ABSTRACT

Title of Dissertation: FROM THE 1996 WELFARE LAW TO THE GREAT RECESSION: ESSAYS ON THE EFFECT OF SAFETY NET CHANGES ON EMPLOYMENT AND INCOME TRENDS

Danilo Leandro Trisi, Doctor of Philosophy, 2016

Dissertation directed by: Carol Graham
Professor, School of Public Policy

The United States safety net has undergone significant changes over the last three decades. In the early 1990s the Earned Income Tax Credit was expanded. The 1996 welfare law dramatically reduced access to cash assistance. SNAP (formerly food stamps) declined in the aftermath of the 1996 welfare law but rebounded during the 2000s. This dissertation analyzes how these safety net changes have affected the employment trends of single mothers and the income trends of families with children.

The first essay examines different ways of measuring how cash assistance changed after the 1996 law. It reviews previous approaches and introduces two measures that meet the objectives of capturing the benefit level and accessibility of a safety net program independent of economic conditions and allowing for variation by year, state, and family size. The essay concludes by discussing how this methodology can be adapted to measure changes in SNAP and EITC policies.

The second essay examines the employment trends of single mothers. The descriptive analysis shows how single mothers with the least educational attainment and those with the youngest children increased their employment the most between 1992 and 1999. The econometric analysis uses the safety net measures developed in the first essay to analyze the effect of safety net changes on the employment of single mothers. It finds that the EITC accounted for 36 percent of the employment increase among single mothers with a high school education or less between 1992 and 1999. The economy accounted for 20 percent, changes in cash assistance for 10 percent, and SNAP changes for 4 percent.

The third essay examines how the level and composition of incomes of families with children changed between 1993 and 2012. These data show how the safety net has become more focused on supporting families with earnings and less helpful to families during periods of joblessness. Changes in the safety net drove a 16 percent decline in post-tax post-transfer family income of the poorest five percent of children between 1995 and 2005. The paper concludes by looking at the characteristics of children at different points in the income distribution.

FROM THE 1996 WELFARE LAW TO THE GREAT RECESSION: ESSAYS ON THE EFFECT OF SAFETY NET CHANGES ON EMPLOYMENT AND INCOME TRENDS

By

Danilo Leandro Trisi

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2016

Advisory Committee:
Professor Carol Graham, Ph.D., Chair
Professor Christopher Foreman, Ph.D.
Professor Judith K. Hellerstein, Ph.D.
Professor Peter Reuter, Ph.D.
Professor Luke Shaefer, Ph.D.

Dedication

Para mi Familia:

Stephy, Danel, Mamá, Papá y la Abuela Mam

Acknowledgements

Completing this dissertation, especially as a part-time student, was one of the most difficult projects I’ve ever done. I would not have been able to get through it without the love and support from many people. My deepest gratitude goes to my wife, Stephanie. She helped me overcome so many challenges, and stood by my side through thick and thin. She even gave me a jar full of inspirational notes written by my family and friends. My brother Danel, my mom, my dad and my grandmother, to whom this dissertation is also dedicated to, were also constant sources of love, support and encouragement every time I needed them.

In addition, I want to thank my dissertation committee, especially my chair, Carol Graham. Thank you for your guidance, feedback and encouragement throughout this process. I also want to thank Dr. Chen who helped me figure out how to get this dissertation done.

Finally, I want to thank my colleagues at the Center on Budget and Policy Priorities, especially Arloc Sherman, LaDonna Pavetti and Sharon Parrott. Over the last ten years, they have been mentors, role models, and have taught me how to do analytical research that moves policy in the direction of increasing opportunity for the most disadvantaged among us. I’m grateful for every day that I’ve gotten to work with them.

Table of Contents

List of Tables

List of Figures

Chapter 1: Measuring the Reach of the Safety Net Before and After the 1996 Welfare Law: A Comparison of Different Measures

1.1 Introduction

The 1996 welfare law eliminated the Aid to Families with Dependent Children (AFDC) program and replaced it with a block grant program called Temporary Assistance for Needy Families (TANF). The law ended the entitlement of poor families to assistance from the federal government, instituted a five-year time limit on federal cash benefits, imposed stronger work requirements on recipients and devolved most details of welfare policy making to the fifty states. The goal of these changes was to move single mothers with children who had been receiving AFDC out of "dependency" on government assistance and into work outside the home. The law aimed to reduce TANF caseloads, increase work participation, reduce poverty, and promote marriage. Under TANF states were given a significant amount of flexibility in how to design their TANF programs. States have significant flexibility in their choice of benefit levels, entry and work participation requirements, sanctions, time limits, family caps, earning disregards, exemptions, and other policies.

States were also given a lot of flexibility in how to spend their TANF block grant. When TANF began, 70 percent of TANF funds were used for cash assistance to families. Over time, states shifted TANF funds for other purposes such as child care, child welfare, and other services. In some cases, this was not new spending, but replacing state dollars previously used for those purposes. By 2014, only 26 percent of combined federal and state TANF funds were used for cash assistance (Schott, Pavetti and Floyd 2015).

Policy makers have a keen interest in understanding the impact of the 1996 welfare reform law on a range of outcomes such as employment and poverty levels. One of the most common approaches scholars have used to answer these questions is to construct econometric analyses that take advantage of variation of welfare policies across time and by state in order to try to isolate the impact of such policies. Choosing how to parameterize welfare policies is one of the most important decisions in any such analysis. This paper will provide an overview of how various scholars have measured welfare reform policies, will provide a framework of how we should evaluate these various approaches, and it will propose some new measures. In addition, the paper will look at the issue more broadly beyond welfare reform and investigate different ways of measuring the reach of other safety net programs such as the Earned Income Tax Credit (EITC) and SNAP (formerly, food stamps).

1.2 Overview of Previous Approaches

A couple of very thorough summaries of the welfare reform literature exist. Rebecca Blank wrote a review of the literature in 2002 and in 2009. Jeffrey Grogger and Lynn A. Karoly did a synthesis of the literature in 2002 and a meta-analysis in 2005. In total, these four publications reviewed over 70 econometric studies that aimed to establish a causal link between welfare policy reforms and various outcome variables such as welfare use, employment, and income levels. In this section, I draw heavily from the work of Grogger and Karoly (2005) since they included as part of their meta-analysis a detailed discussion of how researchers characterized state-by-state welfare policies.

One of the most common approaches taken by researchers is to measure policy changes based on when a specific policy was implemented. The analyst codes a dummy variable that is equal to one after the policy was implemented and zero beforehand. That dummy variable is then included in the regression model, usually within a state and year fixed effects framework. The coefficient attached to such a variable indicates how much the outcome changed in the states that implemented that policy once that policy was implemented. Some studies analyzed welfare reform policies "as a bundle" and some analyzed specific policies such as for example, time limits, work-related activity requirements, sanctions, and financial work incentives. The Urban Institute has collected and coded a number of these state policy choices in their Welfare Rules Database. Prior to welfare reform many states applied for waivers that allowed them to implement some of these policies before the implementation of TANF in 1996. Many previous studies use dummy variables to differentiate between years before and after TANF, and years before and after a state implemented a waiver. Some papers that follow this methodology include Bitler, Gelbach and Hoynes (2002), Schoeni and Blank (2002), and Grogger (2003).

Grogger and Karoly (2005) discuss several drawbacks from this methodology. Here I focus on three of the concerns they raised. One concern is that this methodology only captures one dimension of policy variation. It only divides the sample into pre- and post-reform periods. It provides no information about other dimensions of variation that might have an important effect on behavior. For example, one might expect that the specific characteristics of the earnings disregards or the sanction policy that is implemented could influence behavior. Secondly, Grogger and Karoly (2005) argue that focusing solely on enactment or implementation dates may result in a regression specification that is particularly susceptible to bias from unobservable trends. If the researcher fails to control for state-specific trends post-reform, the policy coefficients may provide biased estimates of the effects of reform. Thirdly, many states implemented many policies at once, making it very difficult to isolate the effects of individual policies. When each policy is identified as a dummy variable, and all policies are adopted together, the lack of variation along each individual policy makes it impossible to separately measure the effect of individual policies.

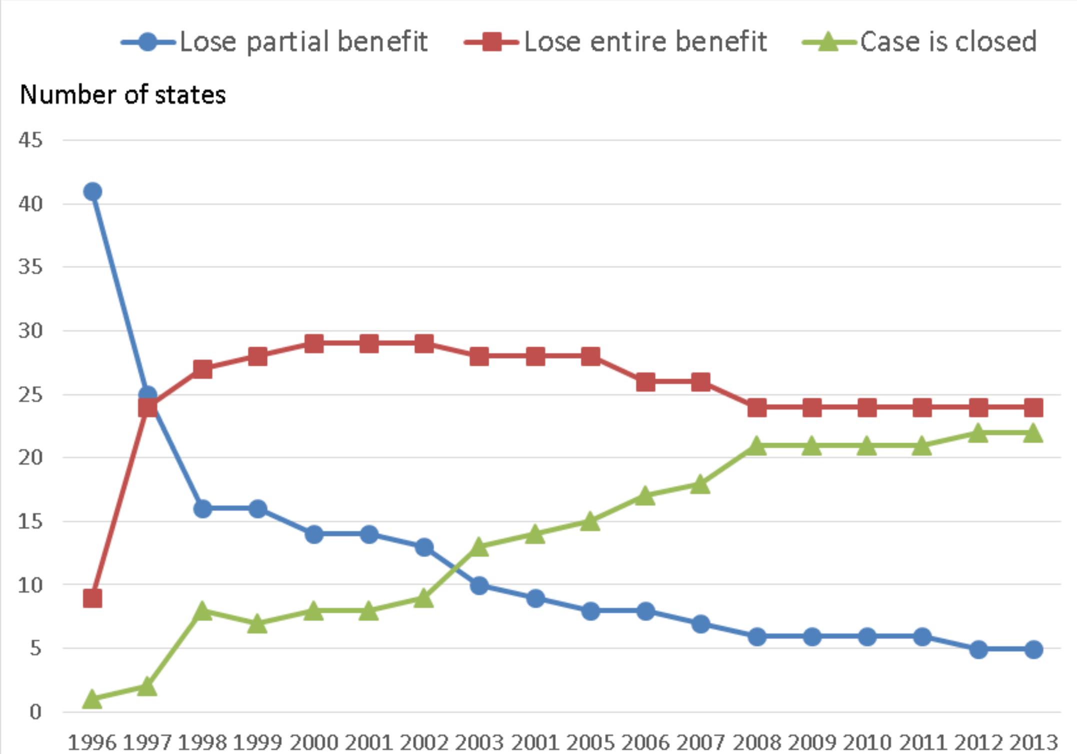
Grogger and Karoly (2005) suggest that one approach to address these drawbacks is to characterize the intensity of reforms as opposed to just identifying the adoption of reforms. For example, one could create a variable that tries to capture the generosity of a financial work incentive or the severity of a sanction policy. Researchers that have followed this approach include Fang and Keane (2004), Looney (2005) and McKernan and Ratcliffe (2006).

