5D_jX_{ij}) \) represents a unique slope for each organization. Together, Equation (3.4) is now a random coefficient model, because the slope and intercept coefficients vary randomly across organizations. Finally, the variance in \( Y \) is now explained by the organization main effect \( (D) \) and its interaction with individual-level predictor \( (DX) \) as well as individual-level predictor \( (X) \), organization-level predictor \( (Z) \), and their interactions \( (XZ) \).

In Equation (3.3), the first term \( B_1X_{ij} \) corresponds to the main effect of \( X \), the term \( B_2Z_j \) corresponds to the main effect of organization-level variable, the next term \( B_3X_{ij}Z_j \) models the interaction effect between \( X \) and \( Z \), the next term \( B_4D_j \) models the main effect of organizations, and the final term \( B_5D_jX_{ij} \) models
the interaction of organizations with X. Thus, this MMR modeling strategy provides the answers for the interaction effects: does the slope coefficient vary across organizations?; and if slopes vary, what organizational variables might account for that variation?

However, two issues are still problematic. First, this MMR modeling strategy is quite complex because it needs to include \( m(k + 1) \) terms in the MMR equations, if there are \( m \) organizations and \( k \) predictors. And this number sharply increases as the number of organizations (\( m \)) and predictors (\( k \)) increases. For example, if we want to explore the effects of only two state-level variables in the 50 states, then 150 \([50 \times (2+1) = 150]\) terms are required in MMR equations making this approach limited to analysis with small number of organizations and predictors. Thus, MMR models consume many degrees of freedom in estimation.

Second, in practice, this method uses either aggregated data at the state level or disaggregated data at the individual level to estimate model parameters \( (B_0 \sim B_5) \). Aggregation method is to aggregate the individual-level variables to the organization level by taking, for example, mean or median, while disaggregation method assigns the same values for the organization variables to each individual within the organization. We introduce in detail how to build these aggregation and disaggregation models and their limitations in estimating parameters below.

**Aggregation Method**

A conventional statistical technique used to deal with different levels of analysis is to aggregate lower-level (i.e., individual) variables to a higher level
(i.e., organization or state). For example, in an example of the effects of unemployment rate on the earned incomes of welfare leavers, a researcher can aggregate individual-level information by taking a representative index, such as, average or median earned income of all leavers, in a state and conduct an analysis at the state level. As a result, the aggregation methods estimate the “average” effects of the higher-level variables (i.e., state unemployment rate) on the “average” unit (i.e., individual) at the lower level. Using representative index, such as mean or median, implies that aggregation method ignores individual differences in characteristics and outcomes among individuals within the same higher-level unit (i.e., state).

As discussed before, Lynn, Heinrich, and Hill (2000) build a model of program outcomes as a function of individual characteristics, $C$, environment, $E$, treatment, $T$, structure, $S$, and management, $M$. Using this model, the modeling of the aggregation method takes the following statistical form:

$$O_j = B_0 + B_1C_j + B_2E_j + B_3T_j + B_4S_j + B_5M_j + B_6C_jT_j + \gamma_j, \quad (3.4)$$

where $O_j$ is an average outcome of clients for state $j$ ($j = 1, ..., m$), $C_j$ is an average value of client’s characteristics in state $j$. $E_j$, $T_j$, $S_j$, and $M_j$ are state-level variables for environment, treatment, structure, and management factors, respectively. And $C_jT_j$ is the interaction term between individual characteristics and state treatment variables. The error term, $\gamma_j$, is assumed to be normally distributed. In equation (3.4), since environment, treatment, structure, and
management variables are measured at the state level, each state has a unique value for these variables. However, the individual-level variables, $O$ and $C$, have multiple units (i.e., individuals) and to use these information in estimating equation (3.4), we need to aggregate them. For example, we can use a mean value for all individuals in the same state and use them with the other state-level variables. Thus, in this approach, the total sample size is $m$, which is the number of states in the sample, and the unit of analysis is at the state level.

The aggregation method suffers from several limitations for estimating cross-level interaction effects in a hierarchical data structure. First, many researchers have noticed a potential aggregation bias in this approach (Bryk and Raudenbush, 1992; Hanushek, Rivkin, and Taylor, 1996; Heinrich and Lynn, 2000). According to Bryk and Raudenbush (1992), aggregation bias can occur when an aggregated variable takes on different meanings. For example, consider the average years of education of welfare recipients in a state. The aggregated years of education may have an effect on individual outcomes above and beyond the effects of the individual’s years of education. At the individual level, years of education provide a measure of individual characteristics, but at the state level, it is a proxy of state environment.

Second, the information produced by this approach is hardly ever straightforward because it produces “average” information mixing the variations among individuals across all higher-level units (i.e., states). As a result, the analysis using this approach rarely provides detailed policy insights. Heinrich and Lynn (2000) noted “the variation being explained in site- or program-level
models is not variation in earnings or other individual-level outcomes but rather variation between sites or programs in average outcomes (p.8).” They further warned that the use of research findings from such an analysis might lead to “ecological fallacy,” which occurs when lower-level outcome inferences are made from the estimation of higher-level variables.

Finally, another problem with aggregation could be instances of “Simpson’s Paradox”, when erroneous inferences that may be drawn if “grouped data, drawn from heterogeneous populations, are collapsed and analyzed as if they came from a single homogeneous population (Hox, 1995, p.5).” One example of this type of problem is misestimated standard errors since aggregation fails to take into account the dependence among individual level variables within the same states. Also, spurious significant findings are more likely to happen and result in erroneous inferences.

In summary, the aggregation method is straightforward in that it uses aggregated single unit of analysis and, to the extent, it lessens computational burdens in estimating cross-level interaction effects. However, this method can cause aggregation bias, provide little information on variations in individuals, and result in erroneous estimates. Also, if the sample size is small, the use of this method is limited.

Disaggregation Method

In contrast, disaggregation method decomposes higher-level data (for example, state) into lower level (for example, individuals) by assigning the same
value for state-level variables for all individuals of the state. In the example of the effects of unemployment rate on the earned incomes of welfare leavers, disaggregation method uses the individual as the unit of analysis and, as a result, this approach ignores the grouping of individuals into states and the data are treated as a single sample.

The modeling of the disaggregation method for individual $i$ in state $j$ using the governance model by Lynn, Heinrich, and Hill (2000) takes the following statistical form:

$$O_{ij} = B_{0j} + B_1C_{ij} + B_2E_{ij} + B_3T_{ij} + B_4S_{ij} + B_5M_{ij} + B_6C_{ij}T_{ij} + \gamma_{ij}, \quad (3.5)$$

where $O_{ij}$ is an outcome of individual $i$ ($i = 1, \ldots, n$) in state $j$ ($j = 1, \ldots, m$), and $E_{ij}, T_{ij}, S_{ij},$ and $M_{ij}$ are state-level variables of environment, treatment, structure, and management variables, respectively. The values of these state-level variables are the same for all individuals within a state. And, $C_{ij}T_{ij}$ is the interaction term between $C$ and $T$. In this approach, the individuals in the same state have the same value for these variables. $C_{ij}$ is the unique client $i$’s characteristic in state $j$ and the error term, $\gamma_{ij}$, is assumed to be normally distributed. Thus, in this approach, the unit of analysis is the individual and so the total sample size equals the number of individuals across all states.

Similar to the aggregation method, several problems are noticeable in this approach. First, this method typically accounts for only a small portion of the total variance in individual outcomes (Hanushek, Rivkin, and Taylor, 1996).
Since there is more variance between individuals than between states, more variability in individual-level data is likely to produce the more unexplained co-variation between variables as compared to the aggregation method.

Next, this method also misestimates standard errors because all individuals in the sample are treated as being drawn from the same population. It is reasonable to think that the individuals who are nested within the same state share more homogeneous experiences than individuals across states. They may encounter the same policies, face similar environmental conditions, and even have homogeneous demographics. Thus, there may be a certain degree of dependence among individuals within the same state. This dependency may arise because of shared experiences within the state or because of the ways in which individuals were initially drawn into the state. Ignoring this kind of interdependency causes small standard error estimates and, in turn, a higher probability to reject a null hypothesis (Osborne, 2000).

In sum, most empirical studies of interaction effects have used MMR models shown in Equations (3.2) and (3.3). The AM MMR method is easy to implement and valid for all cases when the basic OLS assumptions are met. However, there is a violation of the homogeneous assumption of variances across organizations, the AM method no longer produces reliable estimates. By introducing dummy variables for each organization as in Equation (3.3), we can overcome the above shortcoming of the AM model. However, researchers have reported several important problems with this method: the improper conceptualization of the hierarchical organization system, aggregation bias,
misestimated standard errors, and loss of information (Bryk and Raudenbush, 1992; Hanushek, 1979; Hanushek, Rivkin, and Taylor, 1996; Heinrich and Lynn, 2000; Raudenbush and Willms, 1995). Thus, these problems are all associated with the inability of this methods to appropriately treat multi-level data in multilevel, nested organizational systems. Recent advances in statistical techniques have addressed multilevel data issues in modeling moderation or interaction effects (Bryk and Raudenbush, 1992; Goldstein, 1987). In the next section, we introduce a multilevel model and discuss its strengths and weaknesses.

### 3.1.3 Multilevel or Hierarchical Linear Models

Many limitations of the conventional statistical methods cited above can be overcome using multilevel linear models (MLM), in which each of the levels in the multilevel, nested data structure is formally represented by its own linear sub-model. These sub-models express relationships among variables within a given level, and specify how variables at one level influence relations occurring at another. Suppose there are two levels of data: state and individuals. The individual-level equation is for each state $j$:

$$Y_{ij} = B_{0j} + B_{1j}X_{ij} + \varepsilon_{ij}, \quad (3.6)$$

where $Y_{ij}$ is an outcome variable for the $i$th individual in the $j$th state, $X_{ij}$ is individual-level predictor variable, $B_{0j}$ is the intercept, $B_{1j}$ is the regression
coefficient, and \( \varepsilon_{ij} \) is random error term with mean 0 and variance \( \sigma^2 \). And the state-level equation is:

\[
B_{0j} = \gamma_{00} + \gamma_{01}Z_j + \nu_{0j}, \quad (3.7)
\]
\[
B_{1j} = \gamma_{10} + \gamma_{11}Z_j + \nu_{1j}, \quad (3.8)
\]

where \( \nu_{0j} \) and \( \nu_{1j} \) are assumed to be normally distributed with mean 0 and variances \( \sigma_{0j}^2 \) and \( \sigma_{1j}^2 \), respectively. Equations (3.7) and (3.8) show that the regression coefficients at the individual-level equation are function of state-level predictor \( Z_j \). Substituting these equations into Equation (3.6) yields a combined model:

\[
Y_{ij} = (\gamma_{00} + \gamma_{01}Z_j + \nu_{0j}) + (\gamma_{10} + \gamma_{11}Z_j + \nu_{1j})X_{ij} + \varepsilon_{ij}
\]
\[
= \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{01}Z_j + \gamma_{11}X_{ij}Z_j + \nu_{0j} + \nu_{1j}X_{ij} + \varepsilon_{ij}, \quad (3.9)
\]

Like the previous MMR models, the combined equation models individual outcome (\( Y_{ij} \)) as a function of individual-level predictor (\( X_{ij} \)), state-level predictor(\( Z_j \)), their interaction term (\( X_{ij}Z_j \)). Also, this model does not assume homogeneous error variances across states; that is the reason why this model builds individual and state equations separately.

At the same time, several differences from the previous MMR models exist. First, this model has error term \( (\nu_{0j} + \nu_{1j}X_{ij} + \varepsilon_{ij}) \), which is not normally
distributed because it varies upon the values of $X_{ij}$. Thus, standard OLS technique is not proper to estimate the parameters, but instead iterative maximum likelihood procedures can be used. Second, more fundamentally, this modeling differs from the MMR models in that

### 3.2 A Simulation: Performance of MMR and MLM

**Criteria of Comparison**

Several criteria are used to evaluate the relative performance of the MMR and the MLM methods in this dissertation. First, we evaluate which method conceptually reflects complex, hierarchical relationships among variables into the model. Second, we also assess the generalizability of findings across different higher-level units (i.e., state or organization) with varying characteristics. Third, we compare how much information about the amount of variation each statistical model explains at the different levels of analysis. Fourth, we inspect the efficiency of estimates, i.e., which model produces estimates closer to the true parameter values. Finally, we examine standard errors of estimates from two estimations.

---

4 An addition of two normally distributed error terms ($\nu_{0j} + \epsilon_{ij}$) is normally distributed with mean 0 and variance $\sigma^2 + \sigma_{0j}^2$.

5 Various sub-models and estimation methods of MLM are thoroughly discussed in Bryk and Raudenbush (1992) and briefly applied in a data set shown in Appendix C.
Comparison of MMR and MLM

To begin a comparison of MMR and MLM, we show Equations (3.2) and (3.9), which represent these models.

MMR: \( Y_{ij} = B_0 + B_1 X_{ij} + B_2 Z_{ij} + B_3 X_{ij}Z_{ij} + \varepsilon_{ij}, \)  \hspace{1cm} (3.2)

MLM: \( Y_{ij} = \gamma_{00} + \gamma_{10} X_{ij} + \gamma_{01} Z_{ij} + \gamma_{11} X_{ij}Z_{ij} + \nu_{0j} + \nu_{1j} X_{ij} + \varepsilon_{ij}, \)  \hspace{1cm} (3.9)

Two equations are the exact same except that the MLM equation has a compounded error term, which relaxes the homogeneous error variance assumption of the MMR model. The basic research strategy used here is first to build a model, which we know the true parameter values of all regression coefficients. Second, we generate a set of hypothetical data on X, Z, XZ, Y, and error variance. Third, using the generated data set, we estimate Equations (3.2) and (3.9) and compare their performance.

First, an equation of true parameters is set as below:

\( Y_{ij} = 3 + 2X_{ij} + 2Z_{ij} + 3X_{ij}Z_{ij} + \varepsilon_{ij}, \)  \hspace{1cm} (3.10)

We set the constant to be 3, the regression coefficients on X, Z, and XZ to be 2, 2, and 3, respectively.

Second, we generated a 150 set of data with Equation (3.10) and compare how two different estimation techniques approach to the true parameter values. Each dataset had 30 pseudo organizations with various numbers of individuals.
within each organization and various error variances. One example of the dataset is shown in Table 3.1. In this exemplary set, each organization has 30 individuals. The values of X and Z are generated by random normal distribution. And XZ is the product of X and Z. The values of Y are calculated so that the model has error variance of 20 after considering X, Z, and XZ. In this example, each organization has the same numbers of individuals and the error variances across organizations are also same satisfying all assumptions of OLS estimation methods.

An estimation result from MMR and MLM using an “ideal” dataset is presented in Table 3.2. We set the error variances across organizations to be equal and each of the 30 organizations has 30 individuals each. As we expected, the results from two estimation techniques are exactly same implying no differences in estimating moderation effects using MMR and MLM when the data structure is “ideal,” i.e. satisfy all OLS assumptions including homogeneous organizational variances.

The true parameter values of the intercept, X, Z, and XZ are 3, 2, 2, and 3, respectively. The estimates are 2.55, 1.88, 2.13, and 3.06, respectively. We cannot evaluate how much the estimates approach to the true values because there is no objective criterion to evaluate. However, no matter how the estimates perform well, two estimation techniques, MMR and MLM, produce the same result from an “ideal” dataset.

The next step is to randomly vary the values of the number of individuals within each organization and the amounts of error variances in each equation to

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*A SAS program to generate the dataset is in Appendix D.*
track influences of these changes on regression coefficients. A randomly generated 150 dataset is used to estimate Equation (3.10) using MMR and MLM and the estimation results are shown in Table 3.3 and Table 3.4. Overall, the result of this experiment implies that MMR method is likely to be more generous in producing smaller standard errors and making regression coefficients statistically significant, while MLM method is rather stricter.

Table 3.3 compares the estimation results at the 99% significance level. Because the variables Z and XZ are set to be fixed in Equation (3.10) and the statistical program used for this analysis (SAS) first finds solutions for fixed effects, the regression coefficients on these fixed effects terms will always be statistically significant close to the true values. Thus, the interest here lies in how two different methods produce estimates of random effects, which are intercept and X in Equation (3.10).

Table 3.3 provides several evidences why MMR method is more generous and MLM method is more conservative in producing significant regression coefficients. First, using MMR method, 148 and 137 regression coefficients of intercept and X (out of total 150 experiments) were statistically significant at the 99% significance level, while those numbers are 147 and 132, respectively, using MLM method.

Second, the minimum and maximum values of those significant coefficients indicate that MLM method has narrower range of coefficients around the true values than MMR method has both for intercept estimate and X estimate. The minimum values of intercept estimate that is significant are 1.6870.
for MMR method and 1.7943 for MLM method. The maximum values of significant intercept estimates are 3.7632 for MMR method and 3.7237 for MML method. The minimum and maximum values of significant X slope estimates are 1.1592 and 2.7609, respectively, in MMR method, while those values are 1.2588 and 2.7525 in MLM method. Thus, considering that the true values for intercept and X are 3 and 2, it can be said that the MLM method is more rigorous in estimating significant regression coefficients that the MMR method is. In terms of the mean of the significant regression coefficients, the MMR method performs better in estimating intercept, while the MLM method does better in estimating X. However, the differences are minimal and the means are very close to the true values.

