The Economy's Impact on Welfare Reform Participants' Employment Opportunities In Ramsey County, Minnesota: A Mixed Effects Regression Analysis

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than in making money.

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Abstract

Like its predecessor Aid to Families with Dependent Children (AFDC), Temporary Assistance for Needy Families (TANF), the most recent program for means-tested public assistance at the federal level, emphasizes work over welfare as a means to decrease dependency on government assistance. TANF began at a time when the United States was experiencing a robust economy; caseloads decreased and welfare participants seemed to be moving from welfare into employment. Now that two decades and one Great Recession have passed since TANF's inception, it is time to examine the economy's role in facilitating welfare participants' employment prospects. This research poses the following question: to what extent do economic conditions (particularly during economic recessions), and person-level differences (race, Latino ethnicity, gender, age, and education) influence welfare participants' employment opportunities in terms of earnings and work hours? It utilizes secondary data from the Minnesota Family Investment Program (MFIP) in Ramsey County, Minnesota, and provides an example of one county's experiences with welfare reform and fluctuating economic conditions. A two-level, mixed effects linear regression analysis was done, with time nested in individuals, to examine the effects of local and national economic indicators on MFIP participants' employment opportunities. Results indicate that the condition of the local economy plays a much greater role in providing such opportunities, than does a national recession. Economic indicators used to measure local economic conditions (real GDP for the metropolitan area of Minneapolis-St.Paul-Bloomington, MN-WI, and county-level data for median income, unemployment rate, and poverty rate) lag behind indicators used to measure national recessions; this indicates a need for proactive programming at the

state and local levels as the United States enters recessions such that highly economically vulnerable members of the community experience the effects of a shrinking economy to a much lesser extent.

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Chapter 1

Introduction

Problem Statement

In a country as wealthy as the United States, one might wonder how 45.3 million people can be living in poverty (DeNavas-Walt & Proctor, 2014). This is an indication that the United States' welfare state is largely ineffective in confronting economic hardship despite decades' worth of efforts to design and implement welfare programs that address the needs of low-income families. Perhaps it is due to the fact that reputed anti-poverty programs are not designed to reduce poverty as much as they intend to decrease dependence on government assistance by encouraging participation in the labor market and by strengthening families. Through the most recent effort, the Personal Responsibility and Work Opportunities Reconciliation Act (PRWORA) of 1996, Temporary Assistance to Needy Families (TANF) replaced Aid to Families with Dependent Children (AFDC) (Public Law No. 104-193). Its stated goals are: to "provide assistance to needy families so that children can be cared for in their own homes; reduce the dependency of needy parents by promoting job preparation, work and marriage; prevent and reduce the incidence of out-of-wedlock pregnancies; [and] encourage the formation and maintenance of two-parent families" (U.S. Department of Health & Human Services, 2015). In the immediate years following PRWORA, welfare caseloads and unemployment decreased, causing George W. Bush on behalf of the federal government to declare, "The welfare law is a success because it puts government on the side of personal responsibility, and it has helped people change their life for the better --

helped people realize their dreams; helped people help themselves" (Office of the Press Secretary, 2003).

Post-PRWORA research focuses mainly on the impact of welfare reform policies and programs on welfare recipients' financial well-being. As the economy continued to grow in the late 1990s and early 2000s and welfare cases declined (Center on Budget Policies and Priorities, 2014), many welfare analysts declared PRWORA a success (Haskins & Greenberg, 2006). Even in the early years of TANF's purported success, social welfare and policy researchers viewed such findings with skepticism. For example, Primus, Rawlings, Larin, & Porter (1999) point out that a reduction in welfare caseloads is not an indication by itself that TANF is working; rather, a robust economy creates more jobs for employable welfare recipients. Researchers in areas of social justice challenged the claims about welfare reform's effectiveness on the basis that decreased caseloads only provide a partial story and are not the only way to measure success (Schram & Soss, 2001; Hawkins, 2005). Despite efforts to advocate on behalf of welfare participants who continued to struggle (Abramovitz, 2001; Baptist & Bricker-Jenkins, 2001; Burnham, 2001; Mink, 2001; Marchevsky & Theoharis, 2008), attention to PRWORA's efficacy faded from the forefront of social work literature during the first decade of the new millennium. Furthermore, regardless of efforts by researchers and advocates for the poor, TANF has remained virtually unchanged since its inception in 1996 (Danziger, Wiederspan, & Douglas-Siegel, 2013). Bitler and Hoynes (2016) draw attention to the inextricable link between "labor market opportunities, economic growth, and poverty" and conclude that TANF's role as a social safety net has diminished, and that it did not sufficiently address the needs of those eligible for it during the Great

Recession (p. S404). More research is needed to provide evidence for changing welfare policy again such that the goals of the program are more aligned with the needs of the participants.

Considering the economic upheaval during the mid-2000s and the overall increase in poverty since 1996 (Lamison-White, 1997; DeNavas-Walt & Proctor, 2014), welfare reform once again needs to be at the forefront of social policy research. Two decades and one Great Recession later, it is possible to more fully examine the effects of the economy versus the effects of TANF's work requirements on welfare participants' ability to find employment that dissuades dependence on public assistance. This dissertation will provide insight into welfare reform's impact from a longitudinal perspective; twenty years have passed since TANF began, and now it is not only possible, but also essential, to consider the fluctuations in the economy over time as a factor in analyzing the impact of welfare reform in order to make recommendations for improving the way public assistance programs help those who need them.

The problem, as defined by this dissertation, is that antipoverty programs do not aim to reduce poverty, and that the "opportunities" piece of the Personal Responsibility and Work Opportunities Reconciliation Act of 1996 is lacking during slow economies. Given that even skilled workers have difficulty finding employment during economic recessions, this dissertation explores the particular challenges faced by TANF participants who, in order to receive cash assistance, must comply with work requirements. The Minnesota Family Investment Program (hereafter, MFIP) will be used as an example of one state's TANF implementation to add to a body of research on individual states in the upper Midwest (Michigan: Danziger, Wiederspan, & Douglas-

Siegel, 2013; Wisconsin: Kwon & Meyer, 2011). This study builds on existing research by providing another Midwestern state's example of the economy's impact on TANF participants. Minnesota is of particular interest due to its reputation as generous to its welfare participants and because of the researcher's location and access to data.

In addition to the unique struggles welfare participants face in finding employment during economic downturns, research also shows that race plays a role in the challenges welfare participants encounter, particularly for African Americans (Sheely, 2012; Kwon & Meyer, 2011). In Minnesota, over a six-and-a-half year period between 2004 and 2010, African Americans and American Indians experienced lower rates of MFIP success as compared to Non-Somali Black Immigrants, Somali, Hmong, Hispanic, White, Non-Hmong Asians (Minnesota Department of Human Services, 2011). Therefore, this research will also examine the impact of race on welfare reform participants' experiences in looking for and finding employment as the economy ebbs and flows.

Research Question

Based on welfare reform literature, most notably the speculation that the economy plays a crucial role in TANF participants' opportunities to transition off cash assistance, this dissertation poses the following research question: to what extent do economic conditions (particularly during economic recessions), and person-level differences (race, Latino ethnicity, gender, age, and education) influence MFIP participants' employment opportunities in terms of earnings and work hours?

The next chapter of this dissertation begins with a review of the literature, which provides historical context for welfare reform as it is known today, as well as what research on TANF shows. Chapter 3 provides the theoretical context for this dissertation, and states the hypothesis. The research methods are described in Chapter 4, and include a detailed description of the population, justification for using linear mixed effects modeling, operational definitions of the predictor and response variables, and mathematical notation of the statistical models. The findings are presented in Chapter 5, and include both descriptive statistics and the results of the mixed effects models. Chapter 6 is a discussion of the findings, and this dissertation concludes with Chapter 7, policy implications.

Chapter 2

Literature Review

This literature review examines the impact of welfare reform and the greater economy on participants' success in finding and maintaining employment. To provide the necessary background information for this research study, this paper begins with a brief discussion on welfare reform's evolution and examines what the literature shows in terms of welfare reform's success. The literature is then linked to this dissertation research project to more fully analyze Minnesota's implementation of TANF, the Minnesota Family Investment Program (MFIP), in Ramsey County. Although this study focuses on Minnesota, the literature review is based on research on federal welfare reform because it is important to understand MFIP in the broader context of TANF.

Welfare Reform: History and Policy Context

Of particular importance is that even at its establishment in 1935, means-tested public assistance was not intended as an anti-poverty program, which is perhaps a major reason it receives criticism from advocates on behalf of those participating in the it. Furthermore, even though TANF is the most current means-tested public assistance program, the competing values of family and work have been prominent throughout all of its modifications. This is especially important when considering that TANF's main objectives are to promote strong families and financial independence, similar to Aid to Dependent Children in 1935.

At its inception as Title IV of the 1935 Social Security Act, Aid to Dependent Children (ADC) was intended to provide income assistance for children whose families had suffered due to the loss (including death, desertion, or incapacitation) of a male breadwinner, and was meant to help surviving mothers care for their children in the home (Public Law No. 74-271). When the Social Security Act was amended in 1939, many widows became eligible for Old Age Insurance, which left ADC to support the remaining families, most of which were headed by single mothers (Abramovitz, 1996). In 1950, the Social Security Act was amended again to extend ADC benefits to caretakers of dependent children, who were most often mothers (Mink & Solinger, 2003).

In the 1950s, the ADC rolls began to change. The population was growing, people experienced increased mobility in terms of residence, the formal labor market was not meeting the economic needs of certain segments of the population, and family structures were changing due to increased divorce and out-of-wedlock births; therefore, the demographics of ADC changed as well. Increasing numbers of families became eligible for ADC, many of whom were African American, whose unemployment rate was double that of Caucasians (Mink & Solinger, 2003). What had once been a program intended for Caucasian, widowed mothers was now comprised of unmarried mothers and African Americans, and was seen as a threat to the traditional family structure by the early to mid-1950s (Abramovitz, 1996). In response, the Social Security Act underwent legislative changes in 1956 that aimed to decrease dependence on public assistance "by strengthening family life and facilitating self-support" (Abramovitz, 1996, p. 330). ADC was changed to Aid to Families with Dependent Children (AFDC) by the Public Welfare Amendments of 1962 (Public Law No. 87-543), which gave the program a family focus and extended eligibility to families whose breadwinner lost income due to unemployment (Abramovitz, 1996).

Throughout the 1960s and 1970s, AFDC, unlike social insurance programs, was under constant scrutiny and subject to reform proposals that emphasized working to merit the receipt of cash benefits. For example, Richard Nixon's Family Assistance Plan, announced in 1969, attempted unsuccessfully to introduce a work requirement to AFDC; however, Nixon's efforts to attach work stipulations to public assistance were eventually incorporated into AFDC, as more states throughout the 1970s and 1980s began to require some of their cash assistance recipients to work at least part time in exchange for benefits (Mittelstadt, 2005), and were legally actualized when President Clinton responded to the calls for welfare reform in 1996 by declaring, " 'From now on our nation's answer to this great social challenge will no longer be a never-ending cycle of welfare: it will be the dignity, the power, and the ethic of work' " (Mink & Solinger, 2003, p. 59), and by signing the Personal Responsibility and Work Opportunities Reconciliation Act (PRWORA), which changed AFDC into TANF (Public Law No. 104-193).

Although AFDC had undergone several legislative changes by the time President Clinton signed PRWORA, TANF constituted a major policy overhaul at the federal level, the first of its kind since the Social Security Act introduced ADC in 1935. For the first time in public assistance history, states were given control of a federally governed program. What began in 1996 with PRWORA continued through the first federal block grant expiration in 2002 as TANF was reauthorized many times thereafter, as part of omnibus legislation. The main changes under TANF include mandatory work activities in exchange for welfare receipt, a lifetime limit to participate in the program, block grant funding from the federal government to states, and devolution of responsibility from federal to state governments. Above all, TANF discourages welfare dependence; its primary objective is to "help needy families achieve self-sufficiency" by promoting labor market participation, and marriage and two-parent families, rather than government aid, as the means to support one's family (U.S. Department of Health & Human Services, 2015). It seeks to move participants into employment as quickly as possible by mandating work activity, and enforces adherence to work requirements through sanctioning participants' benefits for non-compliance. TANF also established a 60-month lifetime limit to receive federal cash assistance, and shifted federal responsibility to each individual state for developing welfare programs in accordance with federal regulations. Through block grants, the federal government funds states' programs, but TANF does not guarantee continued federal funding, and the amount allocated is fixed regardless of caseload size (PL 104-193). Thus, for the first time since the federal government took charge of redistributing means-tested benefits to poor families, entitlement to welfare at the federal level was rescinded, and responsibility for those in poverty was diffused to the states (Zylan & Soule, 2000).

When TANF expired in 2002, it was first reauthorized under the Job Creation and Worker Assistance Act of 2002, which provided continued federal funding through December 30, 2005 (Public Law No. 107-147). President George W. Bush reauthorized it again under the Deficit Reduction Act of 2005. The reauthorization, which extended federal TANF funding through 2010, resulted in stricter work requirements for states, requiring them to have 50% (rather than 25%, as was the case in the 1996 TANF legislation) of their single-parent family cases in employment or job search status, and 90% (as opposed to 75%) of their two-parent family cases in employment or job search status (Public Law No. 109-171). States failing to comply with these new requirements risk a loss of federal funding (Center on Budget and Policy Priorities, 2005). The Great Recession began before TANF's 2010 expiration date, and the American Recovery and Reinvestment Act (ARRA) of 2009 provided extra temporary funding to states to help offset the impact of the recession (Public Law No. 111-5). TANF was scheduled to undergo reauthorization again in 2010, but instead of proposing further reform, Congress extended federal block grant funding through September 2011 under the Claims Resolution Act of 2010, while the policy changes made in 2006 remained (Public Law No. 111-291). Thereafter, Congress passed short-term TANF funding resolutions through Continuing Appropriations Acts, and aside from a brief funding lapse during the 2013 federal government shutdown, TANF funding continued (House Ways & Means Committee, 2014). Rather than expanding or reforming TANF during and after the Great Recession, the Obama administration created different acts to address poverty and high unemployment, such as the American Recovery and Reinvestment Act of 2009 (Public Law No. 111-5) and the Hiring Incentives to Restore Employment (HIRE) Act of 2010 (Public Law No. 111-147), neither of which specifically targeted TANF participants. TANF funding is currently part of continuing resolutions and needs to be renewed year after year (Falk, 2015), and is at risk for considerably reduced funding as part of President Trump's proposed 2018 budget (Parrott & Shapiro, 2017).

Literature on TANF Outcomes

Shortly after PRWORA was signed in 1996, welfare reform research was abundant; policy analysts and social workers alike routinely studied its efficacy. Welfare reform research slowly faded from the literature as the years passed, much like it faded from being its own congressional act to being part of omnibus acts. Some welfare reform research in the immediate years following PRWORA focuses mainly on TANF's efficacy in terms of caseload decline (The White House, 2002), and it is interpreted with caution by other researchers, for the main measure of success was smaller caseloads, which could have happened as a result of many factors other than TANF itself (Blank, 2002). At the time, little attention was given to economic factors that could affect TANF's success. This makes sense, given that many years need to pass for economic conditions as impactful time periods can be studied; however, long before researchers could test welfare reform's success, some questioned the economy's role in welfare caseload reduction. Prior to Clinton's 1996 PRWORA, Ziliak, Figlio, Davis, and Connolly (2000) considered the factors contributing to the 1993-1996 decline in AFDC caseloads, after several states began implementing work-focused programs in anticipation of federal welfare reform. Results indicate that the economy, rather than states' experiments with welfare-to-work activities and waivers from federal policies, was largely responsible for the decline in the number of AFDC participants. The researchers conclude that a strong economy is a better indicator of declining welfare caseloads than welfare reform policies themselves prior to PRWORA. They also suggest that the impact of welfare reform is not instantaneous and that work incentive waivers may increase caseloads at first, but they predict that over time, welfare caseloads should decline as a result of PRWORA, except during economic recessions. Ziliak et al. (2000) also suggest that economic recessions play a role in welfare reform outcomes. Blank's (2002) conclusion about the impact of TANF is quite insightful: "Most important, perhaps, is the question of how much the remarkable U.S. economy in the late 1990s was fueling the declines in caseloads, and increases in work and income among low-wage single mothers. Only as we experience economic cycles will we be able to effectively separate the economic effects from the policy effects of welfare reform" (p. 1159). Research such as this is evidence of the need to approach with wariness studies that tout TANF as a success, and the current dissertation research builds on Ziliak et al.'s (2000) and Blank's (2002) conjecture now that twenty years of post-PRWORA economic cycles have occurred.

From a purely objective standpoint, welfare reform research that focuses mainly on the success of the program in terms of caseload reductions and participants leaving welfare for work is in congruence with welfare reform's goals. However, to what extent did TANF programs themselves contribute to decreased caseloads? Social workers and other advocates for welfare reform participants doubt whether welfare reform is working simply because caseloads have declined; there are many other factors that influence fluctuations in caseload size, and some question whether a robust economy plays a larger role in moving people off welfare than welfare itself. For example, Kwon and Meyer (2013) consider employment retention of welfare leavers in 1998 and 2001, years in which welfare reform was working in conjunction with a growing economy, and conclude that the success of welfare reform in terms of people leaving it for employment is difficult to parse apart from the influence of economic conditions. Based on qualitative interviews done in Michigan in 2007 (prior to the Great Recession), Danziger, Weiderspan, & Douglas-Siegal (2013) are skeptical of how successful a work-first approach can be in times of economic recessions. Their study shows that the general consensus among participants is that there is a need for better-paying, stable jobs with health insurance and paid time off that could realistically and permanently remove them from poverty, and the vast majority of participants were dissatisfied with the services they received as part of the TANF program in Michigan. Sheely (2012) critically examines census data and questions welfare reform's success because child poverty during the 2007-2009 recession and welfare cases did not increase at the same rate (child poverty increased by nearly 12%, whereas caseloads increased by nearly 6%). Furthermore, caseload quantities varied by state, with some states experiencing slight increases during the recession and others experiencing decreases in this same time period. Sheely suggests it is time to return focus to the efficacy and advantages of state-controlled welfare programs after they faded from the literature during the economic boom of the early millennium; additionally, Sheely points out that much of the research focuses on periods during economic growth and suggests a need for researchers to evaluate welfare reform's success when the economy is worse.

Considering that welfare reform research has been scant for several years and that the body of recent research that does exist is rather small, more scrutiny needs to be given to how well TANF has worked over time. Researchers call for a TANF policy shift; new policies should focus on reducing poverty instead of just caseloads, and the federal government should provide more financial assistance to states through the TANF Contingency Fund, particularly during times of economic downturns (Sheely, 2012). Danziger, Wiederspan, and Douglas-Siegal (2013) recommend that program participants should be given a chance to voice individual concerns and have services tailored to their specific needs because the work-first approach is not effective for people with multiple and diverse barriers, particularly during economic recessions; they suggest that TANF's unyielding endorsement of labor market participation hinders states' attempts to provide appropriate resources to families in need. Minnesota is noteworthy from this perspective because MFIP's stated goals include moving participants "out of poverty" (Minnesota Department of Human Services, 2017). Owing to the fact that policy change occurs slowly, in order to accomplish any change, be it modifications or an overhaul, more research is needed to show the impact of the greater economy on TANF's ability to address the needs of its participants. Given that states are in control of their own public assistance programs, such research needs to be done at the state level, both to improve TANF programs specific to a particular state, and to provide opportunities for policymakers to learn from what works and does not such that they may apply it to their own states.

Conclusions and Contribution to Existing Research

The literature on welfare reform, past and present, shows that competing values of family and work have been an integral part of means-tested public assistance programs ever since they began. Although policies have expanded to make more low-income families eligible for aid, their crucial guiding force is to move families into self-sufficiency through work and family stabilization, and ultimately away from depending on government assistance.

Now that two decades have passed since PRWORA, during which the United States experienced the Great Recession of 2007-2009, what can we learn by looking at welfare participation during periods of economic booms and during recessions? The economy has been growing and shrinking in smaller waves since welfare reform's inception in 1996, but the Great Recession was the first major economic downturn.

The research that does exist on post-recession welfare reform shows that social workers and some politicians are highly skeptical of TANF's ability to move people out of poverty, which is not surprising, since that is not one of its stated goals. The general consensus among researchers is that welfare reform needs to be reformed. This is not likely to happen without more evidence to support TANF's widespread failure to adequately support low-income families. As a result of devolution, there is much variation among states in how TANF is implemented. For example, Minnesota's goals address poverty, whereas federal goals do not (see Table 2.1).

Table 2.1. Minnesota's Welfare Reform Goals and Federal Welfare Reform Goals

Minnesota: MFIP's Goals	**Federal: TANF's Goals**
"To encourage and enable all families to find employment."	"Provide assistance to needy families so that children can be cared for in their own homes."
"To help families increase their income and move out of poverty."	"Reduce the dependency of needy parents by promoting job preparation, work and marriage."
"To prevent long-term dependence on welfare as a primary source of family income."	"Prevent and reduce the incidence of out-of-wedlock pregnancies."
	"Encourage the formation and maintenance of two-parent families."

Sources:
Minnesota Department of Human Services (2017); U.S. Department of Health & Human Services (2015)

There is a great need for research from many states to show how TANF could be improved for participants in ways specific to each state.

This dissertation will provide an example of Minnesota's efforts to provide cash, food and employment assistance to low-income families during both strong and weak economies. It will examine the extent to which economic conditions impact MFIP participants' employment opportunities in terms of income and work hours so that they may support their families. Additionally, it will consider the many factors that contribute to MFIP participants' opportunities to leave public assistance for paid employment. Not all MFIP participants have an equal chance to succeed in the program. For example, both Hollister, Martin, Toft, Yeo, & Kim (2003) and McDonnell (2004) agree that MFIP appears to better serve those who are higher educated and have more job skills. Racial disparities appear to be notable in MFIP. Hollister et al. (2003) report that the wage-earned income of Caucasians is much higher than that of any other ethnicity or race, a difference that was statistically significant. Additionally, “[m]inority MFIP recipients also described rude and demeaning treatment and asserted that job counselors withheld information and resources that could help them” (McDonnell, 2004, p. 4). There are also reports from nonwhite MFIP recipients of “bias and lack of understanding of their challenges and cultural values among job counselors” (McDonnell, 2004, p. 12). Since paid employment is the focus of welfare reform, and employment counselors are responsible for carrying out services that promote work activity, it is reasonable to assume that if minorities, who make up more than half of Minnesota's welfare caseload (DeMaster & Crichton, 2006), are experiencing any discrimination from their employment counselors, MFIP does them a disservice at a very fundamental level. Furthermore, Caucasian adults are far less likely to participate in MFIP than any other racial group, and according to the disparity index in Minnesota in 2007, which measures the probability of minority groups’ participation in MFIP compared to that of Caucasians, African American or African-born immigrants are “eighteen times more likely” to be MFIP participants and American Indians are “twenty-two times more likely” (DeMaster, 2009, p. 12). Finally, in light of the latest Census data that still show racial disparities in earnings in Minnesota, this study will consider racial inequality in MFIP outcomes, particularly for African Americans, whose median income is about half that of Caucasians and Asian Americans (Collins & Xaykaothao, 2015).

Chapter 3

Theoretical Context and Hypothesis

This chapter examines social welfare policy and economic theory as it pertains to this dissertation. It begins by presenting a definition of social welfare policy in the context of welfare reform. This definition is then linked to the theory behind economists' definition of a recession, and based on these theories, this dissertation's main research question is re-stated and the hypothesis is presented.

To help understand the impact of the economy on TANF/MFIP participants' employment outcomes, it is important to consider that policy scholarship is inundated with definitions of social welfare policy. These definitions range from relatively simple descriptive statements about welfare provision to those in need (Chatterjee, 1996; Gilbert & Terrell, 2005) to critical examinations of such provision in maintaining social order (Abramovitz, 2000; Piven & Cloward, 1971). Although the various definitions of social welfare policy each contribute to the understanding of welfare reform, the utility of each depends on the lens through which one is using to examine policy. For the purposes of this paper, Chatterjee's (1996) definition is the most relevant to understanding TANF from a longitudinal perspective because it encompasses the nature of the political and economic structures of the United States. According to Chatterjee (1996), social welfare policy is the culmination of strategies to transfer goods and services from a unit of organization (such as a government or private charity) to those who face challenges in meeting basic needs. Chatterjee also contends that social welfare policy is comprised of ideologies that often conflict (such as capitalism and socialism) in terms of the role of government, and that social welfare policy is inextricably linked with economic policy because it utilizes income redistribution as a means to address basic needs.

Chatterjee approaches social welfare policy by providing a general definition and by acknowledging conflicting ideologies that are a part of policy development. Chatterjee focuses on people whose basic needs are jeopardized because of economic insecurity, and connects social and economic policy, which is essential for understanding policy in the United States because of the government's reliance on income redistribution for social welfare provision. Chatterjee's (1996) definition allows for the understanding of the many complexities that comprise social welfare policy, particularly that which is intended for those who grapple with economic challenges. TANF fits particularly well with Chatterjee's (1996) definition because its units of organization range from federal and state governments to county-based and non-profit organizations that carry out its programs. It is a means-tested program designed to help those who struggle to meet their basic needs. It is the source of many debates concerning the government's role (at the state and federal levels) in means-tested benefit provision. Finally, TANF is the product of a dominant ideology that promotes the work ethic and family stability (defined as two-parent families) in the United States (Blank & Haskins, 2001; Mead, 1997), and is a compromise between social welfare expenditure to redistribute income (by encouraging and rewarding work) and an economy with little government intervention.

This research is informed by Chatterjee's (1996) definition of social welfare policy and economic theory as it relates to social work, specifically in terms of how economic theory helps inform social welfare policies, which aim to redistribute societal resources among those in need. Economic theory at its most basic level is concerned with the distribution of goods and services to society members as a means to address the "economic problem" of how to divide limited resources amid conflicting perspectives regarding who receives what, and from whom (Lewis & Widerquist, 2001, p. 5). Societies establish economies, or social systems, to address the aforementioned economic problem. Societies also establish governments, one role of which is to counterbalance market failures and redistribute goods and services to those in society who struggle most, regardless of market conditions.

This research focuses on the government's role in addressing the economic problem because it centers around a government-subsidized program, TANF at the federal level, and MFIP at the state level. TANF (and its state-run implementations) is an example of government intervention to offset market failures which affect a subset of the population whose income is low enough even in robust economies to render them eligible for public assistance. It is informed by the relationship between microeconomics and macroeconomics in that it addresses how macroeconomic conditions (recessions and their indicators) have a microeconomic impact on MFIP participants.

This research uses the National Bureau of Economic Research's (NBER's) definition of an economic recession: "a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales" (NBER, n.d.a). Recessions occur as a result of decreased GDP and income, and may trigger increased unemployment rates and increased poverty rates; all of these factors influence people to greater and lesser degrees, regardless of income, but are perhaps especially hard on low-income families.