Grogger and Karoly (2005) point to several advantages of this approach. It measures a more policy relevant effect. For example, it doesn't merely measure the effect of the average financial incentive, but the effect of incentives of various sizes. This allows the researcher to analyze whether the strength of the reform has an effect on the outcome variables. In addition, this approach may reduce collinearity and improve the precision of the estimates of specific reforms. There may be less correlation among quantitative measures of bundled policies than among the dummy indicators since the intensity of reforms varies even among states that implemented the same mix of reforms at the same time.

However, even after explaining the advantages of using more detailed and quantitative measures of each policy, Grogger and Karoly (2005) point out how difficult this can be. For example, time limits vary in their length, the magnitude of benefit reduction once the time limit is reached, and in the availability of exemptions and extensions. Sanction policies also vary by a number of details that make it difficult to code into a specific “sanction policy” variable. Grogger and Karoly show how four different sets of analysts attempted to characterize state sanction policies as either lenient, intermediate, or stringent. The four sets of analysts only agreed in twenty-eight of the fifty states and DC. In Pennsylvania, for example, sanction policies were rated as lenient by one set of analysts, intermediate by two sets of analysts, and stringent by the other. Karoly and Grogger raise the concern that if analysts cannot agree on what a strict sanction policy is, the effects of a “strict” sanction policy may vary across studies for reasons that have to do more with measurement than with the policy’s effect on behavior. Grogger and Karoly also raise the concern that these detailed measures of policies are usually based on official statues and regulations. However, even though states might have similarly written policies, they might implement them very differently. For example, there’s evidence that states with similar time-limit policies vary in the proportion of people who receive extensions when they reach the time limit.

Most research papers on the impact of welfare reform were written in the early and mid-2000s. Using dummy variables to differentiate between years before and after TANF, and years before and after a state implemented a waiver will not work for my analysis given that I also want to analyze the impact of how TANF programs evolved during the 2000s. A dummy variable that turns on in 1996 and stays on thereafter will not be able to capture how a TANF program continued to change since 1996. In addition, dummy variables that indicate when a specific policy change was implemented have become less useful during the last decade given that state policy variation has decreased. This trend of reduced policy variation can be seen, for example, by looking at states' most severe sanction policy for noncompliance with work requirements. This is a key policy variable that many researches have included in their econometric studies. In 1996, the most severe sanction that 41 states imposed on recipients was a partial benefit reduction. By 2003, only 10 states had a partial benefit reduction as their most severe sanction and most states opted for a more severe sanction of either entire benefit loss or case closure. See Figure 1.1.

Figure 1.1: Number of States, by Most Severe Sanction Policy for Noncompliance with Work Requirements



Note: DC is included in this graph, therefore the total number of "states" adds up to 51.

Source: Author's coding of data from the Urban Institute's Welfare Rules Database.

Figure 1.1 also shows how most states changed their sanction policies during the first few years after 1996, but there have been less policy shifts since then. A similar convergence of state policy choices and reduced variation within states over time exist if one analyzes other state policies such as the length of time limits, the existence of a formal diversion program, or family caps. However, if one were to analyze caseload or TANF spending trends over this time period one would find that there is more state-by-state and within state over time variation that these policy variables capture.

1.3 My Approach and Characteristics of An Ideal Measure

My measurement approach starts with the premise that a program's benefit levels and accessibility matter the most in terms of influencing the behavior of individuals and impacting their incomes. A program's benefit levels and its accessibility to people with earnings below the poverty line can largely determine how much a program reduces poverty. One would also expect that if a program is to influence behavior such as whether to enter the paid labor market, then the size and availability of benefits would play a very important role.

There are various ways that one could measure both benefit levels and program access. Before I delve into the data and measurement issues involved let me discuss some of the features that I would want an ideal measure to have. At minimum, a safety net measure should be able to capture variation by state and by year. In addition, it would be helpful for it to capture variation by family size and types. For example, many EITC studies were able to draw causal conclusions from changes in EITC policies by comparing families with one child to families with two children given that from 1993 to 1996 the maximum EITC for families with two children increased by $2,045 while it increased by $718 for families with one child. Some analysts have also tried to draw causal conclusions by comparing differences in how safety net programs are structured for childless, single-parent, and married-couple families.

My ideal measure would allow me to compare TANF, SNAP, and EITC policies in a consistent way. That would allow me to equitably compare how benefit levels and accessibility of each program impact outcomes such as employment and poverty status.

An ideal measure would be able to isolate policy choices and not vary by the poverty level or employment in a state in a given year. For example, it could be that per-capita spending on SNAP is higher in Mississippi than in Florida because of higher poverty rates in Mississippi. Therefore, per-capita spending on SNAP would not be a good measure to compare SNAP policies in Mississippi and Florida. Similarly, per-capita SNAP spending in 2008 might be higher than in 2004 because 2008 was a recession year. I would like a measure that varied by policy choices rather than changes in economic conditions.

My preferred measure would be transparent and easy to explain and replicate. A measure that is transparent and easy to explain can be more influential in policy debates given that it can be better understood by non-technical but very influential audiences such as policy makers, journalists, and policy advocates.

My ideal measure would take advantage of the best available data. As explained in the data section below, different sources of data can vary in quality. Household survey data can be less reliable than administrative data given sample size and underreporting issues. If both are feasible, I would prefer to use administrative data instead of survey data.

In addition to analyzing the 2000s and 2010s, I would like to analyze the pre-welfare reform period of the 1980s and early 1990s, therefore my ideal measure would go back to 1980.

My ideal measure would combine both benefit levels and accessibility levels into a single measure. That would provide a single metric with which to analyze both the generosity and accessibility of a program. I think that by themselves, benefit levels or an access measure provide only an incomplete picture. In order to understand a program's impact on poverty or behavior I need to know both its benefit levels and how widely accessible it is.

I've outlined above what I would like the ideal measure to be. In developing a measure, I will need to balance trade-offs between some of the characteristics discussed above. In the following sections I will delve deeply into the data and methodological issues involved in creating a benefit level and accessibility measure. In the next section I'll discuss the pros and cons of different data sources that can be used to create a safety net measure.

1.4 Data Sources

There are three main types of data that can be used to analyze the reach and the generosity of safety net programs. The first type of data are a program's eligibility and benefit rules. For example, this can include the maximum benefit amount a family can receive; the earnings at which a family starts and stops receiving benefits, and the reasons for which one could get sanctioned away from a program. The Urban Institute has collected and coded a number of these state policy rules for TANF in their Welfare Rules Database.

A second type of data are the administrative records that are collected by the agencies that administer programs. For example, the U.S. Department of Health and

Human Services and many state agencies regularly publish data on how many people participate and how much money is spent on various aspects of a program.

A third type of data are large household surveys like the ones that the U.S. Census bureau produces. Like many previous researchers, I have chosen to use the Annual Social & Economic Supplement (ASEC) from the Current Population Survey (CPS), commonly known as the March CPS. The CPS microdata which is publicly available provides information on labor market participation, family structure, demographics, receipt of government benefits, and many other variables. The March CPS sample size currently stands at about 100,000 households per year. (U.S. Census Bureau, 2010).

When using CPS data to analyze different sub-groups within states one needs to be very careful about whether one has enough sample size. A rough rule of thumb for CPS analyses is that any statistic should be based on at least 30 unweighted households. If for example, we were interested in some characteristic of families with two children with pre-government income below the poverty line in a single year we would quickly run into sample size issues. For example, the CPS unweighted data for 2005 included 173 such families in California, but only 25 such families in Mississippi and 14 such families in Idaho. Some strategies to address this include combining multiple years of data and/or analyzing a larger group like for example all families with children instead of just families with two children.

Similarly to other household surveys, the CPS suffers from some underreporting of income and benefits. The total amount of government benefits that people report receiving in the CPS falls short of the actual figures according to administrative data. Changes in the degree of underreporting over time could be particularly problematic for time series analyses. (Wheaton, 2007) One way to address this issue is to augment CPS data using a microsimulation model that corrects for underreporting. Sherman and Trisi (2015) use this approach, and that's also my approach here. I correct for the tendency of CPS data to underreport income from three government assistance programs: Temporary Assistance for Needy Families (TANF), Supplemental Security Income (SSI), and the Supplemental Nutrition Assistance Program (SNAP, formerly food stamps). To make these corrections, I use baseline data from the Transfer Income Model Version III (TRIM III) policy micro-simulation model developed by the Urban Institute under contract with the U.S. Department of Health and Human Office of the Assistant Secretary for Planning and Evaluation. TRIM starts with Census survey data but uses a different method of filling in questions skipped by survey respondents regarding program participation and benefit income, in order to closely match actual numbers and characteristics of benefit recipients shown in administrative records. As shown in Table 1.1, the problem of underreporting of AFDC/TANF cash assistance has gotten worse over time. However, TRIM corrections can help fix this problem by keeping totals closer to the administrative data.