The next table expands the above analysis into the 95% significance level. As shown in Table 3.4, the results are very similar to the results of the 99% significance level analysis. The minimum and maximum values of MLM estimates of intercept and X have a narrower range than MMR estimates have.

Also, the mean of the estimates shows that MMR produces a better average of intercept estimates, while MLM produces a better average of X estimates. However, the differences are trivial. With the 95% significance level, all 150 estimates of the intercept, Z, and XZ terms are statistically significant across both estimation methods. Only 5 and 7 estimates of the X slopes are not significant in MMR and MLM estimations, respectively.

In sum, MMR method and MLM method provide an identical estimation results when error variances of organizations are homogeneous. In most cases,
however, this assumption does not hold. As shown in Tables 3.3 and 3.4, MLM method provides more conservative statistically significant estimates than MMR method does in the existence of heterogeneous error variances across organizations. In the above simulation, we set Z and XZ to be fixed, but it is often not the case in the practice. If you further assume randomly varying Z and XZ, the differences between MMR and MLM methods would be more profound than found in Tables 3.3 and 3.4.

The MLM method has several advantages. First, it allows differences between organizations to be explored by both features of organizations and characteristics of individuals. In so doing, multilevel techniques model both the direct effects of organizations on outcome and the indirect effects of organizations on qualities of individuals that predict outcome by allowing cross-level interactions between individuals and organizations (Von Secker and Lissitz, 1999). Second, multilevel techniques produce statistically efficient parameter coefficient estimates and provide correct standard errors for computing confidence intervals and statistical tests of significance (Bryk and Raudenbush, 1992). Finally, they use generalized least squares estimators that take into account the precision of the estimates based on number of organizations within each organization and produce accurate, but conservative estimates of organization effects (Goldstein, 1995). In general, these multilevel models allow for accurate measurement of “macro processes that are presented to have an impact on the individual actor over and above the effects of any individual-level variables that may be operating (Blalock, 1984, p.354).”
While MLM method has conceptual and empirical advantages over MMR, the application of MLM method requires a large set of data, which has large numbers of organizations and individuals within each organization. It is because HLM builds two different models, i.e., higher- and lower-level models, and each sub-model has to include enough observations to ensure degree of freedom. For example, suppose the minimum number of samples for a robust estimate is 30. Because the unit of analysis for aggregated method is the state level, the required sample size would be 30 states. And, because the unit of analysis for disaggregated method is the individual level, the required sample size would be 30 individuals. However, because MLM build two separate models and a combined model to estimate interaction effects, the required sample size would be 30x30 = 900. Thus, to promise reliable and robust estimates, MLM are more demanding than aggregated and disaggregated methods in terms of the sample size.

3.3 An Example: A Comparison of MMR and MLM Methods

This section presents a comparison of OLS regression method and multilevel model method in estimating cross-level interaction effects.
**Data and Variables**

For an empirical comparison of traditional MMR and MLM methods, we utilized the third wave of the 1996 Survey of Income and Program Participation (SIPP) dataset for individual-level information, which covers from August 1996 to February 1997, and Moffitt’s welfare benefits file for state-level information, such as AFDC/TANF maximum amount paid per month for family of 4, personal income per capita, and unemployment rate. SIPP reports information on individual’s income, governmental program participation, individual background, and job experiences. In this study, total family earned income is used as the outcome variable. The dataset contains two different levels of data: the individual level and the state level. The dataset consists of information for 2,418 individuals in 36 states.

The individual-level (Level 1) outcome is TFEARN, which represents total family earned income. And, the individual-level covariates include individual sex (SEX: 0 for female and 1 for male) and race (RACE: 0 for white and 1 for non-white). And two state-level variables used are state unemployment rate (URATE) and maximum benefit for a family of three (MAXBNFT). The descriptive statistics for the variables used for this example is shown in Table 3.5.

As shown in Table 3.5, welfare recipients in the sample had an average of $880.70 earned income per month including an average of $428.33 of TANF grants. 39% of the sample is male and 45% of the sample is non-white. State unemployment rates vary from 3.50% to 7.80% with an average of 5.23%. The
question to be pursued below is how state policy on maximum benefit interacts with individuals’ race using MMR and MLM methods.

\textit{Model Specifications for MMR Analysis}

For MMR analysis, the statistical model for individual \(i\) in state \(j\) is:

\[
\text{TFEARN}_{ij} = B_0 + B_1\text{SEX}_{ij} + B_2\text{RACE}_{ij} + B_3\text{UNEMP}_j + B_4\text{MAXBNFT}_j + B_5\text{RACE}_{ij}\ast\text{MAXBNFT}_j + \epsilon_{ij}
\]  

(3.11)

where \(\epsilon_{ij}\) is assumed to have normal distribution, \(\epsilon_{ij} \sim N(0, \sigma^2)\). There are two individual-level variables, \(\text{SEX}\) and \(\text{RACE}\), and two state-level variables, \(\text{UNEMP}\) and \(\text{MAXBNFT}\), and an interaction term between \(\text{RACE}\) and \(\text{MAXBNFT}\) in this model. The coefficient, \(B_5\), represents an interaction effect of race and maximum benefit on total family earned income.

\textit{Model Specifications for Multilevel Analysis}

The individual-level model is:

\[
\text{TFEARN}_{ij} = B_0 + B_1\text{SEX}_{ij} + B_2\text{RACE}_{ij} + \gamma_{ij}
\]  

(3.12)
where $\gamma_{ij}$ is assumed to have normal distribution, $\gamma_{ij} \sim N(0, \sigma^2)$. And the state-level model uses variables measured at the state level to predict the individual-level coefficients. The equations are:

$$B_0 = r_{00} + r_{01}UNEMP + r_{02}MAXBNFT$$
$$B_1 = r_{10}$$
$$B_2 = r_{20} + r_{21}MAXBNFT + u$$

In this model, the relationships between the state-level variables and the effects of individual-level explanatory variables on individual outcomes are fixed ($B_1$) and random ($B_2$). Substitution of equation (3.13) in equation (3.12) yields a combined model:

$$TFEARN_{ij} = r_{00} + r_{10}SEX_{ij} + r_{20}RACE_{ij} + r_{01}UNEMP_j + r_{02}MAXBNFT_j + r_{21}RACE_{ij}*MAXBNFT_j + \gamma_{ij} + u$$

Through a comparison of Equations (3.11) and (3.14), we can obtain how MMR and MLM methods estimate interaction effect.
Comparison of MMR and MLM Results

The findings from MMR and MLM analyses are shown in Table 3.6. In this table, the coefficient estimates of Equation (3.11) are directly compared to the MLM beta coefficient estimates of equation (3.14).

To begin with the comparison of these modeling strategies, it is apparent that the MMR and MLM estimated regression coefficients are very close for the direction and size of impacts of predictors on the outcome variable. In general, this finding confirms that where a small percentage of variation occurs at the state level, OLS and MLM methods are likely to produce comparable estimates of individual- and state-level effects (Bryk and Raudenbush, 1992; Heinrich and Lynn, 2000).

One of the interesting findings from Table 3.6 is that MMR method provides smaller standard errors making estimates statistically significant. For example, the regression coefficient for the interaction term is significant at the 95% confidence level using MMR method, but it is not at the same level using MLM method. Because MLM is more robust than OLS estimation in measuring the impacts of higher level on lower-level outcomes, as Bryk and Raudenbush (1992) argue, this result implies that we may be misleading to conclude that there exists an interaction effect between race and maximum benefit even when there is not. The finding implies that ignoring the variation among organizations may lead to inaccurate estimates of what most policy and evaluation studies seeks to measure: the interaction effects between individual and organizational variables.
In sum, there appear to be significant advantages to using multilevel modeling strategy when it is possible: (1) conceptually, the MLM method provides a fuller and more precise understanding of complex, hierarchical relationships among variables, (2) the MLM method has more rigorous generalizability of findings than the MMR method by allowing each higher-unit (i.e., state or organization) to have varying characteristics, (3) it also provides more information about the amount of variation explained at the individual- and state-level, and (4) the MLM method provides more precise estimates than the MMR method. However, we find that standard errors of estimates from two models show a mixed result.
Figure 3.1  Nested Data Structure

State 1

\[ \text{Individual: } 1 \sim i \]

State 2

\[ \text{Individual: } 1 \sim i \]

\[ \ldots \]

State N

\[ \text{Individual: } 1 \sim i \]
Figure 3.2(a) ~ (c) Graphical Representation of Heterogeneous Error Variances
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<th>Y</th>
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<td>1.70</td>
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Table 3.1 A Generated Dataset
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<tr>
<th>Regression Coefficients</th>
<th>MMR Method</th>
<th>MLM Method</th>
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<tr>
<td></td>
<td>Parameter estimate*</td>
<td>Standard error</td>
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<tr>
<td>X</td>
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<tr>
<td>Z</td>
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* All parameter estimates are significant at p < .01.

Table 3.2 Estimation Result of Equal Variance Models by MMR and MLM

<table>
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<td>Intercept</td>
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<tr>
<td>X</td>
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<td>Z</td>
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<tr>
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<td>3.0056</td>
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<table>
<thead>
<tr>
<th></th>
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<th>MLM results</th>
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<tr>
<td>Std. Dev.</td>
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<td>0.3898</td>
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<tr>
<td>Min.</td>
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<tr>
<td>Max.</td>
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<tr>
<td>Range</td>
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Table 3.3 Simulation Results at the 99% Significance Level
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<th>MLM results</th>
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</thead>
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<tr>
<td></td>
<td>Intercept</td>
<td>X</td>
<td>Z</td>
<td>XZ</td>
</tr>
<tr>
<td>Mean</td>
<td>2.8201</td>
<td>1.8498</td>
<td>2.0044</td>
<td>3.0055</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.4301</td>
<td>0.3008</td>
<td>0.0183</td>
<td>0.0226</td>
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<tr>
<td>Min.</td>
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<td>0.9957</td>
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<tr>
<td>Max.</td>
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<tr>
<td>Range</td>
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<tr>
<td>Count</td>
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<td>145</td>
<td>150</td>
<td>150</td>
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</table>

Table 3.4 Simulation Results at the 95% Significance Level

<table>
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<th>Min.</th>
<th>Max.</th>
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</thead>
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<tr>
<td>RACE</td>
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<td>.50</td>
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<td>TFEARN</td>
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Table 3.5 Descriptive Statistics
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<td>T-ratio</td>
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<td>Sex</td>
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<td>.87</td>
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<tr>
<td>Race</td>
<td>701.43</td>
<td>330.07</td>
<td>2.13**</td>
</tr>
<tr>
<td>Unemployment</td>
<td>72.33</td>
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<tr>
<td>Max benefit</td>
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</tr>
<tr>
<td>Race*Max benefit</td>
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<td>.72</td>
<td>-2.29**</td>
</tr>
</tbody>
</table>

* p < .01, ** p < .05

Table 3.6 Results of MMR and MLM Estimation
CHAPTER 4

EMPIRICAL ANALYSIS OF THE WELL-BEING OF WELFARE LEAVERS

The goal of this empirical analysis is to explore the determinants of the successful public cash assistance programs. To achieve this purpose, we (1) reviewed literature on welfare leavers and governance framework and built an analytical framework of the dissertation based on the review in Chapter 2; and (2) introduced multilevel linear models (MLM) as a newly advanced technique to estimate cross-level interaction effects in Chapter 3. This chapter involves an empirical MLM analysis of governance and program outcomes. This chapter begins with a description of data and sample used in this empirical analysis. The second section introduces measures and variables and builds research hypotheses to be tested in the third section through various models of MLM.

4.1 Data and Sample

Data

To investigate the determinants of the economic well-being of welfare leavers using moderated multiple regression (MMR) models and multilevel linear
models (MLM), this dissertation has utilized several sources of information. These sources include the 1996 panel of the Survey of Income and Program Participation (SIPP), Welfare Rules Database (WRD, Rowe, 2000), the U.S. Census Bureau website, Moffitt (2000), Blank (2000), and Jennings and Ewalt’s survey (2000).

First, the primary data source for empirical analyses in this dissertation is the SIPP collected and maintained by the U.S. Census bureau. The SIPP is a longitudinal survey of a multistage-stratified sample of the U.S. civilian non-institutionalized population. The SIPP includes information, such as source and amount of income, labor force information, government program participation and eligibility data, and general demographic characteristics. The dissertation used the 1996 panel, which consists of 40,188 sample units (households) at the first wave. In the 1996 panel, households are interviewed 12 times from April 1996 through March 2000. The survey used a 4-month recall period, with approximately the same number of interviews being conducted in each month of the 4-month period for each wave. We extracted people who left the public cash assistance programs between January 1998 and December 1998 and examined their total family income one year later.

Table 4.1 shows the monthly numbers of welfare recipients and leavers during the sample period. A total of 1,658 people left the system between January 1998 and December 1998 and stayed off at least for two consecutive months. Among the 1,658 people, 37 people had no record on total family income, which
is the main dependent variable in this analysis, and thus, removed from the sample resulting in 1,621 people.

It is assumed that the SIPP over-sampled low-income families because the average percentage of welfare recipients in the survey was over 4%, while the population on welfare in 1998 was 3.2% (http://www.acf.dhhs.gov/news/stats/6097rf.htm). As an example, in January 1998, there were 79,061 people surveyed by the Census Bureau across the nation and, among them, 4.04% (3,198 people) were on welfare.

Second, states’ TANF policies in 1998 are obtained from Welfare Rules Database (WRD, Rowe, 2000) and Mandayam (2001). The database includes TANF rules in effect for all 50 states and the District of Columbia by state for 1996 through 1999. These provide information on diversion payment provisions, types of special restrictions on two-parent units’ eligibility, initial eligibility threshold at application, earned income disregards for benefit computation, maximum monthly benefit for a family of three with no income, family cap policies, most severe sanction policy for noncompliance, and the availability of supportive services.

Third, information on implementation activities of state welfare agencies mainly come from Jennings and Ewalt (2000). Jennings and Ewalt (2000) provide data on administrative priorities and goals, strategies, and actions from a survey conducted between June 1998 and January 1999. Using survey of state government administrators, they examined state TANF administrators’ perceptions of the importance of various goals, implementation strategies, and
administrative activities to their welfare reform programs. 44 states of the 50 states responded to the survey, and states not responded are California, Hawaii, Massachusetts, New Hampshire, Oregon, and South Dakota.

Finally, information on states’ environment is gathered from several different sources. The U.S. Census Bureau data on State Income and Poverty Estimates provides the economic conditions with which each state faces, measured by unemployment rate and percentage of people in poverty in a state. Professor Blank at University of Michigan and Professor Moffitt at Johns Hopkins University provided me with a wide range of environmental variables, including state population, female population, percent of black population, percent of new immigrants, percent of non-marital births, median wages in the state, 20th percentile wages in the state, percent of the elderly, and percent of households with single female heads. The sources of the information used in this dissertation are shown in Table 4.2.

Even though the individual-level data are from the national randomized survey, the individuals in the sample do not represent a random sample of welfare leavers in the nation. Rather they represent the welfare leavers in the 1996 SIPP sample, which stratified sample of the U.S. civilian non-institutionalized population. Also, the final sample is from 25 states. In this regard, we have to pay caution in interpreting any results of the following empirical analysis. Finally, the results also can be generalized only to welfare leavers not recipients, because the sample consists of welfare leavers who left the welfare system at least for two months.
Sample

Several data filters are applied to the 1,621 people who left the public cash assistance programs between January 1998 and December 1998 and stayed off at least for two consecutive months.

First, individuals from states of Maine, North Dakota, South Dakota, Vermont, and Wyoming are excluded because the original SIPP dataset has aggregated information for those states for confidentiality reason, making it impossible to distinct individuals from those states. The number of those individuals was 34 resulting in 1,586 people 43 states. Second, states must contain at least ten individuals per state to assure adequate within-state sample sizes for the multilevel analyses. Arkansas, Connecticut, D.C., Iowa, Kansas, Maryland, New Hampshire, New Mexico, Oregon, Rhode Island, Utah, and Wisconsin include less than 10 individuals and, thus, deleted from the sample. This results in total 1,518 individuals in 31 states. Finally, individuals in several states, such as Alaska, California, Florida, Hawaii, Kentucky, Massachusetts, and Texas, were deleted due to the lack of large part of the data. This filter results in 919 individuals in 24 states with an average of 38 people per state.

Thus, the final sample of the dissertation consists of 919 welfare leavers in 24 states and the descriptive statistics of the sample is shown in Table 4.3.