This dissertation explores the impact of recessions on members of society, specifically MFIP participants, who struggle financially both in recessions and robust economies, and poses the following main research question: to what extent do economic conditions (particularly during economic recessions), and person-level differences (race, Latino ethnicity, gender, age, and education) influence Ramsey County MFIP participants' employment opportunities in terms of earnings and work hours? This dissertation hypothesizes that economic conditions, particularly those of local economic sectors, have a significant impact on MFIP participants' earnings and work hours. The next chapter details the methods used to explore the research question and to test the hypothesis.

Chapter 4

Methods

Previous literature calls for more research on economic conditions and their impact on welfare reform participants, and this dissertation aims to answer such calls. Although it is beyond the scope of any research to provide definitive findings that apply to all situations, this dissertation contributes more knowledge in this area by looking at Minnesota's implementation of TANF and how Ramsey County participants are impacted by the condition of the national and local economy. This chapter centers around the methods used to address the research question: to what extent do economic conditions (particularly during economic recessions), and person-level differences (race, Latino ethnicity, gender, age, and education) influence Ramsey County MFIP participants' employment opportunities in terms of earnings and work hours? This research question tests the hypothesis that economic conditions have a significant impact on employment opportunities for Ramsey County MFIP participants. This chapter first presents the main research question divided into three parts, provides a brief description of the variables, and then continues with a description of the design, data, and the population, and then illustrates the steps taken from pre-analysis to fitting the linear mixed effects models to the dataset.

Research Questions and Hypotheses

Although this research centers around one main question, it is divided into three parts to test one hypothesis: economic conditions have a significant impact on Ramsey County MFIP participants' earnings and work hours. There are three parts to the research questions because there are three dependent (response variables): 1) whether or not

Ramsey County MFIP participants earn income; 2) Ramsey County MFIP participants' monthly earnings; and 3) Ramsey County MFIP participants' monthly work hours.

Research Question 1: To what extent does the condition of the economy predict whether or not Ramsey County MFIP earn income?

Research Question 2: To what extent does the condition of the economy influence Ramsey County MFIP participants' employment opportunities in terms of earnings?

Research Question 3: To what extent does the condition of the economy influence Ramsey County MFIP participants' employment opportunities in terms of hours worked? Additionally, Research Question 3 has a sub question: To what extent does time, particularly during the years in which the United States experienced two economic recessions, influence Ramsey County MFIP participants' employment opportunities in terms of work hours?

For all three research questions, the following independent (predictor) variables are used: the condition of the national and local economy, as measured by a dummy coded variable indicating whether or not the United States is in a recession, the local real GDP for the metropolitan area of Minneapolis-St. Paul-Bloomington, MN-WI, Ramsey County unemployment rate, Ramsey County median income, and Ramsey County poverty rate. The sub question for Research Question 3 uses dummy coded year variables in place of all economic indicator predictor variables.

Design

This is a quasi experimental, longitudinal panel study. Participants are not randomly assigned to control and experimental groups. It covers a total of 17 years, starting with January 2000 (four years after PRWORA was signed into law, when TANF replaced AFDC) and ending with December 2016. Although data exist into 2017, the data for this study were extracted in May 2017, and only included “frozen” data for January and February 2017; furthermore, data on economic indicators (poverty rate, median income, and real GDP) are collected annually and were not available for 2017 at the time of data analysis. This study uses a panel design because all participants’ data occur in multiple time points, and linear mixed effects models were used for analysis because data are comprised of multiple observations over time (204 months), but the number of observations per participant vary, as do the months over which each observation occurs.

Data: Secondary Data Analysis and Human Subjects Considerations

Data for the economic conditions predictor variables come from multiple sources. A dummy coded variable indicating whether the United States is in a recession for each month of this study was created by the researcher based on the National Bureau of Economic Research’s (hereafter, NBER) (n.d.a) declaration of whether or not the United States was in a national recession. The U.S. Bureau of Economic Analysis (BEA) was used for real GDP in the Minneapolis-St. Paul-Bloomington, MN-WI metropolitan area (n.d.). The metropolitan GDP variable includes all industry totals, and are in chained 2009 dollars. Real GDP for the Minneapolis-St. Paul-Bloomington, MN-WI metropolitan area is the most local dataset available; the BEA currently has a research agenda to collect real GDP data at the county level, but at the time of this research, had not begun to do so (furthermore, this research dates back to 2000, and county-level real GDP does not exist yet) (Guci, Mead, & Panek, 2016). The BEA recommends using chained dollar estimates for making comparisons across time, as in doing longitudinal research. The U.S. Census Bureau (2017) was used for Ramsey County’s median income. To be consistent with previous research, the Ramsey County monthly unemployment rate was used in conjunction with the first four predictor variables (Minnesota Department of Employment and Economic Development, 2017). The poverty rate for Ramsey County (U.S. Census Bureau, 2017), was also used as a predictor variable because this study involves a low-income population, and national, state, and local metropolitan recession indicators, as well as the unemployment rate, may not adequately reflect economic experiences for this population. It is important to note that NBER does not characterize poverty rate as a factor that impacts economic activity; however, it is a lagging indicator of economic declines. How economic conditions are defined and measured is described in the section on variables.

Secondary data, collected by Ramsey County Community Human services, were used for the response variables and the control variables. A Senior Program Evaluator from Ramsey County Community Human Services provided de-identified MFIP data from the MAXIS data system for all of the dependent and person-level predictor (control) variables. The Senior Program Evaluator used Access to randomly generate ID numbers specific to this project to remove the MAXIS ID, which is linked to participants' Social Security Numbers; the researcher asked that new IDs be generated so there would be no possibility of identifying any of the participants, and the researcher had no contact with any participant. This research qualified for an expedited review by the University of Minnesota IRB, and was found exempt from the full review. The researcher complied with the Ramsey County MFIP data sharing protocol.

MAXIS is the name of the database used to establish eligibility and distribute benefits to participants in MFIP and other public assistance programs; the letters do not stand for anything (Minnesota Department of Human Services, 2016b). MAXIS consists of all data pertaining to MFIP participants, and includes all of the months in which a participant is active on MFIP, even when there are no reported work hours or earned income.

All MFIP data collected are used to determine eligibility and benefit amounts. MFIP data are entered into MAXIS, the database for MFIP eligibility, by Ramsey County Financial Workers and are based on MFIP participants' self-reports during the application process and every month for the duration they participate in the program. Hours worked and wages are reported on the Household Report Form (HRF), and submitted to Financial Workers monthly. The HRF is required in order for participants to remain eligible for MFIP benefits, all earned income must be reported, and Financial Workers enter the HRF data into MAXIS (M. Herzfeld, personal communication, Dec. 3, 2016). Demographic data are collected as part of the application process.

The researcher was given all data from January 2000 through December 2016. No sample was drawn because all of the data are available; for greater statistical power, population data were used. Results show the true results for the population, rather than inferences about the population based on a sample.

Population

MFIP-eligible adults. Data extracted by the Senior Program Evaluator for Ramsey County Community Human Services include all participants who meet the following criteria: all MFIP-eligible adults who have participated in MFIP in Ramsey County for at least one month, and who are required to participate in Employment Services (even though at some points they may be exempt from participating in

Employment Services). MFIP-eligible refers to adults who meet income eligibility requirements for cash, food and childcare assistance. Some participants in the population will be receiving food and childcare assistance, but no cash. Ramsey County keeps cases open for participants whose incomes hover around eligibility to avoid having participants go through the application process multiple times (M. Herzfeld, personal communication, May 12, 2017). Financial Workers assist participants with deciding whether or not to opt out of MFIP for a particular month when their cash grant would be low so they do not use months against their 60-month clock; any amount of cash counts against the clock, even $1.00, and it does not behoove participants to collect cash during the months when their income reduces their cash grant to a great extent; however, they are still MFIP-eligible because their income meets the eligibility requirement for the food portion and child care assistance. In addition to the cases who are kept MFIP-eligible when the household income hovers around the eligibility line, there are also cases that get suspended. This happens in months when there are three paydays (on a bi-weekly paycheck schedule), and the extra paycheck puts participants over income for that month; rather than closing the case when it is clear the income increase is temporary and due to a paycheck schedule, Ramsey County suspends it, and then it is automatically unsuspended the following month when there are just two paychecks again (D. DeMaster, personal communication, May 31, 2017).

The federal work participation rate is the guiding force behind states' implementations of TANF employment services. There are few exemptions to employment services participation, yet many MFIP participants face multiple obstacles in their attempts to remain in compliance with work requirements. Due to the expectation that states meet the federal work participation rate, and because work (and/or work activity) is a condition of TANF/MFIP receipt, the population for this study is specifically defined as: active MFIP-eligible adults (parents) in Ramsey County who are required to participate in Employment Services between January 2000 and December 2016, regardless of whether or not they were exempt at any point, and regardless of whether their cash assistance funding source is federal or state and does or does not count against their 60-month lifetime limit. The participants in this study include those who have been active on MFIP for at least three months. It does not include those who received MFIP for less than three months in Ramsey County because it often takes three months to establish participants in WorkForce One (WF1) and Employment Services. Because this research specifically addresses employment, a three-month minimum was recommended (A. Wanless, personal communication, June 8, 2017). Furthermore, although it takes three months for participants to become enrolled in Employment Services, the three month-minimum does not refer to three consecutive months because the data should reflect the true population as close as possible. Since this research considers the cyclical nature of MFIP, participants who received MFIP for at least three non-consecutive months need to be included to accurately represent recurring episodes of MFIP participation.

The participant population for this study is at the individual level, rather than at the case level. In MFIP, each individual is required to participate in Employment Services (unless s/he is temporarily exempt). Even in two-parent families, each parent is expected to contribute to the work participation rate. Although two-parent families are given one cash grant, it is based on the income earned by each parent, and each parent submits an individual HRF reporting her/his own income and hours worked; both parents' HRFs are used to calculate the cash portion, which is then issued to the head of the household (D. DeMaster, personal communication, August 14, 2017). Two-parent families in which one parent is ineligible would not be reflected as two-parent families by this data because the data only include MFIP-eligible adults. There are instances in which a family has two parents, but one parent is ineligible for MFIP for various reasons like being a recipient of other unearned income (i.e. disability), being a non-citizen, having a fraud conviction, or having used up all 60 months of the lifetime limit (M. Herzfeld, personal communication, May 24, 2017). Families with one eligible parent and one ineligible parent are technically two-parent families, but they are not represented as such in this dataset. All two-parent families in this study include parents who are both required to participate in Employment Services.

There are three main groups of MFIP participants whose Employment Services participation data may look different from the rest of the MFIP population: teen parents who are still in high school (under age 18), Family Stabilization Services participants, and MFIP participants whose cash portion is paid with state, rather than federal, funds. Their circumstances and justifications for including them in the population are discussed next.

Teen parents who are still in high school and are under age 18. Although the focus of this study is adults who are active in MFIP, teenage parents, even those under age 18, are grouped with active MFIP-eligible adults for data reporting purposes because they are required to participate in Employment Services. MFIP participants who are under age 18 and still in high school are required to participate in a modified form of

Employment Services focused on finishing high school. Their Employment Services are provided by public health nurses within Workforce Solutions, and although the main emphasis is on completing a high school degree, some do report work hours and income. Once they turn 18, they have the option to continue with the public health nurse and remain in high school if they do not have a high school diploma yet, or they can go to Employment Services. They are required to do one or the other for the receipt of MFIP. Any participant under age 20 without a HS diploma or GED can receive MFIP cash without losing months against the federal 60-month clock while in high school or pursuing a GED (Minnesota Department of Human Services, 2017a).

Family Stabilization Services participants. In the early half of this study's timeline, specifically prior to February 2008, active MFIP-eligible adult parents who were experiencing many barriers to employment were held to the same work activity expectations as those whose barriers were more limited or easier to address. In February 2008, Minnesota began a program called Family Stabilization Services (FSS) to assist the hardest-to-serve MFIP participants (Minnesota Department of Human Services, 2016a). Those who qualified for FSS were still required to participate in Employment Services, but their employment plans and other activities vary considerably from Employment Services activities of MFIP participants who are not in FSS. FSS participants' MFIP cash portion is state-funded, so they are not counted in the federal work participation rate requirements. This allows Minnesota to continue tailoring services specific to a high needs population without risking the loss of federal block grant funding for not being in compliance with the federal work participation rate (A. Wanless, personal communication, May 30, 2017).

FSS participants are included in the population because FSS did not begin until February 2008, this study goes back to 2000, and the data need to be comparable across all years. Excluding FSS participants could significantly bias the results due to their potentially lower employment rates. Without them, data may show participants leaving MFIP faster or having more success in employment activities. If FSS participants are excluded from this study, a sudden decrease in the number of individuals participating in MFIP may appear in 2008. Since 2008 was right in the middle of the Great Recession, it is essential for analyses to include FSS participants so that there does not appear to be a decrease in caseload size.

MFIP participants whose cash portion is paid with state, rather than federal, funds. Although MFIP is the Minnesota's state-run version of TANF, some participants are funded by the state, not the federal government. States are allowed to use their own funds to provide MFIP to participants. Nationwide, it is common for states to fund two-parent families (if they allow two-parent families to participate in TANF at all) because the federal government expects them to have higher work participation. When two-parent families are on the cash portion of MFIP, both parents are required to participate in Employment Services, unless they meet criteria for an exemption. (D. DeMaster, personal communication, May 31, 2017). This study includes two-parent families in which both parents are required to participate in Employment Services.

MFIP-eligible, food-portion-only participants. There are many cases in which participants' income renders them ineligible for the cash portion of MFIP, but they are still eligible for food and child care assistance. Incomes in this population tend to hover around the income eligibility criterion, and those who are just receiving food and/or childcare assistance are still considered MFIP-eligible and still required comply with work requirements and report their income to their Financial Workers, so they will also be included in this population. Their cases are kept open to avoid the closing and re-opening that tends to happen when people's incomes are on the border of eligibility. To further clarify, MFIP food-only cases are included, but not SNAP-only cases because the latter either voluntarily opt out of MFIP or their incomes are too high to make them MFIP-eligible.

MFIP participants exempt from Employment Services. MFIP allows participants to be temporarily exempt from Employment Services for reasons such as being pregnant, having a child under age one in the house, being temporarily incapacitated, caring for an ill or incapacitated relative, being a new immigrant, having a Family Violence Waiver, are in the midst of a personal or family crisis, or for some other exemption reason that may eventually change so that they are no longer exempt (Minnesota Department of Human Services, 2017). Although participants may opt out of Employment Services for the duration of an exemption, many do continue to work. Therefore, all participants are included in the analyses regardless of their exempt status.

Some exemptions are due to conditions that render a participant unemployable for an indefinite amount of time, but MFIP does not divide exemptions into permanent versus temporary categories because many of these exemption conditions can change for participants such that they become employable and can participate in Employment Services. Although some of the exemption statuses count against the clock despite not ever changing, as in having an IQ below 80, there are also extension reasons to justify keeping participants on MFIP beyond the 60 months (however, states cannot have more than 20% of their cases on an extension). Participants who fall into these exemption categories are still included in the analyses because some do opt to work in spite of an exemption and/or long term condition that could hinder work opportunities.

Exclusions from the population. Participants who were new to MFIP in November 2016 or December 2016 are excluded from the population because not enough time elapsed for them to meet the three-month minimum inclusion criterion. Aside from those, no participants are completely excluded except children and adults who are not eligible (as in an ineligible adult in a two-parent family). This section describes those who do not meet the inclusion criteria and why.

Child-only MFIP cases do not meet the study's inclusion criteria simply because there is no adult who is MFIP-eligible in a child-only case. Child-only cases occur when the adult in the family is not eligible for MFIP for a variety of reasons, such as not being a United States citizen or receiving other unearned income such as Social Security. Child-only cases could be headed by an adult who has a disability and gets disability income through Social Security, but the total income meets the MFIP eligibility requirements. Adults in child-only cases are not required to participate in Employment Services. (D. DeMaster, personal communication, May 31, 2017).

Diversionary Work Program (DWP) participants also do not meet this study's inclusion criteria. DWP began in 2004 to divert families in crisis situations from having to apply for MFIP by addressing the crisis and transitioning adult care-givers into unsubsidized employment as quickly as possible. Families are allowed to participate in DWP for up to four months before having to apply for MFIP (Minnesota Department of

Human Services, 2016a). In this study, former DWP participants who eventually apply for MFIP are included, but are not identified as having participated in DWP.

Pre-Analysis

Data cleaning. The original extracted data include all adult, MFIP-eligible, and active on MFIP for at least one month in Ramsey County at any point between January 2000 and December 2016. The dataset also includes months in which MFIP was received in other counties (as long as the *active on MFIP for at least one month in Ramsey County* criterion was met). For those participants, the data show their MFIP months outside of Ramsey County in addition to the month(s) in Ramsey County. The original dataset includes all such persons so the researcher may show an estimate of the percentage of MFIP participants in Ramsey County who also participate in MFIP in other counties.

After a discussion with a researcher from Ramsey County who works with Workforce One data, it was decided to exclude participants who did not participate in MFIP in Ramsey County for at least three months, because that is approximately how long it takes to get them established in Employment Services (A. Wanless, personal communication, June 8, 2017). The first step of data cleaning was eliminating those who did not receive MFIP in Ramsey County for at least three months. The three months need not be consecutive; although those whose months are not consecutive will not necessarily be enrolled in Employment Services, their data are still important because they do represent a subset of the population who uses MFIP for very short durations and should be included since they are part of Ramsey County MFIP participants. Approximately 7.9% of the participants in the original data were removed due to having only received MFIP for one or two months in Ramsey County.

The second step in the data cleaning process was to identify the percentage of MFIP participants who participated in Ramsey County only, and those who moved from other counties to Ramsey County, and/or who moved from Ramsey County to other counties, and/or who moved in and out of Ramsey County during their months of MFIP participation. Data cleaning revealed that of those who received MFIP for at least three months in Ramsey County, approximately 37.8% of participants received it in Ramsey County *and* other counties, which is indicative of the high mobility of this population. Data cleaning also showed that 80.5% of the participants who received MFIP in Ramsey County for at least three months and in other counties spent the majority (greater than 50%) of their total months on MFIP in Ramsey County.

Due to the facts that the majority of MFIP participants in Ramsey County tend to stay in Ramsey County, and that this study focuses specifically on Ramsey County, the months in which MFIP is received in other counties are not included in the analyses. If someone received MFIP in other counties in addition to Ramsey County, her/his data only include the months spent in Ramsey County for two main reasons. First, this study focuses on Employment Services, which is administered at the county level. Each county in Minnesota has a different database to track Employment Services, and it is beyond the scope of this study to connect 87 different county databases. Second, if data from other counties were considered, they would not accurately represent Ramsey County. Although all of the participants in this study spent some time in Ramsey County, 19.5% spent the majority of their MFIP months in counties other than Ramsey. Data on such a mobile population can only reflect snapshots of MFIP participants' time in Ramsey County. Research is limited to the data that exist, which can only be collected while participants are temporarily part of the system and required to report job search hours, work hours, and income for eligibility purposes. Therefore, data were cleaned to only include MFIP participants while they received MFIP services from Ramsey County, for an *n* of 53,007 individual MFIP participants who participated in MFIP in Ramsey County for at least three months between January 2000 and December 2016. Statistical analyses are limited to those earning income and reporting work hours, so the final *n*s for the analyses are smaller, but all 53,007 participants are included in the descriptive statistics to provide a clearer picture of the MFIP population in Ramsey County.

Outliers and errors. Once data had been cleaned to only include MFIP participants who were active on MFIP for at least three months, simple descriptive tests were run to gain a sense of population demographics. During this process, errors were discovered.

Age. Of the 53,007 participants, 146 (approximately 0.03%) were between ages 0 and 15. Since this dataset includes only adults, the researcher consulted with the Senior Program Evaluator in Ramsey County. Although there may be some rare instances of 14- or 15-year-old parents, the youngest parent should be age 16, and it was recommended that all ages from 0 to 15 be re-coded as missing (M. Herzfeld, personal communication, August 2, 2017).

Age of youngest child. Descriptive statistics showed some errors in the age of the youngest child. Due to birthdate entry errors and missing birthdates for approximately 2% of the data, some participants' youngest children ages are missing, and some appeared to be over age 18. All of these values were changed to missing because once a child turns 18, her/his parents are no longer eligible for MFIP. It is likely that there are more families with young children than this dataset shows.

Monthly earnings and work hours. Descriptive statistics revealed errors in monthly earnings and work hours. Some participants had monthly earnings much higher than expected, given the income eligibility requirements to participate in MFIP. For example, one participant's income for March 2009 was reported as $64,999.57. Upon further investigation, the researcher found 3,524 months with reported incomes of $3000 or higher (approximately 0.3% of the total months). The researcher spoke with the Supervisor of the Office of Research and Evaluation at Ramsey County for guidance on how to handle such outliers in the data.

The Office of Research and Evaluation Supervisor explained why such outliers are present in the data. Worker errors (entering the earned income incorrectly) account for much of these, and because of federal audits, the data cannot be corrected once it is frozen so that it is consistent with what Ramsey County reports to the federal government. Although these errors are corrected for calculating the cash grant, they are not corrected in the source system, which is the database that provided the data for this study. It was not possible to correct the outliers with the actual earned income; however, to address these outliers, the Office of Research and Evaluation Supervisor recommended to first check whether or not the participant was active on MFIP immediately following a large income month, and if so, assume the high income was not a mistake. Due to retrospective income reporting and a two-month lag in cash grant determination, the cash grant would not reflect that same month's high income. It is possible someone legitimately earned what seems like a high income for this population, and then s/he would exit the program in the following month, in which case those months would not be errors and should be kept in the data for this study. The Office of Research and Evaluation Supervisor provided options for how to handle potentially inaccurate data. One possibility was to delete the outlying cases entirely; another was to right censor the data by cutting the income off at a certain level, at which point the income would be assumed a mistake. (D. DeMaster, personal communication, July 7, 2017.)

For those whose large income months do not result in MFIP exit, the Office of Research and Evaluation Supervisor recommended that the researcher use the Minnesota Department of Human Services Combined Manual (which includes MFIP and other services provided by DHS) to find the highest family wage level that would allow a participant to remain active on MFIP, and assume that if the income entered was higher than that, it would be an error. According to the Combined Manual, a family of 10 may receive up to $2517 per month to be eligible for MFIP (Minnesota Department of Human Services, 2016, October). Income eligibility is based on family size; however, most MFIP families are not large; in 2010, the average family was three, with one adult and two children (Minnesota Department of Human Services, 2010), and the Minnesota Department of Human Services has continued to use this family composition as an example and guideline for brochures and fact sheets (Minnesota Department of Human Services, 2017b; Minnesota Department of Human Services, 2017c).

To assess the scope of the outliers (in terms of income reporting errors in the dataset) and their potential impact on data analysis, the researcher began by identifying report months (variable name: *ReportMonth*) in which income over $2517 was entered. The 53,007 participants in this study have a total of 1,338,355 *ReportMonths* (each participant has between three and 204 *ReportMonths*, or observations). Of the 1,338,355 *ReportMonths*, 9,960 (less than 1%) had incomes of greater than $2517. Of the 53,007 participants included in the dataset, there were 5,044 with at least one *ReportMonth* of greater than $2517 (9.5%). Of those, 60 participants had incomes of $6000 or greater, and of those, 36 participants' incomes were deemed to be an error. Although there were likely to be a few errors in income reported between $2517.01 and $5999.99, it was not practical to look at 4,984 individual participants and assess for errors when the dataset is large enough to handle errors in reporting. The incomes that appeared beyond a reasonable doubt to be in error were changed to missing in the dataset, for a total of 63 *ReportMonths* affecting 39 participants. However, this does not impact the overall n for the study because only the months with errors in reported income were changed to missing; each individual participant who had errors in reported income had one or two months of errors, and since the errors were changed to missing values, no participant was deleted entirely due to missing income values.

Finally, a few values reflecting income and hours were changed to eliminate as much missing data as possible, although with such a large dataset, it is unlikely to impact the results. For example, one participant reported 160 hours for three months in a row, and an income of $2052.80 for the first and third months, but $6090.90 was entered for the second month; rather than replacing this with a missing value, academic judgment was used and the income was changed to $2052.80. Someone else reported working 160 hours and earning $1640/month for five months, and working 160 hours but earning $7640 for one month. This particular month was changed to $1640 for the income earned. Eleven participants had months of suspected income errors, but there was not enough evidence to support changing the income to a missing value. Errors in hours worked were also discovered during the data cleaning process; some participants had reported more monthly hours than there are hours in a month. Because there are approximately 730 hours in a month, reports of 600 or more hours worked in a month were re-coded as missing; however, this only impacted 19 of the 53,007 participants. Although these few outliers in such a large dataset are unlikely to affect the overall results of the study, the researcher strove to have the cleanest possible data, and therefore adjusted them.

Operational definitions of variables.

Predictor (independent) variables. The predictor (independent) variable in this study is economic conditions, more specifically, the condition of the local economy, particularly Ramsey County. Due to the complexity in defining economic conditions in a measurable way, this research uses the National Bureau of Economic Research's (NBER) definition of an economic recession as a guideline for the independent variable. Many researchers who consider the economy's role in TANF's success use the unemployment rate as the main economic indicator (for example, Ziliak et al., 2000; Kwon & Meyer, 2011; Pilkauskas, Currie, & Garfinkel, 2012). However, the unemployment rate alone is insufficient to define an economic recession for this study. First, NBER contends that it is a "lagging indicator," a result of a recession, and there is considerable variation in the length of time it correlates directly with an economic recession (NBER, n.d.b). Second, the unemployment rate for those participating in MFIP would likely be higher than the unemployment rate in the general population because many people who apply for MFIP are unemployed or underemployed. To be consistent with previous research, county-level monthly unemployment data (*RamseyCountyUnempl_Rt*) are used for this study in conjunction with other economic indicators that are consistent with NBER's definition of a recession: a dummy coded independent variable *Recession_or_Not* to represent national-level recessions, and annual real GDP in 2009 chained dollars for metropolitan area Minneapolis-St. Paul-Bloomington, MN-WI (*RealGDP_Metro*) to represent economic conditions at the state and local levels. Annual median income (*MedianIncome_RamseyCo*) is also used to provide another more locally nuanced economic indicator. Furthermore, because MFIP is designed to address the needs of families with low incomes, and one of its goals is to move families out of poverty, and poverty data for Ramsey County (*PovertyRate_RamseyCo*) is used as an additional economic indicator. All economic indicators except *Recession_or_Not* were obtained using web-based interactive data mapping tools (Minnesota Department of Employment and Economic Development, 2017; U.S. Bureau of Economic Analysis, (n.d.); U.S. Census Bureau, 2017). *Recession_or_Not* was determined manually by the researcher by looking at NBER's business cycles, and the months during which a recession began and ended (National Bureau of Economic Research, n.d.a). *Recession_or_Not* is dummy coded (1 = recession; 0 = not) and is at the national level.

Response variables. This study has two main response (dependent) variables that focus on the economy's impact on various aspects of MFIP participants' employment opportunities: earned income and work hours. The first response variable is earnings per month (*EarnedIncome*), MFIP participants' gross income, measured in dollars earned per month. The second response variable is the number of hours worked per month (*MAXISHours*), measured in hours worked per month. It is important to note that the MFIP cash portion is calculated based on the gross income reported, but 40% of the gross income is disregarded (Minnesota Department of Human Services, 2017a). Income in the *EarnedIncome* variable only includes that which is from employment; the cash portion is not considered income in this variable.