Table 1.1: Comparison of Administrative AFDC/TANF data to CPS data, 1993-2012

	Total expenditures on cash AFDC/TANF assistance (in billions of current dollars)			Percent of administrative total captured by:	
	Admin. data	CPS data	CPS data augmented by TRIM	CPS data	CPS data augmented by TRIM
1993	22.3	17.1	20.8	77%	93%
1996	20.4	13.2	17.7	65%	87%
2000	11.2	5.7	9.4	51%	84%
2003	10.2	5.7	9.1	56%	89%
2006	9.9	4.1	8.5	42%	86%
2009	9.3	4.6	8.3	49%	89%
2012	9.0	4.3	8.2	48%	91%

Source: AFDC/TANF administrative expenditure data from U.S. Department of Health and Human Services (1998) and Schott, Pavetti and Floyd (2015). CPS and CPS TRIM analysis conducted by author.

The data necessary to do this underreporting correction is currently available for the years 1993-2012. Given the underreporting issues, to the extent possible, I use CPS data augmented by the TRIM model. For the pre-1993 period when TRIM is not available, I use administrative data to adjust raw figures from the CPS. The methodology I use for this adjustment is explained below.

1.5 Potential Measures

In this section I present six potential measures to capture the reach of AFDC/TANF programs by state and year. I will briefly describe each measure and discuss some of its advantages and disadvantages.

1.5.1 Average AFDC/TANF Benefits per Family in Poverty

This measure uses March CPS data and is calculated by dividing the total amount of AFDC/TANF cash assistance received by families with children and private income below the poverty line in each state by the number of families with children and private income below the poverty line. In 2012, the poverty line for a family of two parents and two children was at about $23,000.

A very appealing characteristic of this measure is that it takes into account both participation rates and benefits generosity. That's because the numerator uses dollars spent as opposed to number of participants and the denominator includes all families with children and private income below the poverty line regardless of whether they participate in AFDC or TANF. Table 1.2 shows these calculations for four hypothetical states that have 100,000 families in poverty but vary in terms of the generosity of their TANF benefits (see column A) and the reach of their TANF programs (see column B). The average annual TANF benefits per family in poverty measure (column F) captures differences between these four states in both their benefit levels and the reach of their TANF programs.

Table 1.2: Example Calculations of Average Annual TANF Benefits per Family in Poverty for Four Hypothetical States

	A	B	C	D	E	F
	Mean annual TANF benefits for participants	Number of TANF families	Number of families in poverty	Ratio of families on TANF to families in poverty = B ÷ C * 100	Total annual TANF spending = A * B	Average annual TANF benefits per family in poverty = E ÷ C
State 1	$8,400	20,000	100,000	20	$168,000,000	$1,680
State 2	$3,600	20,000	100,000	20	$72,000,000	$720
State 3	$8,400	50,000	100,000	50	$420,000,000	$4,200
State 4	$3,600	50,000	100,000	50	$180,000,000	$1,800

A disadvantage of this measure is that it's solely based on March CPS data and therefore can suffer both from underreporting and sample size issues. The sample size in the March CPS is not large enough so that I could do this analysis by state and by family size which was one of the characteristics that I wanted in my ideal measure. Even to create a measure that groups all families together regardless of family size, I need to merge multiple years of CPS data in order to create state-by-state measures. For this measure, I use three-year averages of CPS data. Therefore, for example, my measure for Wisconsin for 1994, would average together 1993-1995.

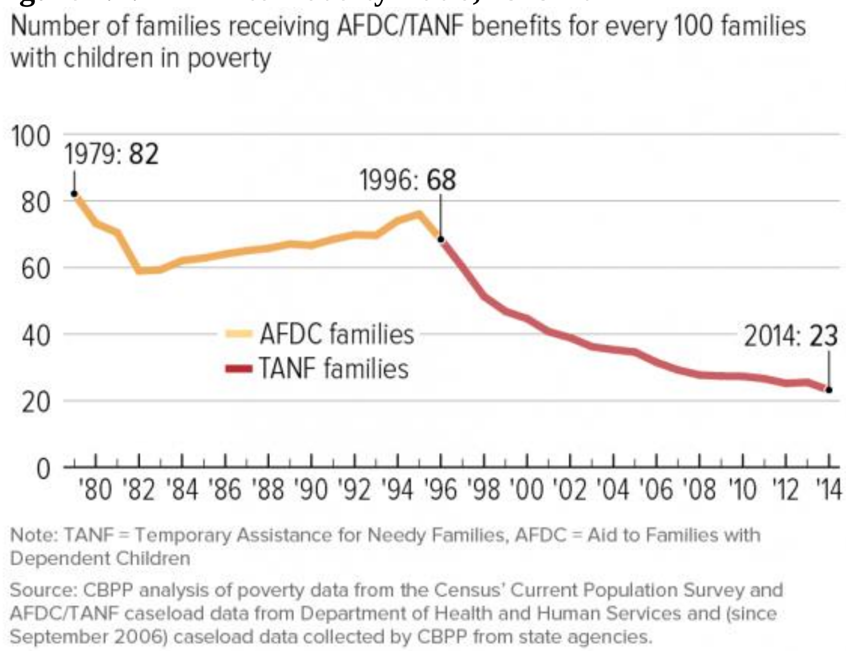
In order to diminish the impact of underreporting I use TRIM data which is available between 1993 and 2012. Before 1993 when TRIM data are not available, I calculate the percent of total AFDC spending found in the CPS that went to families with children and private income below the poverty line. I then apply that percent to the administrative data on total AFDC cash assistance spending, and divide that figure by the number of families with children in poverty to get an average benefits per family in poverty figure.

Another disadvantage of this measure is that it could be influenced by variation of economic conditions between states and across time. Using a denominator of families with pre-government income below the poverty line helps to take into account various levels of need across states, but it does not take into account the fact that some states might vary in terms of their depth of poverty.

1.5.2 The TANF-to-Poverty Ratio

The TANF-to-Poverty Ratio is a measure that I helped develop at the Center on Budget and Policy Priorities (CBPP). Trisi and Pavetti (2012) provide state by state data on the ratio of the number of families receiving AFDC/TANF benefits to the number of families with children in poverty. Floyd, Pavetti and Schott (2015) extended these data up to 2014. These papers find that in 1996, for every 100 families with children living in poverty, TANF provided cash aid to 68 families. By 2014, it provided cash assistance to only 23 such families for every 100 in poverty. See Figure 1.2. We refer to these as TANF-to-poverty ratios.

Figure 1.2: TANF-to-Poverty Ratio, 1979-2014



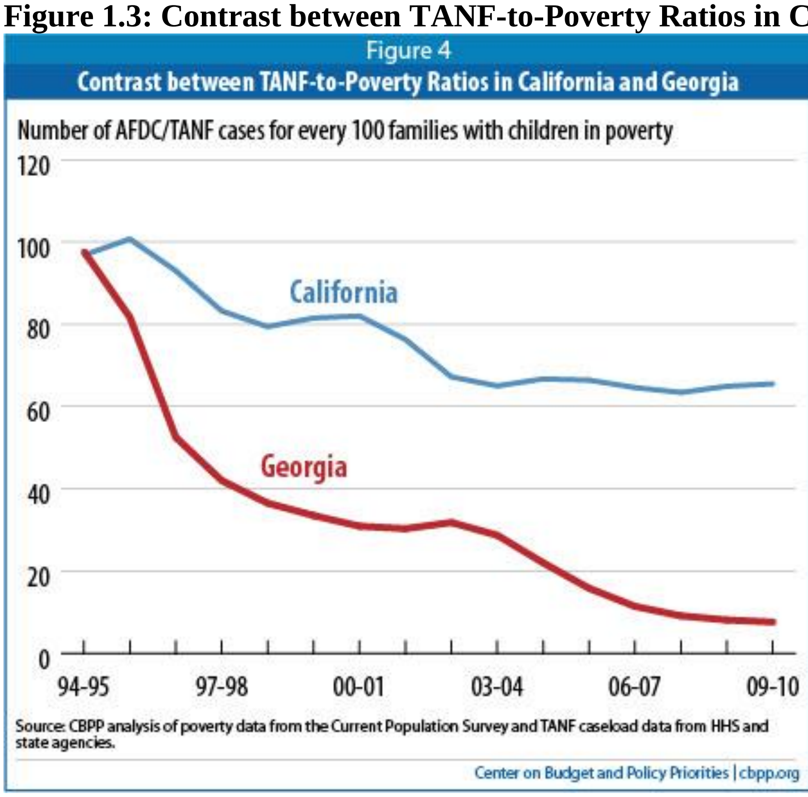
The TANF-to-Poverty ratios are calculated by dividing the number of TANF cases by the number of families with children in poverty. The number of TANF cases come from administrative data from the U.S. Department of Health and Human Services (HHS) or, since September 2006, data collected from state TANF agencies by CBPP[1]. The poverty data comes from the CPS. Two-year averages of CPS data are

[1] The TANF caseload data that CBPP collected from state agencies differ from the official HHS TANF data in two important ways. First, they include cases from solely state-funded programs. Second, unlike the HHS data, the data collected by CBPP exclude cases in worker supplement programs. These modifications allow for a more consistent trend of the number of families receiving cash assistance in each state over time. See Trisi and Pavetti (2012) for more details. (http://www.cbpp.org/sites/default/files/atoms/files/3-13-12tanf.pdf)

used to improve reliability given the relatively small sample size of the CPS in some states.