As shown in Table 4.3, among the sample, 377 (41%) people are male and 542 (59%) are female. And 432 people (47%) are white, 487 people (53%) are non-white. 17% (156) of the sample are married and spouse is present, while 83%
(763) are never married, divorced, or widowed. The individuals in the sample had average 2.26 children in the family and earned average of $1,725.70 per month one year after they left the welfare system. Also, they received average of $105.16 as Food Stamps per month.

### 4.2. Measures and Models

As discussed in Chapter 2, the governance framework for program evaluation has five dimensions: individual characteristics, program policies, agencies’ structure and implementation activities, environment, and program outcomes. Here we describe measures for these dimensions to evaluate the success of the public cash assistance program for welfare leavers.

**Program Outcomes**

In this dissertation, we utilized two variables to measure outcomes of public cash assistance programs. The first measure is total family earned income one year after welfare leavers left the system (TFEARN). And the other measure is the difference in total family earned income between the last month on welfare and one year after the exit (D_TFEARN)). The descriptive statistics of these two outcome variables are shown in Table 4.4.

As shown in Table 4.4, one year after they exited the public cash assistance programs, the welfare leavers in the sample earned about $1,726 per month on average, which is $350 more than the earned income when they were on welfare.
In terms of total family income (TOTINC), welfare leavers had an average of $2,228.80, which is $94.40 more than the total family income before they were on welfare one year ago. Total family earned income and total family income differ in that the latter includes all types of incomes including supports from participation in government programs, such as Social Security and Food Stamp. The changes in differences in total family earned income and total family income imply that welfare leavers in the sample made more money through work rather than participation in other government programs after they left the welfare rolls.

Several measures can be used as alternatives to total family earned income as the dependent variable: consumption and expenditure data and household and individual income. Even though data on consumption and expenditure of a family are more reliable measures of one’s economic status, these data are not available as far as we know. As a second best, we used earned income data in this dissertation. Also, we used “family” earned income rather than “household” or “individual” incomes, because we think that the decision to work or not depends on the earnings of total family members rather than total household income or individual earnings.

**Individual Characteristics**

As discussed in Chapter 2, individual characteristics are categorized into demographics, participation in other governmental programs, and human capital factors in this dissertation.
First, variables measuring individual demographics include gender, race, marital status, disability status, and number of children in the family. We have constructed a dichotomous variable for gender (1 for male and 0 for female), race (1 for whites and 0 for all other races), marital status (1 for married and 0 for all other cases), and disability status (1 for disabled and 0 for not disabled). Second, to measure participation in other governmental programs, this dissertation used three incomes other than earned income. They are total family Social Security income, total family Supplemental Security Income (SSI), and total family Food Stamps received (FDSTP). They are all in dollar amounts and from the SIPP. Third, the level of education is used to measure individuals’ human capital. If one has less than high school or equivalent education level, s/he is coded as 0. And if one is high school graduate or more, s/he is coded as 1.

Even though the dataset includes a number of individual-level variables, multilevel modeling with a small number of individuals per state necessitates restrictions on the number of within-state parameters. Thus, only some combination of individual-level variables will be used for different model specifications. However, the selective inclusion of these variables relies on the literature to confirm or disagree of earlier results.

*State Economic and Demographic Environment*

Several variables are used to measure state demographic and economic environment. In this dissertation, we have utilized information on
unemployment rate, out-of-wedlock birth rate, per capita income, percent of elderly, and median state education level. Like individual characteristic variables, some combinations of these variables are used depending on model specification in the empirical analysis.

Previous studies on welfare caseloads indicate that economic condition, often measured as unemployment rate, have a salient impact. For example, Ziliak et al. (1997), using multilevel data on recipients and state policies, find strong evidence that the business-cycle factors, measured in employment/unemployment rate, explain nearly 80% of the caseload decline. These studies have used a wide range of variables to measure the economic condition of states, including unemployment rate, personal income per capita, median income, 10th and 20th percentile of usual weekly earnings, and mean weekly earnings of production workers in manufacturing. In this dissertation, we mainly use unemployment rate to measure economic conditions of states.

State AFDC/TANF Policy

As discussed in Chapter 2, there are 5 broad dimensions in state welfare policies: policies on initial eligibility, benefits, requirements, ongoing eligibility, and transitional services. Among these, several important aspects of states’ welfare policies are incorporated into the analyses. These policies include maximum AFDC/TANF benefit for a 3-person and 4-person family, existence of various state waivers on work requirement, time limit, family cap policy, earnings disregards policy, sanctions waiver, and supportive services. In particular, this
dissertation has widely utilized data on supportive services because supportive services are mainly targeted toward welfare leavers or welfare recipients with employment. These services include several components, such as, childcare subsidy, housing assistance, case management, education and training after employment, and diversion grant. These waiver variables are all dichotomous variables, which take the value of 1 if a state has the policy and 0 if not. One of interest in the empirical analysis is how these policies interact with individual characteristics in influencing program outcomes. Through various models of potential interactions, we will examine the existence and the extent of the interaction effects.

State Implementation Activities

Jennings and Ewalt (2000) surveyed state administrators to collect information on state welfare reform goals and implementation activities. In this dissertation, we utilized their survey results on implementation activities. The original survey collected state welfare administrators’ perceptions of the importance of implementation activities¹. And the descriptive statistics of these implementation activities is shown in Table 4.3.

As can be seen in Table 4.3, state welfare administrators think that activities related to enhancing relationships with private employers, providing transitional childcare and health care services, effective coordination among agencies, and enhancing transportation assistance are relatively important

¹ The original survey instrument is shown in Appendix E.
among the implementation activities. The four variables that measure state implementation activities are constructed through a factor analysis\(^2\). The process of obtaining four factors on implementation activities is shown below.

First, we examine the correlations among the survey questions. The correlations among 12 original questions on implementation activities are shown in Table 4.5.

Inspection of the correlation matrix reveals that 36 of the 66 correlations (55 percent) are significant at the .1 level. Also the Bartlett test indicates the overall significance of the correlation matrix is significance at the .01 level (\(\chi^2 = 206.09, \text{ d.f.} = 66\)). This provides an adequate basis for proceeding factor analysis.

A principal component analysis is performed and the results for extraction of component factors are shown in Table 4.6. And the scree test for component analysis is shown in Figure 4.1.

Table 4.6 and Figure 4.1 contains the information regarding how many number of components to be retained for further analysis. If we apply the latent root criterion, we can retain 4 factors and the 4 factors represent 68% of the variance of the 12 variables.

The results of rotated component analysis factor matrix are shown in Table 4.7. The first component extracted includes implementation activities, such as Improve Client Assessment Protocols, Provide Transitional Childcare, Provide Transitional Healthcare, Enhancing Transportation Assistance, and Changing Way Client Processed. These activities are all related to provision of services.

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\(^2\) A detailed description of factor analysis for implementation activities is shown in Appendix F.
Thus, I named this factor as FAC_SRV. And it is assumed that this factor is positively related to total family earned income. The second component includes only two implementation activities: Improving Remedial Education and Improving Job Training. This factor is named as FAC_HC after human capital approach, which was the main focus of implementation activities in the pre-reform era. Contrary to the second factor, the third factor emphasizes “work first approach.” It includes implementation activities, such as Enhance Relations w/ Private Sector Employers, Effective Coordination among Agencies, and Developing Employment Opportunities. These activities are strongly emphasized under the welfare reform in 1996, according to many studies that reveal, “work first approach” works better. The final factor includes implementation activities, such as Improve Job Placement Skills of Staff and Incentives for Staff-Job Placement Rates. These are activities to improve staff productivity via skill improvement or incentives. Thus, I named this factor as FAC_STF, implying factor focused on staff improvement to achieve program goals.

4.3 Empirical Analysis of the Economic Well-being of Welfare Leavers

This section examines the effects of individual characteristics, environment, welfare policies, and implementation activities on program outcomes as measured by total family earned income. We use various MMR and MLM models, which allow for the assessment of direct effects on the individual
outcomes and cross-interaction effects between state and individual variables on the program outcome.

4.3.1 Basic MMR and MLM Models

The first step is to build basic MMR and MLM models to estimate the amount of variances in the outcome variable that are unexplained and that can be explained by additional individual- and state-level variables. In particular, it is possible to decompose the amount of total variances into within-state variances, i.e., variances explainable by individual-level variables, and between-state variances, i.e., variances explainable by state-level variables in MLM.

Basic MMR model includes only the outcome variable and no state- and individual-level predictors:

\[ TFEARN_{ij} = B_{ij} + u_{ij} \]  \hspace{1cm} (4.1)

where \( u_{ij} \sim N(0, \sigma^2) \). In Equation (4.1), the function of total family earned income (TFEARN) is expressed as a deviation (\( u_{ij} \)) from sample mean of total family earned income (\( B_{ij} \)). Table 4.8 shows the estimation result of Equation (4.1).

As shown in Table 4.8, the intercept estimate is the sample mean of total family earned income and is statistically significant at the 99% confidence level. Also, the table indicates that there are substantial variances in the outcome variable that are not explained by Equation (4.1). We can reduce the amount of
total variances by incorporating additional individual- or state-level variables, as we will do later in this chapter.

Basic MLM model is called unconditional multilevel model or one-way ANOVA with random effect model in that it has, like basic MMR model, no state- and individual-level independent variables in the equation. The Level-1 model using total family earned income (TFEARN) is:

$$L1: TFEARN_{ij} = B_{0j} + r_{ij} \quad (4.2)$$

where $r_{ij} \sim N(0, \sigma^2)$ and $\sigma^2$ is the individual-level variance. Throughout this chapter, $L1$ indicates that the equation is a Level-1 equation or an individual-level equation, $L2$ indicated a Level-2 equation or a state-level equation, and $C$ indicates combined equation. The Level-2 model is:

$$L2: B_{0j} = r_{00} + u_{0j} \quad (4.3)$$

where $u_{0j} \sim N(0, \tau_{00})$ and $\tau_{00}$ is the state-level variance. Combining these Level-1 and Level-2 equations yield:

$$C: TFEARN_{ij} = r_{00} + u_{0j} + r_{ij} \quad (4.4)$$

By estimating two different error components ($r_{ij}$ and $u_{0j}$), which represent the between- ($u_{0j}$) and within-state ($r_{ij}$) components of total variances in the
outcome variable, we can estimate how much variance is attributable to individual- and state-level variables each. The proportion of the total variance in the outcome that is explainable by differences between states is called the Intraclass Correlation Coefficient (ICC) and is represented by $\rho$. And the value of $\rho$ is calculated by:

$$\rho = \frac{\tau_{00}}{\sigma^2 + \tau_{00}}$$  \hspace{1cm} (4.5)

Table 4.9 shows the estimation results of unconditional multilevel models using total family earned income as program outcome. Table 4.9 shows that total variance in the outcome variable is about 5,745,477, which is a little larger that that in basic MMR model estimation. Also, the estimation results indicate that two estimates for within-state variance and between-state variance are 4,887,958.27 and 857,518.42, respectively, yielding ICC of .15. It implies that 15% of the variance in total family earned income is between Level-2 units. The amount of between-state variance in total family earned income is sufficient to justify the use of multilevel modeling for examining state effects. The estimate for the average family earned income of the sample (the estimate for the intercept) is $1,691.66$, and the estimated reliability of total family earned income model (.83) indicates that this estimate is a reliable indicator of the true mean.
4.3.2 Effects of Individual Characteristics

The total variance unexplained by basic MMR and MLM models further can be explainable by incorporating additional individual- or state-level variables. Here, we first include individual variables in the basic models. A MMR model with one individual-level variable is:

\[ Y_{ij} = B_{0j} + B_{1j}X_{ij} + r_{ij} \]  

(4.6)

where \( r_{ij} \sim N(0, \sigma^2) \), \( Y_{ij} \) is an outcome variable, and \( X_{ij} \) is an individual-level variable. An addition of \( X \) variable will reduce total variance in the outcome variable and we can reduce further by adding more individual-level variables.

An equivalent model of MLM to Equation (4.6) takes the following form:

\[ \textbf{L1: } Y_{ij} = B_{0j} + B_{1j}X_{ij} + r_{ij} \]  

(4.7)

And the level-2 equations are:

\[ \textbf{L2: } B_{0j} = r_{00} + u_{0j} \]  

(4.8a)

\[ \textbf{L2: } B_{1j} = r_{10} + u_{1j} \]  

(4.8b)

where \( \begin{pmatrix} u_{0j} \\ u_{ij} \end{pmatrix} \sim N \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_{00}, \tau_{01} \\ \tau_{10}, \tau_{11} \end{pmatrix} \). Substitution of Equations (4.8a) and (4.8b) into Equation (4.7) yields a combined model:
\[ Y_{ij} = r_{00} + u_{0j} + (r_{10} + u_{1j})X_{ij} + r_{ij} = r_{00} + r_{10}X_{ij} + u_{0j} + u_{1j}X_{ij} + r_{ij} \]  \( (4.9) \)

Comparing to the MMR model with one independent variable, Equation (4.6), this MLM model has two additional error components: \( u_{0j} \) and \( u_{1j}X_{ij} \). These error terms attribute total variance in the outcome variable to variances in the state-level variables.

For an empirical analysis, we have utilized several individual-level variables from the SIPP: individual’s sex (SEX: female = 0, male = 1), race (RACE: white = 0, non-white = 1), marital status (MARRIED: married = 1, otherwise = 0), education level (EDUC: less than high school = 0, more than high school = 1), and disability status (DISABILITY: non-disabled = 0, disabled = 1), and the amount of Food Stamps received (FDSTP).

Equation (4.10) specifies MMR model to explore the effects of individual characteristics on total family earned income (TFEARN).

\[ TFEARN_{ij} = B_{0j} + B_{1j}SEX_{ij} + B_{2j}RACE_{ij} + B_{3j}MARRIED_{ij} + B_{4j}EDUC_{ij} + B_{5j}DISABL_{ij} + B_{6j}FDSTP_{ij} + u_{ij} \]  \( (4.10) \)

It is expected that added individual-level variables explain some portion of unexplained variances in the outcome variables estimating basic MMR model. An equivalent MLM model to Equation (4.10) has the same individual variables in the level-1 equation:
\textbf{L1:} \[ \text{TFEARN}_{ij} = B_{0j} + B_{1j} \text{SEX}_{ij} + B_{2j} \text{RACE}_{ij} + B_{3j} \text{MARRIED}_{ij} + B_{4j} \text{EDUC}_{ij} + \\
B_{5j} \text{DISABL}_{ij} + B_{6j} \text{FDSTP}_{ij} + r_{ij} \] (4.11)

And the following two Level-2 (state-level) equations are feasible:

\textbf{L2:} \[ B_{0j} = r_{00} + u_{0j}, B_{1j} = r_{10} + u_{0j}, B_{2j} = r_{20} + u_{0j}, B_{3j} = r_{30} + u_{0j}, B_{4j} = r_{40} + u_{0j}, \]
\[ B_{5j} = r_{50} + u_{0j}, B_{6j} = r_{60} + u_{0j} \] (4.12)

In Equation (4.12), we assume that the intercept \((B_{0j})\) and individual-level slopes \((B_{1j} \sim B_{6j})\) are assumed to be random. This modeling allows the effects of individual-level variables to be random over each state. Substituting Equation (4.12) into Equation (4.11) yields the combined models:

\textbf{C:} \[ \text{TFEARN}_{ij} = r_{00} + r_{10} \text{SEX}_{ij} + r_{20} \text{RACE}_{ij} + r_{30} \text{MARRIED}_{ij} + r_{40} \text{EDUC}_{ij} + \\
r_{50} \text{DISABL}_{ij} \]
\[ + r_{60} \text{FDSTP}_{ij} + r_{ij} + u_{0j} + u_{1j} \text{SEX}_{ij} + u_{2j} \text{RACE}_{ij} + u_{3j} \text{MARRIED}_{ij} + u_{4j} \text{EDUC}_{ij} + \\
+ u_{5j} \text{DISABL}_{ij} + u_{6j} \text{FDSTP}_{ij} \] (4.13)

Comparing two equations of MMR and MLM model, Equations (4.10) and (4.13), we can notice that MLM model has multiple error terms. These additional error terms represent between-state error variances \((r_{ij})\), within-state error variances \((u_{0j})\), and random effects of each state on the individual-level slopes \((u_{1j} \text{SEX}_{ij} \sim u_{6j} \text{FDSTP}_{ij})\). The estimation results of two equations are shown in Table 4.10.
Two estimation results are widely different in terms of the magnitude and direction of the estimates and their statistical significance. First, the MMR estimation result shows that individual’s gender, marital status, disability status, and the amount of Food Stamps received have statistically significant effects on total family earned income. While being male and married are positively related to the outcome, having disability and receiving more Food Stamps are negatively related to family earned income. RACE and EDUCATION variables are not statistically significant, while being non-white is negatively related to family earned income and being high school graduate is positively related the outcome variable.

On the other hand, the MLM estimation result shows that only MARRIAGE variable is statistically significant and being married is positively related to total family earned income. All other estimates are not statistically significant, and even the estimate of the effect of RACE variable has a different direction of influence from the MMR estimation result. Before we discuss this difference, we need to check error variances after including these 6 individual-level variables.