A third response variable is used to consider the extent to which economic conditions (local and national) impact whether or not MFIP participants earn income. This is a dummy variable (*Income_or_not*), and divides participant observations into two categories: income (1), or not (0). It is important to note that the two categories are not mutually exclusive; many participants report zero earnings at some point during their MFIP participation and earnings at other points. This variable is only used to examine the extent to which the predictor variables, particularly those concerning economic conditions, impact whether or not MFIP participants earn income.

Predictor (control) variables. The following demographic variables will also be predictor variables: race, Latino ethnicity, gender, age, and education level. Race (*Race*) is operationalized according to Ramsey County's categories: Asian, African American or African Immigrant, Native American, Pacific Islander, White. The population includes Native American participants, but none who live on Reservations because there are no Reservations in Ramsey County. MFIP participants may identify as more than one race; there are 26 race categories in the data, including "unknown." The researcher combined the race categories according to the way Ramsey County collapses them such that six race categories remain: Asian, Pacific Islander, Asian/Pacific Islander; African American or African Immigrant; Native American; White; Multiple Races; Unknown. Ethnicity (*Latino_Ethnicity*) is defined as Hispanic/Latino/Latina or not because that is how it is defined in MAXIS; the researcher acknowledges that it is not possible to represent all ethnicities and will need to rely on Ramsey County's categorization to convey it at all. Gender is defined as female or male. Age (*Age*) is the current age of the participant for each observation. Education (*Education*) is defined as having a high school diploma/GED or not. These control variables were chosen because of previous research showing racial disparities in MFIP outcomes, particularly for African Americans (Hollister et al., 2003; McDonnell, 2004; DeMaster, 2009; Collins & Xaykaothao, 2015; Minnesota Department of Human Services, 2011; Kwon & Meyer, 2011). Given that racial disparities exist, it is possible that disparities in Hispanic/Latino/Latina ethnicity are present as well. Although the majority of MFIP participants in this population are female, gender is a control variable because females are overrepresented in the MFIP population and have historically been at a disadvantage for government assistance, being recipients of means-tested public assistance to a greater extent than social insurance programs like Social Security (Abramovitz, 1996; Abramovitz, 2000; Abramovitz, 2001; Brush, 2003; Mink & Solinger, 2003). This study controls for age because other studies on low-income families consider age and education level as a factor in explaining outcomes (Kwon & Meyer, 2011; Hanratty, 2016). This study controls for education level to be consistent with previous research (Hollister et al., 2003; McDonnell, 2004). Finally, due to the variation in the length of time participants utilize MFIP, this study also controls for the number of months each person remains in the program (*monthcount*).

Limitations of variables

Predictor (independent) variables. Due to the various ways there are to define economic conditions, this study relies on several measures of "recession." First, it uses a dummy coded independent variable to define months in which the United States was in an economic recession, based on NBER's monthly determination of an economic recession at the national level (NBER, n.d.a). Given that this study focuses specifically on Ramsey County, Minnesota, national recession data may not accurately reflect local economic conditions; therefore, real GDP for the metropolitan area of Minneapolis-St. Paul-Bloomingtin (MN-WI) (U.S. Department of Commerce, Bureau of Economic Analysis, n.d.), and median income for Ramsey County (U.S. Census Bureau, 2017) are used as supplemental economic indicators to reflect the condition of the local economy. Data do not exist for metropolitan area real GDP until the year 2001, so it is missing for the year 2000. The unemployment rate (Minnesota Department of Employment and Economic Development, 2017) is used as a lagging indicator of a recession. The poverty rate for Ramsey County (U.S. Census Bureau, 2017) is also used as a lagging indicator, and at the time of analysis, poverty rate data were only available through 2015.

Response variables. *MAXISHours* and *EarnedIncome* captures employment and earnings reported by participants while participating in MFIP and turning in their monthly Household Report Form (HRF), which includes the total number of hours worked per month as well as the income earned per month. All MFIP participants are required to submit the HRF every month in order to remain active on MFIP. The HRF can be mailed, faxed or dropped off in person. The HRF goes to the scan center at Ramsey County and gets scanned into the laser fiche system, which sends them to the Financial Worker's laser fiche queue. Then the Financial Worker physically sits at a computer and enters these data manually (D. DeMaster, personal communication, May 31, 2017). Both of these variables are highly reliable and valid because they are required for eligibility and grant determination. Financial Workers at Ramsey County enter earnings and employment together, based on the Household Report Form (HRF), which participants must complete and submit along with paycheck stubs to their Financial Worker. The HRF includes all income reported by participants, including formal labor market work and informal work arrangements such as self-employment, like contractors, child care providers, and taxi drivers. If a participant is self-employed, there is an indirect measure to calculate wage and hours. For example, taxi drivers may wait for a long time before a customer requests services. They would report the number of hours they spent waiting for business. To calculate the number of hours worked, Financial Workers divide the total income by the minimum wage, and that number is entered into MAXIS (M. Herzfeld, personal communication, May 12, 2017). In the case of self-employment, income may be underreported, but there is no way of knowing the extent to which this may or may not happen.

Predictor (control) variables. Most of the control variables require little caution when assessing their reliability and validity; however, it is important to acknowledge some potential issues with how these variables are reported. Race and ethnicity are both self-reported, and if this is left blank systematically more frequently with certain races, the racial composition of MFIP may not be accurately reflected, and there is no way of knowing this. Ethnicity is defined as Hispanic/Latino/Latina or not, so does not capture all ethnicities. Gender is coded female or male, and does not accurately reflect transgender MFIP participants because there is no transgender option. Age (measured by date of birth) is the most accurate.

Education level is the least reliable and valid of the control variables because it is determined at the time of application to MFIP, reflects the level of education at that time, is not reliably updated, and is therefore underreported, especially for those without a high school diploma or GED at the time of application. For participants who first apply to MFIP while in high school or without a high school diploma/GED and then obtain one while receiving MFIP, achieving a high school diploma/GED will be underreported. According to the Office of Research and Evaluation Supervisor at Ramsey County, variables such as education that don't affect eligibility, are likely correct at the time of MFIP application, but are not updated in MAXIS (D. DeMaster, personal communication, May 26, 2017). However, if someone subsequently reapplied for MFIP after not having participated in it for several years and had obtained more education since prior MFIP applications, education status would be updated then. This study only controls for high school education because of the low rates of higher education in this population (11.4% of MFIP participants in this dataset have education beyond high school). Furthermore, there is no way of knowing if education level data are collected the same way, every time, for every person, particularly if the participant is an immigrant, and especially if an immigrant is a refugee and is fleeing a country in which there was little or no formal education. Validity is also a concern because of how accurately education reflects reality. Although education level is not a perfect measure, it is the best available.

The *monthcount* variable is limited to representing the total number of months someone participates in MFIP, and does not account for spells of MFIP participation; if someone participated for 20 months, this variable does not show gaps in MFIP participation, or if the participant received MFIP for 12 months, exited, reapplied, and participated for eight more months. Furthermore, *monthcount* for the analyses on income and hours only includes the months in which income/hours are reported, so it underrepresents the length of time a participant received MFIP for those who, for one or more months, report zero income.

Potentially confounding variables that cannot be assessed. Due to fluctuating living, work, financial, and other circumstances which abound in this population, MFIP exit status is not a valid control variable because there is no valid way to measure participants' MFIP exit reasons. If someone exited because s/he reached the lifetime limit, that person would look the same as someone who exited because s/he found a job with a livable wage. Both would simply be "off MFIP" but their living situations could be vastly different. Furthermore, if someone MFIP, that person could move to a different state, apply for TANF, and continue to receive cash assistance; this person's exit status would provide no more information about why s/he left MFIP in Ramsey County than the first two examples. Once participants leave MFIP, they are no longer tracked in MAXIS unless they reapply.

Statistical Methods: Linear Mixed Effects Modeling

Statistical Software. Data were originally provided in an Excel spreadsheet, were cleaned in Excel, and imported into R. R was used for all analyses from descriptive statistics to running the mixed effects models (R Core Team, 2016). R is a powerful statistical package that offers many options for analysis and can handle large, complicated datasets with missing values (i.e. variation in the number of observations for each individual results in purposefully missing data).

Descriptive statistics. Descriptive statistics (including the creation of new dummy variables) were done on the control and dependent variables prior to analyses, using R (R Core Team, 2016) and the following R packages: *readxl* (Wickham & Bryan, 2017), *dplyr* (Wickham, Francois, Henry, & Muller, 2017), *lubridate* (Grolemund & Wickham, 2011), *reshape2* (Wickham, 2007), and *ggplot2* (Wickham, 2009). Upon receiving and reviewing the data, the researcher began by running descriptive statistics to understand the data and determine the best statistical methods to answer the research questions and account for the numerous types of MFIP participation circumstances. Existing knowledge of the MFIP population informed the researcher's decision to start with descriptive statistics, although based on input from statisticians, mixed effects models were the method of choice prior to completing descriptive statistics. Analyses were done at the individual level because each parent in a family with two MFIP-eligible adults is required to participate in Employment Services and reports income and hours separately to the Financial Worker.

Due to the complexity of the dataset, descriptive statistics were done in two ways as a means to understand the data and to confirm that mixed effects models would be the best statistical methods to use during analysis. First, the participant IDs were unduplicated such that each of the 53,007 participants had one race, one Latino ethnicity code, one gender, one age (the mean age of all of the months s/he was active on MFIP), and one level of education (if someone completed a high school diploma or GED while active on MFIP and it was updated in the MAXIS database, the higher level of education was used). If participants reported more than one race or race combination (as in cases that were re-opened and a different race was reported), the most recent race reported was used for that participant. If Latino ethnicity was reported as both yes and no, the last entered report of Latino ethnicity was used. If participants reported both female and male for gender (this was the case for 31 individual participants), the last entered report of gender was used, according to recommendations by the Supervisor of Ramsey County's Office of Research and Evaluation (D. DeMaster, personal communications, August 2 and 3, 2017). Second, the researcher considered the composition of MFIP participants over time; each of the 204 months has a unique demographic composition in terms of race, Latino ethnicity, gender, age, and education. Descriptive statistics were also done separately for working participants. Findings from the descriptive statistics tests are discussed in the Findings chapter.

The results from the descriptive statistics tests provide insight into Ramsey County's MFIP population's demographics between January 2000 and December 2016. Descriptive statistics were run on the entire dataset of 53,007 participants, and again on the datasets for only those who report income (n = 34,437) and work hours (n = 34,485) to see if there were sizable differences between the working and non-working participants.

Justification for mixed effects modeling. MFIP is designed so that participants may be active in the program for a few months, end their participation, and reapply so they can participate in it again. There are multiple observations per participant during the 204-month time frame for this study. Each participant has a minimum of three observations (three months of being active on MFIP), based on inclusion criteria set by the researcher. There is no maximum number of observations except for the 204-month duration of the analysis, and the maximum number of months reported in this dataset is 204 (19 participants of the 53,007 received MFIP for all 204 months). Due to the 60-month lifetime limit, most participants will have fewer than 60 observations; however, TANF allows states to grant extensions to up to 20% of their caseloads. Given that there are repeated observations (*ReportMonth*) for each individual, that the number of observations differs across individuals, and that there are varying lengths of time between each observation, data analysis for this study requires sophisticated statistical methods to account for missing data (for example, the vast majority of participants will not have every *ReportMonth* because most do not participate in MFIP for more than 60 months), and multiple observations that are likely dependent on each other. Simple linear regression assumes independent observations, but repeated observations of the same individual are inherently correlated with each other, and therefore not independent (Winter, 2013). Repeated measures in simple linear regression assumes that each participant is observed the same number of times, and with the same amount of time passing between each observation, which is not a realistic representation of MFIP participants. Therefore, linear regression is insufficient for these analyses because it cannot account for the relationships between each observation of each individual participant. A sample of participants could have been drawn such that this study would include participants who meet more stringent selection criteria (for example, participants who received MFIP for the same set number of months in a particular time period to fit a linear regression model), but that would have considerably reduced generalizability because it would exclude participants who are active on MFIP for a short time as well as long-term MFIP users, who are a highly vulnerable subset of the population.

The method of choice is hierarchical linear modeling (HLM), also known as mixed effects modeling and multilevel modeling (Bryk & Raudenbush, 1992). Mixed effects modeling "is generally more flexible in terms of its data requirements because the repeated observations are viewed as nested within the person rather than as the same fixed set for all persons as in [multivariate repeated measures methods]. In an HLM, both the number of observations per person and the spacing among observations may vary" (Bryk & Raudenbush, 1992, p. 133). Mixed effects modeling can handle the complexities of large datasets with missing values (in this case, data will be missing for the months in which a participant is not active on MFIP), and with multiple levels of data in which variables are nested within each other (in this case, *ReportMonth*, or time/observation is nested within each individual MFIP participant), resulting in non-independence of residuals. Figure 4.1 shows a visual representation of the nesting structure, and uses five fictitious participants as an example. In the mixed effects models used for analyses, time is nested within each person; the inner boxes with months and years represent the first level of the nesting structure, the multiple observations within each person. The outer boxes represent the second level of the nesting structure, each individual participant and her/his characteristics, to show the between-person differences that could impact income and work hours.

Figure 4.1. Nesting Structure

Mixed effects modeling is a powerful statistical method for analyzing longitudinal panel data when participants have multiple observations over varying lengths of time, and is particularly appropriate for this dataset because it can handle the relationship between repeated observations within each individual (Bryk & Raudenbush, 1992).

Given the cyclical nature of poverty and cash assistance receipt, it is necessary to use mixed effects models that are able to adequately address questions regarding variance in MFIP participants' employment outcomes. By doing so, the researcher will be able to consider participants who use MFIP briefly, for lengthy spells, and those who participate multiple times with varying lengths of spells. Clearly, many factors are at work when examining any employment data for welfare reform. By considering several predictor variables, including economic indicators and person-level differences, mixed effects modeling allows the researcher to explain the extent to which the economy can account for differences in employment opportunities for MFIP participants, and whether or not the economy plays a statistically significant role in the variation of hours worked and earnings.

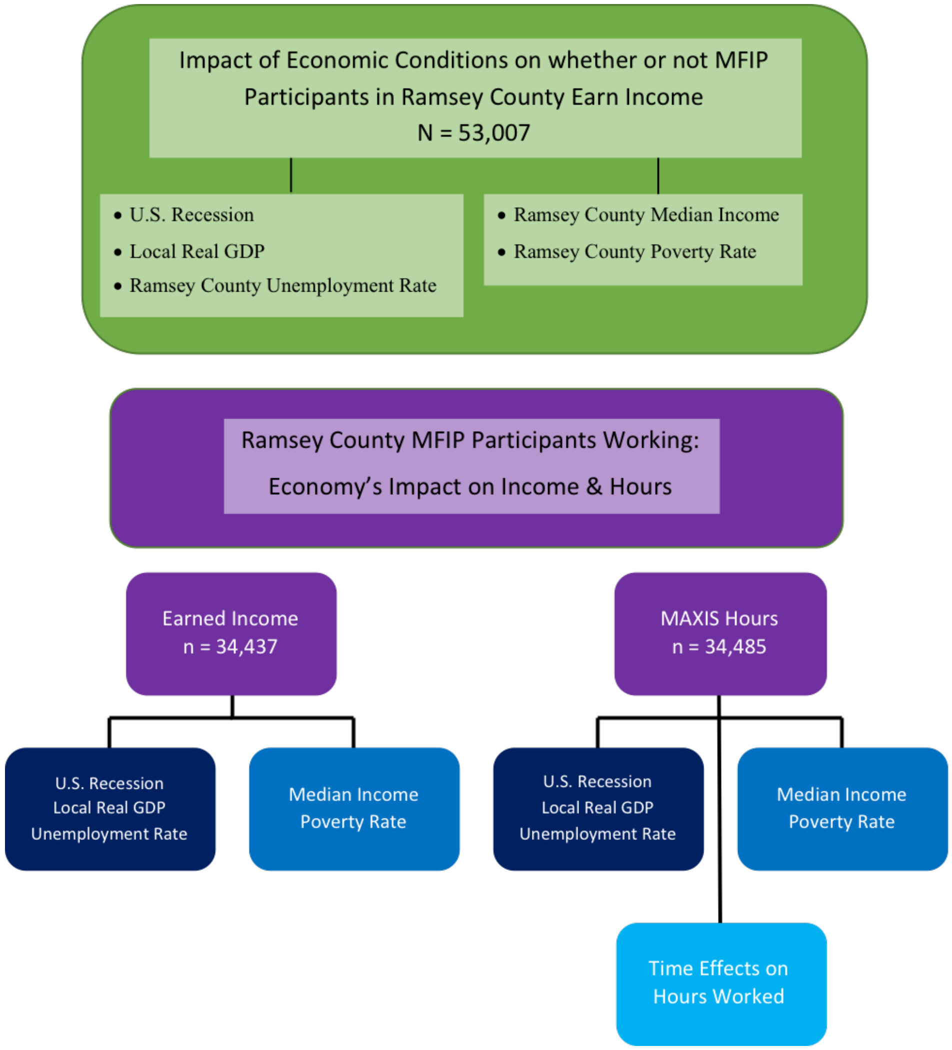
Fitting the first model and testing assumptions. R, with the *ggplot2*, *lme4*, *lmerTest*, *nlme*, and *lattice* packages, was used to test for assumptions and to run linear mixed effects analyses on the effects of economic conditions on income earned and hours worked (R Core Team, 2016; Wickham, 2009; Bates, Maechler, Bolker, & Walker, 2015; Kuznetsova, Brockhoff, & Christensen, 2016; Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., & R Core Team, 2017; Sarkar, D., 2008). (For a detailed description of the models and the R code used to run them, please see Appendices C and D.)

Prior to determining the final mixed effects model for analysis, a linear mixed effects model was fit for the entire dataset. The residual plot revealed non-linearity and a non-normal distribution. Data were skewed because a large proportion of MFIP participants report zero income and work hours. Using a linear model on a non-linear dataset would render meaningless interpretation of the results; Singer & Willett (2003) recommend using a square root transformation on multi-level, longitudinal data to assume linearity at each level, and suggest that it is preferred to "fit a linear model to transformed variables instead of a nonlinear model to raw variables" (p. 76). Understanding that this works better for response variables with arbitrary scaling, as in Likert responses, results for this analysis are interpreted with caution because they are no longer meaningful in dollar-for-dollar or hour-for-hour amounts. Transforming the response variable reduces meaning, but increases the ability of the model to draw important conclusions about the relationship between economic conditions and MFIP participants' employment opportunities.

To address the problems of heteroscedasticity and non-normality, participants with zero income and zero work hours were removed from the final model, and the data were square root transformed. Transforming the data allowed for the fit of a linear mixed effects model that provides insight into the impact of economic conditions on MFIP participants who are earning income. Excluding those with zero income improved normality in the data, which resulted in better representation of those who are working. MFIP participants report zero income for a variety of reasons, which may not have anything to do with economic conditions or lack of available work. For example, perhaps they are exempt from participating in Employment Services (for reasons such as caring for an infant or ill family member, being a new immigrant, or having a domestic violence waiver), in which case they do not need to be looking for work or working. However, many people who are exempt from Employment Services choose to work anyway, and their data are included for the months they report income.

Fitting the final models. Due to the myriad ways to assess the impact of economic conditions on MFIP participants' employment opportunities, three main models were fit, one for each response variable: 1) *Income_or_Not*, 2) *EarnedIncome*, and 3) *MAXISHours*. These models address the main research question in several parts. Figure 4.2 shows a visual representation of the three main models.

Figure 4.2. Three Main Models



First, a model was fit to assess economic conditions on whether or not MFIP participants earn income. The corresponding research question is: to what extent does the condition of the economy predict whether or not Ramsey County MFIP participants earn income? Second, two models were fit to assess economic conditions on Ramsey County MFIP participants' earned income. The corresponding research question for these models is: to what extent do economic conditions, as measured by *Recession_or_Not*, *RealGDP_Metro*, and *RamseyCountyUnempl_Rt* (the first model), and as measured by

MedianIncome_RamseyCo and *PovertyRate_RamseyCo* (the second model), influence Ramsey County MFIP participants' employment opportunities in terms of earnings? Third, two models were fit to assess economic conditions on Ramsey County MFIP participants' work hours. The corresponding research question for these models is: to what extent do economic conditions, as measured by *Recession_or_Not*, *RealGDP_Metro*, and *RamseyCountyUnempl_Rt* (the first model), and as measured by *MedianIncome_RamseyCo* and *PovertyRate_RamseyCo* (the second model), influence Ramsey County MFIP participants' employment opportunities in terms of hours worked? An additional model was run for hours, which considers the impact of time on hours worked; this model replaces all economic indicator predictor variables with dummy-coded year variables to show how work hours change between 2001 and 2016. (A time effects model was not run on the income response variable because participants' income is not adjusted for inflation.). The corresponding research question for that model is: to what extent does time, particularly during the years in which the United States experienced two economic recessions, influence Ramsey County MFIP participants' employment opportunities in terms of work hours?

Unconditional models. To begin estimating a mixed effects model, an unconditional (or null) model should be fit (Hayes, 2006). A null model is a model without predictors (in this case, the variables for individual factors and economic conditions are left out of the model), and assesses the between-person differences in MFIP participants on the outcome variables, earned income and hours worked. For example, do MFIP participants differ from each other, on average, in their income earned and hours worked? (The below example of the null model uses *EarnedIncome* as the response variable; a null model with *MAXISHours* was also fit, but is not shown here.)

Level 1: $Y_{tj} = \beta_{0j} + r_{tj}$ $(EarnedIncome_{tj} = Participant_j + r_{tj})$
Level 2: $\beta_{0j} = \gamma_{00} + u_{0j}$ (Mean_$EarnedIncome_{0j}$ = Grand_Mean_$EarnedIncome_{00} + u_{0j}$)

In the Level 1 null model, Y_{tj} is how much income is earned by participant *j* in month *t*, β_{0j} is the average income participant *j* earns, and r_{tj} is the difference between participant *j*'s average earnings and how much participant *j* earns in month *t* (the residual error at Level 1). In the Level 2 null model, γ_{00} is the grand mean, the average income all MFIP participants earn aggregated across participants, and u_{0j} is the difference between participant *j*'s average and γ, the grand mean (the error term at Level 2, or the random intercept).

The null mixed effects model combines Levels 1 and 2:

$Y_{tj} = \gamma_{00} + u_{0j} + r_{tj}$ ($EarnedIncome_{tj}$ = Grand_Mean_$EarnedIncome_{00} + u_{0j} + r_{tj}$)

In the null mixed effects model, participant *j*'s income (*Y*) in month *t* (Y_{tj}) is a function of three contributing factors: MFIP participants' average earned income (γ_{00}), the difference between participant *j*'s average income and the grand mean for all MFIP participants (u_{0j}), and the difference between participant *j*'s income in month *t* and participant *j*'s own average income (r_{tj}). This model assumes a random intercept consisting of the grand mean of participant income (γ_{00}) added to the difference between each participant's income and the grand mean (u_{0j}), which allows for the model to account for participants starting at different income levels when they apply for MFIP;

(γ_{00}+ u_{0j}). The difference between participant *j*'s average earnings and how much participant *j* earns in month *t* (r_{tj}) is the residual error from the Level 1 null model (Hayes, 2006). The null model for hours worked (*MAXISHours*) is the same, except *MAXISHours* becomes the response variable.

Conditional models: correlations between predictors. Because real GDP is used to help determine whether or not the economy is in a recession, and because median income, unemployment rate, and poverty rate are all lagging indicators of recessions, collinearity between the economic conditions predictor variables was assumed (see Figures 4.3 and 4.4; due to the scaling of the variables, the relationships between the economic indicators are shown on two graphs, Figures 4.3 and 4.4).

Figure 4.3. National Recessions, Local Real GDP, Ramsey County Unemployment Rate, and Ramsey County Poverty Rate Between 2000 and 2016

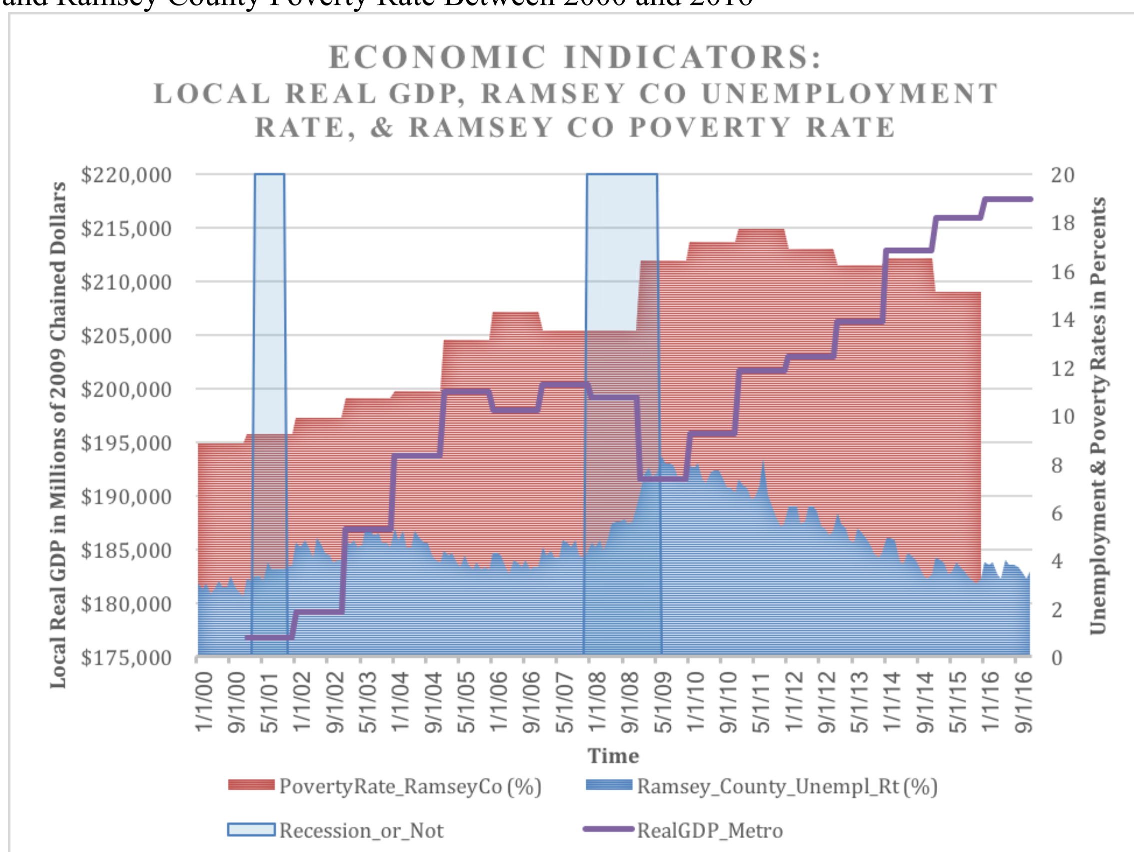


Figure 4.3 shows how local real GDP, Ramsey County unemployment rate, and Ramsey poverty rate changes over time. The left-side y-axis shows real GDP for the metropolitan area of Minneapolis-St. Paul-Bloomington, MN-WI in millions of 2009 chained dollars). The right-side y-axis shows the poverty rate for Ramsey County and the unemployment rate for Ramsey County in per cents. The bars represent the two recessions that occurred within the duration of this study (a shorter recession from March 2001 – December 2001, and the Great Recession, from December 2007 – May 2009). Figure 4.3 indicates that the unemployment rate and poverty rate remained fairly stable during the 2001 recession, and increased slightly in 2002. The years between 2004 and 2006 show that unemployment decreased while poverty increased, and both rose sharply after the Great Recession began, as the local real GDP was decreasing. Both unemployment and poverty show a downward trend after 2012, but overall, poverty remains higher than it was before the start of the Great Recession.