Many of the welfare policies that states implemented influence these ratios given that they impact the ease of access to TANF programs and how likely recipients are to be sanctioned off the program. Policies that states implement that determine the requirements and benefits that recipients face also influence these ratios by impacting whether current recipients want to continue in the program or whether potential recipients want to apply to the program. Therefore, these ratios can provide a good summary of the impact of such policies. These ratios can capture both differences between states and across time. For example, Georgia's TANF-to-poverty ratio dropped from 98 to 8 between 1994-95 and 2009-10, while California's ratio dropped from 97 to 66 over the same time period. See Figure 1.3.

Figure 1.3: Contrast between TANF-to-Poverty Ratios in California and Georgia



This measure scores high on many of the characteristics that I outlined I would want in an ideal measure. For example, it can be constructed for all 50 states and DC back to at least 1980. It consists of high quality data by using administrative caseload data and the CPS for poverty data which is the source for official U.S. government poverty statistics. It is also easy to explain and to replicate. The main drawback is that the TANF-to-poverty measure is mostly only an accessibility measure. I'm seeking a single metric that captures both a program's benefit levels and accessibility. For example, Tennessee and Wisconsin had similar TANF-to-poverty ratios in 2013-2014, 24.9 and 26.4 respectively. However, in 2014 the maximum TANF benefit in Tennessee for a family of three was $185, while it was $653 in Wisconsin. The TANF-to-poverty ratio is not able to capture this important difference between Tennessee's and Wisconsin's TANF program.

In this paper, I make two adjustments to the way that the TANF-to-Poverty ratios are calculated compared to the CBPP papers. First, I use three years of CPS data for each state instead of two-year averages. I do this to improve reliability, and so that I can use the middle year of the three year average as the measurement year that I can use to compare this measure to other annual data. Secondly, I create the denominator for the ratios by counting up the number of families with children with non-government income below 100 percent of the poverty line instead of the number of families with children in poverty according to the official poverty measure. For the low income population, non-government income means mostly earnings, but can also include other sources of private income such as rents, interest, and pensions. The official poverty measure counts all cash income which includes private income plus income from cash public benefits such as TANF, unemployment insurance, Supplemental Security Income (SSI), Social Security and workers compensation.

I do this because I'm interested in understanding how TANF and other safety net programs reach families at different points in the earnings distribution. I don't want my findings to be confounded by what cash government benefits those families are receiving. It's possible for a family to be above the poverty line when private income plus TANF or other cash government income are counted, but below the poverty line when only private income is counted. For my analysis of the reach of safety net programs, I prefer to keep those families in my denominator, and therefore I prefer to define my denominator using only the pre-government income of families. (In this paper, I use pre-government and private income interchangeably.) Overall, this adjustment does not change much the state-by-state and over-time trends found in the CBPP papers. For example, using this methodology, I find that in 1996, for every 100 families with children with private income below the poverty line, TANF provided cash aid to 58 families. By 2012, it provided cash assistance to only 22 such families for every 100 with private income below the poverty line.

1.5.3 Maximum Benefit Amount

Maximum benefit level amounts by state and year are widely available. The University of Kentucky's Center for Poverty Research's national welfare data set includes maximum AFDC/TANF benefits for various family sizes for 1980-2013. They collected these data from the Green Book published by the Committee on Ways and Means of the United States House of Representatives, the Congressional Research Service, and the Urban Institute's Welfare Rules Database.

Many researchers have used the state-level maximum AFDC/TANF benefit for a family of three as one of the policy variables in their regressions. However, the maximum benefit amount by itself provides an incomplete measure of the reach of a safety net program. That's because it doesn't take into account both what share of program participants receive the maximum benefit and what share of the eligible population participates. If those two rates change over time or differ between states, this wouldn't get captured by this measure.

1.5.4 Maximum Benefit Amount Adjusted by TANF-to-Poverty Ratio

This measure consist of multiplying together the two measures explained in the last two sections. This creates a measure that tries to both capture the generosity and availability of benefits.

This measure ranks high in terms of transparency and using the best available data given that it uses program eligibility data for the maximum benefits, administrative data for the caseload counts, and only relies on survey data to create the denominator of families with private income below the poverty line. This measure can easily be created to go back to at least 1980, and doesn't require adjusting the CPS data for underreporting of TANF benefits since the TANF data it uses doesn't come from the CPS.

This measure can also be used to create a variable that varies by family size given that the maximum benefit levels are available for different family sizes. The sample size in the CPS is not large enough to be able to calculate TANF-to-Poverty ratios for different family types in each state. Therefore, I use the same state-level

TANF-to-poverty ratio to adjust the maximum benefit amounts for different family sizes in a given state and year.

The adjustment by TANF-to-Poverty Ratio is important given that not all eligible families receive benefits. U.S. Health and Human Services (HHS) publishes an annual report to Congress that includes national level AFDC/TANF take-up rates going back to 1981. That report shows that between 1981 and 1996 participation rates in the AFDC program ranged from 77 percent to 86 percent. After TANF was implemented in 1996, participation rates declined. The participation rate for AFDC/TANF in 1996 was 79 percent. By 2012, only 32 percent of eligible families participated in the TANF program.

Although trends in the TANF-to-Poverty ratio are similar to trends in AFDC/TANF participation rates, I prefer using the TANF-to-Poverty ratio for the purpose of comparing the reach of AFDC/TANF across time and between states. That’s because a TANF-to-Poverty ratio allows me to more equitably compare states that might differ in their eligibility rules. A state can enact restrictive eligibility rules such as short time limits and low earnings thresholds that shrink the pool of eligible families, yet have a high participation rate if a high percentage of those eligible families participate. In the case of two states that have similar participation rates, but differ in the restrictiveness of their eligibility rules, the TANF-to-Poverty ratio would perform better than a pure participation measure in identifying the state that reaches a higher percent of families in poverty.

1.5.5 Simulated Average Benefits per Family in Poverty

This measure is similar to the one used by Hoynes and Patel (2015). The goal is to create a metric like the "Average AFDC/TANF Benefits per Family in Poverty" described in section 1.5.1 that keeps differences in demographics and economic conditions between states and across time constant.

A problem of the average benefits per family in poverty measure is that changes over time could be driven by changes in a state's demographics or depth of poverty instead of policy changes or changes in participation rates. For example, given that benefits are generally larger for families with more children, a decline in the average TANF benefits per family in poverty could be driven by families having less kids. Similarly, given that benefits are generally larger for families with less earnings, a decline in average TANF benefits per family in poverty could be caused by more families increasing their earnings but still remaining below the poverty line.

One option to deal with these issues is to select a sample of families with children and calculate for each of them what AFDC/TANF benefits they would be eligible for in each year and each state included in the analysis. One could then aggregate those benefits across all families with private income below the poverty line, and divide that by the number of families with private income below the poverty line. That would provide an average AFDC/TANF benefit eligible for amount for families with children and private income below the poverty line for each state and year.

TANF benefit and eligibility rules are quite complex and can vary greatly by state. Constructing a TANF benefits calculator that takes into account all the rules in every state for each year between 1980 and 2012 is beyond the scope of this paper. Instead, I've created a generic TANF benefits calculator that estimates a family's annual AFDC/TANF benefits based on their earnings and number of children and the maximum benefits amount in their state and year.

$$EligibleAnnualBenefits = MaximumMonthlyBenefits*12 - .67*FamilyAnnualEarnings$$

The MaximumMonthlyBenefits vary by state and year and family sizes of two, three or four people. The FamilyAnnualEarnings vary by each family. The phasedown rate of 33 percent was chosen because that's been the most common phasedown rate for AFDC/TANF programs. The MaximumMonthlyBenefit for a family of four is used for families larger than four people.

Hoynes and Patel (2015) use an AFDC/TANF benefits calculator that includes state and year specific parameters for phasedown rates and earnings disregards which they've compiled. The use of those parameters would improve my benefits calculator.

Hoynes and Patel (2015) create their simulated AFDC/TANF benefits variable by starting with a sample of single women from the March 1983 CPS. They then replicate that sample for each year in their analysis (1985-2014) and adjust each source of income for inflation. Then they pass each sample through their AFDC/TANF benefits calculator for each year and take average AFDC/TANF benefits by year, state and family size.

I follow a very similar procedure, but in my starting sample I include all years in my analysis, 1980-2012. I do this to make sure that my results are not driven by my choice of sample year. I then run the entire USA sample of single women through my calculator for each state and year in my analysis (1980-2012). That way my variable will vary by state-year-family size only due to policy differences, not due to demographic or economic differences between states or across time.