By including 6 additional individual variables, the MMR model has reduced total error variances by 8.15% (455,806) from 5,590,963 in basic MMR model to 5,135,157 in Equation (4.10). In the MLM estimation result, the error variance in the outcome variable has been reduced by 49.21% (2,405,387) from 4,887,958 to 2,482,571. While the MMR model produces smaller standard error and, thus, more significant coefficient estimates of the effects of individual
characteristics, it can reduce only 8% of total error variances by including 6 more variables. It is quite contrary to the result of MLM estimation because even though the result shows only one statistically significant estimate (MARRIAGE), the total variance is reduced almost by half by including 6 individual-level variables.

Overall, as reviewed and expected in Chapter 3, the MMR estimation method presents smaller standard errors than the MLM estimation method does. However, the MMR method leaves much more rooms for unexplained effects of independent variables than the MLM method does. As long as there is a lot amount of unexplained error variances, the estimation results are not stable. It may imply that the estimation results of the MMR method are only temporary; even they produce more significant coefficients. As a research explains more and more error variances, the effects of independent variables can be altered.

**4.3.3 Effects of State-Level Variables**

In this section, we include several state-level variables to explore how these variables explain total error variances unexplained by basic MMR and MLM models. We have utilized three state-level variables: income per capital (INCOME), unemployment rate (UNEMP), and maximum benefit for family of three (MAX). The MMR model with these state-level variables is:

\[
T_{FEARN_{ij}} = B_{0j} + B_{1j}INCOME_{j} + B_{2j}UNEMP_{j} + B_{3j}MAX_{j} + u_{ij} \quad (4.14)
\]
In Equation (4.14), individual-level family earned income (TFEARN$_{ij}$) is expressed as a function of three state-level variables (INCOME$_j$, UNEMP$_j$, MAX$_j$) and an error term, u$_{ij}$. Again, the addition of these state-level variables is expected to reduce error variances in the outcome variables estimated by basic MMR model.

For the MLM method, the individual-level equation is the same as Equation (4.2) in basic MLM model because we consider only state-level variables in this modeling strategy:

\[ \textbf{L1: } TFEARN_{ij} = B_{0j} + r_{ij} \]  \hspace{1cm} (4.2)

However, the state-level equation now includes three variables:

\[ \textbf{L2: } B_{0j} = r_{00} + r_{01} \text{INCOME}_j + r_{02} \text{UNEMP}_j + r_{03} \text{MAX}_j + u_{0j} \]  \hspace{1cm} (4.15)

Combining these two equations yields:

\[ \textbf{C: } TFEARN_{ij} = r_{00} + r_{01} \text{INCOME}_j + r_{02} \text{UNEMP}_j + r_{03} \text{MAX}_j + u_{0j} + r_{ij} \]  \hspace{1cm} (4.16)

The only difference between the MMR model with state-level variables and the MLM model is that the MLM model has an additional error term (u$_{0j}$), which represents between-state variances. The estimation results of the effects of state-level variables on total family earned income are shown in Table 4.11.
As shown in Table 4.11, only unemployment rate is estimated to have statistically negative effect on total family earned income in the MMR model. The estimate indicates that as unemployment rate increases 1%, total family earned income decreases about $485. However, this estimate is not statistically significant using the MLM estimation method. The MLM method produced larger standard error than the MMR method did making the unemployment coefficient insignificant. Other estimates are similar across models and all insignificant.

In terms of error variances, the MMR model has reduced by 4.19% (234,178) from 5,590,963 in the basic model to 5,356,776 in this model with 3 state-level variables, while the MLM method has reduced state-level error variances by 24.42%3 (209,421) from 857,518 in the basic MLM model to 648,097 in Equation (4.16). Because the between-states model only includes state-level variables, there is virtually no change in the estimate of the variance within state (σ²) from 4,887,958 in the basic model to 4,888,465. The intraclass correlation coefficient (ρ) is now .12 indicating 12% of the variances in the outcome variable in between Level-2 units, i.e., between-states after controlling for three state-level variables used in Equation (4.16).

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3 The proportion of variance explained by the state-level variables is calculated by the following equation (Bryk and Raudenbush, 1992, p.65): Proportion variance explained = \( \frac{\tau_{00} \text{ (basic)} - \tau_{00} \text{ (between-states)}}{\tau_{00} \text{ (basic)}} \)
4.3.4 Effects of Individual- and State-Level Variables

The next step incorporates both individual- and state-level variables and their interactions to estimate their effects on the outcome variables. For the MMR model, the equation with individual- and state-level variables is specified as:

\[
\text{TFEARN}_{ij} = B_0 + B_1 \text{SEX}_{ij} + B_2 \text{RACE}_{ij} + B_3 \text{MARRIAGE}_{ij} + B_4 \text{DISABL}_{ij} + B_5 \text{FDSTP}_{ij} + B_6 \text{FAC_OPEN}_{j} + B_7 \text{FAC_STF}_{j} + B_8 \text{FAC_SRV}_{j} + B_9 \text{FAC_HC}_{j} + B_{10} \text{UNEMP}_{j} + B_{11} \text{MAX}_{j} + B_{12} \text{CHILDCRE}_{j} + B_{13} \text{TRANS}_{j} + B_{14} \text{RACE}_{ij} \cdot \text{MAX}_{j} + \gamma_{ij} \tag{4.17}
\]

Equation (4.17) consists of five individual-level variables (individual’s sex, race, marital status, disability status, and the amount of Food Stamps received), following by four variables for state welfare agencies’ implementation activities (FAC_OPEN, FAC_STF, FAC_SRV, and FAC_HC), one state environmental variable (unemployment), three state welfare policy variables (maximum benefit for family of three and the existence of child care transportation services after employment), and an interaction term between individual’s race and maximum benefit. This interaction term is added to test whether being non-white is positively or negatively related to earnings of welfare leavers. As Lower-Basch (2000) reported that different outcomes by race would be due to different treatments that African-American leavers may have experienced, we will explore how race interacts with increased monthly benefit.

For the MLM method, the individual-level equation is:
L1: TFEARN\textsubscript{ij} = B\textsubscript{0j} + B\textsubscript{ij}SEX\textsubscript{ij} + B\textsubscript{2j}RACE\textsubscript{ij} + B\textsubscript{3j}MARRIAGE\textsubscript{ij} + B\textsubscript{4j}DISABL\textsubscript{ij} + B\textsubscript{5j}FDSTP\textsubscript{ij} + r\textsubscript{ij} \quad (4.18)

And, the state-level equations are specified as:

L2: B\textsubscript{0j} = r\textsubscript{00} + r\textsubscript{01}FAC\_OPEN\subscript{j} + r\textsubscript{02}FAC\_STF\subscript{j} + r\textsubscript{03}FAC\_SRV\subscript{j} + r\textsubscript{04}FAC\_HC\subscript{j} + r\textsubscript{05}UNEMP\subscript{j} + r\textsubscript{06}MAX\subscript{j} + r\textsubscript{07}CHILDCRE\subscript{j} + r\textsubscript{08}TRANS\subscript{j} + u\textsubscript{0j}, B\textsubscript{ij} = r\textsubscript{10} + u\textsubscript{ij}, B\textsubscript{2j} = r\textsubscript{20} + r\textsubscript{21}MAX\subscript{j} + u\textsubscript{2j}, B\textsubscript{3j} = r\textsubscript{30} + u\textsubscript{3j}, B\textsubscript{4j} = r\textsubscript{40} + u\textsubscript{4j}, B\textsubscript{5j} = r\textsubscript{50} + u\textsubscript{5j} \quad (4.19)

In this modeling, the intercept (B\textsubscript{0j}) and individual-level slopes (B\textsubscript{ij} ~ B\textsubscript{6j}) are assumed to be random. Also, the race slope (B\textsubscript{2j}) is assumed to be a function of maximum benefit to explore whether maximum benefit policy has different effects by race, i.e., interaction effect between race and maximum benefit policy. Substituting Equation (4.19) into Equation (4.18) yields the combined models:

C: TFEARN\textsubscript{ij} = r\textsubscript{00} + r\textsubscript{01}FAC\_OPEN\subscript{j} + r\textsubscript{02}FAC\_STF\subscript{j} + r\textsubscript{03}FAC\_SRV\subscript{j} + r\textsubscript{04}FAC\_HC\subscript{j} + r\textsubscript{05}UNEMP\subscript{j} + r\textsubscript{06}MAX\subscript{j} + r\textsubscript{07}CHILDCRE\subscript{j} + r\textsubscript{08}TRANS\subscript{j} + u\textsubscript{0j} + (r\textsubscript{10} + u\textsubscript{0j})SEX\textsubscript{ij} + (r\textsubscript{20} + r\textsubscript{21}MAX\subscript{j} + u\textsubscript{2j})RACE\textsubscript{ij} + (r\textsubscript{30} + u\textsubscript{3j})MARRIAGE\textsubscript{ij} + (r\textsubscript{40} + u\textsubscript{4j})DISABL\textsubscript{ij} + (r\textsubscript{50} + u\textsubscript{5j})FDSTP\textsubscript{ij} + r\textsubscript{ij}
= r\textsubscript{00} + r\textsubscript{10}SEX\textsubscript{ij} + r\textsubscript{20}RACE\textsubscript{ij} + r\textsubscript{30}MARRIAGE\textsubscript{ij} + r\textsubscript{40}DISABL\textsubscript{ij} + r\textsubscript{50}FDSTP\textsubscript{ij} + r\textsubscript{01}FAC\_OPEN\subscript{j} + r\textsubscript{02}FAC\_STF\subscript{j} + r\textsubscript{03}FAC\_SRV\subscript{j} + r\textsubscript{04}FAC\_HC\subscript{j} + r\textsubscript{05}UNEMP\subscript{j} +
\( r_{06} \text{MAX}_j + r_{07} \text{CHILDCRE}_j + r_{08} \text{TRANS}_j + r_{21} \text{RACE}_{ij} \ast \text{MAX}_j + [u_{0j} + u_{1j} \text{SEX}_{ij} + u_{2j} \text{RACE}_{ij} + u_{3j} \text{MARRIAGE}_{ij} + u_{4j} \text{DISABL}_{ij} + u_{5j} \text{FDSTP}_{ij} + r_{ij}] \)  \hspace{1cm} (4.20)

Equation (4.20) is comparable to Equation (4.17) in that it consists of the same individual- and state-level variables and an interaction term between race and maximum benefit. One difference is that the error components in the MLM modeling are much more complicated than the MMR model is. These error components represent individual-level variance (within-state variance), state-level variance (between-state variance), and random effects of each state on the individual-level slopes \((u_{ij} \text{SEX}_{ij} \sim u_{5j} \text{FDSTP}_{ij})\). The estimation results of these MMR and MLM models are shown in Table 4.12.

First, in terms of the estimates of the individual-level variables, both MMR and MLM methods produced similar results. Being male, being married, and being non-disabled are positively related to the outcome variables. The magnitude of those regression coefficients is also similar in both methods. Also, the amount of Food Stamps received is negatively related to total family earned income: a $1 increase in Food Stamps amount is estimated to decrease $2.70 \sim $2.90 in total family earned income. The interpretation of the estimation result of Food Stamps can be different. First explanation is that Food Stamps supplement welfare leavers’ efforts in earning more money. In this case, welfare leavers are assumed to dislike working and the causal direction is from Food Stamps to income. Second explanation is that only those who have low income apply for Food Stamps, and the poorer gets higher amounts of Food Stamps. As a
result, we face a simultaneous problem in interpreting the estimation result of Food Stamps. Using two-stage least square method, we can fix this problem with the MMR method. However, as far as we know, there is still no tool to deal with simultaneous problems in the MLM method leaving rooms to incorporate such problems. Finally, the effect of race on the outcome variable is estimated to have no significant effect.

Second, the MMR model indicates that only one state implementation activity (FAC_SRV) is statistically significant, while the MLM model indicates that three of the four state implementation activities are statistically significant: FAC_OPEN, FAC_SRV, and FAC_HC. Across the models, the emphasis on the activities that aimed to enhance relationships with private sector employers, to effectively coordinate among agencies, and to develop employment opportunities is estimated to have positive effects on the outcome variable. These work-oriented activities are strongly emphasized under the welfare reform in 1996, according to many studies that reveal, “work first approach” works better than investment on the enhancement of human capital. Implementation activities related to service provision (FAC_SRV), enhancement of human capital (FAC_HC), and improvement of staff productivity are all estimated to have negative effects. This result implies that these state welfare agencies’ activities are not effective than work-oriented activities for welfare leavers to earn income. These activities may deprive of limited time and resources that state welfare agencies have. Thus, more focus on these activities implies less time and
resources on work-oriented activities, which are estimated to have positive effect on family earned income.

Third, we have utilized only one state environmental variable: unemployment rate. And both models indicate unemployment rate is negatively related to family earned income. The MMR estimation indicates that a 1% increase in unemployment rate leads to about $447 decrease in family earned income, while the MLM estimation indicates that the same percentage of increase in unemployment rate leads to about $231 decrease in the outcome variables. However, the MMR estimate is statistically significant at the 95% confidence level, while the MLM estimate is statistically significant at the 90% confidence level.

Fourth, three state welfare policy variables are utilized as shown in Table 4-12: maximum benefit for family of three and the existence of child care services and employment assistance services after employment. Table 4-12 shows that a $1 increase in maximum benefit leads to about $2.53 to $2.95 increase in total family earned income. It implies that the higher amount of benefit is beneficial to low-income family. Before welfare leavers earn enough income to leave the system, they receive monthly TANF benefits and at the same time, they can keep their earnings by various governmental supports like earned income tax credits. The higher benefits with the presence of these supports lead to increased income of welfare leavers. Much research has indicated that child care (Kisker and Ross 1997; Smith, 1995) and transportation services (Community Transportation Association of America, 1998) are essential in keeping employment and self-sufficiency. The estimation results indicate that these services have positive
effects on total family earned income and the estimates range from $442 to $639 for childcare services and from $545 to $617 for transportation.

Finally, an interesting result is found in the estimates of the interaction term between race and maximum benefit. The MMR method indicates that individual’s race and the amount of maximum benefit interact each other to influence on the outcome, while the MLM method indicates that there is no interaction between these two variables. According to the MMR result, non-white tends to make less money when they receive higher maximum benefits, while the estimation result of the MLM method does not support this interpretation. These conflicting results make it difficult to conclude whether the effect of race on the outcome variable depends on generous or sparing benefit levels. Special caution is required in interpreting the MMR estimation result because the MMR method ignores the variation among states, which violates one of the OLS assumptions. We prefer the MLM estimation result to the MMR result because the MLM method fully and more precisely specifies multilevel data structure.