Figure 4.4. National Recessions, Local Real GDP, and Ramsey County Median Income Between 2000 and 2016

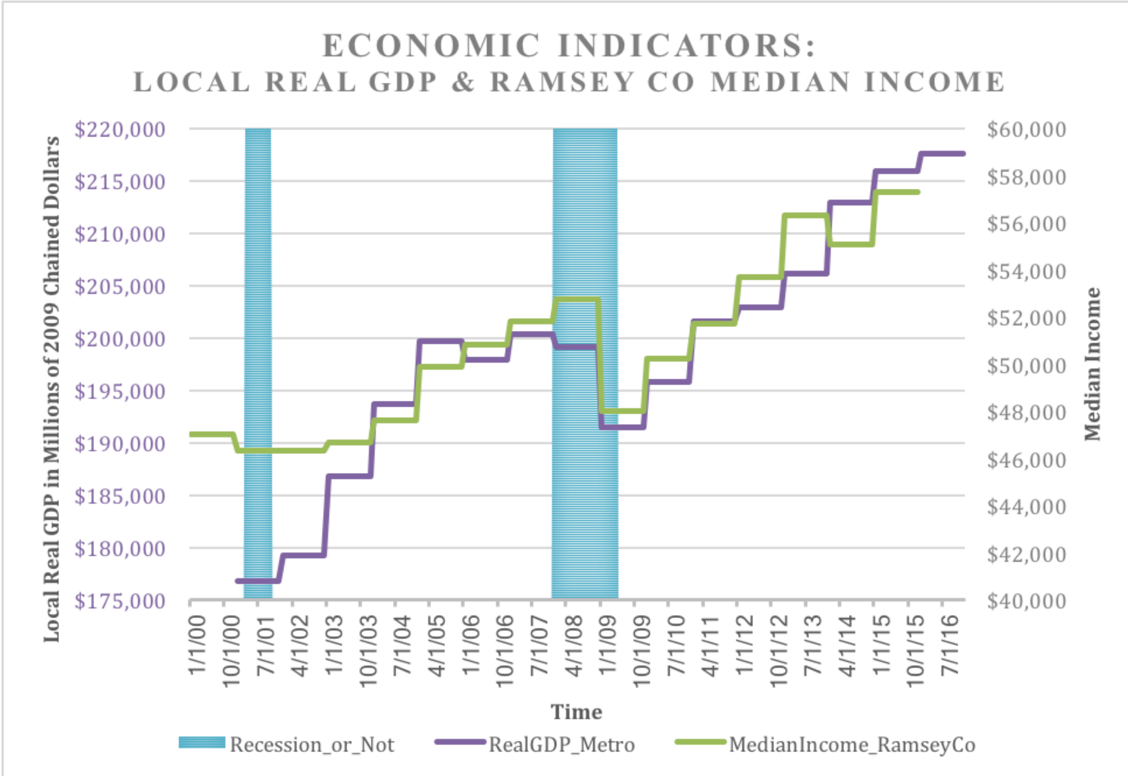


Figure 4.4 shows how local real GDP and the median income for Ramsey County change over time, and that neither started to drop until well into the Great Recession of 2007 – 2009. The left-side y-axis shows real GDP for the metropolitan area of Minneapolis-St. Paul-Bloomington, MN-WI in millions of 2009 chained dollars). The right-side y-axis shows Ramsey County's median income (in tens of thousands of dollars). Figure 4.4 indicates that local real GDP and median income stayed approximately the same during the 2001 recession, but the local real GDP increased sharply once it ended, and increased steadily over the next few years. Local real GDP and median income remained fairly stable until around early 2009, months before the Great Recession ended; in early 2009, both dropped, and remained lower until the end of 2009, and then began to increase again. This is evidence of the national recession's lagging

impact on the local economy. In terms of economic recovery from the Great Recession, when comparing real GDP to poverty and unemployment (Figure 4.3), and real GDP to median income (Figure 4.4), median income increases at approximately the same rate as real GDP, whereas there is not a comparable decline in poverty and unemployment. This indicates that while the increase in median income shows evidence of economic recovery, the slower decrease in poverty and unemployment is evidence of slower recovery for those who have lower incomes and are more economically vulnerable.

A correlation table was created to assess the degree of correlation between these predictors. Given the high collinearity between the local economic indicators: *RealGDP_Metro* and *MedianIncome_RamseyCo* (0.92), *RealGDP_Metro* and *PovertyRate_RamseyCo* (0.74), *MedianIncome_RamseyCo* and *PovertyRate_RamseyCo* (0.72), and between *Ramsey_County_Unempl_Rt* and *PovertyRate_RamseyCo* (0.65), models with the three response variables (*Income_or_not*, *EarnedIncome*, and *MAXIXHours*) were run twice, each time with different economic conditions predictor variables to address the possibility that the collinear variables could unpredictably account for the shared variance that is also shared with the response variables (see Table 4.1).

Table 4.1. Correlations Between Local Economic Indicators

	Local Real GDP	*Ramsey Co. Median Income*	*Ramsey Co. Unemployment Rate*	*Ramsey Co. Poverty Rate*
Local Real GDP	1	0.92	-0.06	0.74
Ramsey Co. Median Income	0.92	1	0.08	0.72
Ramsey Co. Unemployment Rate	-0.06	0.08	1	0.65
Ramsey Co. Poverty Rate	0.74	0.72	0.65	1

The models for the *Income_or_Not* response variable include 1) *RealGDP_Metro* and *Ramsey_County_Unempl_Rt* (and *Recession_or_Not* as the national recession variable), and 2) *MedianIncome_RamseyCo* and *PovertyRate_RamseyCo* (and *Recession_or_Not* as the national recession variable). There is debate among statisticians with regard to addressing collinearity in predictor variables; one method is to remove one or more of them even though this results in the inability to compare predictors to each other (Mason and Perreault, 1991). Given that the data for these analyses required transformation to meet the assumptions of normality, the coefficients cannot be interpreted in a way that shows which predictors are more significant than others. Transformed data does not produce literally interpretable coefficients. Therefore, separate models were run to address the issue of collinearity, knowing that this only provides a partial explanation in variance of income and work hours.

Conditional models: U.S. recession, Metro GDP, and Ramsey County unemployment rate as predictors. To look at the impact of economic conditions and person-level differences on MFIP participants' income and work hours, predictor variables for economic conditions and person-level differences are added to the equation and this replaces the unconditional model with a conditional model, which creates regression models for each MFIP participant *j* (Woltman, Feldstain, MacKay, & Rocci, 2012). The mixed effects model applies to the two main response variables in this study, *EarnedIncome* and *MAXISHours*, and the additional *Income_or_not* response variable that includes all of the MFIP participants, regardless of whether or not they are working; however, only one model is presented here. The only part that changes for *MAXISHours* and *Income_or_not* is that $Y_{tj\ (EarnedIncome)}$ would become $Y_{tj\ (MAXISHours)}$ and $Y_{tj\ (Income\_or\_not)}$, respectively.

Level 1: time-level variables ($_{tj}$)

$$Y_{tj(EarnedIncome)} = \beta_{0j} + \beta_{1j(Age)}X_{tj} + \beta_{2(Recession\_or\_Not)j}X_{tj} + \beta_{3(RealGDP\_Metro)j}X_{tj} + \beta_{4(Ramsey\_County\_Unempl\_Rt)j}X_{tj} + \beta_{5(monthcount)j}X_{tj} + r_{tj(residual\ error)}$$

Level 2: person-level variables ($_{0j}$)

$$\beta_{0j} = \gamma_{00} + \gamma_{0\text{-}6(Race)} + \gamma_{70(Latino\ Ethnicity)} + \gamma_{80(HS\_GED\_or\_NOT)} + \gamma_{90(Gender)} + u_{0j(random\ intercept)} +$$
$$\beta_{1j} = \gamma_{10(Age)}$$
$$\beta_{2j} = \gamma_{20(Recession\_or\_Not)}$$
$$\beta_{3j} = \gamma_{30(RealGDP\_Metro)}$$
$$\beta_{4j} = \gamma_{40(Ramsey\_County\_Unempl\_Rt)}$$
$$\beta_{5j} = \gamma_{50} + u_{5j(monthcount\ +\ random\ slope\ \text{for}\ monthcount)}$$

The conditional model contains two levels, representing time nested in participants. The time variables are at Level 1, and the person variables are at Level 2.

Level 1. In the Level 1 model, Y_{tj} is how much income is earned by participant *j* in month *t*. β_{0j} is the average income participant *j* earns (the intercept, or the predicted value of participant *j*'s income as a function of the predictor variables). Adding the predictor variables *X*, $\beta_{1j}X_{tj} + \beta_{2j}X_{tj} + \beta_{3j}X_{tj} + \beta_{4j}X_{tj} + \beta_{5j}X_{tj}$, quantifies the relationship between participant *j*'s earned income in month *t* as a function of all Level 1 predictor variables ($Age_{(1)}$, $Recession\_or\_Not_{(2)}$, $RealGDP\_Metro_{(3)}$, $Ramsey\_County\_Unempl\_Rt_{(4)}$, and $monthcount_{(5)}$) and represents the slope of the regression lines, or the predicted change in MFIP participants' earned income corresponding to a change in the predictor variables. Finally, r_{tj} is the difference between participant *j*'s average earnings and how much participant *j* earns in month *t* (the residual error).

Level 2. The Level 2 model contains the Level 1 predictors for person *j* at time *t*, and the Level 2 predictors. In the Level 2 model, β_{0j} is equal to the sum of γ_{00} (the grand mean of all MFIP participants' earnings aggregated across participants) and all of the Level 2 predictor variables (Race$_{(0\text{-}6,\text{ for the six categories of this variable})}$, Latino Ethnicity$_{(7)}$, HS_GED_or_NOT$_{(8)}$, and Gender$_{(9)}$), and the random intercept, u_{0j}, the difference between each participant's income and the grand mean. Including a random intercept for *participant* accounts for variance in income at the time of MFIP application. It is assumed that MFIP participants do not begin MFIP with the same income level (i.e. when $person_{j(1)}$ applied for MFIP, her/his earnings would likely be different from $person_{j(2)}$ at that person's time of application), and including a random intercept accounts for that variation.

The mixed effects model combines Levels 1 and 2:

$$
\begin{aligned}
Y_{tj\,(EarnedIncome)} &= \gamma_{00} + (\gamma_{10(Age)}X_{tj}) + (\gamma_{20\,(Recession\_or\_Not)j}X_{tj}) + (\gamma_{30(RealGDP\_Metro)j}X_{tj}) \\
&+ (\gamma_{40(Ramsey\_County\_Unempl\_Rt)j}X_{tj}) + (\gamma_{50(monthcount)j}X_{tj}) + \gamma_{0\text{-}6(Race)} + \gamma_{70(Latino\ Ethnicity)} + \\
&\gamma_{80(HS\_GED\_or\_NOT)} + \gamma_{90(Gender)} + u_{5j(random\ slope\ \text{for}\ monthcount)} + u_{0j(random\ intercept)} + r_{tj(residual\ error)}
\end{aligned}
$$

Mixed effects model. In the mixed effects model, the predicted value of *Y*, earned income, equals the grand mean of all participants' aggregated earned income, plus the grand mean change in earned income per every unit increase in the Level 1 predictor variables, plus the grand mean of each Level 2 predictor variable, plus the random slope for *monthcount* (u_{5j}, which accounts for variation in the rate at which participants earn income), plus the random intercept (u_{0j}, the difference between an individual's earned income at the time of MFIP application and the grand mean of earned income), plus the residual error (r_{tj}).

Fixed and random effects. The fixed and random effects stay the same for each of the models, and the model with *EarnedIncome* as the response variable is used to explain the fixed and random effects for each of the models. In this equation, $EarnedIncome_{tj}$ is dependent (response) variable, predicted by *Race*, *Latino Ethnicity*, *Education*, *Gender*, *Age*, *Recession_or_Not*, *RealGDP_MN*, *RealGDP_Metro*, *MedianIncome_RamseyCo*, *Ramsey_County_Unempl_Rt*, and *monthcount*. Although variation may exist, the model estimates the predictor variables as fixed effects because they are the same across individuals. For example, economic conditions are the same for each individual; person-level differences exist between individuals, but not within an individual. The Level 2 fixed effects stay the same within each participant. Although the Level 1 fixed effects change over time, they change in the same way across participants (for example, the unemployment rate will change in the same way for every participant). The variable *monthcount* is used as both a Level 1 predictor variable (a fixed effect) and the random slope (u_{5j}, a random effect). It is a predictor variable because it is assumed that there is variation in the length of time participants receive MFIP assistance. For example, one person may participate in MFIP for 15 months, and another may participate for 40 months. The length of time someone participates in MFIP could impact her/his earned income. The variable *monthcount* is also included as a random slope (random effect) because it is assumed that participants earn income at varying rates, and u_{5j} accounts for each participant's unique slope. For example, two people could apply for MFIP with incomes of $200/month, and both may participate for 15 months, but one exits earning $400/month and the other exits earning $800/month.

The other random effect in the mixed effects equation is u_{0j}, which is the random intercept. The model has a random intercept because it is assumed that there is considerable variability in income across participants when they apply for MFIP, and u_{0j} accounts for different starting points for each participant. For example, one person may be earning $500/month at the time of MFIP application, and another could be earning $200/month. The random intercept allows for such variation.

Hypothesis. The hypothesis for the conditional models with *Recession_or_Not*, *RealGDP_Metro*, and *Ramsey_County_Unempl_Rt* as predictor variables is: *Recession_or_Not*, *RealGDP_Metro*, and *Ramsey_County_Unempl_Rt* have a significant impact on whether or not Ramsey County MFIP participants earn income, and on their earnings and work hours.

Conditional models: Ramsey County Median Income and Ramsey County poverty rate as predictors. The following conditional models replace *Recession_or_Not*, *RealGDP_Metro*, and *Ramsey_County_Unempl_Rt* with *MedianIncome_RamseyCo* and *PovertyRate_RamseyCo*. The equations for these models are the same as the previous ones, minus one economic conditions predictor. These models apply to the other response variables, *MAXISHours* and *Income_or_not*, in which $Y_{tj(EarnedIncome)}$ would become $Y_{tj(MAXISHours)}$ and $Y_{tj(Income\_or\_not)}$. (The model with *Income_or_not* as the response variable also includes *Recession_or_Not* as a predictor; this particular variable was removed for the other conditional models after having shown no significance in the models run on *Income_or_not*, *EarnedIncome*, and *MAXISHours*.)

Level 1: time-level variables ($_{tj}$)

$$Y_{tj(EarnedIncome)} = \beta_{0j} + \beta_{1j(Age)}X_{tj} + \beta_{2(MedianIncome\_RamseyCo)j}X_{tj} + \beta_{3(PovertyRate\_RamseyCo)j}X_{tj} + \beta_{4(monthcount)j}X_{tj} + r_{tj(residual\ error)}$$

Level 2: person-level variables ($_{0j}$)

$$\beta_{0j} = \gamma_{00} + \gamma_{0\text{-}6(Race)} + \gamma_{70(Latino\ Ethnicity)} + \gamma_{80(HS\_GED\_or\_NOT)} + \gamma_{90(Gender)} + u_{0j(random\ intercept)}$$
$$\beta_{1j} = \gamma_{10(Age)}$$
$$\beta_{2j} = \gamma_{20(MedianIncome\_RamseyCo)}$$
$$\beta_{3j} = \gamma_{30(PovertyRate\_RamseyCo)}$$
$$\beta_{4j} = \gamma_{40} + u_{4j(monthcount\ +\ random\ slope\ \text{for}\ monthcount)}$$

The mixed effects model combines Levels 1 and 2:

$$Y_{tj\ (EarnedIncome)} = \gamma_{00} + (\gamma_{10(Age)}X_{tj}) + (\gamma_{20\ (MedianIncome\_RamseyCo)j}X_{tj}) + (\gamma_{30(PovertyRate\_RamseyCo)j}X_{tj}) + (\gamma_{40(monthcount)j}X_{tj}) + \gamma_{0\text{-}6(Race)} + \gamma_{70(Latino\ Ethnicity)} + \gamma_{80(HS\_GED\_or\_NOT)} + \gamma_{90(Gender)} + u_{4j(random\ slope\ \text{for}\ monthcount)} + u_{0j(random\ intercept)} + r_{tj(residual\ error)}$$

Hypothesis. The hypothesis for the conditional models with *MedianIncome_RamseyCo* and *PovertyRate_RamseyCo* as predictor variables is: *MedianIncome_RamseyCo* and *PovertyRate_RamseyCo* have a significant impact on whether or not Ramsey County MFIP participants earn income, and on their earnings and work hours.

Conditional model: time effects as predictors. The following model looks at the effect of time on Ramsey County MFIP participants' work hours. The time effects model only applies to hours because income, unless adjusted for inflation, is not comparable across time in the same way work hours are.

Level 1: time-level variables ($_{tj}$)

$$Y_{tj(MAXISHours)} = \beta_{0j} + \beta_{1j(Age)}X_{tj} + \beta_{2(year\_2001)j}X_{tj} + \beta_{3(year\_2002)j}X_{tj} + \beta_{4(year\_2003)j}X_{tj} + \beta_{5(year\_2004)j}X_{tj} + \beta_{6(year\_2005)j}X_{tj} + \beta_{7(year\_2006)j}X_{tj} + \beta_{8(year\_2007)j}X_{tj} + \beta_{9(year\_2008)j}X_{tj} + \beta_{10(year\_2009)j}X_{tj} + \beta_{11(year\_2010)j}X_{tj} + \beta_{12(year\_2011)j}X_{tj} + \beta_{13(year\_2012)j}X_{tj} + \beta_{14(year\_2013)j}X_{tj} + \beta_{15(year\_2014)j}X_{tj} + \beta_{16(year\_2015)j}X_{tj} + \beta_{17(year\_2016)j}X_{tj} + r_{tj(residual\ error)}$$

Level 2: person-level variables ($_{0j}$)

$\beta_{0j} = \gamma_{00} + \gamma_{k\text{-}19(Race)} + \gamma_{20,0(Latino\ Ethnicity)} + \gamma_{21,0(HS\_GED\_or\_NOT)} + \gamma_{22,0(Gender)} + u_{0j(random\ intercept)}$
$+$
$\beta_{1j} = \gamma_{10(Age)}$
$\beta_{2j} = \gamma_{20(year\_2001)}$
$\beta_{3j} = \gamma_{30(year\_2002)}$
$\beta_{4j} = \gamma_{40(year\_2003)}$
$\beta_{5j} = \gamma_{50(year\_2004)}$
$\beta_{6j} = \gamma_{60(year\_2005)}$
$\beta_{7j} = \gamma_{70(year\_2006)}$
$\beta_{8j} = \gamma_{80(year\_2007)}$
$\beta_{9j} = \gamma_{90(year\_2008)}$
$\beta_{10j} = \gamma_{10(year\_2009)}$
$\beta_{11j} = \gamma_{11(year\_2010)}$
$\beta_{12j} = \gamma_{12(year\_2011)}$
$\beta_{13j} = \gamma_{13(year\_2012)}$
$\beta_{14j} = \gamma_{14(year\_2013)}$
$\beta_{15j} = \gamma_{15(year\_2014)}$
$\beta_{16j} = \gamma_{16(year\_2015)}$
$\beta_{17j} = \gamma_{17(year\_2016)} + u_{18j(random\ slope\ \mathrm{for}\ monthcount)}$

The mixed effects model combines Levels 1 and 2:

$$Y_{tj\ (MAXISHours)} = \gamma_{00} + (\gamma_{10(Age)}X_{tj}) + (\gamma_{20\ (year\_2001)j}X_{tj}) + (\gamma_{30(year\_2002)j}X_{tj}) + (\gamma_{40(year\_2003)j}X_{tj}) + (\gamma_{50(year\_2004)j}X_{tj}) + (\gamma_{60(year\_2005)j}X_{tj}) + (\gamma_{70(year\_2006)j}X_{tj}) + (\gamma_{80(year\_2007)j}X_{tj}) + (\gamma_{90(year\_2008)j}X_{tj}) + (\gamma_{10,0(year\_2009)j}X_{tj}) + (\gamma_{11,0(year\_2010)j}X_{tj}) + (\gamma_{12,0(year\_2011)j}X_{tj}) + (\gamma_{13,0(year\_2012)j}X_{tj}) + (\gamma_{14,0(year\_2013)j}X_{tj}) + (\gamma_{15,0(year\_2014)j}X_{tj}) + (\gamma_{16,0(year\_2015)j}X_{tj}) + (\gamma_{17,0(year\_2016)j}X_{tj}) + \gamma_{k\text{-}19(Race)} + \gamma_{20,0(Latino\ Ethnicity)} + \gamma_{21,0(HS\_GED\_or\_NOT)} + \gamma_{22,0(Gender)} + u_{18j(random\ slope\ \mathrm{for}\ monthcount)} + u_{0j(random\ intercept)} + r_{tj(residual\ error)}$$

The time effects model replaces the economic conditions predictor variables with year variables as a means to consider the impact of time, regardless of economic conditions. There is also no *monthcount* predictor variable in this model because having an extra time variable in the equation generated errors when running the model; however, *monthcount* is still a random slope. The hypothesis for the time effects model is: Time has a significant impact on predicting Ramsey County MFIP participants' work hours.

Re-testing assumptions. To make sure the transformed data were a good fit for the model, tests were run to confirm the assumptions of linear mixed effects models were sufficiently met.

Assumption 1. $r_{tj} \sim N(0, \sigma_A^2)$: The error (*r*) for participant *j* at time *t* is normally distributed (N) with a mean of zero and some constant variance, σ_A^2, which is the specified covariance structure: there is variability within subject (variability from month to month); the model uses an AR1 covariance structure, which means that month *1* is correlated with month *2*. In other words, multiple observations in months for each participant are inherently related to each other and therefore, not independent. Using the AR1 covariance structure accounts for this.

Assumption 2. $\text{Participant}_j \sim N(0, \sigma_B)$: The random intercept ($\text{Participant}_j$) is normally distributed with a mean of zero and some constant; each participant is independent of one another. This dataset includes two-parent families, which conflicts with this assumption to some extent because individual participants in two-parent families are not independent of one another. However, this assumption is reasonably satisfied because two-parent families comprise approximately 25% of the data; and it can be assumed that 75% of the participants are independent of one another. Furthermore, of those who are in two-parent families, many are single-parent families for part of their time on MFIP.

Assumption 3. $r_{tj} \perp \text{Subject}_j$: The error (*r*) for participant *j* at time *t* is independent the random intercept.

The residual plots and Q-Q plots in Appendix A show these assumptions are reasonably satisfied for the models that include only those earning income and reporting work hours. The models that include all participants and assesses the impact of economic conditions on whether or not MFIP participants earn income do not sufficiently meet these assumptions; therefore, results are limited and interpreted with caution. The residual plots and Q-Q plots for these models are in Appendix B.

Chapter 5

Findings

This chapter presents the findings of the linear mixed effects models described in the previous chapter. It begins with a discussion of what the descriptive statistics show, which is necessary to provide a clearer representation of the population and how it changes over time. Then, it parses apart the main research question regarding the economy's impact on Ramsey County MFIP participants' earnings and work hours. This is divided into several sections. First, the findings are described for the model that tests for the economy's impact on whether or not Ramsey County MFIP participants earn income. Second, the null and conditional models for working participants are described. Finally, the results of the conditional models for the economy's impact on income earned, and the economy's impact on hours worked are presented.

Descriptive Statistics

Descriptive statistics on MFIP participants who earn income do not differ much from the entire population; this indicates that the working and non-working participants are similar. Since the descriptive statistics on income-earning participants closely reflect that of the entire population, it could be assumed that many of those who are not earning income at one point, eventually do. The categories for those reporting income and those with zero income are not mutually exclusive. The descriptive statistics do not reflect those who never report income versus those who do; participants who report income for any months during their MFIP participation and also report zero income in other months appear in both sets of descriptive statistics. The final analyses include observations for anyone who is working, regardless of whether they reported zero income at some point.

(There are 48 more participants who reported work hours than who reported income; this could be due to errors or people reporting hours for which they are not paid. Due to the possibility of the latter, those who reported hours but not income are kept in the analyses.)

Control variables. Due to the complexity of running descriptive statistics on a population in which there is substantial demographic variation, Table 5.1 shows a summary of the descriptive statistics for race, Latino ethnicity, and gender. It includes percentages for the entire dataset, percent ranges to show variation in each of these demographics over the 17-year period, and it includes percentages for working participants, as well as percent ranges to show variation between 2000 and 2016.

Table 5.1. Descriptive Statistics on Race, Latino Ethnicity, and Gender

All Participants				Working Participants		
	% of all participants	Lowest and highest % between 2000-2016	Average number of months in MFIP*		% of working participants	Lowest and highest % between 2000-2016
Race				**Race**		
AA	42.6%	32.3% - 53.5%	28.3 months	AA	44.8%	32.2% - 63.5%
AP	22.4%	14.3% - 24.6%	23.4 months	AP	20.0%	12.5% - 27.7%
MR	1.7%	0.7% - 3.7%	30.3 months	MR	1.8%	0.6% - 3.5%
N	2.7%	2.3% - 3.5%	27.9 months	N	2.3%	1.1% - 2.7%
W	29.4%	21.7% - 32.6%	24.3 months	W	29.8%	18.0% - 33.1%
U	1.1%	0.1% - 1.9%	15.8 months	U	1.1%	0.5% - 2.3%
Ethnicity				**Ethnicity**		
Latino	5.9%	5.0% - 6.71%	26.3 months	Latino	6.3%	4.3% - 7.7%
not Latino	94.1%	93.29% - 95.0%	25.8 months	not Latino	93.7%	92.3% - 95.7%
Gender				**Gender**		
Female	74.3%	78.7% - 83.3%	27.4 months	Female	74.7%	73.9% - 82.4%
Male	25.7%	16.6% - 21.3%	18.8 months	Male	23.5%	17.6% - 26.1%

* Average number of months in MFIP for total population: 25.25

Race: All participants. Between January 2000 and December 2016, the racial composition of the 53,007 Ramsey County MFIP participants is as follows: 22.4% Asian, Pacific Islander, Asian/Pacific Islander; 42.6% African American or African Immigrant; 2.7% Native American; 29.4% White; 1.7% Multiple Races; and 1.1% Unknown. Race composition for the 17-year period for this study changes over time. Asian, Pacific Islander, Asian/Pacific Islander ranges from 14.3% at its lowest (June 2004) to 24.6% at its highest (April 2006). African American or African Immigrant ranges from 32.3% at its lowest (March 2000) to 53.5% at its highest (November 2016). Native American ranges from 2.3% at its lowest (July 2008) to 3.5% at its highest (April 2014). White ranges from 21.7% at its lowest (June 2016) to 32.6% at its highest (April 2003). Multiple Races ranges from 0.7% at its lowest (February 2000) to 3.7% at its highest (August 2015). Unknown ranges from 0.01% at its lowest (November 2006) to 1.9% at its highest (February 2001).