1.5.6 Simulated Average Benefits per Family in Poverty Adjusted by TANF-to-Poverty Ratio

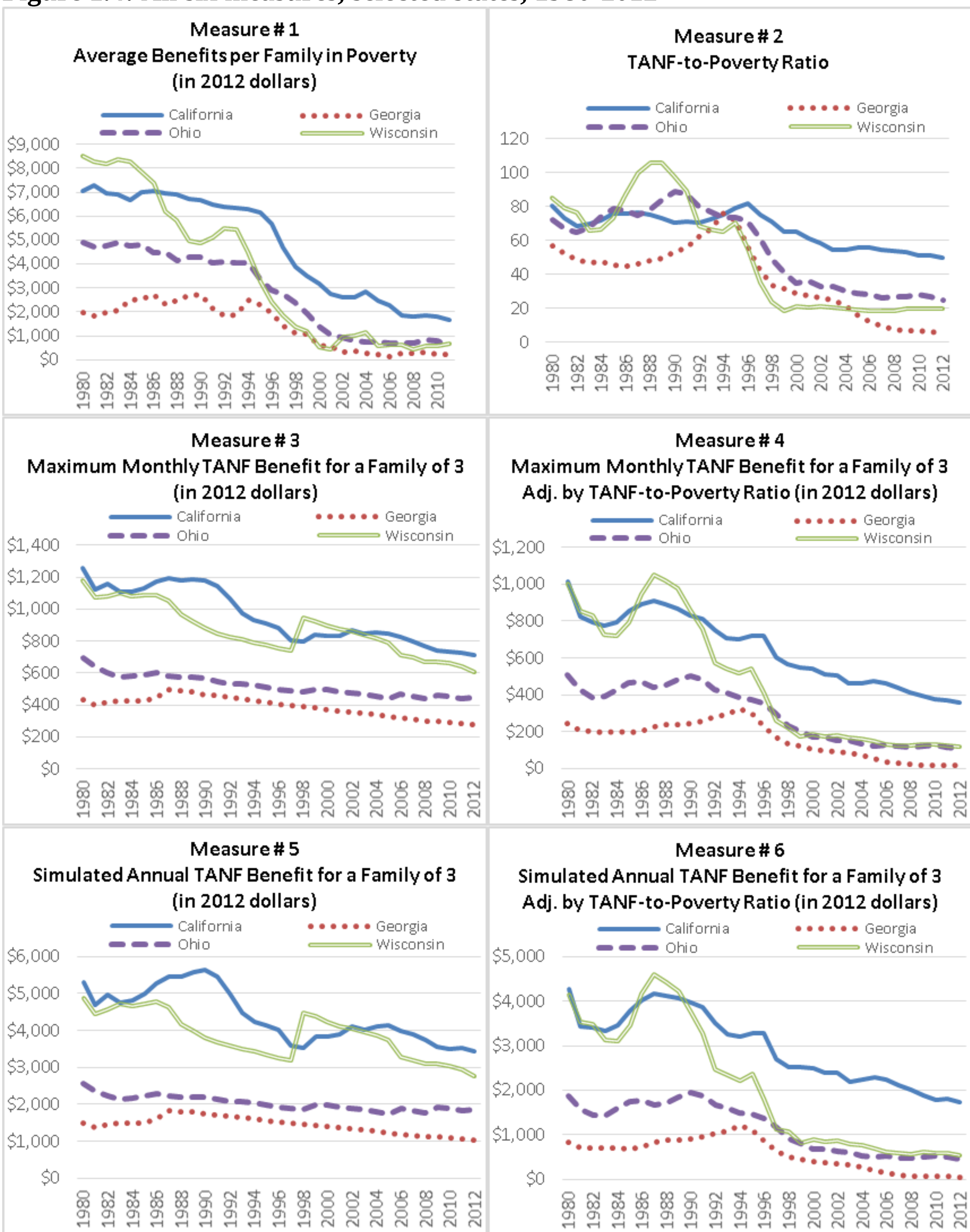
This measure consists of multiplying together the simulated average benefits explained in the previous section with the TANF-to-Poverty ratio explained in section 1.5.2. This creates a measure that tries to both capture the generosity and availability of benefits. As explained in section 1.5.3, this adjustment is important given that not all eligible families receive AFDC/TANF benefits and access to benefits varies by state and has changed over time.

1.6 Compare Measures to Each Other

In this section I will evaluate the proposed measures by analyzing how they perform in tracking changes in the reach of AFDC/TANF in California, Georgia, Ohio and Wisconsin. I chose these four states because they vary in terms of their TANF-to-Poverty Ratios and their maximum AFDC/TANF benefits. California and Wisconsin have higher AFDC/TANF benefits than Georgia and Ohio. TANF-to-Poverty Ratios dropped dramatically after 1996 in Georgia, Ohio, and Wisconsin, but not as much in California. (See Figure 1.4.)

The average benefits per family in poverty explained in section 1.5.1 can serve as a validity check for the other measures. That measure does a good job of differentiating between the four states in terms of how much AFDC/TANF benefits families in poverty receive. It shows how California is a high AFDC/TANF state, Georgia a low one, and Ohio more of a median one. It also shows the dramatic drop in the amount of benefits provided by Wisconsin's AFDC/TANF program. (See Measure # 1 in Figure 1.4)

Figure 1.4: All six measures, selected states, 1980-2012



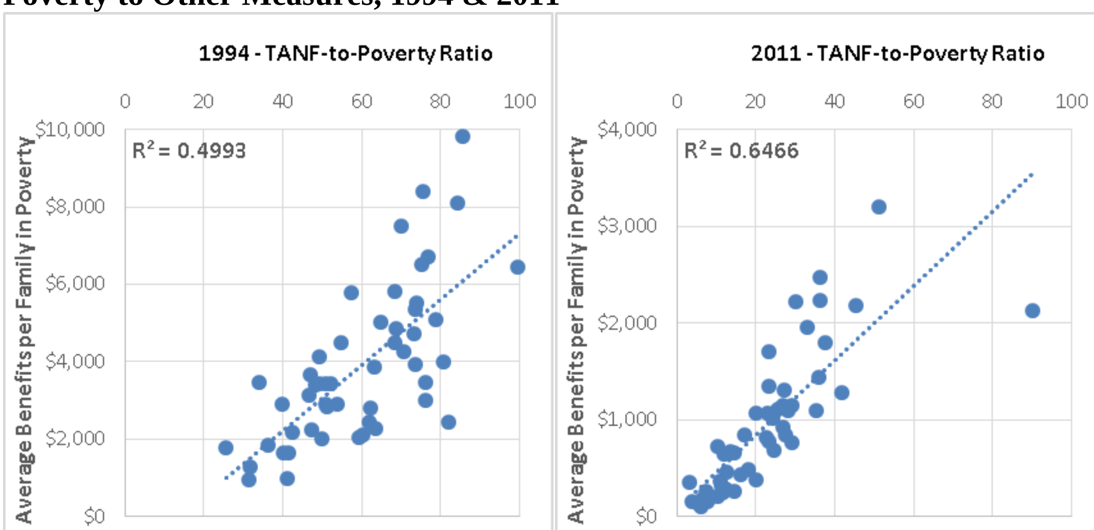
The TANF-to-Poverty Ratio by itself captures the dramatic decline of TANF's reach after 1996. However, it does not differentiate between the four states in 1994-1996 since it shows all four states to be at about the same level. (See Measure # 2 in Figure 1.4) This is potentially problematic since we know from the average benefits per family in poverty measure that, for example, AFDC was a more important income support in California than in Georgia.

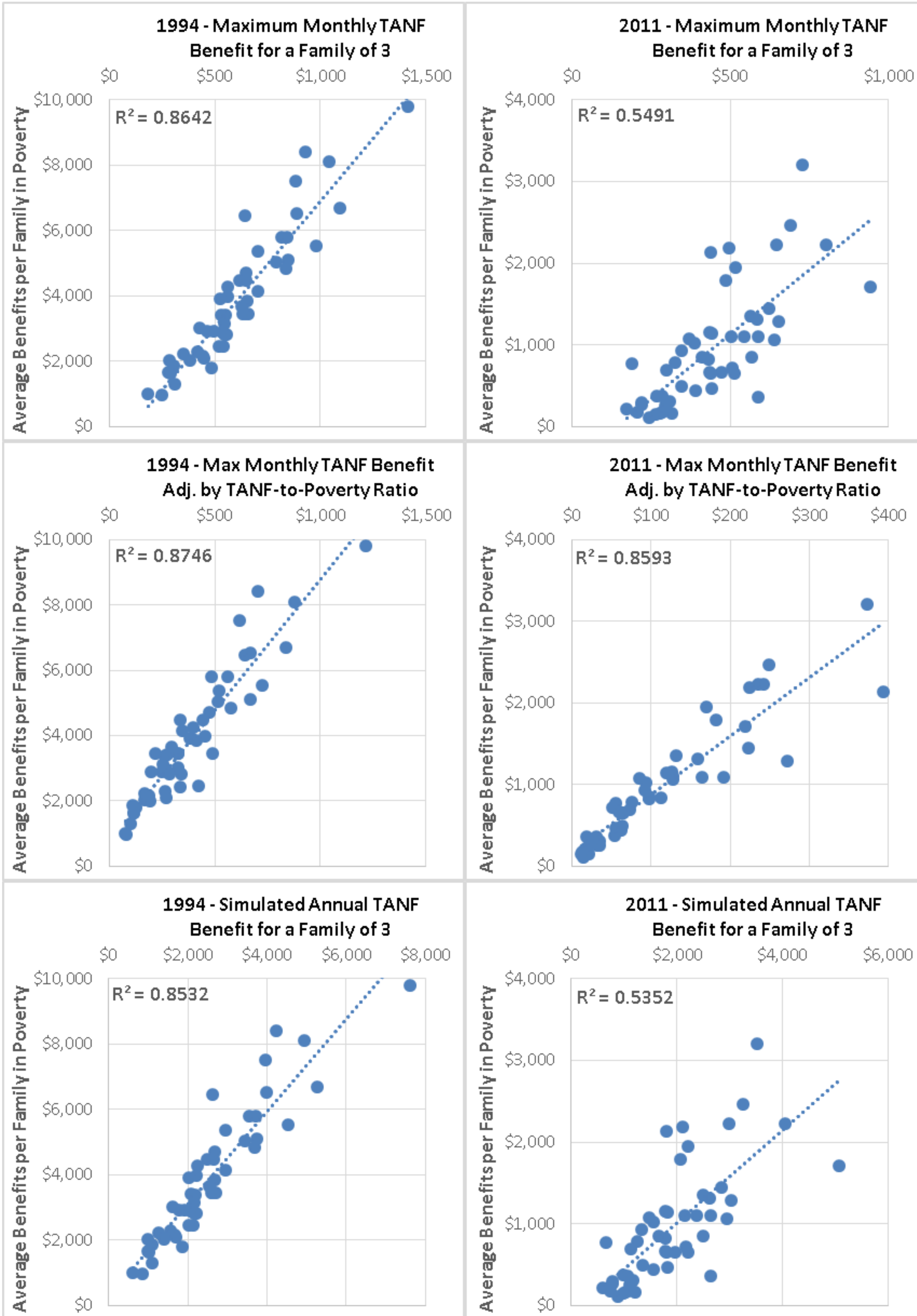
The Maximum Monthly TANF Benefits for a family of three reveals some differences between states, but it fails to capture the steep decline in the importance of TANF as an income support in Wisconsin. (See Measure # 3 in Figure 1.4) This shows why the Maximum Monthly TANF Benefit for a Family of 3 Adjusted by the TANF-to-Poverty Ratio is a superior measure. It does a good job of capturing Wisconsin's decline, and it also does a good job differentiating California from Georgia during the early 1990s period. (See Measure # 4 in Figure 1.4.)