Table 4.13 presents the changes in error variances using individual- and state-level variables from both methods. As shown in Table 4.13, using the same set of variables, the MLM method has reduced much more error variances than the MMR method does. The MLM method reduced individual-level variances (within-state variances) by 28.5% and state-level variances (between-state variances) by 35.25%, while the MMR model reduced 18.51% of total error variances.
Table 4.1 Monthly Numbers of Welfare Recipients and Leavers in the SIPP

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<td>Recipients</td>
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<td>146</td>
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<td>149</td>
<td>148</td>
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</tr>
</tbody>
</table>

Table 4.2 Sources of Data Utilized in the Dissertation

<table>
<thead>
<tr>
<th>Levels</th>
<th>Dimensions</th>
<th>Examples</th>
<th>Sources</th>
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<tbody>
<tr>
<td>Individual</td>
<td>Program Outcomes</td>
<td>Total family earned income</td>
<td>SIPP</td>
</tr>
<tr>
<td></td>
<td>Individual Characteristics</td>
<td>Sex, Race, Marital status</td>
<td>SIPP</td>
</tr>
<tr>
<td></td>
<td>Participation of Other</td>
<td>Food Stamp amount, SSI amount</td>
<td>SIPP</td>
</tr>
<tr>
<td></td>
<td>Governmental Programs</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Environment</td>
<td>Unemployment rate</td>
<td>Blank, Moffitt, U.S. Census</td>
</tr>
<tr>
<td>Implementation Activities</td>
<td>Minimum</td>
<td>Maximum</td>
<td>Mean</td>
</tr>
<tr>
<td>---------------------------------------------------------------</td>
<td>---------</td>
<td>---------</td>
<td>-------</td>
</tr>
<tr>
<td>Enhancing relations w/ private employers</td>
<td>3</td>
<td>5</td>
<td>4.34</td>
</tr>
<tr>
<td>Providing transitional childcare</td>
<td>4</td>
<td>5</td>
<td>4.59</td>
</tr>
<tr>
<td>Providing transitional healthcare</td>
<td>4</td>
<td>5</td>
<td>4.57</td>
</tr>
<tr>
<td>Developing employment opportunities</td>
<td>0</td>
<td>5</td>
<td>3.82</td>
</tr>
<tr>
<td>Improving job placement skills of staff</td>
<td>0</td>
<td>5</td>
<td>3.32</td>
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<tr>
<td>Incentives for staff-job placement rates</td>
<td>0</td>
<td>5</td>
<td>2.64</td>
</tr>
<tr>
<td>Effective coordination among agencies</td>
<td>3</td>
<td>5</td>
<td>4.27</td>
</tr>
<tr>
<td>Improving remedial education</td>
<td>2</td>
<td>5</td>
<td>3.41</td>
</tr>
<tr>
<td>Changing way client processed</td>
<td>2</td>
<td>5</td>
<td>3.75</td>
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<td>Improving job training</td>
<td>2</td>
<td>5</td>
<td>3.55</td>
</tr>
<tr>
<td>Improving client assessment protocols</td>
<td>2</td>
<td>5</td>
<td>3.64</td>
</tr>
<tr>
<td>Enhancing transportation assistance</td>
<td>2</td>
<td>5</td>
<td>4.05</td>
</tr>
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</table>

Table 4.3 Descriptive Statistics of Implementation Activities

<table>
<thead>
<tr>
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<th>Mean</th>
<th>Std. Dev.</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>.41</td>
<td>.49</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Marital Status</td>
<td>.17</td>
<td>.38</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Race</td>
<td>.53</td>
<td>.50</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Disability</td>
<td>.22</td>
<td>.41</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Number of Kids</td>
<td>2.26</td>
<td>1.59</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Total Family Earned Income</td>
<td>1,725.70</td>
<td>2,364.52</td>
<td>0</td>
<td>13,321</td>
</tr>
<tr>
<td>Food Stamps Amount</td>
<td>105.16</td>
<td>161.11</td>
<td>0</td>
<td>803.00</td>
</tr>
<tr>
<td>TFEARN</td>
<td>1,725.70</td>
<td>2,364.52</td>
<td>0</td>
<td>13,321.00</td>
</tr>
<tr>
<td>D_TFEARN</td>
<td>349.93</td>
<td>1,756.49</td>
<td>-6,662.00</td>
<td>10,500.00</td>
</tr>
<tr>
<td>TOTINC</td>
<td>2,228.80</td>
<td>2,366.31</td>
<td>0</td>
<td>13,913.00</td>
</tr>
<tr>
<td>D_TOTINC</td>
<td>94.40</td>
<td>754.89</td>
<td>-6,462.00</td>
<td>10,500.00</td>
</tr>
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</table>

Table 4.4 Descriptive Statistics of the Sample
Table 4.5 Correlation Matrix of Implementation Activities

<table>
<thead>
<tr>
<th></th>
<th>X1</th>
<th>X2</th>
<th>X3</th>
<th>X4</th>
<th>X5</th>
<th>X6</th>
<th>X7</th>
<th>X8</th>
<th>X9</th>
<th>X10</th>
<th>X11</th>
<th>X12</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1 Priv. Employer</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X2 Client Assess.</td>
<td>-.33**</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X3 Trans. Childcare</td>
<td>-.56***</td>
<td>-.33**</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X4 Trans. Health</td>
<td>-.44***</td>
<td>-.30**</td>
<td>.86***</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X5 Staff Skills</td>
<td>.25**</td>
<td>-.43***</td>
<td>.16</td>
<td>.13</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X6 Transp. Service</td>
<td>-.51***</td>
<td>-.31**</td>
<td>.49***</td>
<td>.44***</td>
<td>.18</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X7 Incentive for Staff</td>
<td>.19</td>
<td>.01</td>
<td>.02</td>
<td>.05</td>
<td>.30**</td>
<td>.105</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X8 Effec. Coord.</td>
<td>.49***</td>
<td>-.13</td>
<td>.22*</td>
<td>.16</td>
<td>-.09</td>
<td>.24*</td>
<td>-.02</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X9 Client Process</td>
<td>.18</td>
<td>.37***</td>
<td>.36***</td>
<td>.40***</td>
<td>.10</td>
<td>.41***</td>
<td>.10</td>
<td>.21*</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X10 Remedial Educ.</td>
<td>.27**</td>
<td>.34**</td>
<td>.08</td>
<td>.05</td>
<td>.28**</td>
<td>.27**</td>
<td>.17</td>
<td>-.09</td>
<td>.15</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>X11 Job Training</td>
<td>.26**</td>
<td>.22*</td>
<td>.17</td>
<td>.21*</td>
<td>.20*</td>
<td>.25**</td>
<td>.05</td>
<td>.02</td>
<td>.09</td>
<td>.69***</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>X12 Employ. Opport.</td>
<td>.51***</td>
<td>.18</td>
<td>.22*</td>
<td>.21*</td>
<td>.12</td>
<td>.35**</td>
<td>-.05</td>
<td>.27**</td>
<td>.00</td>
<td>.10</td>
<td>.44***</td>
<td>1.00</td>
</tr>
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</table>

* p < .1, ** p < .05, *** p < .01

Table 4.6 Results of the Extraction of Component Factors

<table>
<thead>
<tr>
<th>Component</th>
<th>Eigenvalues</th>
<th>% of Variance</th>
<th>Cumulative % of Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.752</td>
<td>22.935</td>
<td>22.935</td>
</tr>
<tr>
<td>2</td>
<td>2.099</td>
<td>17.494</td>
<td>40.429</td>
</tr>
<tr>
<td>3</td>
<td>1.959</td>
<td>16.326</td>
<td>56.755</td>
</tr>
<tr>
<td>4</td>
<td>1.367</td>
<td>11.391</td>
<td>68.146</td>
</tr>
<tr>
<td>5</td>
<td>.923</td>
<td>7.689</td>
<td>75.835</td>
</tr>
<tr>
<td>6</td>
<td>.832</td>
<td>6.930</td>
<td>82.765</td>
</tr>
<tr>
<td>7</td>
<td>.594</td>
<td>4.948</td>
<td>87.714</td>
</tr>
<tr>
<td>8</td>
<td>.518</td>
<td>4.319</td>
<td>92.032</td>
</tr>
<tr>
<td>9</td>
<td>.467</td>
<td>3.890</td>
<td>95.922</td>
</tr>
<tr>
<td>10</td>
<td>.237</td>
<td>1.973</td>
<td>97.895</td>
</tr>
<tr>
<td>11</td>
<td>.137</td>
<td>1.141</td>
<td>99.036</td>
</tr>
<tr>
<td>12</td>
<td>.116</td>
<td>.964</td>
<td>100.000</td>
</tr>
</tbody>
</table>

Table 4.6 Results of the Extraction of Component Factors
Figure 4.1 Scree Test for Component Analysis
<table>
<thead>
<tr>
<th>Component</th>
<th>Component 1</th>
<th>Component 2</th>
<th>Component 3</th>
<th>Component 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1 Enhance Relations w/ Private Sector Employers</td>
<td>.400</td>
<td>.231</td>
<td>.708</td>
<td>.244</td>
</tr>
<tr>
<td>X2 Improve Client Assessment Protocols</td>
<td>.581</td>
<td>.451</td>
<td>-.205</td>
<td>.159</td>
</tr>
<tr>
<td>X3 Provide Transitional Childcare</td>
<td>.835</td>
<td>2.971E-02</td>
<td>.299</td>
<td>-2.997E-02</td>
</tr>
<tr>
<td>X4 Provide Transitional Healthcare</td>
<td>.837</td>
<td>1.890E-02</td>
<td>.225</td>
<td>-4.948E-02</td>
</tr>
<tr>
<td>X5 Improve Job Placement Skills of Staff</td>
<td>.212</td>
<td>.346</td>
<td>-8.945E-02</td>
<td>.636</td>
</tr>
<tr>
<td>X6 Enhancing Transportation Assistance</td>
<td>.566</td>
<td>.239</td>
<td>.386</td>
<td>.121</td>
</tr>
<tr>
<td>X7 Incentives for Staff-Job Placement Rates</td>
<td>-3.158E-02</td>
<td>-4.711E-02</td>
<td>9.900E-02</td>
<td>.882</td>
</tr>
<tr>
<td>X8 Effective Coordination among Agencies</td>
<td>9.202E-02</td>
<td>-.213</td>
<td>.792</td>
<td>-1.447E-02</td>
</tr>
<tr>
<td>X10 Improving Remedia Education</td>
<td>6.926E-02</td>
<td>.822</td>
<td>-3.924E-02</td>
<td>.223</td>
</tr>
<tr>
<td>X11 Improving Job Training</td>
<td>4.936E-02</td>
<td>.864</td>
<td>.211</td>
<td>-3.325E-02</td>
</tr>
<tr>
<td>X12 Developing Employment Opportunities</td>
<td>5.667E-02</td>
<td>.442</td>
<td>.660</td>
<td>-.132</td>
</tr>
</tbody>
</table>

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a Rotation converged in 7 iterations.

Table 4.7 Rotated Component Analysis Factor Matrix
Table 4.8 Estimation Result of Basic MMR Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>T-ratio</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept (Bij)</td>
<td>1,725.70</td>
<td>200.37</td>
<td>8.61</td>
<td>.00</td>
</tr>
<tr>
<td>( \sigma^2 )</td>
<td></td>
<td></td>
<td></td>
<td>5,590.963.22</td>
</tr>
</tbody>
</table>

Table 4.9 Estimation Results of Basic Multilevel Model

<table>
<thead>
<tr>
<th>Properties</th>
<th>Dependent Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total Family Earned Income (TFEARN)</td>
</tr>
<tr>
<td>Within-state Variance (( \sigma^2 ))</td>
<td>4,887,958.27</td>
</tr>
<tr>
<td>Between-state Variance (( \tau_{oo} ))</td>
<td>857,518.42</td>
</tr>
<tr>
<td>Intraclass Correlation Coefficient (ICC)</td>
<td>.15</td>
</tr>
<tr>
<td>Reliability</td>
<td>.83</td>
</tr>
<tr>
<td>Intercept (r_{oo})</td>
<td>1,691.66***</td>
</tr>
</tbody>
</table>

*** p < .01
### Table 4.10  Estimation Result of Individual-Level MMR and MLM Models

<table>
<thead>
<tr>
<th>Variables</th>
<th>MMR</th>
<th>MLM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Std. Error</td>
</tr>
<tr>
<td>Intercept</td>
<td>1,725.70</td>
<td>200.37</td>
</tr>
<tr>
<td>SEX</td>
<td>315.72</td>
<td>107.23</td>
</tr>
<tr>
<td>RACE</td>
<td>-598.11</td>
<td>423.20</td>
</tr>
<tr>
<td>MARRIAGE</td>
<td>1,155.20</td>
<td>169.98</td>
</tr>
<tr>
<td>EDUCATION</td>
<td>16.96</td>
<td>65.05</td>
</tr>
<tr>
<td>DISABILITY</td>
<td>-661.08</td>
<td>154.78</td>
</tr>
<tr>
<td>FOOD STAMPS</td>
<td>-2.56</td>
<td>.81</td>
</tr>
</tbody>
</table>

| FOOD STAMPS | -2.56       | .81        | -3.16   | .002    | -4.53       | 2.73        | -1.66   | .110    |

### Table 4.11  Estimation Results of State-Level MMR and MLM Models

<table>
<thead>
<tr>
<th>Variables</th>
<th>MMR</th>
<th>MLM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Std. Error</td>
</tr>
<tr>
<td>Intercept</td>
<td>1,634.33</td>
<td>167.53</td>
</tr>
<tr>
<td>INCOME</td>
<td>.04</td>
<td>.07</td>
</tr>
<tr>
<td>UNEMP</td>
<td>-484.65</td>
<td>196.14</td>
</tr>
<tr>
<td>MAX</td>
<td>1.70</td>
<td>1.92</td>
</tr>
</tbody>
</table>

Table 4.11  Estimation Results of State-Level MMR and MLM Models
### Table 4.12 Estimation Results of Full MMR and MLM Models

<table>
<thead>
<tr>
<th>Variables</th>
<th>MMR</th>
<th>MLM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Std. Error</td>
</tr>
<tr>
<td>Intercept</td>
<td>3,638.67</td>
<td>825.64</td>
</tr>
<tr>
<td>SEX</td>
<td>290.00</td>
<td>108.68</td>
</tr>
<tr>
<td>RACE</td>
<td>-269.78</td>
<td>477.11</td>
</tr>
<tr>
<td>MARRIAGE</td>
<td>1,110.83</td>
<td>165.27</td>
</tr>
<tr>
<td>DISABILITY</td>
<td>-678.09</td>
<td>148.01</td>
</tr>
<tr>
<td>FOOD STAMP</td>
<td>-2.70</td>
<td>.77</td>
</tr>
<tr>
<td>FAC_OPEN</td>
<td>130.51</td>
<td>84.16</td>
</tr>
<tr>
<td>FAC_STF</td>
<td>-202.85</td>
<td>139.58</td>
</tr>
<tr>
<td>FAC_SRV</td>
<td>-409.96</td>
<td>119.87</td>
</tr>
<tr>
<td>FAC_HC</td>
<td>-147.11</td>
<td>130.80</td>
</tr>
<tr>
<td>UNEMP</td>
<td>-446.78</td>
<td>177.26</td>
</tr>
<tr>
<td>MAX</td>
<td>2.95</td>
<td>1.23</td>
</tr>
<tr>
<td>CHILDCRE</td>
<td>441.75</td>
<td>307.92</td>
</tr>
<tr>
<td>TRANS</td>
<td>617.34</td>
<td>217.30</td>
</tr>
<tr>
<td>RACE*MAX</td>
<td>-4.78</td>
<td>2.42</td>
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</table>

Table 4.13 Changes in Error Variances in Full MMR and MLM Models

<table>
<thead>
<tr>
<th></th>
<th>MMR Method</th>
<th>MLM Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Basic Model</td>
<td>Full Model</td>
</tr>
<tr>
<td>Within-state error variances</td>
<td>5,590,963</td>
<td>4,556,207</td>
</tr>
<tr>
<td>Between-state error variances</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Table 4.13 Changes in Error Variances in Full MMR and MLM Models
Chapter 5
Conclusions and Discussions

The passage of the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996 created an unprecedented atmosphere of the welfare system in the United States: the entitlement to aid has been abolished and much authority for program design and service delivery has been given to the states. States have experimented many innovative programs to move welfare recipients from dependency to self-sufficiency. This also created many opportunities for evaluation studies of the success of the reform.

This dissertation has examined the determinants of success of public cash assistance programs for welfare leavers during the PRWORA era. The main research question is how state welfare policies, implementation activities of state welfare agencies, the environment, and individual characteristics interact and affect the economic self-sufficiency of former welfare recipients. This dissertation also asks what are the advantages and disadvantages of using different statistical methods in estimating interaction effects among individual- and state-level variables when there is significant within-state homogeneity and between-state variation. The results of this study can lead to a better understanding of what works and what does not in achieving the goals of the welfare programs providing
direction for future policy making, program evaluation, and research. The following is a discussion of the implications of the findings of this dissertation.

5.1 Policy Implications of the Findings of the Dissertation

The welfare reform in 1996 has aimed to “end welfare as we know it” mainly by making welfare recipients working. This new focus on work appears to reflect past dissatisfaction with education- or training-oriented focus of welfare programs. Although states have greater freedom in designing their own programs based on their own needs, the emphasis on work is the central component of the programs in each state after the reform. With time-limited provision of services, this new focus is expected to move welfare recipients from poverty to self-sufficiency more effectively.

A result of this dissertation indicates that the emphasis on work-oriented activities of state welfare agencies is positively related to the outcome variable of interest across the two estimation methods. This finding suggests that the “work first approach” is helping welfare leavers to successfully transit from welfare to self-sufficiency. One of the major concerns about the work first approach is that placing welfare recipients in entry-level jobs, which do not require higher education or job skills, will not help them in the long run and they will return to the program (Mandayam, 2001). However, the findings of this dissertation suggest that one year after welfare recipients left the system, they earned about $1,726 per month on average, which is $350 more than the earnings when they
were on welfare. This means that the major concern about the work first approach may not necessarily be supported for former welfare recipients.

Policy actions should keep emphasizing work and the program design also should reinforce such components. These policy orientations may require the enhancement of relationships with private sector employers, the coordination among governmental agencies, and the development of employment opportunities. Also, improving the quality of entry-level jobs may be helpful in improving the ability and job retention of welfare recipients in the long run. Many studies suggest that joblessness is the main cause of being and dependent on welfare (Wilson, 1993). With limited time and resources that state welfare agencies have, removing joblessness should be considered as a top priority of policy actions and job placement should be viewed as a staring point for self-sufficiency of welfare leavers.