Race: Working participants. Between January 2000 and December 2016, the racial composition of working participants is as follows: 20.0% Asian, Pacific Islander, Asian/Pacific Islander; 44.8% African American or African Immigrant; 2.3% Native American; 29.8% White; 1.8% Multiple Races; and 1.1% Unknown. Racial composition for Asian, Pacific Islander, Asian/Pacific Islander and African American/African Immigrant changes 2.4% and 2.2%, respectively, from the entire population. Percent changes in the other race categories is less than 1%. In general, the racial composition of working participants reflects the racial composition of the entire dataset. Racial composition of working MFIP participants fluctuates for the 17-year period of time this study covers. Of those who report earnings, Asian, Pacific Islander, Asian/Pacific

Islander comprise between 12.5% (December 2016) and 27.7% (August 2007) of working MFIP participants. African Americans or African Immigrants comprise 32.2% (March 2000) to 63.5% (December 2016) of working MFIP participants. Native Americans make up 1.1% (June 2010) to 2.7% (June 2004) of MFIP workers. Whites make up 18.0% (June 2016) to 33.1% (February 2004) of MFIP workers. Multiple Races ranges from 0.6% (February 2001) to 3.5% (July 2016), and Unknown race ranges from 0.05% (January 2007) to 2.3% (July 2005).

Latino Ethnicity. Of the 53,007 Ramsey County MFIP participants between January 2000 and December 2016, 5.9% identify as Latino and 94.1% do not. Over the 17-year period for this study, Latino ethnicity ranges from 5.0% at its lowest (January 2014) to 6.71% (September 2004). Of MFIP participants who are working, 6.3% identify as Latino, and 93.7% do not. Over the 17-year period for this study, 4.3% to 7.7% identify as Latino (February 2007 and November 2005, respectively).

Gender. Of the 53,007 Ramsey County MFIP participants between January 2000 and December 2016, 74.3% are female and 25.7% are male. When looking at the gender composition of this population over the time period for this study to see if it changes month-to-month, females comprise 78.7%-83.3% of MFIP-eligible adults, and males comprise 16.6%-21.3% of MFIP-eligible adults in any given month. The gender percentages are higher when looking at monthly composition because females tend to participate in MFIP for an average of 27 months, whereas males' MFIP duration is about 19 months; thus, this increases the percentage of female MFIP participants per month. It is also important to note that 89.0% of the single-parent families in this study are headed by females, and 11.0% are headed by males. Females are overrepresented in single-parent households. In terms of working MFIP participants, gender composition reflects the full dataset. Of working participants, 74.7% are female, and 25.3% are male. Over time, females comprise between 73.9% and 82.4% of working MFIP participants (and males comprise between 17.6% and 26.1% of working MFIP participants).

Age. The mean age for Ramsey County MFIP participants between January 2000 and December 2016 is 30.8 years for all participants in this population. Since participants under age 18 who have not graduated from high school have school-focused Employment Services, it is important to note that in this population, 4.1% of the participants are ages 16 or 17, and likely working on finishing high school instead of working in the formal or informal labor market. Approximately 85.4% of the participants in this study who are ages 16 or 17 do not have income and work hours reported; approximately 14.6% do. The mean age of participants with income is 30 years, which is nearly the same as the mean age of the entire population.

Education. Individual participant IDs were unduplicated such that each participant occurred once in the descriptive statistics. If more than one education level was associated with an individual, the highest level was chosen. Results showed that 39.4% of the participants in this population do not have a high school diploma or GED, and 60.6% do. For MFIP participants earning income, 40.9% do not have a high school diploma or GED, and 59.1% do.

Dependent variables: income and hours. When considering the entire 53,007 participants over the course of January 2000 until December 2016, approximately 69% of MFIP participants report having earned income and work hours at some point during their MFIP participation. This percentage changes when looking at earned income work hours over time; in any given month between January 2000 and December 2016, approximately 25% - 41% of MFIP participants report income and work hours. December 2016 had the highest percentage of MFIP participants reporting income and hours, and February 2006 had the lowest percentage. These percentages show that people do not tend to remain in MFIP for very long once they obtain employment. Monthly earnings average $976.70 for those who report income ($545.62 for parents under age 18); hours worked per month average 102 for those who report hours (67 for parents under age 18).

Upon initial examination of the data, those who were exempt from Employment Services were going to be excluded from analyses for the duration of the exemption; however, despite being exempt, many participants report income and hours during the months they are exempt. For example, over the course of the 17-year period for this study, between 12.6% and 55.2% of exempt participants report income and work hours while they are exempt from Employment Services. Therefore, all MFIP-eligible adults are included for all analyses, regardless of exempt status.

Mixed Effects Models

Impact of economy on earning income or not. The first models address the following research question: to what extent do economic conditions influence whether or not Ramsey County MFIP participants earn income? The hypothesis is: economic conditions have a significant impact on whether or not Ramsey County MFIP participants earn income. Results of these models must be interpreted with caution because the assumptions associated with mixed effects models are not satisfactorily met when including all participants; those with zero income skew the data. Therefore, only results from the F-tests are included here, and are shown in Table 5.2.

Table 5.2. Local and National Economic Indicators' Impact on Whether or Not MFIP Participants in Ramsey County Earn Income

Model 1: National Recession, Local Real GDP, Ramsey County Unemployment Rate	ANOVA F-test	ANOVA p-value	Model 2: National Recession, Ramsey County Median Income, Ramsey County Poverty Rate	ANOVA F-test	ANOVA p-value
National Recession	0.84	0.3601	National Recession	2.37	0.1240
Local Real GDP	8.8	**0.0030**	Ramsey County Median Income	2.54	0.1111
Ramsey County Unemployment Rate	734.23	**<0.0001**	Ramsey County Poverty Rate	492.30	**<0.0001**

$\alpha = 0.01$

U.S. Recession and local real GDP. The first model considers the extent to which a national recession and real GDP for the metropolitan area of Minneapolis-St. Paul-Bloomington, MN-WI impact whether or not MFIP participants earn income. After controlling for age, race, Latino Ethnicity, education, and gender, *RealGDP_Metro* and *Ramsey_County_Unempl_Rt* (p = 0.0030, p = <0.0001, respectively) have a significant impact on whether or not Ramsey County MFIP participants earn income. *Recession_or_Not* (the variable representing a national recession) does not significantly impact whether or not Ramsey County MFIP participants earn income. The hypothesis is partially supported; whether or not the United States is in a national recession does not significantly predict earnings, whereas measures of the condition of the local economy, the local real GDP and Ramsey County's unemployment rate, do have a significant impact on whether or not MFIP participants earn income. This suggests that the condition of the local economy has a larger impact on MFIP participants than does the condition of the national economy.

Ramsey County median income and Ramsey County poverty rate. The second model considers the extent to which a national recession, and the median income and poverty rate for Ramsey County impact whether or not MFIP participants earn income. After controlling for age, race, Latino Ethnicity, education, and gender, *Recession_or_Not* and *MedianIncome_RamseyCo* do not have a significant impact on whether or not Ramsey County MFIP participants earn income ($p = 0.1240$ and $p = 0.1111$, respectively); *PovertyRate_RamseyCo* does ($p = <0.0001$). Again, the hypothesis is partially supported; whether or not the United States is in a national recession does not significantly predict earnings, nor does the median income of Ramsey County; the Ramsey County poverty rate does have a significant impact on whether or not MFIP participants earn income. This suggests that the local poverty rate is far more indicative of whether or not MFIP participants earn income, which makes sense, given that MFIP eligibility depends on having little to no income, and that MFIP participants' income is far below the median income.

Null models for working participants. The null models do not include a random slope because by definition, there are no predictor variables in a null model. To be consistent with the conditional models, the AR1 covariance structure is also used in the null models.

Results of the first null model show that 32.0% of the total variation in *EarnedIncome* is due to variation between people; 68.0% is due to within-person differences (how much variation occurs from someone's first MFIP month to the second, third, et cetera). Results of the second null model show that 27.6% of the total variation in *MAXISHours* is due to variation between people; 72.4% is due to within-person differences (see Table 5). This is good evidence for using a multi-level model because it will provide between-person estimates rather than just within-person (time only) estimates. The multi-level model can account for time differences (within a person) and person differences (between each participant), rather than only one or the other.

Table 5.3. Variance Correlations for Null Models					
Model 1: ***EarnedIncome* as Response Variable**			Model 2: ***MAXISHours* as Response Variable**		
	Variance	Std Dev		Variance	Std Dev
(Intercept)	39.27108	6.266664	(Intercept)	2.832218	1.68292
Residual	83.37084	9.130763	Residual	7.427788	2.725397

Conditional models for working participants. The conditional models include both a random intercept for person, and a random slope for time because it is assumed that MFIP participants neither begin MFIP with the same income and work hours, nor progress at the same rate in terms of earnings or hours while participating in MFIP. All of the conditional models were fit using Restricted Maximum Likelihood to achieve the most accurate variance estimates, which is important for this dataset because of the between-person variance shown by the null models (32.0% and 27.6% of the variation in income and hours, respectively) is due to differences between individuals. Two main conditional models were run, one with *EarnedIncome* as the response variable, and one with *MAXISHours* as the response variable.

Random effects for the conditionals model for *EarnedIncome* show that the residual error (r_{tj}) is reduced by 11.7% with *Recession_or_Not*, *RealGDP_Metro*, and *Ramsey_County_Unempl_Rt* as the predictor variables, and by 13.8% with *MedianIncome_RamseyCo* and *PovertyRate_RamseyCo* as the predictor variables. Random effects for the conditional model for *MAXISHours* show that the residual error

(r_{tj}) is reduced by 6.7% with *Recession_or_Not*, *RealGDP_Metro*, and *Ramsey_County_Unempl_Rt* as the predictor variables, and by 6.5% with *MedianIncome_RamseyCo* and *PovertyRate_RamseyCo* as the predictor variables. Random effects for both response variables are shown in Tables 5.4 and 5.5.

Table 5.4. Random Effects for National Recession, Local Real GDP, and Ramsey County Unemployment Rate

Model 1: ***EarnedIncome* as Response Variable**			Model 2: ***MAXISHours* as Response Variable**		
	Std Dev	Corr		Std Dev	Corr
(Intercept)	6.836614	(Intr)	(Intercept)	1.7978316	(Intr)
monthcount	0.1564715	-0.483	*monthcount*	0.0375611	-0.555
Residual	8.5436289		Residual	2.6328969	

Table 5.5. Random Effects for Median Income and Poverty Rate in Ramsey County

Model 1: ***EarnedIncome* as Response Variable**			Model 2: ***MAXISHours* as Response Variable**		
	Std Dev	Corr		Std Dev	Corr
(Intercept)	6.6427786	(Intr)	(Intercept)	1.79382495	(Intr)
monthcount	0.1575742	-0.456	*monthcount*	0.03925831	-0.554
Residual	8.4794474		Residual	2.63599182	

Comparing the intercepts of the null and conditional models (Tables 4, 5, and 6) provides an estimate of the percentage by which the conditional models impact variation in the intercept. To compute this:

$$\frac{\text{Intercept Variance (from null model)} - \text{Intercept Standard Deviation (from conditional model)}^2}{\text{Intercept Variance (from null model)}}$$

Subtracting the conditional squared *Intercept Standard Deviation* from the null model's *Intercept Variance*, and then dividing the difference by the null *Intercept Variance* shows that all conditional models increase variation in the intercepts. The conditional model for *EarnedIncome* with the with *Recession_or_Not*, *RealGDP_Metro*, and *Ramsey_County_Unempl_Rt* as the predictor variables increases variation in the intercept by 19.0%, and by 12.4% with *MedianIncome_RamseyCo* and

PovertyRate_RamseyCo as the predictor variables. The conditional model for *MAXISHours* increases variation in the intercept by 14.1% with *Recession_or_Not*, *RealGDP_Metro*, and *Ramsey_County_Unempl_Rt* as the predictor variables, and by 14.0% with *MedianIncome_RamseyCo* and *PovertyRate_RamseyCo* as the predictor variables. Tables 5 and 6 show that the residual error is reduced by a relatively small percentage for all of the conditional models; however, it is important to acknowledge that these models only include five control predictors (age, race, Latino ethnicity, education, and gender), and two or three economic indicators (*Recession_or_Not*, *RealGDP_Metro*, and *Ramsey_County_Unempl_Rt* for the first model, and *MedianIncome_RamseyCo* and *PovertyRate_RamseyCo* for the second model). No model can possibly account for all of the individual factors that impact MFIP participants' earnings and work hours, especially given the complexities of their lives. Greater variation shown by the conditional models gives a more realistic representation of the variation in MFIP participants' starting points in terms of income and work hours when they first apply for MFIP.

Conditional model 1: impact of the economy on income earned. The models in this section address the following research question: to what extent do economic conditions (particularly during economic recessions), and person-level differences (race, Latino ethnicity, gender, age, and education) influence MFIP participants' employment opportunities in terms of earnings? Figure 5.1 shows changes over time in the percentages of MFIP participants in Ramsey County who are earning income.

Figure 5.1.

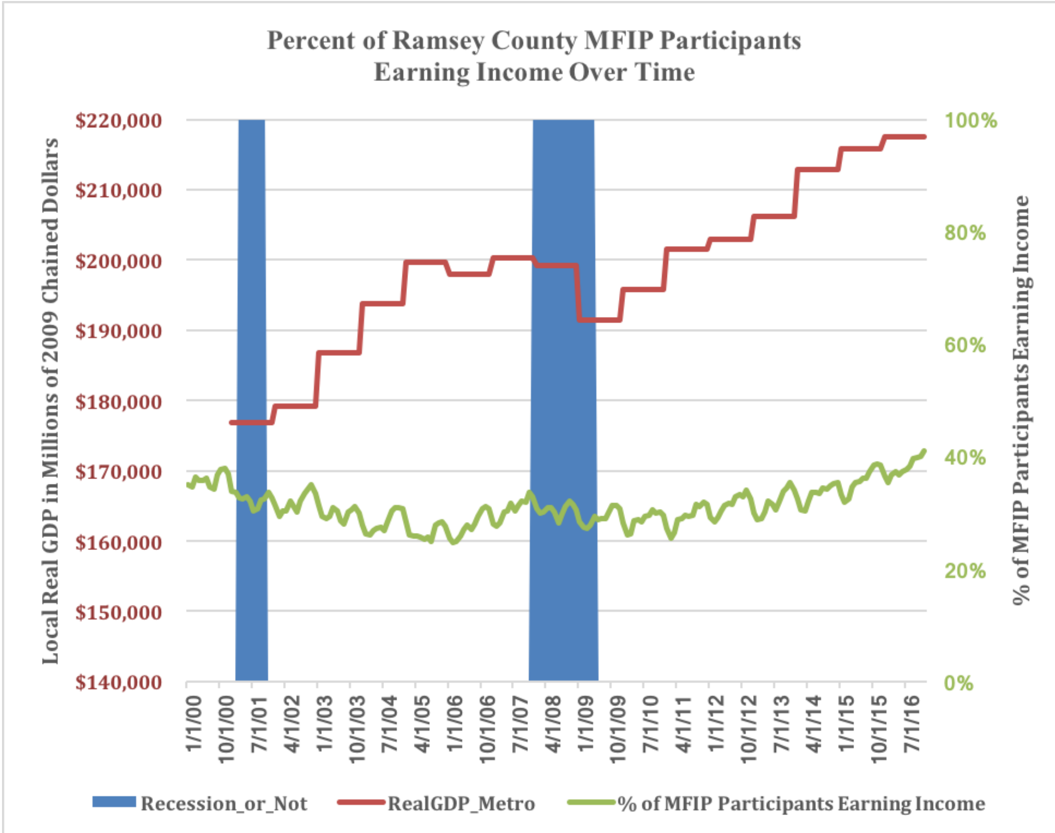


Figure 5.1 shows the two national recessions that occurred between 2000 and 2016, along with real GDP for the local metro area. The lower line represents the percentages of individual adult MFIP participants who are reporting earned income. It tends to fall between 30% and 40% over the entire 17-year period. Although it does not appear to change much, it is important to note that this graph reflects the percentages of income-earning participants; it does not show how much they earn. Figure 5.1 supports what the model with the *Income_or_not* response variable shows, that recessions tend to have little impact as they occur at the national level.

Predictor variables: U.S. Recession, local real GDP, and Ramsey County unemployment rate. ANOVA tests show that the condition of the local economy, as measured by real GDP for the metropolitan area for Minneapolis-St. Paul-Bloomington, MN-WI, and the Ramsey County unemployment rate have a significant impact on MFIP participants' earnings ($p < 0.0001$; $\alpha = 0.01$), but national recessions do not ($p = 0.0222$; $\alpha = 0.01$) (see Table 5.6). The hypothesis that economic conditions have a significant impact on Ramsey County MFIP participants' earnings is rejected at the national level, but supported at the local level, when measured by the local real GDP and the Ramsey County unemployment rate. In terms of the control predictors, race, age, education, and gender show significance (all p-values < 0.0001; $\alpha = 0.01$). Latino ethnicity is not significant (in these results) in predicting earnings ($p = 0.0312$; $\alpha = 0.01$). The variable for time, *monthcount*, also significantly impacts MFIP participants' earnings ($p < 0.0001$; $\alpha = 0.01$).

Table 5.6. ANOVA:
National Recession, Local Real GDP, and Ramsey County Unemployment Rate on Earnings

	ANOVA F-test	ANOVA p-value
Race	539	**<0.0001**
L_Ethnicity	4.6	0.0312
Age	1358.9	**<0.0001**
Education	213.7	**<0.0001**
Gender	404.9	**<0.0001**
National Recession	5.2	0.0222
Local Real GDP	889.1	**<0.0001**
Ramsey Co. Unempl. Rt.	448.7	**<0.0001**
monthcount	1462.2	**<0.0001**

$\alpha = 0.01$

To further examine the variables which have significance, as indicated by the ANOVA table, the unstandardized coefficients of the fixed effects show the direction of significance (see Table 5.7).

Table 5.7. Fixed Effects: National Recession, Local Real GDP, and Ramsey County Unemployment Rate on Earnings					
Predictor	**Unstandardized Fixed Effect Coefficient**	**Std Error**	**df**	**t-value**	**p-value**
Race AA	27.61377	0.1177252	348856	234.56126	**0.0000**
Race AP	4.564302	0.1202074	34429	37.97023	**0.0000**
Race MR	-0.580367	0.3184499	34429	-1.82248	0.0684
Race N	-1.925704	0.2985486	34429	-6.45022	**0.0000**
Race U	0.188553	0.4541324	34429	0.41519	0.6780
Race W	-0.249168	0.1055121	34429	-2.36151	0.0182
L_Ethnicity	0.506634	0.1934215	34429	2.6133	0.0088
Age	0.095745	0.048605	348856	19.69854	**0.0000**
Education	1.04718	0.0767418	348856	13.64551	**0.0000**
Gender	-2.831054	0.1064497	34429	-26.59522	**0.0000**
US Recession	0.129988	0.0610367	348856	2.12967	0.0332
RealGDP_Metro	0.000048	0.000003	348856	16.04837	**0.0000**
RamseyCo_UnemplRt	-0.45145	0.0194284	348856	-23.23657	**0.0000**
monthcount	0.084741	0.0022161	348856	38.23815	**0.0000**

$\alpha = 0.01$

Table 5.7 shows that when the real GDP increases, MFIP participants' earnings increase. When the unemployment rate increases, MFIP participants' earnings decrease. Race is significant, but not for all race categories. Because of previous research showing African Americans being among the most disadvantaged welfare participants (Sheely, 2012; Kwon & Meyer, 2011; Hollister et al., 2003; McDonnell, 2004; DeMaster, 2009; Collins & Xaykaothao, 2015; Minnesota Department of Human Services, 2011), the race category for African American/African Immigrant was used as the comparison race. According to the results, Asian/Pacific Islanders earn significantly more than African Americans, and Native Americans earn significantly less. All other race categories (multiple races, White, and unknown) do not earn significantly more or less than African Americans/African Immigrants. Age is also significant; earnings increase as MFIP participants get older. Education also significantly impacts MFIP participants' earnings; those with a high school diploma or GED earn significantly more than those who have not finished high school. Gender is also significant. Females earn significantly less than males do, even though the majority of MFIP participants are female. Finally, *monthcount* is significant; participants tend to earn more during their later months on MFIP.

Predictor variables: Ramsey County median income and Ramsey County poverty rate. ANOVA tests show that both median income and poverty rate in Ramsey County have a significant impact on MFIP participants' earnings ($p < 0.0001$, $p = 0.0002$, respectively; $\alpha = 0.01$) (see Table 5.8). The hypothesis that local economic conditions, as measured by Ramsey County median income and Ramsey County poverty rate, have a significant impact on Ramsey County MFIP participants' earnings is supported. In terms of the control predictors, race, age, education, and gender show significance (all p-values < 0.0001; $\alpha = 0.01$). Latino ethnicity is not significant (in these results) in predicting earnings ($p = 0.0854$; $\alpha = 0.01$). The time variable, *monthcount*, also significantly impacts MFIP participants' earnings ($p < 0.0001$; $\alpha = 0.01$).

Table 5.8. ANOVA:
Ramsey County Median Income and
Ramsey County Poverty Rate on Earnings

	ANOVA F-test	ANOVA p-value
Race	565.5	**<0.0001**
L_Ethnicity	3	0.0854
Age	1189.9	**<0.0001**
Education	218	**<0.0001**
Gender	473.2	**<0.0001**
Ramsey Co. Median Income	466.1	**<0.0001**
Ramsey Co. Poverty Rate	13.5	**0.0002**
monthcount	1623.5	**<0.0001**

$\alpha = 0.01$

The p-values from the ANOVA table indicate which variables are significant in predicting differences in MFIP participants' income. To understand the direction of significance, examining the unstandardized coefficients of the fixed effects (see Table 5.9).

Table 5.9. Fixed Effects:
Median Income and Poverty Rate in Ramsey County on Earnings

Predictor	Unstandardized Fixed Effect Coefficient	Std Error	df	t-value	p-value
Race AA	27.282284	0.1162729	355124	234.64007	**0.0000**
Race AP	4.593668	0.1192249	33975	38.52942	**0.0000**
Race MR	-0.608988	0.3245876	33975	-1.87619	**0.0606**
Race N	-1.925887	0.2906211	33975	-6.6268	**0.0000**
Race U	0.411311	0.4450229	33975	0.92425	0.3554
Race W	-0.208589	0.1034329	33975	-2.01666	0.0437
L_Ethnicity	0.424628	0.1925108	33975	2.20574	0.0274
Age	0.087869	0.0047977	355124	18.31469	**0.0000**
Education	1.051801	0.0755031	355124	13.93056	**0.0000**
Gender	-2.841983	0.1052589	33975	-26.99971	**0.0000**
MedianIncome_RamseyCo	0.000159	0.0000104	355124	15.27846	**0.0000**
PovertyRate_RamseyCo	-0.135455	0.0130683	355124	-10.36518	**0.0000**
monthcount	0.089738	0.0022272	355124	40.29221	**0.0000**

$\alpha = 0.01$

Table 5.9 shows that when the median income increases, MFIP participants' earnings increase. When the poverty rate increases, MFIP participants' earnings decrease. Race is significant, but not for all race categories. Again, the race category for African American/African Immigrant is used as the comparison race. Results are the same as the previous model: Asian/Pacific Islanders earn significantly more than African Americans, and Native Americans earn significantly less. All other race categories (multiple races, White, and unknown) do not earn significantly more or less than African Americans/African Immigrants when the economic conditions predictor variables are changed. Age is significant; earnings increase as MFIP participants get older. Having a high school diploma or GED significantly increases earnings. Gender is significant again.

Females earn significantly less than males earn. MFIP participants' earnings increase significantly as they progress through the program.

Conditional model 2: Impact of economy on hours worked. The models discussed next address the following question: to what extent do economic conditions (particularly during economic recessions), and person-level differences (race, Latino ethnicity, gender, age, and education) influence MFIP participants' employment opportunities in terms of work hours? Figure 5.2 shows changes over time in the percentages of MFIP participants in Ramsey County who are reporting work hours. Figure 5.3 shows changes over time in the average number of hours worked per week. Figure 5.4 provides a breakdown of people who work less than 15 hours per week, between 15 and 24 hours per week, between 25 and 34 hours per week, and 35 or more hours per week, and shows how this changes over time.

Figure 5.2.

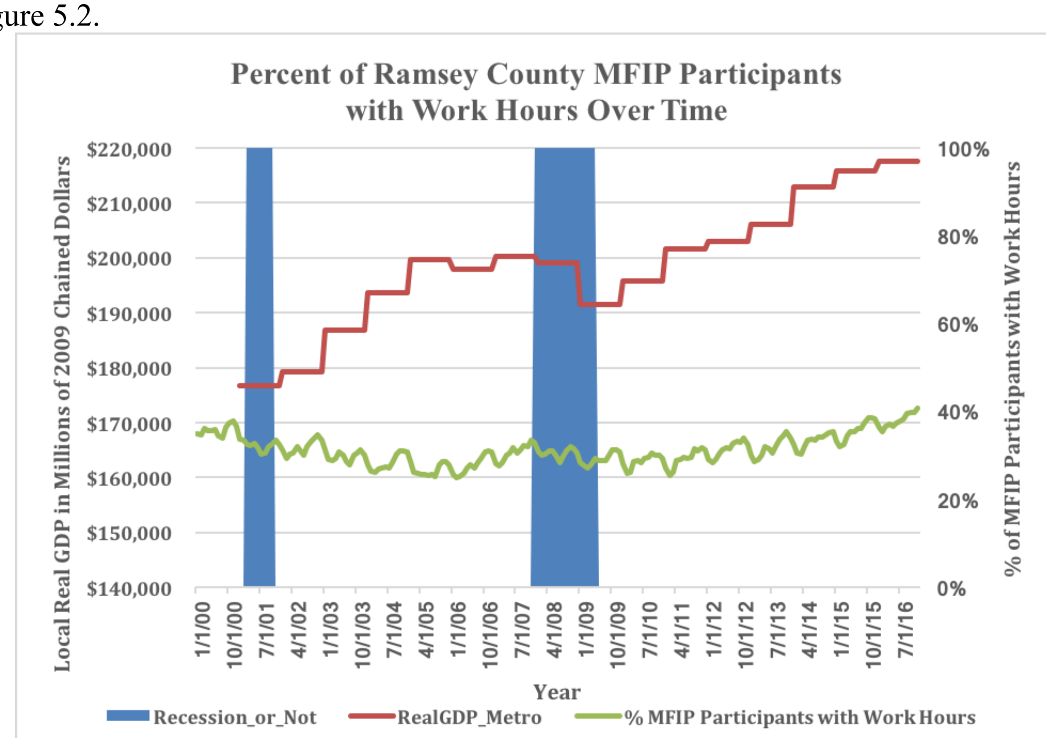


Figure 5.2 shows the two national recessions that occurred between 2000 and 2016, along with real GDP for the local metro area. The lower line represents the percentages of individual adult MFIP participants who are reporting work hours. Percentages of those reporting work hours tend to fall between 30% and 40% over the entire 17-year period, and closely resemble the pattern from Figure 5.1, which shows the percentages of MFIP participants who are earning income. This is to be expected; those who earn income correspondingly report work hours. Like the percentages of those earning income, the percentages for those reporting work hours do not appear to change much, and the graph provides the same information as Figure 5.1 does: the percent of working MFIP participants declined slightly during the 2001 recession, and stayed approximately between 30% and 35% until a slight increase just before the Great Recession, followed by another reduction during the Great Recession until it started rising again in 2014, climbing slightly past 40% again by 2016.