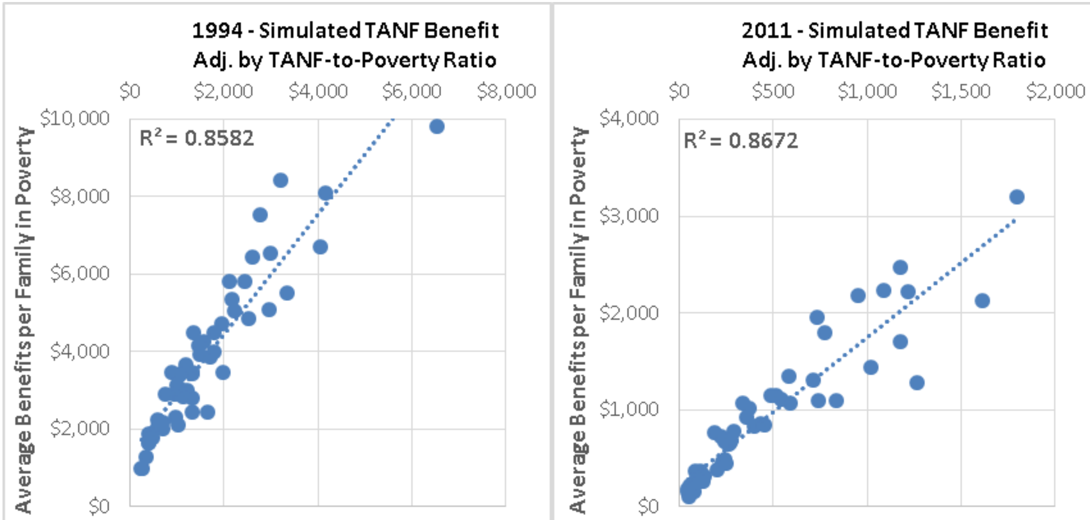
The simulated Annual TANF Benefits measures (# 5 and # 6 in Figure 1.4) reveal almost identical trends to the Maximum Monthly TANF Benefits measures (#3 and #4 in Figure 1.4). This is not surprising given that the Maximum Monthly TANF benefit is the only parameter that varies by state and year in my TANF benefits calculator. It would be interesting to see whether it would make a substantial difference if I also allowed earning disregards and phasedown rates to vary by state and year like Hoynes and Patel (2015) do. My guess is that the trends by state are mostly dominated by differences in maximum benefit levels and participation rates between states. Before 1996 most states had very similar earning disregards and phase-down rates. After 1996, some states adopted much higher earning disregards so that recipients could work full time and still receive welfare benefits. However, Matsudaira and Blank (2014) found that changes in TANF earning disregards after 1996 had little effect on labor supply or income of single mothers. They conclude that was because few women used these earnings disregards.

As I wrote above, I consider comparing my measures to the average AFDC/TANF benefit per family in poverty as a good validity check. Figure 1.5 shows correlations between each of my other measures and the average AFDC/TANF benefit per family in poverty. Each dot in the scatter plots represents a state in a given year. I present these correlations for 1994 and 2011.

Figure 1.5: Correlations between Average AFDC/TANF Benefits per Family in Poverty to Other Measures, 1994 & 2011




1994 - Maximum Monthly TANF Benefit for a Family of 3
R² = 0.8642
2011 - Maximum Monthly TANF Benefit for a Family of 3
R² = 0.5491
1994 - Max Monthly TANF Benefit Adj. by TANF-to-Poverty Ratio
R² = 0.8746
2011 - Max Monthly TANF Benefit Adj. by TANF-to-Poverty Ratio
R² = 0.8593
1994 - Simulated Annual TANF Benefit for a Family of 3
R² = 0.8532
2011 - Simulated Annual TANF Benefit for a Family of 3
R² = 0.5352
Average Benefits per Family in Poverty



It's striking how in 1994 maximum benefits were a good predictor of average benefits for families in poverty, but have become a much worse predictor in 2011. The correlation coefficient declined from 0.86 in 1994 to 0.55 in 2011. In contrast, TANF-to-Poverty Ratios have become a better predictor between 1994 and 2011. This argues for the importance of adjusting the maximum and simulated benefits measures by the TANF-to-Poverty ratios. The simulated TANF measure is a relatively weak predictor of mean TANF benefits per family in poverty in 2011 with a correlation of 0.54, but becomes a much better predictor with a correlation of 0.87 when it is adjusted by TANF-to-Poverty ratios.

1.7 Can these AFDC/TANF measures be applied to other safety net programs?

One of my goals for an ideal measure was one that would compare TANF, SNAP, and EITC policies in a consistent way. That would then allow me to use those measures to equitably compare how each program impacts outcomes such as employment and poverty status.

The methodologies described in sections 1.5.3 and 1.5.5 to create maximum and simulated benefits for AFDC/TANF could be used to create SNAP and EITC measures that are based on their respective program rules. However, if one wanted to create measures that account for differences in program participation and access then one would need to do an adjustment similar to the TANF-to-Poverty ratio adjustment I did for the measures described in sections 1.5.4 and 1.5.6. When thinking about how to do such an adjustment it's important to keep in mind how eligibility rules differ for SNAP and the EITC compared to TANF. For example, the EITC is not available to families without any earnings, but is available to families with earnings that are much higher than the poverty line. Therefore, an EITC-to-poverty ratio that uses all families with children and earnings below the poverty line as its denominator would not make sense as a participation/access measure for the EITC. That's because such a denominator would include a number of families who are not eligible to participate in the EITC given that they lack earnings and would miss EITC recipient families with earnings above the poverty line. Table 1.2 shows the distribution of TANF, SNAP, and EITC benefits for families with children by earnings level.

Table 1.3: TANF, SNAP and EITC Benefits for Families with Children by Earnings Level, 2012

	Total Program Benefits					
	Billions of 2012 Dollars			Percentages		
	TANF	SNAP	EITC	TANF	SNAP	EITC
No earnings	3.6	13.2	0.0	46%	27%	0%
With earnings:						
below 50% of poverty line	2.1	12.5	5.3	27%	26%	12%
between 50-100% of poverty line	1.1	13.8	16.2	14%	28%	38%
between 100-150% of poverty line	0.5	6.1	12.4	7%	12%	29%
between 150-200% of poverty line	0.3	1.8	5.8	4%	4%	14%
between 200-250% of poverty line	0.1	0.6	1.4	2%	1%	3%
above 250% of poverty line	0.1	0.5	1.4	1%	1%	3%
Total	7.9	48.6	42.5	100%	100%	100%

Source: Author's calculations using the March CPS augmented by TRIM data for TANF and SNAP.

For SNAP, a ratio could be calculated using SNAP administrative caseload data for the numerator and March CPS data for the denominator. The numerator would be the number of SNAP cases with children. The denominator could be the number of families with children and earnings below 130 percent of the poverty line. Using a threshold of 130 percent would more closely approach a participation-like measure given that the gross monthly income eligibility limit for SNAP is at 130 percent of the poverty level.

For the EITC, a ratio could be created using IRS EITC filer data for the numerator and CPS data for the denominator. For the numerator, one would ideally want the number of EITC filers with at least one qualifying child per year per state. The IRS's Statistics of Income (SOI) program produces annual individual income tax return reports that include the number of EITC filers per state. However, I have yet to find a data source that provides the number of EITC filers per state and by whether they had any qualifying children with data going back to 1980. For the denominator, one could just use the number of EITC filers according to the CPS EITC variable. That's because EITC benefits are modeled instead of being asked of survey respondents. Therefore, the CPS variable provides a count of all eligible recipients.

A challenge is that this methodology will likely yield a participation rate that is above 100 percent in some states in some years. Table 1.3 compares the number of EITC filers and the amount of EITC they received according to IRS and CPS data for 2012. The main finding of that table is that the number of filers with qualifying children reported by the IRS is much larger than the number of EITC eligible filers according to the CPS. Therefore, the CPS does not seem adequate to use as the denominator for an EITC access measure that would use IRS data as the numerator.

Table 1.4: Comparison of EITC CPS data to IRS data, 2012

	Number of Filers (millions)			Total EITC amount (billions)		
Returns with:	IRS	CPS	Ratio of IRS to CPS data	IRS	CPS	Ratio of IRS to CPS data
no qualifying children	6.9	6.9	99%	$1.8	$1.9	98%
one qualifying child	10.2	6.5	158%	$22.8	$14.2	161%
two qualifying children	7.3	5.2	140%	$25.8	$16.9	153%
three or more qualifying children	3.5	3.3	108%	$13.6	$12.4	110%
All returns	27.8	21.8	128%	$64.1	$45.4	141%

Source: IRS Statistics of Income (SOI) program and author's analysis of March CPS.