Another policy implication of the dissertation is about the provision of supportive services after employment. Many studies indicate that families who left the system have still had substantial needs for supportive services even after they have an employment (Pavetti, 1997; Rangarajan, 1998). Currently, many state welfare programs have several crucial components of supportive services, such as health care, child care, and transportation. The employees that hired welfare leavers are not likely to provide or to pay well enough to purchase these services. Thus, policy design should address the needs for supportive services and provide adequate level of services to welfare leavers even they are employed.
A result of this dissertation indicates that the provision of child care services and transportation services is positively related to the earned income of welfare leavers. The estimates range from $442 to $639 for child care services and from $545 to $617 for transportation services depending on estimation methods. These results are consistent with many previous studies (Anderson, Halter, and Schuldt, 2001; Julnes, Hayashi, and Anderson, 2001; Westra, 2001). For example, Julnes, Hayashi, and Anderson (2001) raised the importance of social support, which includes transportation, for distinguishing leavers in terms of well-being.

While recognizing the importance of support services to TANF leavers, Anderson, Halter, and Schuldt (2001) also reported that leavers rarely use a full package of support services envisioned in welfare policies. If policymakers provide these services in response to specific deficits, under-utilization of supportive services by welfare leavers may indicate no need for such services to policymakers. Alternatively, as Gilbert and Terrell (1998) suggest, policymakers can consider the provision of supportive services based on basic entitlements in support of agreed-on living standards. However, it is not clear whether this alternative can actually improve self-sufficiency of welfare leavers through this dissertation leaving room for direction for future research on supportive services.

The final policy implication of the dissertation raises another opportunity for future research. This dissertation has found that interaction between race and maximum benefit amount for family of three is estimated to exist through the
MMR method, while is not through the MLM method. That is, the MMR method suggests that non-white tends to make less earned income when their monthly benefits go up.

A number of studies have examined the racial differences of welfare outcomes in terms of exit rates (Coulton, Claudia, et al., 2001; Urban Institute’s National Survey of America’s Families), employment rates (Foster, E. Michael and Dana Rickman, 2001; Midwest Research Institute, 2000), and earnings (Coulton, Claudia, et al., 2001; Midwest Research Institute, 2000; Wisconsin Department of Workforce Development, 2001). However, most studies did not report statistical tests of significance for the differences in the outcomes of interest by racial group. They are mainly simple cross-tabulations of racial differences in welfare outcomes. Lower-Basch (2000) reported that different outcomes of welfare leavers by race would be due to different treatments that African-American leavers may have experienced. She further discussed that race may differently affect the state welfare policies chosen by policymakers at the state and local level.

Are the different outcomes by different populations due to different treatments? Because most previous studies only show simple cross-tabulations of racial differences in welfare outcomes, we cannot provide a full, empirical explanation for why these differences in the estimation results using the MMR and MLM methods are occurring. The difference may reflect the differences in estimation methods of the two techniques. Or it may reflect a real racial
difference by welfare benefits, as the MMR method supports. In this case, race
can be thought as a proxy variable for all kinds of hardship and deprivation.

However, some cautions present in interpreting results and making policy
recommendations of this study. First of all, implications of the estimation results
of policy variables are only suggestive mainly because policy variables are
measured at the state level rather than at the individual level. For example, the
presence of childcare and transportation services are measured using
dichotomous variables at the state level, leaving doubts on whether the sample in
the study actually received those services or not. This limitation is from the fact
that those kinds of data are not available as far as we know. Thus, we need to be
more cautious in interpreting policy recommendations of the dissertation.

Also, the survey instrument measures state welfare administrators’
perception on the importance of various implementation activities not the actual
ones implemented at the state or local welfare offices. This limited information
may influence the estimation results of the effects of implementation activities on
the economic well-being of welfare leavers.

5.2 Methodological Implications of the Dissertation
In multilevel, nested data structure, cross-level interaction or moderating effects refer to how variables within the different levels influence each other in accounting for variance in the outcomes of interest. The MMR method adds interaction terms and tests whether the point estimate of the terms are statistically significant or not to detect the existence of interaction effects. Alternatively, the MLM method builds sub-models of each of the multilevel variables in the data structure, representing relationships among variables within a given level and interaction effects across the levels.

This dissertation has found that the MMR and MLM methods produce an identical estimation result if all OLS assumptions including homogeneous variances of organizations are met. This assumption means that the variance in outcome variable unaccounted for by independent variables is equal across higher-level units (i.e., states or organizations). However, in the presence of heterogeneous error variances across organizations, the MLM method conceptually and statistically produces correct standard errors and, thus, parameter estimates. The MMR estimation method produces smaller standard errors than the MLM method does making coefficients significant.

More specifically, there appear to be significant advantages to using multilevel modeling strategy when it is possible. The comparison of the MMR and MLM methods show that conceptually, the MLM method more precisely reflects complex, hierarchical relationships among variables than the MMR method does. The MLM method also increases the generalizability of findings by allowing higher-level units (i.e., state or organization) to have their
characteristics in the analysis. Further, the MLM method provides information about the amount of variation at the different levels of analysis, which the MMR method cannot provide. Also, it produces estimates closer to the true parameter values than the MMR method does.

5.3 Contributions of the Dissertation

This dissertation can be seen as achieving three related but different objectives pertaining to the model, the data set and the analytical tools. First, this dissertation focuses on leavers rather than recipients since they did succeed in getting off welfare. In the analytic model, this dissertation has included various components that previous studies partially incorporated in their analysis. This dissertation attempts to capture various individual, programmatic and environmental factors in a single integrated model as shown in Figure 5.1. This model allows us to examine how individual characteristics, state welfare policies, implementation activities of state welfare agencies, and the environment interact and affect the economic self-sufficiency of welfare leavers.

Second, this dissertation has brought together proxies of the constructs and variables included in the analytic model. Previous studies have often examined the effects of various state- and individual-level variables by taking
aggregation forms or disaggregation form\(^1\). Also, many studies of welfare leavers are only descriptive lacking a model that links welfare policies and other state-level factors to the leavers’ individual well-being. By being able to merge longitudinal data on the leavers, with various state-level data, such as, data on state welfare policies, perceptions of program implementation, and the environment, this dissertation is based on a dataset that reflects the various components of the analytic model. This allows us to examine the effects and interactions of various individual- and state-level factors on the economic well-being of welfare leavers.

Third, this dissertation has estimated the effects of individual characteristics, state welfare policies and implementation activities, and the environment on the economic well-being of welfare leavers using standard statistical techniques and also multi-level methods that better reflect the model and the hierarchical structure of the programs and the data. Overall, the MLM method had conceptual and empirical advantage over the MMR method.

\(^1\) As discussed in Chapter 3, aggregation method aggregates lower-level (i.e., individual) variables to a higher level (i.e., organization or state), while disaggregation method decomposes higher-level data into lower level by assigning the same value for all individuals of the higher-level unit (i.e., organization or state).
Figure 5.1 Analytic Model of the Dissertation

2 This is the same as Figure 1.1.
APPENDIX A

EVOLUTION OF PUBLIC CASH ASSISTANCE PROGRAMS
IN THE UNITED STATES

1. History of the AFDC Program

The origin of federally supported programs in aid of the poor can be traced back to the Social Security Act of 1935, when the Depression exhausted public and private funds for the poor. The Act launched several programs for the destitute elderly, blind, and children, with Aid to Dependent Children (ADC), specially targeted to single parents with children. Since then the federal government has directly assumed a shared responsibility for the economic security of U.S. citizens with the state and local governments.

The Title IV of the Act prescribed the original provisions concerning support for participating states, and participation in the program was voluntary. Participating states received a certain portion of expenditures without any ceiling on the total amount as reimbursement from the federal government. The Act allowed $6 per month for the first child and $4 for each additional child as a
maximum federal reimbursement. Although there was a federal approved process that the states had to submit to for participation in this program, the conditions were, at first, very minimal. In 1936, over a half million people in 147,000 families received ADC. The ADC program was renamed Aid to Families with Dependent Children (AFDC) in 1950.

The original Title IV restricted financial assistance to needy dependent children and excluded a parent or other relatives in the household. However, later the assistance became available to various caretakers, such as an unemployed parent in 1961, “any other individual” in the home deemed essential to the child in 1968, unborn child in 1981, and the families of unemployed parents in 1990. Also, eligible child age for assistance has changed over time. It was originally 15 years, but later it was expanded to include children aged 16 and 17 if regularly attending school, effective in 1940; students aged 18-20 in high school or a course of vocational or technical training in 1964; students aged 18-20 in college or university in 1965; and children aged 18 or, at state option, 19, in high school in 1981.

One of the major changes, starting as early as the 1960s, in welfare policies over time is an emphasis on work and employment among welfare recipients. In 1961, as an unemployed parent became eligible for assistance, states were required to deny assistance if the unemployed parent refused to work without “good causes.” In 1962, Community Work and Training (CWT) programs were established for federally-aided recipients aged 18 and over. CWT programs guaranteed wages equal to the prevailing rates in the community for the same
type of work. Also, states were required to disregard work-related expenses and permitted to exclude income that was saved for future identifiable needs of a dependent child. In 1964, under Title V of the Economic Opportunity Act, Congress authorized the creation of CWT projects in states that had not yet included unemployed parents in their AFDC programs.

In 1968, Congress required states to set up a work and training program called Work and Incentive (WIN) for “appropriate” AFDC recipients. All unemployed fathers had to be referred to the program. In 1971, Congress required that all AFDC parents register for work or training with the WIN program except for mothers with children under age 6. The Family Support Act of 1988 replaced WIN with the Job Opportunities and Basic Skills Training program (JOBS) in a new part IV-F of the Social Security Act. It required states, to the extent resources allowed, to engage most mothers with no child below age 3 in education, work, or training under JOBS.

A new emphasis on employment within AFDC/Temporary Assistance to Needy Families (TANF) programs has been sublimed in the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996. Under PRWORA and TANF, which is the new version of AFDC, work requirements became stricter than ever before, reshaping the provisions of public assistance from entitlement to economic self-sufficiency. The current arrangements of the welfare system molded by PRWORA are discussed in greater detail in the last part of this section.
Another important change in the history of the AFDC/TANF program is the devolution of states’ programs through various waivers from AFDC/TANF law. As early as 1962, Section 1115 of the Social Security Act prescribed the waiver of AFDC law in order to enable a state to carry out the program goals more effectively based on their unique community needs. A few waivers were granted in the 1980s, but widespread, major federal welfare waivers in the states began to be approved in the early to mid-1990s.

These waivers showed wide variations in terms of their specific provisions and time of approval and implementation across states. For example, in terms of work requirement waiver, some states impose immediate work requirement upon receiving benefits, while others require work or participation in training after a specific time period. Also, work requirement waivers in states were approved as early as in July 1992 in New Jersey, while 13 states including Alabama, Colorado, Kentucky, New York, Pennsylvania, and Washington, had no such provisions prior to September 1996 (Ziliak et al., 1997).

With a choice of waivers, states’ TANF policies vary along a number of dimensions, including who can be a recipient, what benefits are provided, what recipients should do in order to receive such benefits, and what penalties are imposed if there is noncompliance with the policy. Many scholars have argued that along with the fluctuations in the economy, the state-specific AFDC/TANF policies have potential impacts on welfare outcomes, such as the caseload and the

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well-being of welfare recipients and leavers, along with the fluctuations in the economy.

The final item studied here is the historical fluctuations of welfare caseloads. As shown in Figure 1-1, there have been wide variations in average monthly welfare caseloads from 1936 to 2001. The average monthly AFDC/TANF caseloads grew by only 892,000 families from 1936 to 1965, while the caseloads sharply grew by 3,993,632 over the next 30 years from 1965 to a peak of 5,032,632 families in 1994 (ACF, 2002).

(Figure 1-1 here)

Over the last 30 years, President Johnson’s “War on Poverty” in the 1960s corresponds to the sharp increase in the caseloads, while Nixon administration’s effort to reduce welfare rolls by complicating the verification process corresponds to a stagnant trend in the 1970s. After a sharp increase in the number of cases in the early 1990s, the welfare caseloads have dramatically decreased, over 50%, from 5,032,632 families in 1994 to 2,214,800 families in 2001. Two primary factors are suggested to explain the caseload variation in the 1990s: the economy conditions of the nation and changes in welfare policy (Schoeni and Blank, 2000). We will revisit this argument in greater detail in Chapter Two.

2. The PRWORA of 1996 and the Major Changes in Welfare Policies
In 1996, Congress passed the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA), which fundamentally changed the focus and the service delivery mechanism of the United States welfare system. Before the welfare reform in 1996, AFDC program focused on a perspective of entitlement and dependency, while states had little authority for service design and administration.

Following the passage and implementation of PRWORA, however, the focus has been changed from a perspective of entitlement and dependency to an environment of economic self-sufficiency through employment. Also, much of authority for service design and implementation has been given to the states. This section provides a brief summary of major changes in state TANF policies brought by PRWORA of 1996 and its policy implications for welfare outcomes.

**Funding Formula**

In the era of AFDC, the basic structure of federal assistance to states was an open-ended appropriation. That is, Congress authorized reimbursement of a certain portion of state expenditures without any ceiling on the total amount. With the federal contribution, states entitled all poor, single-parent families who met income and asset tests to AFDC until their personal income rose above a predetermined threshold, or until their youngest child turned 18. Thus, when AFDC caseloads grew, state officials applied to the federal government for increased funding. And, significant expenditure increases were largely controlled
through incremental benefit reductions or, in times of low unemployment, reduced caseloads.

Under TANF, the entitlement to aid has been abolished. States receive an annual block grant of funding from the federal government that replaces AFDC, JOBS, and Emergency Assistance. State governments are required to maintain their financial commitment to welfare families by allocating between 75% and 80% of the funding they were providing in the early 1990s. This “maintenance of effort” ensures that states will not withdraw their support entirely from the TANF program. If the TANF caseload grows above the block grant allocation, state and local authorities are fully responsible for the additional financial burden. Given this financial disincentive, states may reduce costs by stricter policies, such as benefit reductions, time limits, or targeting strategies (Berrick, 2000).

Time Limits

Under AFDC, poor families were entitled to receive cash assistance for as long as they met the eligibility standards. There was no federal limit on the length of time a family could receive aid, and states could not impose such limits.

Under TANF, various time limits are imposed on welfare recipients. First, the federal government imposed a maximum of 60 cumulative months of lifetime limit for aid, regardless of the age of children or the poverty status of the family. With the discretion to reduce time limits further, many states have adopted more restrictive policies. Second, “work requirement” time limits impose mandatory
work requirements on families. That is, states now require recipients to engage in “work activities” to receive and maintain benefits. Work activities include unsubsidized or subsidized employment, job training, community service, and vocational training. Finally, “reduction” time limits reduced the amount of assistance if a family does not comply with state welfare rules or after they had been on welfare for a certain period of time. The penalties include a reduction of benefits by a set percentage, by removal of the adult portion of the grant, or removal of the entire benefits.

**Work Requirement**

Under AFDC, states could require recipients who did not fall into one of the specific exemption categories to participate in the JOBS program, which provided education, job search, on-the-job training, and work experience activities. Individuals exempted from JOBS participation included people who were ill, incapacitated, or aged; were under age 16 or in school full-time; were already working at least 30 hours per week; were in the second or third trimester of pregnancy; were needed in the home to care for an ill or incapacitated family member; and, were providing care to a child under age 3. Individuals who did not fall into these categories, and who did not have good cause for not participating, were considered JOBS mandatory. In FY 1995, states were expected to achieve a participation rate of 20% of JOBS mandatory individuals, for an average of 20 hours per week. States could be penalized for failure to meet this participation rate by a reduction in the matching rate on JOBS dollars. However, in practice,
even though some states did not meet the participation standard, no state was ever penalized.

TANF removes most of the federal requirements regarding exemptions and required activities, and replaces them with a more stringent participation rate requirement (25% in FY 1997, rising to 50% by FY 2002). The only remaining federal provisions are: single parents of children under age 6 who cannot find child care can not be penalized for failure to meet work requirements; and states can exempt single parents of children under age 1 from the work requirement and can disregard these individuals in the calculation of participation rates for up to a total of 12 months. In general, TANF encourages states to require work and training that is closely linked to work, rather than to place recipients in long-term educational activities. Also, no more than 20% of individuals can be counted as participating based on participation in vocational education or secondary school for teen parents. States that do not meet the participation rate goals will be penalized by a reduction in the amount of their block grant.

_family_cap_provisions_

Under the AFDC rules, a family’s grant amount was based on the payment standard for a family of a certain size. This means that if a family had a baby, thereby increasing the number of people in the family, the grant amount rose.
Some states have argued that this policy creates a perverse incentive for welfare recipients to have children, making self-sufficiency harder. In response to this argument, many states applied for, and received, “family cap” waivers. These waivers allowed states to eliminate, or reduce, the increase in benefits upon the birth of an additional child after the family first began receiving AFDC. TANF does not require states to base levels of assistance on the number of people in the family. States therefore have the flexibility to establish any form of family cap they desire, or none at all. States do not have to include the exceptions required as a matter of federal policy in the waivers. At least one state (Wisconsin) has proposed providing a fixed amount per participating adult, regardless of the number of children in the family.

**Extended Income Disregards**

Under AFDC, all recipients who worked were entitled to a $90 work expense disregard. In addition, for the first four months of AFDC receipt, the next $30 of earned income, plus one-third of the remainder, was disregarded in calculating eligibility and benefits. After four months and until one year, only the $30 disregard continued. After one year, there was no earned income disregard.