Figure 5.3.

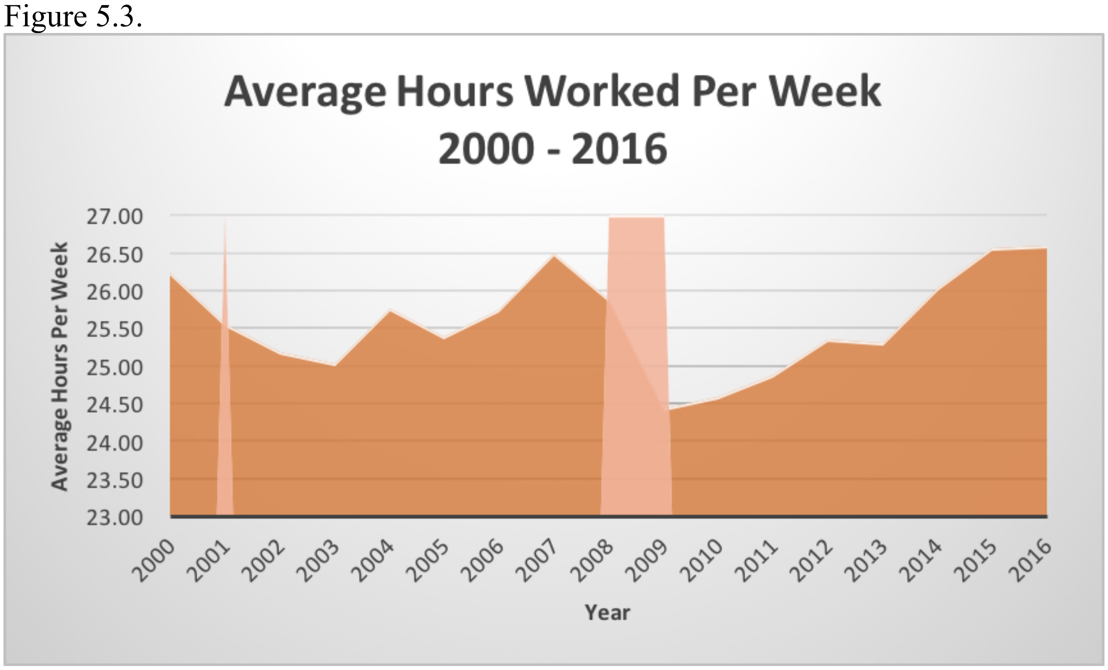


Figure 5.3 shows the average number of hours worked per week between 2000 and 2016. The two bars represent the 2001 and 2007-2009 recessions. The average weekly hours fluctuate between 24 and 27 hours per week, with a relative high in 2007, and a relative sharp decline from 2007 to their lowest in 2009. The decrease in work hours occurred at the end of the Great Recession; hours steadily increased fairly steadily since then.

Figure 5.4.

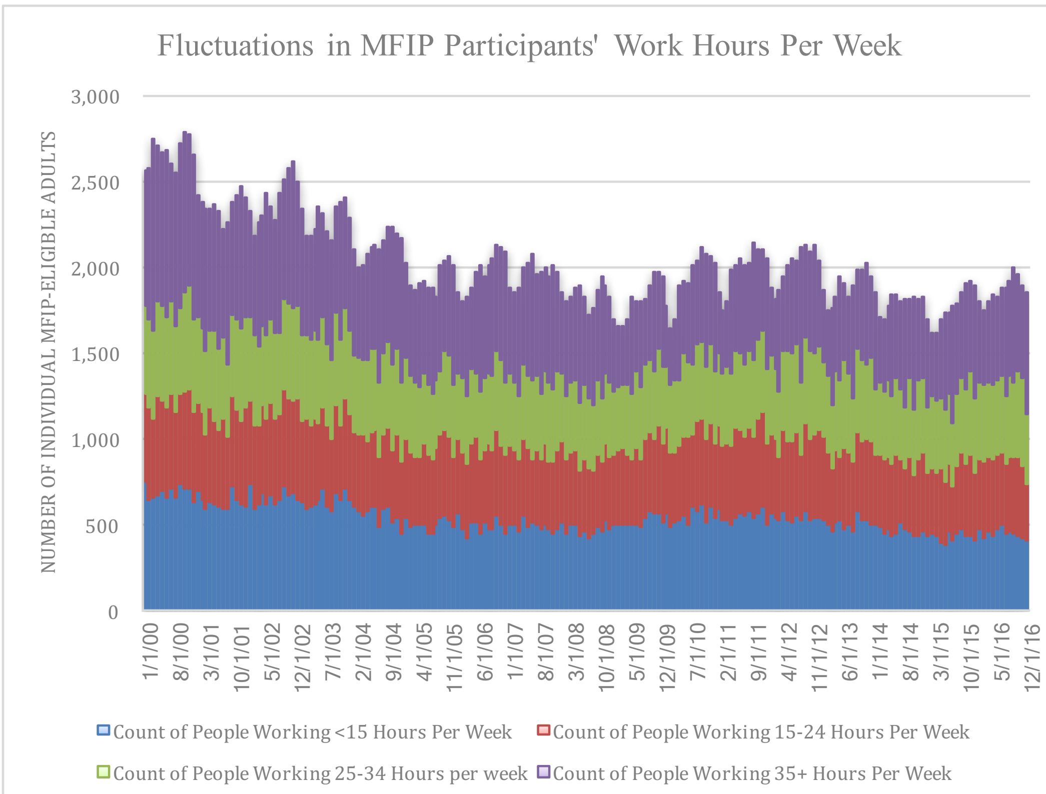


Figure 5.4 shows the monthly count of MFIP-eligible adults from 2000 – 2016 as a stacked column. Each column is broken down into four ranges of hours worked per week: less than 15, 15 to 24, 25-34, and 35 or more. The four ranges of hours remain fairly stable over time, relative to caseload size. Late 2009 to early 2010 shows more participants working less than 15 hours per week, and fewer participants working 35 or

more hours per week compared to most of the other years; aside from that, it appears that there is little fluctuation in the distribution of hours worked per week. However, even minimal changes in hours can greatly impact MFIP participants' financial wellbeing. For example, if someone is earning the state minimum wage ($7.75/hour in 2017), going from 24 hours per week to 30 hours per week means an approximate increase of $186/month in gross income.

Predictor variables: U.S. Recession, local real GDP, and Ramsey County unemployment rate. ANOVA tests show that the condition of the local economy, as measured by the metropolitan area for Minneapolis-St. Paul-Bloomington, MN-WI, and the Ramsey County unemployment rate have a significant impact on MFIP participants' hours ($p < 0.0001$; $\alpha = 0.01$), but national recessions do not ($p = 0.1699$; $\alpha = 0.01$) (see Table 5.10). The hypothesis that economic conditions have a significant impact on Ramsey County MFIP participants' work hours is rejected at the national level, but supported at the local level, when measured by the local real GDP and the Ramsey County unemployment rate. In terms of the control predictors, race, age, and gender show significance (all p-values < 0.0001; $\alpha = 0.01$). Latino ethnicity is not significant (in these results) in predicting hours worked ($p = 0.0379$; $\alpha = 0.01$). Education is also not significant in predicting work hours ($p = 0.0750$; $\alpha = 0.01$).

Table 5.10. ANOVA: National Recession, Local Real GDP, and Ramsey County Unemployment Rate on Hours Worked		
ANOVA F-test		ANOVA p-value
Race	689.2	**<0.0001**
L_Ethnicity	4.3	0.0379
Age	903.3	**<0.0001**
Education	3.2	0.0750
Gender	435.9	**<0.0001**
National Recession	1.9	0.1699
Local Real GDP	95.4	**<0.0001**
Ramsey Co. Unempl. Rt.	388.7	**<0.0001**
monthcount	1016.3	**<0.0001**

$\alpha = 0.01$

Because the ANOVA table cannot provide the direction of significance, the unstandardized coefficients of the fixed effects are necessary to understand how each predictor variable impacts MFIP participants' work hours (see Table 5.11).

Table 5.11. Fixed Effects:
National Recession, Local Real GDP, and Ramsey County Unemployment Rate on Hours Worked

Predictor	Unstandardized Fixed Effect Coefficient	Std Error	df	t-value	p-value
Race AA	9.290082	0.03208305	348744	289.56358	**0.0000**
Race AP	1.325995	0.03228163	34477	41.07583	**0.0000**
Race MR	-0.158615	0.0847623	34477	-1.8713	0.0613
Race N	-0.434261	0.08021405	34477	-5.41378	**0.0000**
Race U	0.063817	0.12319849	34477	0.518	0.6045
Race W	-0.154176	0.02831463	34477	-5.44512	**0.0000**
L_Ethnicity	0.120082	0.05181033	34477	2.31772	0.0205
Age	0.022386	0.00131108	348744	17.07459	**0.0000**
Education	0.046566	0.02133058	348744	2.18304	0.0290
Gender	-0.749089	0.0287777	34477	-26.03019	**0.0000**
US Recession	-0.003992	0.01831912	348744	-0.21789	0.8275
RealGDP_Metro	-0.000001	0.00000084	348744	-1.27581	0.2020
RamseyCo_UnemplRt	-0.122289	0.00566581	348744	-21.58368	**0.0000**
monthcount	0.018284	0.00057353	348744	31.87965	**0.0000**

$\alpha = 0.01$

Table 5.11 shows that when the real GDP increases, MFIP participants' hours decrease; however, this is not a significant fixed effect, so the impact of GDP on work hours, however significant, is minimal. When the unemployment rate increases, MFIP participants' hours decrease. Race is significant, but not for all race categories. African American/African Immigrant is the comparison race, as in the other models. According to the results, Asian/Pacific Islanders work significantly more hours than African Americans, and Native Americans and Whites work significantly fewer hours. Those who identify as having multiple races or unknown races do not work significantly more or fewer hours than African Americans/African Immigrants. As with income, age is also significant; work hours increase as MFIP participants get older. Gender is also significant, as it is with income. Females report significantly fewer work hours than males do. Finally, *monthcount* is significant; participants tend to work more hours during their later months on MFIP.

Predictor variables: Ramsey County median income and Ramsey County poverty rate. ANOVA tests show that both median income and poverty rate in Ramsey County have a significant impact on MFIP participants' work hours ($p < 0.0001$; $\alpha = 0.01$) (see Table 5.12). The hypothesis that local economic conditions, as measured by Ramsey County median income and Ramsey County poverty rate, have a significant impact on Ramsey County MFIP participants' work hours is supported. In terms of the control predictors, race, age, and gender show significance (all p-values < 0.0001; $\alpha = 0.01$). Education is barely significant ($p = 0.0105$; $\alpha = 0.01$). Latino ethnicity is not significant in predicting hours worked ($p = 0.0627$; $\alpha = 0.01$). The time variable, *monthcount*, also significantly impacts MFIP participants' hours ($p < 0.0001$; $\alpha = 0.01$).

Table 5.12. ANOVA: Ramsey County Median Income and Ramsey County Poverty Rate on Hours Worked		
	ANOVA F-test	ANOVA p-value
Race	704.9	**<0.0001**
L_Ethnicity	3.5	0.0627
Age	820	**<0.0001**
Education	6.6	0.0105
Gender	435.9	**<0.0001**
Ramsey Co. Median Income	23.8	**<0.0001**
Ramsey Co. Poverty Rate	81.9	**<0.0001**
monthcount	1130.2	**<0.0001**

$\alpha = 0.01$

In order to understand the significance suggested by the ANOVA table, the unstandardized coefficients of the fixed effects convey the impact of each of these variables on work hours (see Table 5.13).

Table 5.13. Fixed Effects:
Median Income and Poverty Rate in Ramsey County on Hours Worked

Predictor	Unstandardized Fixed Effect Coefficient	Std Error	df	t-value	p-value
Race AA	9.243217	0.03212852	354923	287.69676	**0.0000**
Race AP	1.346988	0.03242077	34027	41.54705	**0.0000**
Race MR	-0.128951	0.08747746	34027	-1.47411	0.1405
Race N	-0.450779	0.07919142	34027	-5.69227	**0.0000**
Race U	0.068314	0.12223477	34027	0.55888	0.5763
Race W	-0.150528	0.02812289	34027	-5.35251	**0.0000**
L_Ethnicity	0.117417	0.05224426	34027	2.24747	0.0246
Age	0.021509	0.00131097	354923	16.40689	**0.0000**
Education	0.065222	0.02125449	354923	3.06864	0.0022
Gender	-0.746053	0.02884342	34027	-29.86561	**0.0000**
MedianIncome_RamseyCo	0.000015	0.00000304	354923	4.90062	**0.0000**
PovertyRate_RamseyCo	-0.054976	0.00379627	354923	-14.48163	**0.0000**
monthcount	0.019753	0.00058755	354923	33.61915	**0.0000**

$\alpha = 0.01$

Table 5.13 shows that when the median income increases, MFIP participants' work hours increase. When the poverty rate increases, MFIP participants' work hours decrease. Race is significant, but again, not for all race categories. As in the other models, African American/African Immigrant is the comparison race. According to the results, Asian/Pacific Islanders work significantly more hours than African Americans, and Native Americans and Whites work significantly fewer hours. Those who identify as having multiple races or unknown races do not work significantly more or fewer hours than African Americans/African Immigrants when the economic predictor variables change. As with income, age is also significant; work hours increase as MFIP participants get older. Gender is also significant, as it is with income. Females report significantly fewer work hours than males do. Finally, *monthcount* is significant again; participants tend to work more hours during their later months on MFIP.

Time effects on hours worked. The time effects model replaces all economic indicator predictor variables with dummy coded year variables for time, as a means to examine the impact of time on MFIP participants' work hours. It is a different way to consider trends over time, outside of economic conditions. The time effects model addresses the following question: to what extent does time, particularly the years covered in this study during which the United States experienced two recessions, influence MFIP participants' employment opportunities in terms of work hours, after controlling for person-level differences (race, Latino ethnicity, gender, age, and education)? Table 5.14 shows the ANOVA results for time effects. All years except 2001 show a significant time effect on MFIP participants' work hours.

Table 5.14. ANOVA:
Time Effects on Hours Worked

	ANOVA F-test	ANOVA p-value
Race	746.0	**<0.0001**
L_Ethnicity	4.8	0.0280
Age	916.8	**<0.0001**
Education	4.0	0.0443
Gender	480.9	**<0.0001**
Year 2001	0.0	0.8696
Year 2002	28.5	**<0.0001**
Year 2003	24.8	**<0.0001**
Year 2004	38.5	**<0.0001**
Year 2005	14.9	**0.0001**
Year 2006	10.4	**0.0013**
Year 2007	25.9	**<0.0001**
Year 2008	8.2	**0.0043**
Year 2009	9.5	**0.0020**
Year 2010	29.2	**<0.0001**
Year 2011	23.9	**<0.0001**
Year 2012	23.0	**<0.0001**
Year 2013	66.5	**<0.0001**
Year 2014	8.4	**0.0038**
Year 2015	11.8	**0.0006**
Year 2016	24.0	**<0.0001**

$\alpha = 0.01$

Table 5.14 provides evidence in support of the hypothesis that time has a significant impact on predicting Ramsey County MFIP participants' work hours. To examine whether each year shows growth or decline in work hours, the coefficients were graphed. Figure 5.5 shows the coefficient change in MFIP participants' work hours.

Figure 5.5.

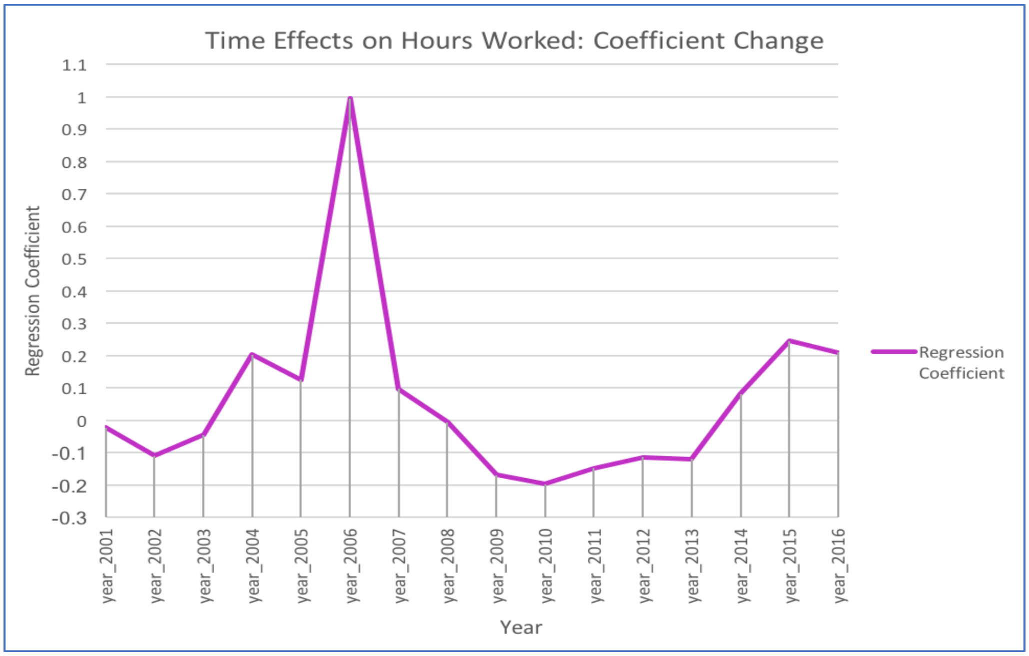


Figure 5.5 shows the coefficient change per year, and provides evidence of a time trend. The coefficients change the most from 2005-2006, and from 2006-2007. It is important to note that this is a graph of coefficient change, not the number of hours worked. The line does not show the direction of change; rather, the positive and negative signs to the left of the coefficients indicate whether there was growth or not. A coefficient above zero shows growth. For example, the perceived "drop" between 2006 and 2007 actually shows that growth occurred, but at a much slower rate because the coefficient is still positive. The years between 2008 and 2013 show negative growth because the coefficients are negative. Figure 5.5 demonstrates the persistent, lasting effect of time on hours worked. It is consistent with what the mixed effects models with economic indicators as the predictor variables show. National recessions tend to have little impact at the time, and the local economy experiences lagging effects, for Ramsey County MFIP participants in particular, as the national economy begins to recover.

Conclusions on findings. Chapter 5 presents the results of descriptive statistics and the final linear mixed effects regression models. Descriptive statistics show that MFIP participants who earn income do not greatly differ from the entire population. This indicates that the working and non-working participants are similar, and is evidence that many of those who are not earning income at one point, eventually do.

The main findings from the mixed effects models show that the condition of the national economy, as measured by a dummy variable based on NBER's definition of a recession, have little impact on whether or not Ramsey County MFIP participants earn income, how much they earn, and how many hours they work. The condition of the local economy, as measured by the local real GDP, Ramsey County unemployment rate, Ramsey County median income, and Ramsey County poverty rate, does have a significant impact on MFIP participants' earnings and work hours. In particular, as the local economy declines, Ramsey County MFIP participants' earnings and work hours significantly decline.

In terms of the control predictor variables, race, age, and gender show significance in predicting both earnings and hours worked. Education is significant for earnings, but not hours worked. Latino ethnicity is not significant in predicting earnings or hours worked. The next chapter more closely examines what these findings mean.

Chapter 6

Discussion

Federal welfare reform, and by extension state- and county-administered programs, aims to decrease dependence on government assistance by promoting labor market participation. Welfare reform contends that employment is a better alternative to public assistance, and it no doubt is, but it does not include stipulations that guard against slow economies, which greatly impact low-income families. At the turn of the millennium, Ziliak et al. (2000) and Blank (2002) surmised that it would be beneficial for welfare reform research to focus on the impact of economic cycles to consider welfare reform's efficacy in the context of the greater economy, particularly since welfare reform encourages work as a means to achieve self-sufficiency. Now that twenty years of post-PRWORA economic cycles data exists, this dissertation examines the degree to which Ramsey County MFIP participants' employment opportunities are limited by both national and local economic conditions by asking the following question: to what extent do economic conditions, particularly those of the local economy, impact welfare reform participants' employment opportunities in terms of earnings and hours worked? Findings indicate that although national recessions tend to have little impact at the time they are occurring, local economies experience lagging effects, to which Ramsey County MFIP participants are highly susceptible. This chapter closely examines what the findings of this study mean and connects them to previous research.

Economic Conditions

In the pre-welfare reform years, when AFDC was still the federal policy for means-tested public assistance, researchers suspected that a strong economy could potentially have a larger impact on the success of welfare-to-work programs than the programs themselves (Ziliak, Figlio, Davis, & Connelly, 2000). In the years following TANF's inception, advocates on behalf of the poor suspected that the corresponding robust economy contributed to welfare reform's declining caseloads (Danziger, Weiderspan, and Douglas-Siegal, 2013). Several researchers agree that the economy plays a larger role than proponents of welfare reform may want to acknowledge. This dissertation provides evidence to support the speculations that economic conditions do, in fact, influence employment opportunities for welfare reform participants, particularly in Ramsey County, Minnesota.

This dissertation asks, to what extent do economic conditions, particularly those of the local economy, impact welfare reform participants' employment opportunities in terms of earnings and hours worked? Findings indicate that the lagging impacts of national recessions, such as increased unemployment and poverty, significantly affect welfare reform participants; however, it takes several months once a national recession begins for this locality to experience the consequences. If the condition of the national economy and the condition of the local economy followed trends parallel to each other, real GDP for the metro area closest to Ramsey County (Minneapolis-St. Paul-Bloomington, MN-WI), would decrease in the months leading to a national recession; however, it remained stable during the March – December 2001 recession; during the Great Recession of 2007 – 2009, it began to decrease as the national recession was ending, then dropped quite a bit, and then started to increase again a few months after the Great Recession ended. This is evidence that Minnesota, particularly the metropolitan area of Minneapolis-St. Paul lags behind the nation in experiencing the impact of a national recession, and therefore, it makes sense that a national recession would have little immediate impact on MFIP participants in Ramsey County.

Previous research suggests a strong need for a closer examination of the economy's role in promoting self-sufficiency for welfare reform participants (Blank, 2000). Given that TANF is a federal program but administered at the state and local levels, it is imperative to consider local economic conditions specific to states and counties when analyzing the impact of economic conditions. For this study, economic indicators that reflect the condition of the local economy are better predictors for MFIP participants' earnings and work hours than national recessions. The real GDP of the metropolitan area of Minneapolis-St. Paul, median income, rising unemployment rates, and rising poverty rates are all significantly linked to Ramsey County MFIP participants' earnings and work hours. As real GDP and median income increase, evidence of a growing economy, MFIP participants' earnings and hours increase. As unemployment and poverty increase, evidence of a shrinking economy, MFIP participants' earnings and work hours decrease. It is possible that there are fewer jobs available in the formal labor market when the economy is slow, particularly for jobs that rely on consumers to purchase goods and services. During recessions, if people in the general population reduce their spending on nonessential items and services (for example, dining out), there may not be as many of these jobs available for MFIP participants who tend to have less education and fewer job skills, and are often employed part time, in jobs that do not offer unemployment insurance, as in service sector industries. Furthermore, with less work available from the formal labor market, it is possible that during times of economic downturns, participants are earning income from informal work arrangements and not reporting it, which means the data may show fewer participants have income than what is actually happening; however, such jobs are unstable and are examples of what people need to do in order to survive when the economy falters, jobs disappear, and services inadequately address their needs and challenges. These findings support what Danziger, Weiderspan, and Douglas-Siegal (2013) assert: that there is a great need for stability in the job market for low-income workers, especially during recessions.

Race, Age, Education, and Gender

This research clearly indicates that local economic conditions impact MFIP participants in Ramsey County. Additionally, it shows that person differences have a significant impact on MFIP participants' employment opportunities in terms of earnings and work hours, regardless of economic conditions, but do not have the same impact across all person-level predictors. In general, the person differences affect earnings more so than they affect hours. This could reflect that people work similar numbers of hours, but do not necessarily earn the same for the for working the same amount of time. This section details the impact of the person-level predictor variables, linking findings to previous research.

Race. Existing research clearly shows that African Americans are among the most disadvantaged welfare reform participants (Hollister et al., 2003; McDonnell, 2004; DeMaster, 2009; Kwon & Meyer, 2011; Minnesota Department of Human Services, 2011; Sheely, 2012; Collins & Xaykaothao; 2015). In this research, race is a significant predictor for both earnings and hours, but not in the same way for both. Due to the strong evidence that African Americans in particular experience considerable discrimination, African American/African Immigrant is used as the comparison race group for this study.

Findings show that Asian/Pacific Islanders earn and work significantly more hours than African Americans/African Immigrants. Native Americans earn and work significantly less than African Americans/African Immigrants. Whites' earnings do not significantly differ from African Americans'/African Immigrants', but they work significantly fewer hours. These significances are constant across models, regardless of the economic conditions predictor variables in each model. Given that African Americans/African Immigrants are over-represented on MFIP in Ramsey County more than any other race group (42.6% of Ramsey County MFIP participants compared to 12.0% of Ramsey County (U.S. Census Bureau, 2016)), that past research has found more evidence of racial disparities particularly for African American MFIP participants, and that the results of this research that indicate they earn less than at least one other racial group is disconcerting. Additionally, given that White participants' earning are similar to African American/African Immigrants' but they work significantly fewer hours indicates that White participants earn more per hours worked. The models in this research assume that there are no interactions between the predictor variables, and therefore do not provide the full impact race may have on earnings and hours. For example, there could be an interaction between race and gender that these models do not show. Furthermore, research using transformed data can only provide distorted interpretations of the results; rather than conclude that race is less significant than it is, the results of this research as they pertain to race are at best, significant in unknown ways, and at worst, inconclusive. It is also important to note that these results are specific to MFIP participants in Ramsey County, and covers a 17-year period. Looking at smaller periods of time may provide a more nuanced understanding of how employment opportunities vary depending on race;

more research is needed to understand its relative impact. Finally, it is essential to understand that race is self-reported by participants, and that employers have their own biases. If someone appears to belong to a particular racial group to an employer, even if that person does not identify as such, s/he could be subject to discrimination in ways that this study cannot capture.