Given the findings above, my plan is to assume a 100 percent participation rate for the EITC and not do any of the access adjustments I did for the TANF measures described in sections 1.5.4 and 1.5.6. I think this is a reasonable approach given that the CPS data seems to be undercounting the impact of the EITC and studies show that participation rates of the EITC have varied relatively little across time or between states. Maynard and Dollins (2002) reviewed studies of the EITC participation rate that covered the 1984 to 1991 period. Those studies estimated the EITC participation rate to be as low as 70 percent and as high as 89 percent and differed in their methodologies and the years covered. The only state-by-state estimates of EITC participation done for multiple years in a consistent way that I was able to find cover the 2008-2012 period. These estimates were done by the U.S. Census Bureau in collaboration with the Internal Revenue Service (IRS) and were based on American Community Survey (ACS) and IRS data[2]. These data show that compared to TANF there is much less variation across states in the EITC participation rate and therefore using a single national participation rate for all the states would not be as problematic as using a single national participation rate for TANF. Table 1.4 shows how SNAP and especially TANF have a greater range in their participation rates across states.

[2] These are available at https://www.eitc.irs.gov/EITC-Central/Participation-Rate (Accessed, October 12, 2015)

Table 1.5: Number of States by EITC, SNAP and TANF Participation Rates, 2008-2012

	EITC	SNAP	TANF
Less than 10% participation rate	0	0	2
10-20%	0	0	13
20-30%	0	0	11
30-40%	0	0	14
40-50%	0	0	6
50-60%	0	9	3
60-70%	0	34	2
70-80%	29	8	0
80-90%	22	0	0
Higher than 90% participation rate	0	0	0
Total number of states + DC:	51	51	51
Lowest participation rate in a state	72.8%	52.1%	6.6%
Highest participation rate in a state	84.0%	76.%	68.9%
50 states + DC average participation rate:	79.1%	65%	30.0%

Over the four year period, 2008-2012, the national EITC participation rate was 79 percent. The highest EITC participation rate was 84 percent in Mississippi and the lowest was 73 percent in Oregon. The range of participation rates for TANF was much greater with a 7 percent participation rate in Wyoming and a 69 percent participation rate in Maine. These data show that it's much less of a problem to not have state-specific participation rates for an EITC measure, while it's very important for a TANF measure to take into account state variation in program access.

1.8 What do these measures say about how the U.S. safety net has changed over the last three decades?

Figure 1.6 shows simulated benefits for AFDC/TANF, SNAP, and the EITC at the national level over the 1990-2010 period. The AFDC/TANF figures take into account access to benefits by adjusting by state TANF-to-Poverty ratios. A similar methodology is used to adjust the SNAP figures using the SNAP quality control (QC) data. The EITC figures are not adjusted for accessibility given the EITC's high participation rate, ease of access and the data issues already discussed.

Figure 1.6: Simulated AFDC/TANF, SNAP, and EITC policy variables, 1990-2010

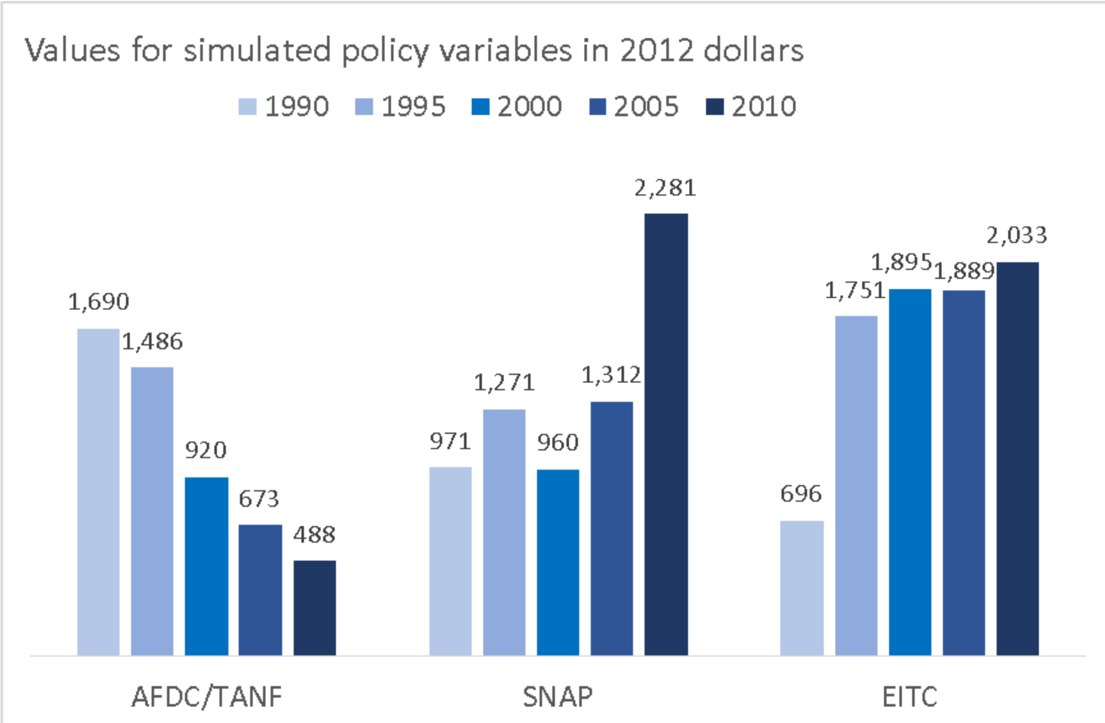


Figure 1.6 shows the trajectory of AFDC/TANF, SNAP, and EITC benefits and access policies during the 1990-2010 period. The mean values show the drop in AFDC/TANF, the drop and increase of SNAP, and the increase of the EITC. The decline in AFDC/TANF is driven by both the erosion of the value of TANF benefits and a reduction in access to cash assistance across states.

The drop of SNAP between 1995 and 2000 reflects the fact that the 1996 welfare law included some cuts in SNAP eligibility and benefits. In addition, SNAP participation declined during that period because of the tightening of access to TANF given that some people used to get SNAP as a result of applying for TANF. The increase in SNAP between 2000 and 2010 captured by the SNAP variable in Figure 1.6 reflect both increases in accessibility and benefit levels. In 2002 and 2008 Congress enacted changes to the SNAP program that made the program more accessible and raised program participation by eligible households. The 2009 Recovery Act passed by Congress included a temporary increase in monthly SNAP benefits which became effective on April 1, 2009 and expired in November 2013. The Recovery Act increased monthly SNAP benefits by an average of 15 percent[3].

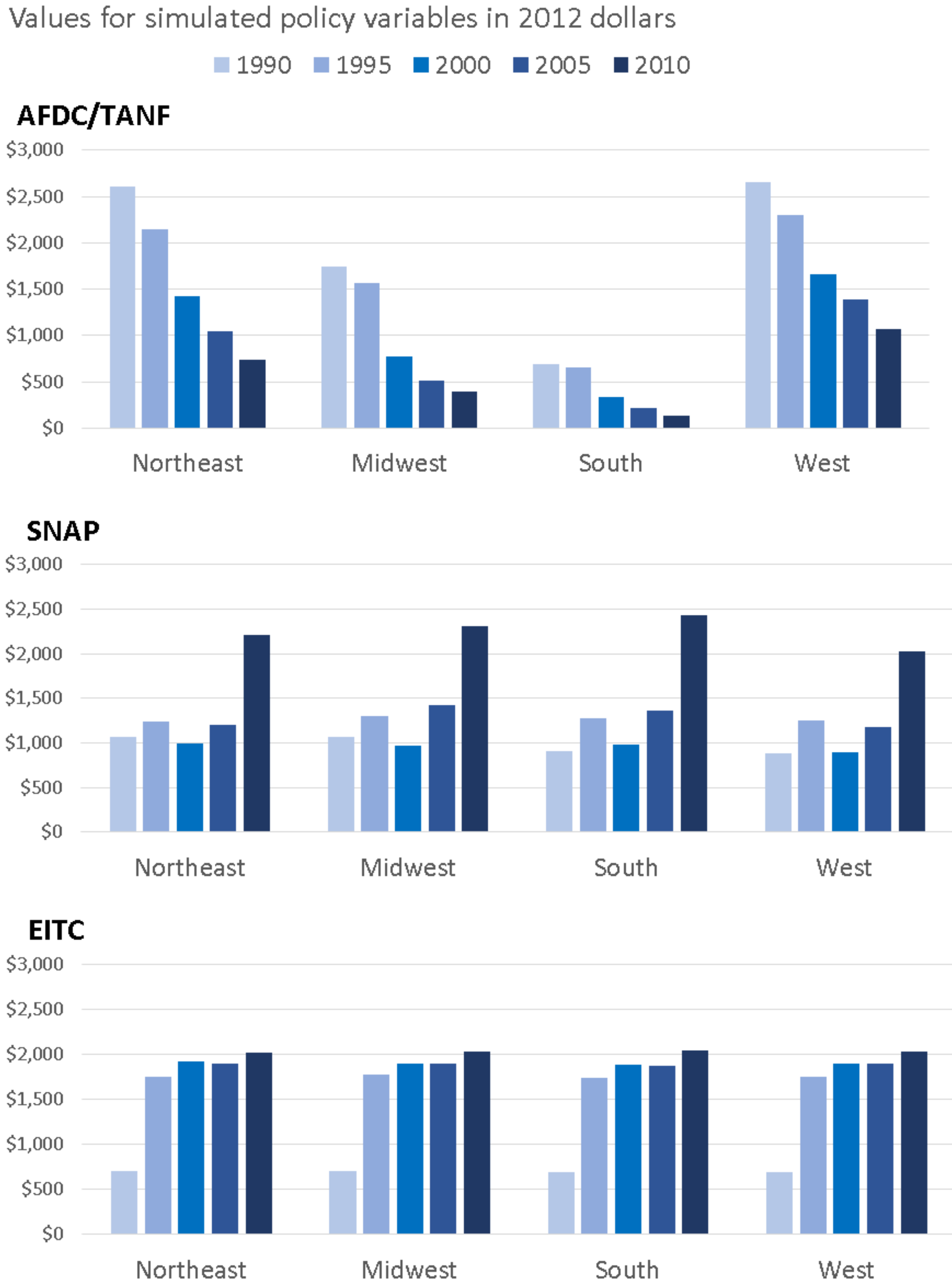
Figure 1.7 shows the data in Figure 1.6, but for each region.[4] This comparison across regions highlights the main difference that exists between AFDC/TANF and SNAP and the EITC. AFDC/TANF benefit levels are set at the state level, and historically, states in the South have provided much less generous AFDC/TANF benefits compared to states in the Northeast or the West. In contrast to AFDC/TANF, access to SNAP and EITC benefits are fairly similar across states as was shown in table 1.5. In addition, SNAP and EITC benefits are determined at the federal level. Also very important, is the fact that SNAP and the EITC are not block grants and are funded by federal dollars. This means that states don't have an incentive to reduce caseloads in order to free up state dollars.