Many states came to the conclusion that the termination of the earned income disregard after a short period removed the economic incentive for AFDC recipients to work. Therefore, as part of a general move to “make work pay,” most states adopted changes to the earned income disregard. TANF does not require
states to adopt any particular earned income disregards. States may provide more or less generous disregards than under the AFDC program. The only requirement is that states have objective criteria for determining who is eligible.

*Extended Transitional Assistance*

Before TANF, welfare recipients were entitled to one year of transitional Medicaid and transitional child care when they lost AFDC eligibility due to increased earnings. And, families who lost eligibility due to collection of child or spousal support were entitled to four months of transitional Medicaid. In order to prevent families from going on welfare for a short period of time in order to become eligible for these transitional benefits, only families who had been on AFDC for at least three of the preceding six months were eligible for transitional assistance.

Under TANF, many states received waivers expanding eligibility for the transitional childcare program and transitional Medicaid commonly by increasing the length of time during which a former recipient could receive transitional assistance. States applied for these waivers because the loss of health and child care benefits were seen as major problems, which often forced poor families back on to welfare.
APPENDIX B

MATHEMATICAL REPRESENTATION OF
HETEROGENEOUS ERROR VARIANCE PROBLEMS

The error variance for each organization is:

\[ \sigma_{e(i)}^2 = \sigma_{Y(i)}^2 (1 - \rho_{XY(i)^2}), \quad (1) \]

where \( \sigma_{Y(i)} \) and \( \rho_{XY(i)} \) are the Y variance and the XY correlation in each organization, respectively. Thus, the error variance for organization 1 can be expressed as:

\[ \sigma_{e(1)}^2 = \sigma_{Y(1)}^2 (1 - \rho_{XY(1)^2}) = V[E(Y_1 - \hat{Y}_1) | X_1] + E[V(Y_1 - \hat{Y}_1) | X_1], \quad (2) \]

where \( E \) is the expectation, \( V \) is the variance, and \( V(Y_1 - \hat{Y}_1) | X_1 \) refers to the error variance at a given \( X_1 \). Homoskedasticity is satisfied if residuals (i.e., \( Y_1 - \hat{Y}_1 \)) are similarly distributed across various points of \( X_1 \). Suppose \( Y_1 \) is similarly
distributed around Ỹ\(_{1}\) (i.e., the mean of errors equals zero), then Equation (2) reduces to:

\[\sigma_{e(1)}^2 = \sigma_{Y(1)}^2 (1 - \rho_{XY(1)^2}) = E[V(Y_1 - \hat{Y}_1) \mid X_1],\]  (3)

Similarly, for organization 2, error variance of organization 2 can be written as:

\[\sigma_{e(2)}^2 = \sigma_{Y(2)}^2 (1 - \rho_{XY(2)^2}) = E[V(Y_2 - \hat{Y}_2) \mid X_2],\]  (4)

Homoskedasticity is satisfied if residuals (i.e., \(Y_2 - \hat{Y}_2\)) are similarly distributed across various points of \(X_2\). To assess whether the homoskedasticity assumption is satisfied for the overall regression model, one needs to examine the \(Y\) on \(X\) regression model including all organizations. The homoskedasticity assumption is satisfied if the \(Y - \hat{Y}\) residuals are similarly distributed across various points of the \(X\) scale.

The assumption of homogeneity of error variances across organizations is represented as:

\[\sigma_{Y_1^2} = \sigma_{Y_2^2}; \sigma_{X_1^2} = \sigma_{X_2^2},\]  (5)

given that:
\[
\beta_{Y, X(i)} = \rho_{XY(i)} \left[ \frac{\sigma_y(i)}{\sigma_x(i)} \right],
\] (6)

The null hypothesis of equal slopes across organizations is identical to the null hypothesis of equal correlation coefficients across organizations. Thus, given Equations (1) and (5), the assumption will always be violated when the null hypothesis is false (Alexander and DeShon, 1994).
APPENDIX C

SUB-MODELS OF MULTILEVEL LINEAR MODELS

Here, this dissertation demonstrates a wide range of sub-models of MLM. These models include a one-way random effects ANOVA model (unconditional means model), a regression model with means-as-outcomes, a one-way analysis of covariance (ANCOVA) model with random effects, a random-coefficients regression model, a model with intercepts- and slopes-as-outcomes, and a model with non-randomly varying slopes. Before we introduce sub-models of multilevel models, we first explain that data used for this section.

Data

For an empirical example of various sub-models of multilevel linear models and for a comparison of OLS and HLM methods, we utilized the third wave of the 1996 SIPP dataset, which covers from August 1996 to February 1997, and Moffitt’s welfare benefits file for state-level information, such as AFDC/TANF maximum amount paid per month for family of 4, personal income per capita, and unemployment rate. SIPP reports information on individual’s
income, governmental program participation, individual background, and job experiences. In this study, total family earned income is used as the outcome variable. The dataset contains two different levels of data: the individual level and the state level. The dataset consists of information for 2,418 individuals in 36 states.

The individual-level (Level 1) outcome is TFEARN, which represents total family earned income. And, the individual-level covariates include individual sex (SEX: 0 for female and 1 for male), disability status (DISABLE: 0 for non-disable and 1 for disable), and total family amount of Food Stamps received (FDSTP). And several state-level variables used in the following two sections include state average personal income per capita (INC_PC), unemployment rate (URATE), maximum benefit for a family of three (MAXBNFT), factor scores of state implementation activities, and the existence of family cap policy.

Factor scores on state implementation activities are constructed from the raw survey data collected by Jennings and Ewalt (2000). They surveyed state welfare administrators’ perception on the importance of a wide range of implementation activities. Through a factor analysis on 12 questions of implementation activities, I extracted four factors: FAC_OPEN, FAC_SRV, FAC_STF, and FAC_HC. While a detailed explanation of factor analysis of implementation activities will be provided in Chapter Four, I here introduce the meaning of each factor and activities that belong to each factor.

First, the FAC_OPEN factor indicates implementation activities aimed to gain external supports for states’ TANF programs. The activities in this factor
include enhancement of relations with private sector employers, development of employment opportunities, and effective coordination among agencies. Second, the FAC_SRV factor is implementation activities related to internal process in order to achieve program goals. These activities include improvement of client assessment protocols, provision of transitional healthcare service, enhancement of transportation assistance, changing way client processed, and provision of transitional childcare service. Next, the FAC_STF factor is implementation activities focused on welfare staffs, such as, improvement of job placement skills of staff and incentives for staff-job placement rates. Finally, the FAC_HC factor is named after human capital approach, which widely used in the pre-reform period. The factor includes implementation activities aimed to human capital of welfare recipients, such as improvement of remedial education and improvement of job training.

**Sub-Models of Multilevel Linear Models**

*(1) One-Way Random Effects ANOVA Model*: One-way random effect ANOVA model or unconditional model is the basis for the comparison of various sub-models of multilevel models. This model provides information on the total amount of variations in outcome variables both in individual and state level.

A common way to build this model is to express the outcome, $Y_i$, as a linear combination of a grand mean, $\gamma_0$, a series of deviations from that grand
mean, $u_{0j}$, and a random error associated with the $i$th individual in the $j$th state, $\gamma_{ij}$. Using two-level approach as in Bryk and Raudenbush (1992), at level 1, an individual’s outcome is the sum of an intercept for the individual’s state ($\beta_{0j}$) and a random error ($\gamma_{ij}$) assuming a simple model where individual outcomes are observed as random variations around an average “state” level outcome:

$$Y_{ij} = \beta_{0j} + \gamma_{ij} \quad \text{where } \gamma_{ij} \sim N(0, \sigma^2) \quad \text{(C.1)}$$

Similarly, at level 2 (the state level), the state-level outcome is modeled as an overall mean ($\gamma_{00}$) with a series of random deviations around that mean ($u_{0j}$):

$$\beta_{0j} = \gamma_{00} + u_{0j} \quad \text{where } u_{0j} \sim N(0, \tau_{00}) \quad \text{(C.2)}$$

Substituting equation (C.2) into equation (C.1) yields the combined model:

$$Y_{ij} = \gamma_{00} + u_{0j} + \gamma_{ij} \quad \text{(C.3)}$$

which is the one-way ANOVA model with grand mean, $\gamma_{00}$, a group (level 2) effect, $u_{0j}$, and with a person (level 1) effect, $\gamma_{ij}$. Estimating equation (C.3) is useful as a preliminary step in a multilevel analysis, because it provides information about the outcome variability at each of the two levels: the $\sigma^2$
parameter represents the within-group variability and the $\tau_{00}$ captures the between-group variability.

Using the third wave of the 1996 SIPP dataset, I estimated Equation (C.3) and the results are shown in Table C.1. The outcome variable is total family earned income of welfare leavers. And I used the SAS MIXED procedure to estimate Equation (C.3)\(^1\).

The first part of Table C.1, Iteration History, shows the number of iterations that meets convergence criterion. As shown in Table C.1, this basic one-way ANOVA model converged quickly after 5 iterations.

The second part, Covariance Parameter Estimates, provides estimates for the random effects portion of the model. The results indicate that estimated individual-level residual ($\sigma^2$) is 3,149,020 and estimated state-level residual ($\tau_{00}$) is 739,795. These two estimates give us intraclass correlation coefficient\(^2\) ($\rho$) of .19, which measures the proportion of the variances in the outcome that is between the level-2 units, i.e., among states (Bryk and Raudenbush, 1992). It means that 19% of the variances in the outcome variable can be explained by state-level variables. This estimate also tells us that there is a fair bit of clustering of outcomes within states implying that an OLS analysis of these data would likely yield misleading results. Hypothesis tests presented in this part also indicate that both variance components are statistically significantly different from 0, suggesting that states do differ in their average outcomes.

\(^1\) The SAS PROC MIXED procedure uses iterative maximum likelihood procedures to estimate parameters.

\(^2\) The formula for intraclass correlation coefficient is $\rho = \frac{\tau_{00}}{\tau_{00} + \sigma^2}$.
The next part of Table C.1, *Fit Statistics*, presents information that can be useful for comparing the goodness of fit of multiple models with the same fixed effects but different random effects. The criterion used here is Akaike’s Information Criterion (AIC) and models that fit better will have values of this statistic that are larger when these values are positive. If these values are negative, smaller numbers in absolute value are preferred. Without a model against which we can compare these statistics they are not very useful. As we use different model specifications later in this chapter, changes in these statistics help assess differences in goodness of fit.

The final section of Table C.1, *Solution for Fixed Effects*, presents parameter estimates for the fixed effects. As there is only one fixed effect ($\gamma_{00}$) in Equation (C.3), the estimate tells us that the average family earned income of the sample states is about $1,424 and this estimate is statistically significant ($p < .01$)\(^3\).

\(^{(2)}\) *Means-as-Outcomes Model*: From the estimation results of unconditional model, we know that 19% of variance in the outcome is in the state level. Suppose we further want to explain these variances in the outcome. One simple way to do so is feasible by incorporating state-level variables into the Level-2 equation (Equation (C.2)) of unconditional model. In this case, we add another source of variations into HLM and, as a result, improve explanatory power of the model in terms of total amount of variance explained. Another

\(^{3}\) The average family earned income of the sample individuals is $1,534.56.
situation that means-as-outcomes model is necessary is when each observation is no longer a random variation around the overall mean.

Under these situations, a strategy to build means-as-outcomes model or between-states models follows: the Level-1 equation is the same as Equation (C.1). However, the Level-2 equation includes state-level variables, \( W_j \):

\[
\beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{0j} \tag{C.4}
\]

Substituting equation (C.4) into the level 1 equation (C.1) yields:

\[
Y_{ij} = \gamma_{00} + \gamma_{01} W_j + u_{0j} + \gamma_{ij} \tag{C.5}
\]

The variance in \( u_{0j} , \tau_{00} \), is now the residual or conditional variance in \( \beta_{0j} \) after controlling for \( W_j \). The first two terms in the right side of Equation (C.5) represent the fixed effects, while the last two terms represent the random effects consisting of the \( u_{0j} \) and \( \gamma_{ij} \). The random error, \( u_{0j} \), represents variation in intercepts or means between states, while another random error, \( \gamma_{ij} \), represents variation within states.

Using the third wave of the SIPP data with several state-level variables, we can empirically explain this within-state model. For the simplicity of the explanation, means-as-outcomes model here includes only one Level-2 policy variable: maximum benefits for a family of three (MAXBNFT). The results of the
estimation of Equation (C.5) using a Level-2 variable MAXBNFT are shown in Table C.2.

The first part of Table C.2, Iteration History, summarizes how convergence criterion met in this modeling. After a short 3 iterations, the model with one state-level variable is converged.

The Covariance Parameter Estimates part tells us about the random effects. The estimates for $\tau_{00}$ and $\sigma^2$ are 609,954 and 3,148,476, respectively, yielding intraclass correlation coefficient ($\rho$) of .16. Notice that the conditional component for the variance within state ($\sigma^2$) has remained virtually unchanged (from 3,149,020 to 3,148,476), while the variance component representing variation between states has diminished noticeably (from 739,795 to 609,954). This tells us that the predictor MAXBNFT explains a significant portion of the state-to-state variation in earned income. One way of measuring how much of the variation in the outcome is explained by the maximum benefits is to compute how much the variance component for this term ($\tau_{00}$) has diminished between the two models. As discussed by Bryk and Raudenbush (1992, p.65), the statistic$^4$ is 0.18. We interpret this by saying that 18% of the explainable variation in state earned income is explained by maximum benefits for a family of three.

The Fit Statistics part shows us a smaller value of AIC in this between-state model than that of AIC in unconditional model. This indicates that by

---

$^4$ The formula for this statistic is $\left( \frac{\tau_{00} \text{ in unconditional model} - \tau_{00} \text{ in between-state model}}{\tau_{00} \text{ in unconditional model}} \right)$. In this example, it is $0.18 = \frac{(739,795-609,954)}{739,795}$. 

162
including one more state-level variable, we have a better statistical model in explaining total family earned income of welfare leavers.

Because there is now additional fixed effect to be estimated other than the intercept, Table C.2 includes two additional sections summarizing relevant hypothesis tests for the fixed effects: Solution for Fixed Effects and Type 3 Tests of Fixed Effects. The results show that the estimate of the intercept ($\gamma_{00}$) is 270.35, which means the average family earned income of states controlling for other factors. The estimate of the other fixed effect for MAXBNFT ($\gamma_{01}$) is 3.38, and tells us about the relationship between earned income and states’ maximum benefit policies. It implies that states that differ by 1 dollar in maximum benefits for a family of three differ by 3.38 dollars in total family earned income. Its standard error of 1.58 yields an observed t-statistic of 2.14 ($p < .05$), which indicates that we reject the null hypothesis that there is no relationship between a state’s maximum benefit policy and the earned incomes of its residents.

Having accounted for 18% of the explainable variation, we might also want to know whether there is still any variation in the outcome that can be accounted for by this model. The output provides two statistics on this question. The first is the test for the residual variance component for intercepts, which rejects the null that $\tau_{00}$ is 0 with a z-statistic of 2.42 ($p < .01$). Although this test is not very reliable, it suggests that even after including maximum benefits, there is additional explainable variation present. The second statistic is intraclass

---

1 It implies that states that differ by 1 dollar in maximum benefits for a family of three differ by 3.38 dollars in total family earned income. Its standard error of 1.58 yields an observed t-statistic of 2.14 ($p < .05$), which indicates that we reject the null hypothesis that there is no relationship between a state’s maximum benefit policy and the earned incomes of its residents.
correlation coefficient of .18 calculated above. We can view this as a partial correlation, which tells us about the similarity in earned income among individuals within states after controlling for the effect of maximum benefits.

We estimate another between-state multilevel model including one more state-level predictor: FAC_OPEN. As explained before, FAC_OPEN is factor score of states’ implementation activities aimed to gain external supports for their TANF programs. The estimation results are shown in Table C.3.

Table C.3 shows that including one more state-level predictor further explains variation between states (from 609,954 to 519,545), while the conditional component for the variance within state ($\sigma^2$) has remained virtually same (from 3,148,476 to 3,148,091). Also, proportion variance explained in $\beta_{0j}$ has increased from 18% to 30% $\frac{(739,795-519,545)}{739,795}$ implying that 30% of the explainable variation in state earned income is accounted for by maximum benefits for a family of three and factor score on implementation activities related to acquiring external resources.