Age. To be consistent with previous research that controls for age (Kwon & Meyer, 2011; Hanratty, 2016), this study includes age as a predictor control variable. Given that the aforementioned studies control for age and use different statistical methods (generalized estimating equation regression models, and Cox proportional hazard models, respectively), and that mixed effects models do not distinguish between control and predictor variables, the findings on age are interpreted differently for this study. Age is a significant predictor in both models that use both earnings and hours worked as response variables. In general, as MFIP participants age, their income and hours increase significantly. The models cannot say how much income and hours increase for every year participants age, but age does appear to be an important factor in employment opportunities. Younger MFIP participants could still be finishing high school or a GED instead while working part time and reporting fewer hours than those who are older, and their reduced hours could be impacting the age variable; however, they make up about 4% of the population, and of the parents under age 18, only 14.6% of them report earnings. As participants age, so do their children; the presence of young children in the home may impact the amount MFIP parents may work, so it is reasonable to conclude that age contributes to more work opportunities simply because children may need less supervision, participants have more time to work, and have gained more experience and transferable skills for better paying jobs.

Education. Previous research on welfare reform outcomes, particularly in Minnesota, shows that education plays a major role in determining the welfare-to-work experience MFIP participants have; those with more education appear to have more success in the program (Hollister et al., 2003; McDonnell, 2004). In this research, results on education are slightly less clear than the other control predictor variables. In the models that use the national recession variable, real GDP for the metropolitan area of Minneapolis-St. Paul, and the Ramsey County unemployment rate, education has a significant impact on earnings, but not work hours. These economic indicators show that earnings increase significantly for those who have a high school diploma or a GED; however, work hours do not significantly increase with a high school education. This may demonstrate that more education, at least having graduated from high school or obtained a GED, may increase earnings, but not hours; thus, with more education, people earn more per hour. In the models that use the median income for Ramsey County and the poverty rate for Ramsey County, education has a significant impact on both earnings and hours. Rather than deem the impact of education ambiguous based on these results, it is noteworthy that having a high school degree accounts for higher income in three of the four models run.

Gender. Although the majority of MFIP participants are female, throughout history, women have been economically disadvantaged, especially when turning to government assistance for a financial safety net in trying circumstances (Abramovitz, 1996; Abramovitz, 2000; Abramovitz, 2001, Brush, 2003; Mink & Solinger, 2003). This research supports what others have found regarding gender, that females tend to have more difficulties in maintaining earnings and work hours sufficient to support a family. Findings from this dissertation show that gender is a significant predictor for Ramsey County MFIP participants' earnings and hours. Despite females comprising three-quarters of this population, they earn significantly less than males do, as evidenced by all models run in the analyses. Females also work significantly fewer hours than males work. At its original inception, ACD was intended to help single mothers, and the results of this study show that TANF, its current successor, is still not adequately addressing their needs or providing enough employment opportunities to move them out of a system that appears to be biased against them. Low-income, single mothers face unique obstacles in moving into work. Childcare needs to be affordable, close, and open during hours that support women who have unpredictable work schedules. As primary care-givers for their children (and overrepresented as heads of single-parent families in this study), they are responsible for raising them and making sure their basic needs are met, and are often forced to choose between working to support them and staying home with them to raise them; choosing the latter means they often turn to public assistance as a way to provide basic necessities. If, as these results indicate, women on MFIP earn less and work fewer hours, they are at a significant disadvantage for moving from welfare to work. Furthermore, as Brush (2003) points out, welfare reform law generates difficulties for single mothers who are trying to balance earning income with family responsibilities by not affording them the opportunity to decide whether working outside of the home or staying at home with their children is the best option for their families.

This dissertation provides a contemporary contribution to research done at the turn of the millennium, when TANF was less than a decade old. Previous research implores those who analyze social welfare policy to seriously consider economic conditions in future studies of welfare reform, long before enough time had passed to examine the impact of economic fluctuations on welfare reform participants (Blank, 2002). This research utilizes a seventeen-year time period, during which the United States experienced two recessions, and finds that when the local economy is experiencing the lagging impact of national economic recessions, especially in terms of increased poverty and unemployment rates, employment opportunities are significantly reduced for MFIP participants in Ramsey County. In light of these findings, the next chapter offers suggestions for how policy can respond and help members of society who, without a sufficient financial safety net, are more apt to struggle in times of economic downturns.

Chapter 7

Implications

As the United States experiences inevitable ebbs and flows in economic conditions, it is imperative to remember that the impact of a recession is disproportionately felt among lower-income families, who in times of financial crisis, have little to no safety net of their own, and who, despite working hard or trying hard to find work, cannot make ends meet when hours are reduced or lay-offs occur, and cannot find work when opportunities retreat as a result of the larger economy. Ample research exists on the impact of recessions, particularly the Great Recession of 2007 – 2009; for example, Krosch and Amodio (2014) examine perceptions of race during and in the aftermath of the Great Recession, Farber (2012) looks at unemployment in conjunction with the housing market crash, and Christensen (2015) critically examines the Great Recession's impact on women, especially women of color. This dissertation fills a gap in the literature by focusing specifically on the impact of the recession on very low-income families.

Given what previous research and this dissertation collectively show regarding the obstacles welfare reform participants face in precarious financial times, social welfare advocates, researchers, and policy makers need to be asking what can be done to address the needs of the most economically disadvantaged families, especially when the economy falters. The final chapter of this dissertation explores possibilities for improving the way existing policies address the needs of low-income families, especially during hard economic times when wealthier families can rely on their own resources until a recession ends.

Policy Implications Considering Economic Indicator Predictors

This dissertation is most concerned with the extent to which economic conditions impact welfare reform participants' work opportunities; the answer to its research question is that local economic conditions play a significant role in Ramsey County MFIP participants' earnings and work hours. Researchers at the beginning of the millennium called for examinations of how economic conditions affect low-income families (Ziliak et al., 2000; Blank, 2002). As years passed and TANF research faded into the background, social welfare advocates repeatedly called for more research to examine its efficacy (Sheely, 2012; Kwon & Meyer, 2013). This dissertation answers those calls and provides evidence for changing welfare policy such that the program's goals are more in line with realistic opportunities, given local economic conditions. Federal welfare reform expects work from its participants, without regard to economic conditions; it requires participants to find and maintain employment, but does not provide adequate work opportunities when the local economy declines. If opportunities were sufficient, the results of this research would not show a significant decrease in income and work hours during times when the local economy is slow. This section describes the federal government's response to the Great Recession's impact on TANF participants, and the section that follows offers suggestions for alternatives to solely focusing on TANF when recessions occur.

Federal government's response to the Great Recession: ARRA. Under the American Recover and Reinvestment Act (ARRA) of 2009, the federal government introduced the TANF Emergency Contingency Fund, which allowed states to apply for emergency funds to supplement state-administered TANF programs to help states fund cash assistance for increased caseloads, subsidized employment programs, and other programs that align with TANF's goals (such as those that aim to reduce teen pregnancies and out-of-wedlock births) (Public Law 111-5). It is important to point out that these contingency funds were not entitlements, automatically granted to states. Were these funds sufficient to offset the impact of the Great Recession? Haskins, Albert, and Howard (2014) provide evidence that that they did, indeed, have a considerable and positive impact on TANF families during and after the Great Recession, particularly in Minnesota, which, according to their report, experienced lower increases in unemployment and lower caseload increases than many other states. The findings from this dissertation suggest that this was not the case for Ramsey County MFIP participants. Furthermore, the 2014 Minnesota Legislature developed a task force to examine TANF's impact on Minnesota families and make recommendations for policy improvements, which is evidence that Minnesota's welfare reform policy stakeholders were skeptical of the federal government's response to helping TANF families during the Great Recession (Minnesota Department of Human Services, 2015). The task force calls attention to an alarming fact: "In 1986, the cash grant provided families with a cash resource that met approximately 70 percent of the federal poverty level. Today, the MFIP cash grant is only worth 32 percent of the federal poverty level, far below the federal definition of deep poverty, which is 50 percent of federal poverty guidelines" (Minnesota Department of Human Services, 2015, p. 5). Their recommendations include increasing the cash grant to reflect inflation and cost of living increases, create programming that addresses building assets and increased financial literacy, increase opportunities to enhance job skills and further education, and remove child support as well as income from training as earnings that count against the cash grant (Minnesota Department of Human Services, 2015). Although all of these recommendations are reasonable and, if implemented as suggested, have considerable potential to improve the quality of life for MFIP participants, the current legislative branch, especially at the federal level, is not likely to favor them.

This dissertation provides evidence that ARRA was not a sufficient response to the Great Recession for Ramsey County MFIP participants, and recommends moving beyond TANF to address the needs of low income families during times of recessions. Other policies that indirectly target TANF participants could have a larger impact on their lives in political climates that do not favor increased funding for TANF. The next two sections offer suggestions for policy reform alternative to changing or expanding TANF.

Policy changes not limited to welfare reform. Recommendations made in previous research center around extending TANF contingency funding (Sheely, 2012; Kwon & Meyer, 2011), but they should not stop there. States are limited by federal requirements, but are given liberty to use state dollars to more fully address the needs of their welfare reform participants. MFIP does, in fact, acknowledge unique hardships its participants experience, and through a combination of using state dollars to fund programs, particularly Family Stabilization Services, and a multitude of exemption categories, addresses these challenges prior to requiring employment. However, it is unrealistic to expect one program, even in conjunction with other programs like it, such as housing and child care subsidies, to sufficiently address the needs of low-income families. Given that MFIP participants are particularly vulnerable to changing local economic conditions, policy reform efforts should not be limited to welfare reform; at the very least, the 60-month lifetime limit to receive cash assistance should be disregarded during recessions (Kwon & Meyer, 2011), and sanction policies should be modified during slow economic times so that when jobs become harder to find, low-income families are not further penalized for not complying with Employment Services.

Rather than only targeting MFIP programs and services, program creation should be done in conjunction with reform efforts that focus on higher level employment policy. If the goal is to depend on work rather than welfare, jobs need to provide elements that foster long term self-sufficiency. Moving MFIP participants into work with wages that put them just above the eligibility threshold is not a viable solution to the issue of welfare dependency. The answer is not simply to create more jobs or to increase the job readiness of MFIP participants; instead, employers and corporations need to be held accountable for providing sustainable employment opportunities for low-income families. Understanding that this could be a challenge in the private employment sector, reform efforts should target laws that private employers are expected to uphold. For example, small businesses (those that employ fewer than 50 people) are not held to the same employee protection laws as their large business counterparts. Increasing government-subsidized grants or loans to small business owners to help offset the costs of complying with stricter employment laws may be a more politically acceptable approach in the current political climate. Constituents may be more likely to support efforts to help small businesses than to increase welfare spending. Emphasizing community engagement by supporting small employers and by lifting their employees away from poverty could reduce poverty while upholding TANF's objective to promote work.

More laws should be created and enforced that foster job security and that protect part time workers, such as paid sick time, no punitive action taken against parents who call in to address the needs of their children, onsite childcare, and possibilities for moving into full time work. Policy changes outside of welfare reform are necessary to address the needs of the most economically vulnerable MFIP participants and ultimately provide them with the financial security necessary to withstand a changing economy.

Policy Implications Considering Significant, Person-Level Predictors

In addition to economic indicators predicting significant declines in earnings and work hours for Ramsey County MFIP participants, this research reflects what past research shows in terms of employment opportunities being significantly impacted by race, gender, and education (Brush, 2003; Hollister et al., 2003; McDonnell, 2004; DeMaster, 2009); therefore, efforts to reform both welfare and employment policies should be particularly concerned with increasing opportunities for women and minorities. Previous research recommends giving a voice to welfare reform program participants in terms of service improvement (Danziger, Wiederspan, & Douglas-Siegel, 2013). One way to do this would be to give participants, particularly single mothers and minority mothers, a voice in such reform efforts, which could lead to increased understanding by employers of the notable challenges single mothers with young children face.

Although the best starting point would be focusing on policy changes to welfare reform at the federal level such that laws include opportunities to resolve the conflicting objectives between full time parenting and employment, simultaneously targeting both welfare reform laws and employment laws may yield better outcomes for welfare reform participants. For example, one option would be to increase tax incentives for employers who pay their employees a livable wage rather than the minimum wage, who provide flexible hours for single mothers, and who offer benefits for part time workers. Another option is for stricter consequences to be imposed on employers who practice racial and gender discrimination, including loss of federal and state business subsidies.

This research, like Hollister et al.'s (2003) research, also provides substantial evidence for continuing to support educational endeavors of welfare participants. Advocacy must continue for young parents who have not yet completed high school. Ramsey County already does this with its teen parent program; however, once participants turn 18, they have the option to stop attending high school and go to work. At the very least, more resources should go toward helping them finish school. Furthermore, policy could also help employers support efforts to finish high school degrees while working. For example, employers could be given government-subsidized financial incentives if they offer paid time off so employees may study for exams, and if they offer raises to employees who obtain a high school degree while working. The reform suggestions given do require subsidies from state and federal governments; however, they may have more political appeal if they do not focus on welfare reform.

This study clearly suggests that the condition of the local economy, race, age, gender, and education are significant factors in predicting employment opportunities for Ramsey County MFIP participants. These findings may serve as ground work for analyzing subsets of this dataset or datasets from other counties in Minnesota to further delve into how local economic conditions impact a very diverse population in various ways.

Limitations and Directions for Future Research

No research design is without limitations, and limitations provide avenues for future research. The researcher fully acknowledges the limitations of this study, knowing that these are the only data available on MFIP participants in Ramsey County, and recognizing the challenges in trying to analyze data on a very diverse population, for whom averages cannot provide a complete picture of their lives.

A major limitation of this research concerns the lack of a literal interpretation of the results; using transformed data corrects for non-linearity, but curtails meaning. Results are limited to stating whether or not economic indicators and person differences are significant; they cannot give comparison estimates, as in saying that MFIP participants work a particular number of hours more during robust economies than during recessions, or that males are a certain amount more likely than females to report earnings.

The results show that MFIP participants in Ramsey County are vulnerable to local economic conditions. However, when interpreting the effects of the control predictors on income and work hours, it is unknown if person-level effects would be different during recessions because the models assume there is no interaction between any of them and the economic indicator predictors. To clarify, females earn significantly less than males, regardless of economic conditions. The models cannot say if recessions impact females differently than males. Future research should consider interactions between the control predictors and the economic indicator predictors, and test for differences in how recessions impact females and males, and how they impact different race categories. Another direction for future research would be to compare the demographics of welfare caseloads during times of recessions to demographics during robust economies.

The measure used for the national recession variable and those used to measure local economic conditions are not the same. The national recession variable, *Recession_or_Not*, reflects NBER's declaration of the monthly state of the economy, but does not provide insight into lagging impacts at the national level, such as the national unemployment rate and national poverty rate. Future research may want to measure national and local economic conditions with the same type of variable to determine whether national economic conditions, as measured by lagging recession indicators, have a similar impact on welfare participants in a particular locality. This research was particularly concerned with Ramsey County's economic conditions in the context of the national economy, when it was in a definitive recession; future research should consider lagging indicators at multiple levels: county, state, and national, as another way to study a complex issue.

Trying to fit statistical models to complex human and social contexts is inherently problematic because of the dubious idea of a normal distribution existing in nature, and therefore the social sciences. While applied statistical models, like linear mixed effects models, are sophisticated enough to account for individual variations by providing a way to analyze nested data, they assume a normal distribution and a linear relationship between the response and predictor variables. Using linear mixed effects models on data with skewed response variables (as in this MAXIS dataset, in which zero income and zero hours skew the data) becomes complicated. If normality and linearity are not reflected in the data, transformations may be utilized such that the model assumptions are met and the model can therefore produce useful results. However, there is debate among statisticians and social scientists regarding the advantages of transforming data. Singer and Willett (2003) recommend it over using non-linear models; Lo and Andrews (2015) recommend against it, and prefer employing highly complex generalized linear mixed effects models so as to avoid implications transformed data creates when interpreting the results. In this case, results are less generalizable because they no longer apply to those who do not earn income or report work hours.

This study has considerable statistical power due to the fact it includes all persons on which inferences are drawn; however, there is so much variation between participants that the results become less generalizable to everyone as an individual. Data collected from people experiencing a wide range of challenges unique to themselves, their families, or a small subset of the population to which they belong is brimming with variation. Variation is important, and should be expected in a population as diverse as MFIP participants; however, future research may benefit from analyzing subsets of the population, compared to the population as a whole. Furthermore, with regard to social science research, Speelman and McGann (2013) posit that "[t]here are so many variables, often interacting in non-linear ways, that generalization to the individual simply cannot be a reasonable aim of the discipline" (p. 8). This is not to discount decades of research; it is merely to acknowledge that caution should be practiced when interpreting any results that use averages to describe a particular group of people, particularly very vulnerable members of the population.

It is clear from this research that MFIP participants do not progress through the program in a linear way. Some will earn enough income such that they no longer need cash assistance; they will report this as required, and will transition off MFIP assistance. These are the participants whose MFIP experiences are easiest to analyze, but whose experiences are not generalizable to many MFIP participants. Some MFIP participants will find work, decide not to report it, and have their grants sanctioned for not complying with Employment Services. Many will move to different counties or states. Others may opt out of MFIP because they no longer want to be a part of a system that requires them to report work activity to Financial Workers and Employment Counselors, and they will leave MFIP even if they do not have a job and are still technically eligible for benefits. Family composition could change such that another adult's income eliminates the need for MFIP, and it could change again but former participants may not reapply. MFIP participants who find themselves in the latter types of circumstances are the families to whom the results of this research should be cautiously applied.

Although this study includes five person-level variables to account for differences in employment opportunities, there are many other factors in addition to race, Latino ethnicity, age, gender, and education that could account for differences in earned income and work hours. During the descriptive statistics process, the researcher identified other potentially confounding variables that are not included in the analysis: immigration status, having a young child in the house, and family composition (i.e. single- or two-parent families). Because these in particular were not identified as such until descriptive statistics on these data suggested they may impact the results, and due to the fact that it is not possible for one study to account for all potentially confounding variables, and given that these in particular were missing for many participants, they were not included in this analysis.

Descriptive statistics showed that approximately 18.1% of the 53,007 participants in this population are immigrants. Due to the high percentage MFIP participants who are immigrants, whose employment history and other factors may impact employment opportunities, future research should take immigration status into account. For this research, immigration status prior to October 2006 (January 2000 until September 2006) is underrepresented because the data were extracted from a data warehouse that did not collect immigration data prior to October 2006. Even after identifying participants who did not have an immigration entry date associated with their IDs prior to October 2006, but did have one after that date, immigrants who entered and exited MFIP prior to October 2006 are not identified, and immigrants in general are underrepresented. Given that the underrepresentation covers approximately 40% of the time this study covers, it was not possible to accurately account for immigration status. Future studies should use data that contains immigration status because being an immigrant (especially a new immigrant) could have a major impact on employment opportunities.

To be consistent with previous research on similar populations (see Hanratty, 2016), future research should account for having young children in the household; in particular, if a participant has a child under age 1, s/he may be exempt from Employment Services, not expected to report income or work hours, and therefore report less. Data for this study are limited in that they only provide the age of the youngest child in the house, so families with several young children will look the same in this dataset as those with one young child. Descriptive statistics showed that at any given point during the 17-year period of this study, approximately 59% of the 53,007 MFIP participants in this population have a child under age one year old. Of those who have a child under age one, approximately 32% of them take exemptions from Employment Services; the majority of MFIP parents with children under age one are active in Employment Services. Approximately 78% have a child under age five years old. Given the high percentages of having young children in the house, and that this could have unique implications for working in terms of child care and parenting commitments that may not be present for older children, future research should consider how having young children in the home affects employment opportunities.

Family composition, in terms of whether a family has one or two parents, should also be accounted for in future research due to possible variation in employment opportunities between single- and two-parent families. Descriptive statistics showed that approximately 75% of the MFIP participants in this data are single parents. When considering family composition over time, the percent of single-parent families ranges from approximately 70% (May 2006) to 79% (June 2000). However, for this study, data extraction criteria specified *MFIP-eligible* adults; thus, families with two parents in which one is ineligible for MFIP would appear as single-parent families in this data. Families in which there is only one MFIP-eligible parent and either another co-parent or adult caregiver are underrepresented; it is likely that less than 75% of the families in this study are single-parent families. Data were extracted to reflect the employment requirements of welfare reform, but future research of this type should consider family composition as a control variable because hours and income for families in which there are two MFIP-eligible parents may differ from single-parent families, given that the work requirements are different for two-parent families. Furthermore, the presence of another adult in the home may impact MFIP-eligible parents' employment situations due the extra help in terms of child care and other support an additional adult could provide (D. DeMaster, personal communication, May 31, 2017).

Another limitation of this study is that it does not take into consideration multiple, discrete periods of MFIP participation, or "spells" to account for the cyclical nature of MFIP use. Those who cycle in and out of the program are included in the analyses;

however, all MFIP participants appear to have only one spell in the models, which is not an accurate reflection of MFIP utilization because many participants exit and need to reapply at some point. In this dataset, the average number of MFIP spells is two. Future research should include MFIP spells in analysis, perhaps with a third level of nesting (time nested in individuals, nested in MFIP spells) to address recurring MFIP participation. Another possibility for analysis would be to consider using Cox proportional hazard models to examine the extent to which recessions contribute to MFIP applications and re-applications (for an example, see Hanratty, 2016).

Finally, this research has limited external validity. It cannot be generalized to states other than Minnesota, and Minnesota counties outside of Ramsey County. However, because of using population data rather than a sample of the population, it may be useful to Ramsey County as programs change and become more tailored to meet the unique needs of MFIP participants. Furthermore, other counties in Minnesota may benefit from the knowledge gained by this research and accordingly modify their own programs. To increase external validity, at least in terms of Minnesota, future research should compare Ramsey County with other Minnesota counties, particularly those close to Ramsey County, because many MFIP participants live in one county but work in a different county. Future research should consider the extent to which work opportunities diminish such that low-income workers need to look outside the counties in which they live to find employment.

Conclusion

TANF itself and its Minnesota counterpart MFIP assume linearity. The main eligibility criterion is income; in order to be eligible, one must have little to no income at the time of application. The program is designed to move participants from welfare income to work income, and assumes this is the progression most participants take. While this is true for some, it is not the case for an unknown percentage of MFIP participants.

Although this study contributes to a growing body of research that suspects the economy plays a crucial role in terms of helping participants transition from welfare to work, and shows that local economic conditions do significantly impact MFIP participants' earning and work hours, more research is needed to assess the extent to which economic conditions impact MFIP participants who are not working. With more knowledge in this area, policymakers and service providers may be able to restructure programming and tailor services to better meet the needs of participants despite fluctuating economic conditions. Furthermore, such understanding may lead to programming that seeks to end poverty rather than welfare dependence. Although many people exit welfare with jobs, they remain in poverty (Mallon & Stevens, 2011); the United States needs a social welfare program that can withstand the effects of changing economic conditions while addressing the challenges specific to those most in need of financial support.

In all of its inceptions, from ADC to AFDC to TANF, public assistance takes punitive measures to address so-called welfare dependency, and leaves many people behind. Perhaps it is time to learn from the past, reform welfare reform, and create a true anti-poverty program, one that defines the problem as poverty rather than dependence, and provides security during unstable economic times for the most economically vulnerable members of society. Devolution may be here to stay; as recessions at the national level begin, states and counties should prepare by proactively upholding the "opportunities" part of the Personal Responsibility and Work Opportunities Reconciliation Act of 1996 and taking steps to ensure welfare participants in their localities have equal employment prospects across time, whether there is a recession or not.

References

Abramovitz, M. (1996). *Regulating the lives of women: Social policy from colonial times to the present.* Boston, MA: South End Press.

Abramovitz, M. (2000). *Under attack, fighting back: Women and welfare in the United States*. New York: Monthly Review Press.

Abramovitz, M. (2001). Learning from the history of poor and working-class women's activism. *The ANNALS of the American Academy of Political and Social Science, 577*, 118-130. doi: 10.1177/000271620157700110

American Recovery and Reinvestment Act of 2009, Pub. Law No. 111-5, 123 Stat. 115 (2009).

Baptist, W., & Bricker-Jenkins, M. (2001). A view from the bottom: Poor people and their allies respond to welfare reform. *The ANNALS of the American Academy of Political and Social Science, 577*, 144-156. doi: 10.1177/000271620157700112

Bates, D., Maechler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1-48. doi:10.18637/jss.v067.i01.

Bitler, M., & Hoynes, H. (2016). The more things change, the more they stay the same? The safety net and poverty in the Great Recession. *Journal of Labor Economics, 34*(1), pt. 2, S403-S444.

Blank, R. (1997). *It takes a nation: A new agenda for fighting poverty*. Princeton, NJ: Princeton University Press.

Blank, R.M. (2002). Evaluating welfare reform in the United States. *Journal of Economic Literature, 40*, 1105-1166.

Blank, R. & Haskins, R. (Eds.) (2001). *The new world of welfare*. Washington, D.C.: The Brookings Institution Press.

Brush, L. (2003). Impacts of welfare reform. *Race, Gender & Class, 10*(3), 173. Retrieved from: http://login.ezproxy.lib.umn.edu/login?url=https://search-proquest-com.ezp2.lib.umn.edu/docview/218833770?accountid=14586

Bryk, A.S. & Raudenbush, S.W. (1992). *Hierarchical linear models*. Newbury Park, CA: Sage.

Burnham, L. (2001). Welfare reform, family hardship, and women of color. *The ANNALS of the American Academy of Political and Social Science, 577*, 38-48. doi: 10.1177/000271620157700104

Center on Budget and Policy Priorities. (2005). *Brief guide to TANF reauthorization legislation.* Retrieved from Center on Budget and Policy Priorities website: http://www.cbpp.org//archiveSite/4-21-05tanf.pdf

Center on Budget and Policy Priorities. (2014). *Chart book: TANF at 18*. Washington, DC. Retrieved from Center on Budget and Policy Priorities website: http://www.cbpp.org/research/chart-book-tanf-at-18

Chaterjee, P. (1996). *Approaches to the welfare state*. Washington, D.C.: National Association of Social Workers Press.

Christensen, K. (2015). He-cession? She-cession? The gendered impact of the Great Recession in the United States. *Review of Radical Political Economics, 47*(3), 368-388. Retrieved from: http://journals.sagepub.com.ezp1.lib.umn.edu/doi/pdf/10.1177/0486613414542771

Claims Resolution Act of 2010, Pub. L. No. 111-291, 124 Stat. 3064 (2010).

Collins, J., & Xaykaothao, D. (2015). *Census: Wages flat as Minnesota unemployment drops, racial disparities remain*. Retrieved from the Minnesota Public Radio website: http://www.mprnews.org/story/2015/09/17/census

Danziger, S.K., Wiederspan, J., Douglas-Siegel, J.A. (2013). We're not all deadbeat parents: Welfare recipient voices on unmet service needs. *Journal of Poverty, 17,* 305-330. doi: 10.1080/10875549.2013.804481

Deficit Reduction Act of 2005, Pub. L. No. 109-171, 42 U. S. C. §1305 (2005).