The terms for FAC_OPEN provide the estimates of the other fixed effects and tell us about the relationship between earned income and states’ implementation activities. It implies that states that differ by 1 point of factor scores on FAC_OPEN differ by 354.66 dollars in earned income implying large impact of implementation activities for external supports. This estimate is statistically significant at the 10% significance level.
(3) **Random Coefficients Model**: While between-state multilevel models include the state-level variables to explain unexplained variances in the outcome variable, we know from the estimation result of unconditional model in Table C.1 that more unexplained variances are in the individual level than are in the state level. By incorporating individual-level variables, we may have a better multilevel model in explain variances in total family earned incomes of welfare leavers. Statistically, the above models are examples of random-intercept models. Only the Level-1 intercept coefficient, $\beta_{0j}$, was assumed to be random whether the Level-2 equation has a predictor or not. In this random coefficients model, Level-1 slopes are conceived as varying randomly over the population of Level-2 units. Thus, the statistical modeling of the Level-1 equation of random coefficients model is:

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \gamma_{ij}$$  \hspace{1cm} (C.6)

and the Level-2 equations are:

$$\beta_{0j} = \gamma_{00} + u_{0j}$$  \hspace{1cm} (C.7)

$$\beta_{1j} = \gamma_{10} + u_{1j}$$  \hspace{1cm} (C.8)

where $\gamma_{ij} \sim N(0, \sigma^2)$ and $N\left[\begin{pmatrix} u_{0j} \\ u_{1j} \end{pmatrix} : \begin{pmatrix} 0 \\ 0 \\ \tau_{00}, \tau_{01} \\ \tau_{10}, \tau_{11} \end{pmatrix}\right]$. In this model, $\gamma_{00}$ is the average intercept across the Level-2 units; $\gamma_{10}$ is the average regression slope across the Level-2 units; $u_{0j}$ is the unique increment to the intercept associated
with Level-2 unit \( j \); and \( u_{1j} \) is the unique increment to the slope associated with Level-2 unit \( j \). We formally represent the dispersion of the Level-2 random effects as a variance-covariance matrix:

\[
\begin{bmatrix}
\var(u_{0j}) \\
\var(u_{1j})
\end{bmatrix}
= \begin{bmatrix}
\tau_{00}, \tau_{01} \\
\tau_{10}, \tau_{11}
\end{bmatrix}
= T
\]

(C.9)

where

\[
\begin{align*}
\var(u_{0j}) &= \tau_{00} = \text{unconditional variance in the Level-1 intercepts}; \\
\var(u_{1j}) &= \tau_{11} = \text{unconditional variance in the Level-1 slopes}; \text{ and } \\
\cov(u_{0j}, u_{1j}) &= \tau_{01} = \text{unconditional covariance between the Level-1 overall means (intercepts) and slopes}.
\end{align*}
\]

We refer to these as unconditional variance-covariance components because no Level-2 predictors are included in either equation (C.7) or (C.8).

Substitution of the expressions for \( \beta_{0j} \) and \( \beta_{1j} \) into Equation (C.6) yields a combined model:

\[
Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + u_{0j} + u_{1j}X_{ij} + \gamma_{ij}
\]

(C.10)

This model implies that the outcome Second, having included this additional fixed effect, we have also included an additional random effect. Thus, not only are we stipulating that an individual’s earned income is related to his or
her individual characteristics, $X_{ij}$, but also that the relationship can vary across states (if we do not want to allow this slope coefficient to vary across states, we could keep it constant by eliminating the term $u_{ij}$ from the equation for the slope $\beta_{ij}$). Third, having allowed the intercepts and slopes to vary across states, we now have a larger tau matrix to represent the random effects across states. Not only are there elements representing the variance components for both the intercept and slope, there is also a covariance component, representing the correlation between intercepts and slopes ($\tau_{10}$).

One estimation result of Equation (C.10) utilizing a one Level-1 predictor, the amount of Food Stamps assistance received (FDSTP), is shown in Table C.4. In the sample, welfare leavers received $101.73 of Food Stamps on average.

First, the estimate for $\gamma_{00}$ indicates that the average family earned incomes of states, controlling for individual’s Food Stamp amounts, is $1,751.75. The results show that the estimate of $\gamma_{01}$ is $-3.47$, and the estimate is statistically significant ($p < .01$). This result implies that a dollar increase in Food Stamps decreases about $3.5 in total family earned income. As hypothesized in Chapter 2, other incomes than earned incomes seem to work as disincentive toward work for welfare leavers.

The Covariance Parameter Estimates part tells us how much these intercepts and slopes vary across states. Although SAS presents these estimated variance-covariance components in list form, we may rewrite the first three elements in the list as:
\[
\begin{pmatrix}
\hat{\tau}_{00}, \hat{\tau}_{01} \\
\hat{\tau}_{10}, \hat{\tau}_{11}
\end{pmatrix} = \begin{pmatrix}
1,110,805 & -2,839.16 \\
-2,839.16 & 7.69
\end{pmatrix}
\]

So, 1,110,805 is the variance of intercepts, 7.69 is the variability in slopes, and -2,839.16 is the covariance between intercepts and slopes. Estimated standard errors and tests of the null hypotheses that each of these components is 0 are given in the remaining columns of the list. From the list, we can see that the intercepts are have a large variance; in other words, states do differ in total family earned income levels even after controlling for the effects of individual Food Stamp amount. Also, the slope is variable (variance component is 7.69 with p < .1). Finally, there is high correlation between intercepts and slopes; in other words, there is evidence that the effects of individual Food Stamp amount differ depending on the earned income in the state.

How much of the within state variance in earned income is co-varies with individual's Food Stamps receipts? Considering residual estimate for unconditional model (3,149,020) in Table C.1, we can conclude that inclusion of individual Food Stamp amount has explained 13.28% \([3,149,020 - 2,730,675]/3,149,020\] of the explainable variation within states. Comparatively speaking, then, state maximum benefit policy explains more of the variation in state level earned income than does individual Food Stamp amount explain the within-state variation in individual earned income.
(4) Intercepts- and Slopes-as-Outcomes Model: Having separately specified models with either just Level-1 variables or Level-2 variables, we can now consider full models, which contain variables from both levels. This modeling strategy is the most complicated of several multilevel sub-models and expected to explain the most variances in the outcome variable. The statistical representation of this sub-model is:

\[
Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \gamma_{ij}
\]  
(C.11)

\[
\beta_{0j} = \gamma_{00} + \gamma_{01}W_{1j} + \gamma_{02}W_{2j} + u_{0j}
\]  
(C.12)

\[
\beta_{1j} = \gamma_{10} + \gamma_{11}W_{1j} + \gamma_{12}W_{2j} + u_{1j}
\]  
(C.13)

The Level-1 equation remains the same as random coefficients model, but each component of the Level-2 sub-model of the model now has one additional fixed effect, as in between-state models. The number of random effects may be increased if an additional Level-1 variable is added to the model. Combing Equation (C.12) and (C.13) yields:

\[
Y_{ij} = \gamma_{00} + \gamma_{01}W_{1j} + \gamma_{02}W_{2j} + \gamma_{10}X_{ij} + \gamma_{11}W_{1j}X_{ij} + \gamma_{12}W_{2j}X_{ij} + u_{0j} + u_{1j}X_{ij} + \gamma_{ij}
\]  
(C.14)
Using the exemplary data set, we estimated Equation (C.14) and Table C.5 shows the estimation results of Equation (C.14) with one Level-1 predictor (FDSTP: Food Stamps amount received) and two Level-2 predictors: FAC_STF is factor score for implementation activities focusing on TANF staff including improving job placement staff skills and incentives for staff-job placement rates, and FAMCAP is a dummy variable denoting whether a state has family cap policy in 1998.

Most regression coefficients on fixed effects term are significantly different from 0 at the 10% significance level. As the existence of family cap policy is a dummy variable, it can be helpful to rewrite a pair of fitted models, one for each status, by substituting in the values of 0 and 1 for family cap policy variable:

Existence of family cap policy:

$\text{Earned Income} = 1,394.41 - 522.58\text{FAC}_{\text{STF}} - 3.01\text{FDSTP} + 2.01\text{FAC}_{\text{STF}} \times \text{FDSTP}$

Absence of family cap policy:

$\text{Earned Income} = 2,291.33 - 522.58\text{FAC}_{\text{STF}} - 4.89\text{FDSTP} + 2.01\text{FAC}_{\text{STF}} \times \text{FDSTP}$

The main effect of family cap policy tells us that the intercepts in these two models are significantly different ($p < .1$). The interaction between implementation activities focused on staff and Food Stamps amount tells us that
the slopes for FDSTP differ depending upon the FAC_STF of the state; the interaction between FDSTP and FAMCAP tells us that the slopes for FDSTP are not significantly different in the two statuses of family cap policy.

The findings with respect to the random effects are a bit different. The variance component for intercepts ($\tau_{ao}$) remains significantly different from 0, suggesting that there is additional variation in earned income that is not explained by these three factors and their interactions. We may also conclude that the variance component for slopes is relatively small (8.41) and also the null hypothesis that the slopes do not differ across states can be rejected ($p=.08$). Similarly, we can reject the null hypothesis that the component representing the covariance between intercepts (average earned income) and slopes is 0 ($p=.05$).
### Table C.1 Estimation Results of Unconditional Model

#### Iteration History

<table>
<thead>
<tr>
<th>Iteration</th>
<th>Evaluations</th>
<th>-2 Res Log Like</th>
<th>Criterion</th>
</tr>
</thead>
<tbody>
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<td></td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>12206.20657890</td>
<td>0.00022877</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>12204.66248125</td>
<td>0.00005398</td>
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<tr>
<td>3</td>
<td>1</td>
<td>12204.32081976</td>
<td>0.00000451</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>12204.29464624</td>
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<tr>
<td>5</td>
<td>1</td>
<td>12204.29441985</td>
<td>0.00000000</td>
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</table>

Convergence criteria met.

#### Covariance Parameter Estimates

<table>
<thead>
<tr>
<th>Cov Parm</th>
<th>Subject</th>
<th>Estimate</th>
<th>Error</th>
<th>Z</th>
<th>Pr Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>STATE</td>
<td>739795</td>
<td>290677</td>
<td>2.55</td>
<td>0.0055</td>
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<td>Residual</td>
<td></td>
<td>3149020</td>
<td>173248</td>
<td>18.18</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

#### Fit Statistics

- -2 Res Log Likelihood: 12204.3
- AIC (smaller is better): 12208.3
- AICC (smaller is better): 12208.3
- BIC (smaller is better): 12210.4

#### Solution for Fixed Effects

| Effect     | Estimate | Error | DF | t Value | Pr > |t| |
|------------|----------|-------|----|---------|-------|---|
| Intercept  | 1424.03  | 203.62| 20 | 6.99    | <.0001|   |
Table C.2 Estimation Results of Means-as-Outcomes Model with One Level-2 Predictor

<table>
<thead>
<tr>
<th>Iteration</th>
<th>Evaluations</th>
<th>-2 Res Log Like</th>
<th>Criterion</th>
</tr>
</thead>
<tbody>
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<td>2</td>
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<td>3</td>
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<td>12197.19664044</td>
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Convergence criteria met.

Covariance Parameter Estimates

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<th>Estimate</th>
<th>Error</th>
<th>Value</th>
<th>Pr Z</th>
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</thead>
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<tr>
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<td>252106</td>
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</table>

Fit Statistics

-2 Res Log Likelihood: 12197.2
AIC (smaller is better): 12201.2
AICC (smaller is better): 12201.2
BIC (smaller is better): 12203.3

Solution for Fixed Effects

| Effect    | Estimate | Error | DF | t Value | Pr > |t| |
|-----------|----------|-------|----|---------|------|---|
| Intercept | 270.35   | 571.23| 19 | 0.47    | 0.6414|
| MAXBNFT   | 3.3844   | 1.5795| 19 | 2.14    | 0.0453|

Type 3 Tests of Fixed Effects

<table>
<thead>
<tr>
<th>Effect</th>
<th>DF</th>
<th>DF</th>
<th>F Value</th>
<th>Pr &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAXBNFT</td>
<td>1</td>
<td>19</td>
<td>4.59</td>
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Table C.3 Estimation Results of Means-as-Outcomes Model with Two Level-2 Predictors

<table>
<thead>
<tr>
<th>Iteration</th>
<th>Evaluations</th>
<th>-2 Res Log Like</th>
<th>Criterion</th>
</tr>
</thead>
<tbody>
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<tr>
<td>1</td>
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<td>2</td>
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</table>

Convergence criteria met.

Covariance Parameter Estimates

<table>
<thead>
<tr>
<th>Cov Parm</th>
<th>Subject</th>
<th>Estimate</th>
<th>Error</th>
<th>Value</th>
<th>Pr Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
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<td>519545</td>
<td>227752</td>
<td>2.28</td>
<td>0.0113</td>
</tr>
<tr>
<td>Residual</td>
<td></td>
<td>3148091</td>
<td>173128</td>
<td>18.18</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

Fit Statistics

-2 Res Log Likelihood 12181.4
AIC (smaller is better) 12185.4
AICC (smaller is better) 12185.4
BIC (smaller is better) 12187.5

Solution for Fixed Effects

| Effect     | Estimate | Error | DF | t Value | Pr > |t|   |
|------------|----------|-------|----|---------|-------|    |
| Intercept  | 197.48   | 535.76| 18 | 0.37    | 0.7167|
| FAC_OPEN   | 354.66   | 184.23| 18 | 1.93    | 0.0702|
| MAXBNFT    | 3.4214   | 1.4736| 18 | 2.32    | 0.0322|

Type 3 Tests of Fixed Effects

<table>
<thead>
<tr>
<th>Effect</th>
<th>DF</th>
<th>Value</th>
<th>Pr &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>FAC_OPEN</td>
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<td>3.71</td>
<td>0.0702</td>
</tr>
<tr>
<td>MAXBNFT</td>
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<td>5.39</td>
<td>0.0322</td>
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Table C.4 Estimation Results of Random Coefficients Model

<table>
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<tr>
<th>Cov Parm</th>
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<th>Estimate</th>
<th>Error</th>
<th>Value</th>
<th>Pr Z</th>
</tr>
</thead>
<tbody>
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<td>422436</td>
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<td>0.0043</td>
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<tr>
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<td>1290.94</td>
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<tr>
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<td>&lt;.0001</td>
</tr>
</tbody>
</table>

Fit Statistics

-2 Res Log Likelihood: 12112.4
AIC (smaller is better): 12120.4
AICC (smaller is better): 12120.5
BIC (smaller is better): 12124.6

Null Model Likelihood Ratio Test

<table>
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<tr>
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<th>Chi-Square</th>
<th>Pr &gt; ChiSq</th>
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</thead>
<tbody>
<tr>
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<td>&lt;.0001</td>
</tr>
</tbody>
</table>

Solution for Fixed Effects

| Effect | Estimate | Error | DF | t Value | Pr > |t| |
|--------|----------|-------|----|---------|-------|---|
| Intercept | 1751.75 | 246.95 | 20 | 7.09    | <.0001|
| FDSTP  | -3.4692 | 0.7454 | 662| -4.65   | <.0001|
Table C.5 Estimation Results of Intercepts- and Slopes-as-OUTcomes Model

<table>
<thead>
<tr>
<th>Cov Parm</th>
<th>Subject</th>
<th>Estimate</th>
<th>Error</th>
<th>Value</th>
<th>Pr Z</th>
</tr>
</thead>
<tbody>
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<td>1414.43</td>
<td>-1.92</td>
<td>0.0549</td>
</tr>
<tr>
<td>UN(2,2)</td>
<td>STATE</td>
<td>8.4077</td>
<td>6.0443</td>
<td>1.39</td>
<td>0.0821</td>
</tr>
<tr>
<td>Residual</td>
<td></td>
<td>2727918</td>
<td>151870</td>
<td>17.96</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

Fit Statistics

-2 Res Log Likelihood 12076.1
AIC (smaller is better) 12084.1
AICC (smaller is better) 12084.1
BIC (smaller is better) 12088.3

Null Model Likelihood Ratio Test

<table>
<thead>
<tr>
<th>DF</th>
<th>Chi-Square</th>
<th>Pr &gt; ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>46.32</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

Solution for Fixed Effects

| Effect   | Estimate | Error  | DF | t Value | Pr > |t| |
|----------|----------|--------|----|---------|-------|---|
| Intercept| 2291.33  | 335.76 | 18 | 6.82    | <.0001|   |
| FAC_STF  | -522.58  | 297.84 | 18 | -1.75   | 0.0963|   |
| FAMCAP   | -896.92  | 467.53 | 18 | -1.92   | 0.0711|   |
| FDSTP    | -4.8893  | 1.1191 | 660| -4.37   | <.0001|   |
| FAC_STF*FDSTP | 2.0126 | 1.0246 | 660| 1.96    | 0.0499|   |
| FAM_CAP*FDSTP | 1.8769 | 1.5862 | 660| 1.18    | 0.2371|   |

Null Model Likelihood Ratio Test

<table>
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<td>3</td>
<td>46.32</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>
APPENDIX D

SAS PROGRAM GENERATING RANDOM DATASET FOR SIMULATION

data name;
  input numstu var z;
cards;
run;

data sample;
  set name;
  do state = 1 to 1;
    do ind = 1 to numind;
      x= rannor(1);
      xz= x*z;
      y = 3 + 2*x + 2*z + 3*xz + sqrt(var)*rannor(2);
      output;
    end;
  end;
run;
REFERENCES


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