DeMaster, D. (2009). *Racial/ethnic and immigrant groups participating in the Minnesota Family Investment Program and the Diversionary Work Program*. (DHS Publication No. 4262N-ENG). St. Paul, MN: Minnesota Department of Human Services. Retrieved from: https://edocs.dhs.state.mn.us/lfserver/Public/DHS-4262N-ENG

DeMaster, D., & Crichton, L.I. (2006). *Characteristics of December 2005 Minnesota Family Assistance Programs: Cases and eligible adults.* (DHS Publication No. 4219G-ENG). St. Paul, MN: Minnesota Department of Human Services. Retrieved from: https://www.leg.state.mn.us/docs/2007/other/070393.pdf

DeNavas-Walt, C., & Proctor, B.D. (2014). *Income and Poverty in the United States: 2013* (U.S. Bureau of the Census, Current Population Reports, Series P60-249). Washington, DC: Government Printing Office. Retrieved from U.S. Census Bureau website: https://www.census.gov/content/dam/Census/library/publications/2014/demo/p60-249.pdf

Falk, G. (2015). *The Temporary Assistance for Needy Families (TANF) block grant: Responses to frequently asked questions.* Retrieved from the Federation of American Scientists website: https://www.fas.org/sgp/crs/misc/RL32760.pdf

Farber, H.S. (2012). Unemployment in the Great Recession: Did the housing market crisis prevent the unemployed from moving to take jobs? *American Economic Review: Papers and Proceedings, 102*(3), 520-525. Retrieved from: http://pubs.aeaweb.org.ezp2.lib.umn.edu/doi/pdfplus/10.1257/aer.102.3.520

Gilbert, N., & Terrell, P. (2005). *Dimensions of social welfare policy* (6th ed.). Boston, MA: Allyn & Bacon.

Grolemund, G., & Wickham, H. (2011). Dates and times made easy with lubridate. *Journal of Statistical Software, 40(3)*, 1-25. URL http://www.jstatsoft.org/v40/i03/.

Guci, L, Mead, C.I., Panek, S.D. (2016). *A research agenda for measuring GDP at the county level*. Retrieved from: https://bea.gov/papers/pdf/BEA%20WP_Research%20Agenda%20for%20GDP%20County.pdf

Hanratty, M. (2016). Family shelter entry and re-entry during the recession in Hennepin County: The role of race, residential location, and family earning. *Housing Policy Debate, 26*(2), 334-345, doi: 10.1080/10511482.2015.1072572

Haskins, R., Albert, V., & Howard, K. (2014). *The responsiveness of the Temporary Assistance for Needy Families program during the Great Recession*. Retrieved from the Brookings Institute website: https://www.brookings.edu/wp-content/uploads/2016/06/responsiveness_tanf_great_recession_haskins.pdf

Haskins, R., & Greenberg, M. (2006). Welfare reform: Success or failure? *Policy & Practice, 64*(1), 10-12. Retrieved from http://web.a.ebscohost.com.ezp3.lib.umn.edu/ehost/pdfviewer/pdfviewer?sid=a1398ad2-75bf-479d-8ce4-b69c54a69bfb%40sessionmgr4001&vid=9&hid=4112

Hawkins, R.L. (2005). From self-sufficiency to personal and family sustainability: A new paradigm for social policy. *Journal of Sociology and Social Welfare, 32*(4), 77-92. Retrieved from: http://web.a.ebscohost.com.ezp2.lib.umn.edu/ehost/pdfviewer/pdfviewer?sid=6c9739d4-1ce6-4bec-a770-cff4f5040f6e%40sessionmgr4003&vid=4&hid=4206

Hayes, A. F. (2006). A primer on multilevel modeling. *Human Communication Research, 32*, 385-410. doi: 10.1111/j.1468-2958.2006.00281.x

Hiring Incentives to Restore Employment, Pub. L. No. 111-147, 124 Stat. 71 (2010).

Hollister, D., Martin, M., Toft, J., Yeo, J., & Kim, Y. (2003). *The well-being of parents and children in the Minnesota Family Investment Program in Hennepin County, Minnesota, 1998-2002*. St. Paul, MN: University of Minnesota, Center for Advanced Studies in Child Welfare.

House Ways & Means Committee. (2014). Temporary Assistance for Needy Families legislative history. *Green Book*. Retrieved from the U. S. House of Representatives Committee of Ways & Means website: http://greenbook.waysandmeans.house.gov/2014-green-book/chapter-7-temporary-assistance-for-needy-families/temporary-assistance-for-needy-2

Job Creation and Worker Assistance Act of 2002, Pub. L. No. 107-147, 116 Stat. 21 (2002).

Krosch, A.R., & Amodio, D.M. (2014). Economic scarcity alters the perception of race. *Proceedings of the National Academy of Sciences of the United States of America, 111*(25). doi:10.1073/pnas.1404448111. Retrieved from: http://www.pnas.org/content/111/25/9079.full.pdf

Kwon, H.C., & Meyer, D.R. (2011). How do economic downturns affect welfare leavers? A comparison of two cohorts. *Children and Youth Services Review, 33*, 588-597. doi: 10.1016/j.childyouth.2010.10.009

Kuznetsova, A., Brockhoff, P. B., & Christensin, R.H.B. (2016). lmerTest: Tests in linear mixed effects models. Rpackage version 2.0-33. https://CRAN.R-project.org/package=lmerTest

Lamison-White, L. (1997). *Poverty in the United States: 1996* (U.S. Bureau of the Census, Current Population Reports, Series P60-198). Washington, DC: Government Printing Office. Retrieved from U.S. Census Bureau website: http://www.census.gov/hhes/www/poverty/publications/p60-198.pdf

Lewis, M.A., & Widerquist, K. (2001). *Economics for social workers*. New York: Columbia University Press.

Lo, S., & Andrews, S. (2015). To transform or not to transform: using generalized linear mixed models to analyse reaction time data. *Frontiers in Psychology, 6*(1171). Retrieved from: http://journal.frontiersin.org/article/10.3389/fpsyg.2015.01171/full

Mallon, A.J. & Stevens, G. V. G. (2011) Making the 1996 welfare reform work: The promise of a job. *Journal of Poverty, 15*, 113-140. doi: 10.1080/10875549.2011.563169

Marchevsky, A., & Theoharis, J. (2008). Dropped from the rolls: Mexican immigrants, race, and rights in the era of welfare reform. *Journal of Sociology & Social Welfare, 2008, 35*(3), 71-96. Retrieved from: http://web.b.ebscohost.com.ezp2.lib.umn.edu/ehost/pdfviewer/pdfviewer?sid=24997a7d-f0d6-496b-b00d-113b123c23f6%40sessionmgr111&vid=3&hid=109

Mason, C.H., & Perreault, W.D. Jr. (1991). Collinearity, power, and interpretation of multiple regression analysis. *Journal of marketing research, 28*(3), 268-280. Retrieved from: http://www.jstor.org.ezp1.lib.umn.edu/stable/pdf/3172863.pdf?refreqid=excelsior:62c416b828c1e62da1f3f2f83e960b0c

McDonnell, L. (2004). *Seven years of welfare reform – Weighing the results: A summary of the research findings on the Minnesota Family Investment Program (MFIP)*. St. Paul, MN: University of Minnesota, Center for Advanced Studies in Child Welfare.

Mead, L.M. (Ed.). (1997). *The new paternalism: Supervisory approaches to poverty*. Washington, D.C.: The Brookings Institution Press.

Mittelstadt, J. (2005). *From welfare to workfare: The unintended consequences of liberal reform, 1945-1965*. Chapel Hill, NC: University of North Carolina Press.

Mink, G. (2001). Violating women: Rights abuses in the welfare police state. *The ANNALS of the American Academy of Political and Social Science, 577*, 79-93. doi: 10.1177/000271620157700107

Mink, G., & Solinger, R. (Eds.). (2003). *Welfare: A documentary history of U.S. policy and politics.* New York, NY: New York University Press.

Minnesota Department of Employment and Economic Development. (2017). *Minnesota unemployment statistics: Local area unemployment statistics data.* Retrieved from: https://apps.deed.state.mn.us/lmi/laus/Results.aspx?geog=2704000123&adjusted=0&periodtype=03&resultset=3&startyear=2007&endyear=2016

Minnesota Department of Human Services (2010). *Welfare in Minnesota: Facts and Figures*. (DHS Publication No. DHS-4737-ENG). Retrieved from: http://kstp.com/kstpImages/flash/images/MN%20Welfare%20Facts.pdf

Minnesota Department of Human Services. (2011). *Racial disparities in MFIP outcomes*. (DHS Publication No. DHS-6373G-ENG 4-11). Retrieved from: https://edocs.dhs.state.mn.us/lfserver/Public/DHS-6373G-ENG

Minnesota Department of Human Services. (2015). *Minnesota Temporary Assistance for Needy Families Expenditures Task Force Final Report*. Retrieved from: https://mn.gov/dhs/assets/TANF_Task_Force_Final_Report_tcm1053-165410.pdf

Minnesota Department of Human Services. (2016a). *History of the Minnesota Family Investment Program*. Retrieved from: https://edocs.dhs.state.mn.us/lfserver/Public/DHS-5891-ENG

Minnesota Department of Human Services. (2016b). *Community Based Services Manual Glossary of Terms and Acronyms*. Retrieved from: http://www.dhs.state.mn.us/main/idcplg?IdcService=GET_DYNAMIC_CONVERSION&RevisionSelectionMethod=LatestReleased&dDocName=id_000801

Minnesota Department of Human Services. (2016, October). *Combined Manual, 20 > – Net income limits > 0020.09 – MFIP/DWP assistance standards*. Retrieved from:

http://www.dhs.state.mn.us/main/idcplg?IdcService=GET_DYNAMIC_CONVERSION&RevisionSelectionMethod=LatestReleased&dDocName=cm_002009#

Minnesota Department of Human Services. (2017a). *MFIP Employment Services Manual*. (DHS Publication No. DHS-290278). Retrieved from: http://www.dhs.state.mn.us/main/groups/manuals/documents/pub/dhs-290278.pdf

Minnesota Department of Human Services. (2017b). *Facts about the Minnesota Family Investment Program*. (DHS Publication No. DHS-5830-ENG). Retrieved from: https://edocs.dhs.state.mn.us/lfserver/Public/DHS-5830-ENG

Minnesota Department of Human Services. (2017c). *Minnesota Family Investment Program*. (DHS Publication No. DHS-3179-ENG). Retrieved from: https://edocs.dhs.state.mn.us/lfserver/Public/DHS-3179-ENG

National Bureau of Economic Research. (n.d.a). *U.S. business cycle expansions and contractions*. Retrieved from: http://www.nber.org/cycles/cyclesmain.html

National Bureau of Economic Research. (n.d.b). *The NBER's business cycle dating procedure: Frequently asked questions*. Retrieved from: http://www.nber.org/cycles/recessions_faq.html

Office of the Press Secretary. (2003, January 14). *President's welfare reform package strengthens families: Remarks by the President to Welfare-To-Work graduates.* Retrieved from George W. Bush White House Archives: http://georgewbush-whitehouse.archives.gov/news/releases/2003/01/text/20030114-6.html

Parrott, S., & Shapiro, I. (2017). *Flawed rationale for cuts in core assistance programs for low-income families*. Retrieved from Center on Budget and Policy Priorities website: https://www.cbpp.org/research/federal-budget/flawed-rationale-for-cuts-in-core-assistance-programs-for-low-income

Pilkauskas, N.V., Currie, J.M., & Garfinkel, I. (2012). The great recession, public transfers, and material hardship. *Social Service Review, 86* (3), 401-427.

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., & R Core Team. (2017). *nlme: Linear and Nonlinear Mixed Effects Models*. R Package version 3.1-131, URL: https://CRAN.R-project.org/package=nlme.

Primus, W., Rawlings, L., Larin, K., & Porter, K. (1999). *The initial impacts of welfare reform on the incomes of single-mother families*. Washington, D.C.: Center on Budget and Policy Priorities.

Personal Responsibility and Work Opportunity Reconciliation Act of 1996, Pub. L. No. 104-193, 110 Stat. 2105 (1996).

Public Welfare Amendments of 1962, Pub. L. No. 87-543, 42 U.S.C. §607 (1962).

R Core Team. (2016). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Sarkar, D. (2008). *Lattice: Multivariate Data Visualization with R*. Springer, New York. ISBN 978-0-387-75968-5. URL: https://www.R-project.org/package=lattice.

Schram, S.F., & Soss, J. (2001). Success stories: Welfare reform, policy discourse, and the politics of research. *The ANNALS of the American Academy of Political and Social Science, 577*, 49-65. doi: 10.1177/000271620157700105

Sheely, A. (2012). Devolution and welfare reform: Re-evaluating “success”. *Social Work, 57*(4), 321-331. doi: 10.1093/sw/sws022

Singer, J. D., & Willett, J.B. (2003). *Applied longitudinal data analysis: modeling change and event occurrence*. New York, New York: Oxford University Press.

Speelman, C.P., & McGann, M. (2013). How mean is the mean? *Frontiers in Psychology, 4*(451), 1-12. doi: 10.3389/fpsyg.2013.00451. Retrieved from: http://journal.frontiersin.org/article/10.3389/fpsyg.2013.00451/full

Social Security Act of 1935, Pub. L. No. 74-271. 49 Stat. 620 (1935).

U.S. Bureau of Economic Analysis. (2005). *Frequently asked questions*. Retrieved from: https://www.bea.gov/faq/index.cfm?faq_id=79

U.S. Bureau of Economic Analysis. (n.d.). Real GDP by metropolitan area (millions of chained 2009 dollars) (Interactive Data > Regional Data > GDP & Personal Income > Begin using the data > Gross Domestic Product by Metropolitan Area > Real GDP in chained dollars > NAICS (1997 forward) > All Industries > Area: Minneapolis-St. Paul-Bloomington, MN-WI (unit of measure = Level) > Time Period: All Years. Retrieved from: https://www.bea.gov/itable/iTable.cfm?ReqID=70&step=1#reqid=70&step=10&isuri=1&7003=900&7035=-1&7004=naics&7005=-1&7006=33460&7036=-1&7001=2900&7002=2&7090=70&7007=-1&7093=levels

U.S. Census Bureau. (2016). *Population estimates*. Retrieved from: https://www.census.gov/quickfacts/fact/table/ramseycountyminnesota,MN/PST045216

U.S. Census Bureau. (2017). *Small area income and poverty estimates*. Retrieved from: https://www.census.gov/did/www/saipe/data/interactive/saipe.html?s_appName=saipe&map_yearSelector=2014&map_geoSelector=aa_c&s_state=27&s_county=2

7123&s_year=2000,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010,2011,2012,2013,2014,2015&menu=grid_proxy

U.S. Department of Health & Human Services. (2004). *Sixth annual report to Congress (November 2004)*. Administration for Children & Families, Office of Family Assistance. Retrieved from: https://archive.acf.hhs.gov/programs/ofa/data-reports/annualreport6/ar6index.htm

U.S. Department of Health & Human Services. (2015). *About TANF*. Administration for Children & Families, Office of Family Assistance. Retrieved from: https://www.acf.hhs.gov/ofa/programs/tanf/about

The White House. (2002). *Working toward independence*. Retrieved from: https://georgewbush-whitehouse.archives.gov/news/releases/2002/02/welfare-reform-announcement-book-all.html

Wickham, H. (2007). Reshaping data with the reshape package. *Journal of Statistical Software, 21(12)*, 1-20. URL http://www.jstatsoft.org/v21/i12/.

Wickham, H. (2009). *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag: New York.

Wickham, H. & Bryan, J. (2017). readxl: Read Excel Files. R package version 1.0.0. https://CRAN.R-project.org/package=readxl

Wickham, H., Francois, R., Henry, L., & Müller, K. (2017). *dplyr: A Grammar of Data Manipulation*. R package version 0.7.0. https://CRAN.Rproject.org/package=dplyr

Wickham, H., & Miller, E. (2016). *haven: Import and Export 'SPSS', 'Stata' and 'SAS' files*. R package version 1.0.0. https://CRAN.R-project.org/package=haven

Winter, B. (2013). Linear models and linear mixed effects models in R with linguistic applications. https://arxiv.org/pdf/1308.5499.pdf%5d

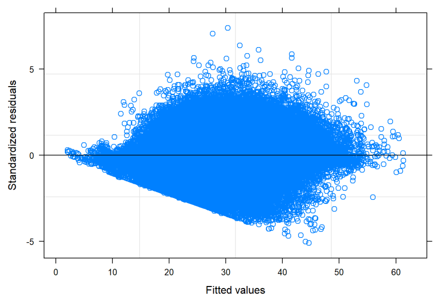
Woltman, H., Feldstein, A., MacKay, J. C., & Rocchi, M. (2012). An introduction to hierarchical linear modeling. *Tutorials in Quantitative Methods for Psychology, 8*(1), 52-69. doi:10.20982/tqmp.08.1.p052

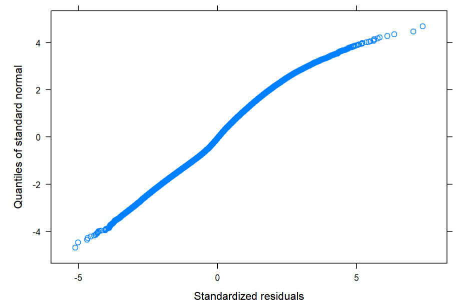
Ziliak, J. P., Figlio, D. N., Davis, E. E., & Connolly, L. S. (2000). Accounting for the Decline in AFDC Caseloads: Welfare Reform or the Economy? *The Journal of Human Resources, 35*(3), 570-586.

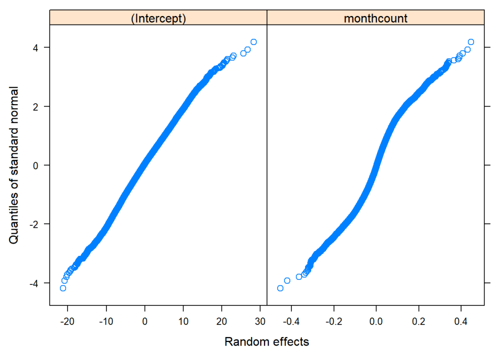
Zylan, Y., & Soule, S. (2000). Ending welfare as we know it (again): Welfare state retrenchment, 1989-1995. *Social Forces, 79 (2),* 623-652. doi: 10.2307/2675511

Appendix A: Testing for Assumptions of Linear Mixed Effects Models (Earned Income and Work Hours)

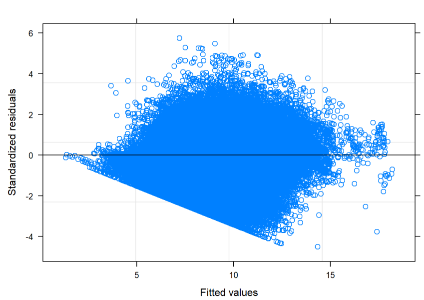
EarnedIncome:

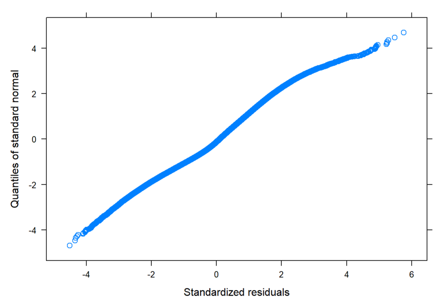


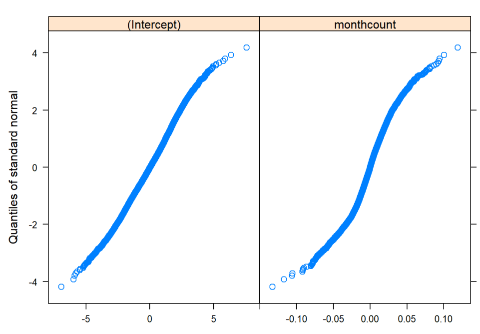




MAXISHours:

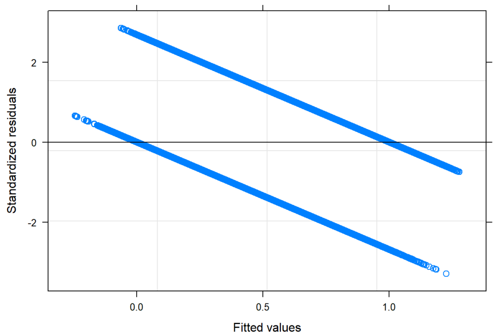


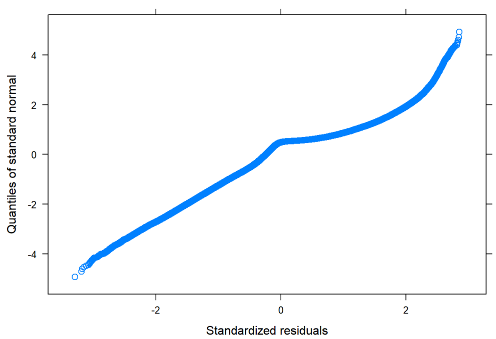


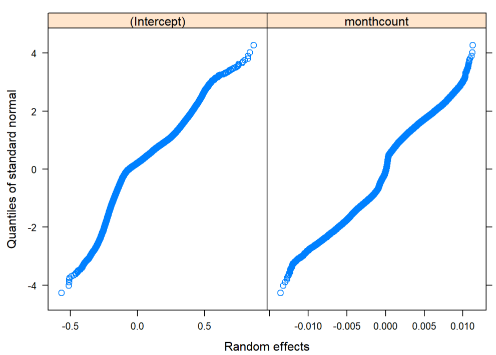


The residual plots of the transformed data still show a straight, diagonal line, which is evidence of a floor effect, meaning that many people are reporting similar income (as in minimum wage). Although the residual plot of the transformed data still contains this line, this likely represents individual participants who do not fit particularly well with the model, rather showing that the entire dataset does not fit. Given the complexity of MFIP participants' lives and the potential for non-linear fluctuations in income, it makes sense that a model which assumes a linear progression of earning income would not fit all MFIP participants. However, the residual plots and Q-Q plots show that in general, the models using transformed data are a good fit.

Appendix B: Testing for Assumptions of Linear Mixed Effects Models (All Participants)







The residual plot and Q-Q plots for the dataset that includes all MFIP participants, including those earning zero income, are clearly not linear or normal; models run on the economy's impact on whether or not Ramsey County MFIP participants earn income should be interpreted with caution.

Appendix C: R Code for Null Models

The null models test for between-person variation in *EarnedIncome* and *MAXISHours*, with a fixed intercept (γ_{00}, specified by ~ 1), and a random intercept at the person level (u_{0j}, specified by "random = ~ 1 | MAXIS_PersonId), with "~ 1" representing the *0* in u_{0j}, and MAXIS_PersonId representing u_j.

```
null_mod <- lme(I(sqrt(EarnedIncome)) ~ 1, random = ~ 1 | MAXIS_PersonId, data =
null_data_final[null_data_final$EarnedIncome>0,], na.action = na.exclude, correlation =
corAR1())

summary(null_mod)

VarCorr(null_mod)
```

```
null_mod_a <- lme(I(sqrt(MAXISHours)) ~ 1, random = ~ 1 | MAXIS_PersonId, data =
null_data_final_a[null_data_final_a$MAXISHours>0,], na.action = na.exclude, correlation =
corAR1())

summary(null_mod_a)

VarCorr(null_mod_a)
```

Appendix D: R Code for Conditional Models

The left side of the models (left of the first " ~ ") show the response variable (I(sqrt(EarnedIncome)) and (I(sqrt(MAXISHours)). Predictor variables and random effects are on the right side of the models. All models are two-level mixed effects models that predict the linear mixed effects of the square root of *EarnedIncome* and *MAXISHours* as a function of all person-level and economic indicator variables, specifies a random slope *monthcount*, and a random intercept at the participant level, specifies two levels of nesting (time, as measured by *monthcount*, nested in *MAXIS_PersonId* (random = ~ 1 + *monthcount* | *MAXIS_PersonId*), and has an AR1 covariance structure.

```
EarnedIncome_conditional_1 <- lme(I(sqrt(EarnedIncome)) ~ Race + CollapsedEthn01 +
I(ReportAge - mean(ReportAge, na.rm=TRUE)) + HS_GED_or_NOT + CollapsedGender01 +
Recession_or_Not + I(RealGDP_Metro - mean(RealGDP_Metro)) + I(Ramsey_County_Unempl_Rt -
mean(Ramsey_County_Unempl_Rt)) + monthcount, data =
MFIP_EI_all[MFIP_EI_all$EarnedIncome>0,], na.action = na.exclude, random = ~ 1 +
monthcount | MAXIS_PersonId, correlation = corAR1())
```

```
MAXISHours_conditional_1 <- lme(I(sqrt(MAXISHours)) ~ Race + CollapsedEthn01 +
I(ReportAge - mean(ReportAge, na.rm=TRUE)) + HS_GED_or_NOT + CollapsedGender01 +
Recession_or_Not + I(RealGDP_Metro - mean(RealGDP_Metro)) + I(Ramsey_County_Unempl_Rt -
mean(Ramsey_County_Unempl_Rt)) + monthcount, data =
MFIP_EI_all[MFIP_EI_all$MAXISHours>0,], na.action = na.exclude, random = ~ 1 + monthcount
| MAXIS_PersonId, correlation = corAR1())
```

```
EarnedIncome_conditional_2 <- lme(I(sqrt(EarnedIncome)) ~ Race + CollapsedEthn01 +
I(ReportAge - mean(ReportAge, na.rm=TRUE)) + HS_GED_or_NOT + CollapsedGender01 +
I(MedianIncome_RamseyCo - mean(MedianIncome_RamseyCo)) + I(PovertyRate_RamseyCo -
mean(PovertyRate_RamseyCo)) + monthcount, data =
MFIP_EI_all[MFIP_EI_all$EarnedIncome>0,], na.action = na.exclude, random = ~ 1 +
monthcount | MAXIS_PersonId, correlation = corAR1())
```

```
MAXISHours_conditional_2 <- lme(I(sqrt(MAXISHours)) ~ Race + CollapsedEthn01 +
I(ReportAge - mean(ReportAge, na.rm=TRUE)) + HS_GED_or_NOT + CollapsedGender01 +
I(MedianIncome_RamseyCo - mean(MedianIncome_RamseyCo)) + I(PovertyRate_RamseyCo -
mean(PovertyRate_RamseyCo)) + monthcount, data = MFIP_EI_all[MFIP_EI_all$MAXISHours>0,],
na.action = na.exclude, random = ~ 1 + monthcount | MAXIS_PersonId, correlation =
corAR1())
```

```
Time_Effects_MAXISHours <- lme(I(sqrt(MAXISHours)) ~ Race + CollapsedEthn01 + I(ReportAge
- mean(ReportAge, na.rm=TRUE)) + HS_GED_or_NOT + CollapsedGender01 + year_2001 +
year_2002 + year_2003 + year_2004 + year_2005 + year_2006 + year_2007 + year_2008 +
year_2009 + year_2010 + year_2011 + year_2012 + year_2013 + year_2014 + year_2015 +
year_2016, data = MFIP_EI_all[MFIP_EI_all$MAXISHours>0,], na.action = na.exclude, random
= ~ 1 + monthcount | MAXIS_PersonId, correlation = corAR1())
```