---

[3] For more information on the Recovery Act's effect on SNAP, see United States Department of Agriculture Economic Research website: http://www.ers.usda.gov/topics/food-nutrition-assistance/supplemental-nutrition-assistance-program-(snap)/arra.aspx

[4] States are grouped by region using the Census Bureau's definition of regions. The Northeast Census region consists of Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island and Vermont. The Midwest region is defined as Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota and Wisconsin. The South region is defined as Alabama, Arkansas, Delaware, District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia and West Virginia. The West region is defined as Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington and Wyoming.

Figure 1.7: Simulated AFDC/TANF, SNAP, and EITC policy variables by region, 1990-2010



In times of increased need such as during the Great Recession, federal dollars automatically become available to fund increases in the SNAP or EITC caseload. TANF's block-grant structure had the opposite effect. During the Great Recession, when the number of families needing cash assistance increased, states were unable or unwilling shift money in their TANF block grant from other purposes to cash assistance. Instead, many states responded by cutting TANF benefits and tightening eligibility rules, often by shortening time limits or making them more severe in other ways (Schott and Pavetti, 2011).

There are a number of actions that states could do to make their TANF programs work as stronger safety nets for families in need. They could increase their maximum TANF benefit levels, and could also implement policies to make it easier for families to receive benefits. If a state wanted to reach out to families in need, all it would need to do is to look at its own SNAP caseload. There are many TANF-eligible families in the SNAP caseloads of many states who are currently not receiving TANF. Some factors that prevent states from expanding TANF include the lack of available funds, the ideological make-up of their legislature, the political dynamics within a state, and the incentive structure created by federal TANF policies.

There are also a number of actions that Congress could take to encourage and/or force states to make their TANF programs work as a better safety net for families in need. The TANF block grant has lost 30 percent of its value since it was created because it has never been adjusted for inflation. Congress could increase the value of TANF block grant and reform the rules so that more of its resources are devoted to the program's core purposes of child care, cash assistance and work-related activities. Congress could also set minimum benchmarks for benefit levels and eligibility rules. Congress could do more to hold states accountable for serving families in need. It could use a TANF-to-poverty measure as a metric to require states to serve some minimum share of families in poverty or deep poverty. Congress could also set up better performance measure to assess the extent to which states help families find jobs. Right now, the federal government asks states to meet a work participation rate. However, it is not working because states primarily meet it by *not* providing assistance to many poor parents who face various barriers to employment (Pavetti & Schott 2016).

1.9 Conclusion

The purpose of this paper was to develop measures that capture variation of safety net program policies across time and by state. I focused on measuring variation in benefit levels and program access because I think those are the most important factors in terms of influencing the behavior of individuals and impacting their incomes. A program's benefits amount and its accessibility can largely determine how much a program reduces poverty. One would also expect that if a program is to influence behavior such as whether to enter the paid labor market, then the size and availability of benefits would matter a lot.

Out of the measures I discussed, the measures described in sections 1.5.4 and 1.5.6 seem the most promising. These are the maximum and simulated benefits measures that are adjusted by the TANF-to-Poverty ratios. Given the dramatic decline in the access to TANF since 1996 and how much variation exists in access to TANF across states, it is crucial that any measure take that variation into account. In section 1.7 I discussed how these measures could be adapted to analyze changes in policies for the SNAP and EITC programs.

The real test for these measures will be done in the next chapter as I use these measures to try to explain changes in the employment of single mothers over the 1980-2012 period. The hope is that these measures will provide enough over time and across state variation that I will be able to isolate the impact of AFDC/TANF, EITC, and SNAP policies on single mother employment trends.

Chapter 2: How did changes in safety net policies during the 1990s and 2000s affect single mother employment trends?

2.1 Introduction

President Bill Clinton's signing of the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA) on August 22, 1996 marked a dramatic change in the history of social policy in the United States. The Act eliminated the Aid to Families with Dependent Children (AFDC) program and replaced it with a block grant program called Temporary Assistance for Needy Families (TANF). The Act ended the entitlement of poor families to assistance from the federal government, instituted a five-year time limit on federal cash benefits, imposed stronger work requirements on recipients and devolved most details of welfare policy making to the fifty states. The goal of these changes was to move single mothers with children who had been receiving AFDC out of "dependency" on government assistance and into work outside the home. The Act aimed to reduce TANF caseloads, increase work participation, reduce poverty, and promote marriage.

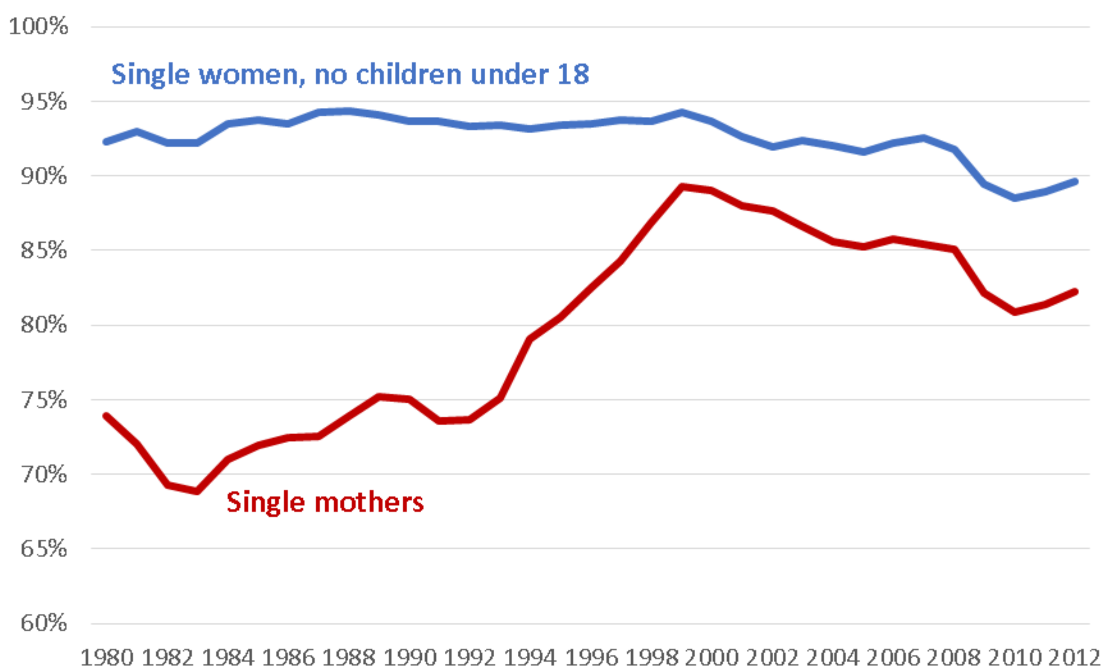
Many policymakers view the 1996 welfare law which created the Temporary Assistance for Needy Families (TANF) program as a major success. They see TANF program's design and block grant structure as a model for the reform of other safety net programs. Therefore, it is very important for policy makers to understand what welfare reform achieved and did not achieve.

This paper aims to contribute to the literature on the impact of welfare reform by analyzing how various policy changes in the 1990s affected the employment trends of single mothers. I choose to focus on this group because historically they have been the most likely to receive welfare benefits and therefore would have been the most impacted by the 1996 welfare reform law. In 2011, 58 percent of children in poverty lived in single mother families. The poverty rate for children in single mother families was 47.7 percent, much higher than the poverty rate for all children, 21.4 percent.

Single mothers increased their employment rate by 15 percentage points from 1992 to 2000. Figure 2.1 shows how single mothers narrowed the gap in employment with single women without any own children. Since 2000, both groups have decreased their employment levels.

Figure 2.1: Employment rates for single women, 1980-2012

Percent of women between the ages of 18 and 54
with any work during the year



Note: Women who did not work during the previous year because of illness, disability or school enrollment are not included in the analysis.
Source: Author's analysis of Current Population Survey.

One would expect that welfare reform would have had a bigger impact on single mothers than other women given that over 80 percent of the TANF caseload has historically been single mother families. However, Figure 2.1 by itself does not let us determine whether it was welfare reform or other factors that drove the increase in employment. This paper will analyze how policy and economic factors affected the employment rate of single mothers in the period between 1992 and 2000, and between 2000 and 2012.

2.2 Literature Review

There is little debate that single mother employment increased during the 1990s. The controversy is over whether the economy, the EITC, welfare reform or other factors were responsible for increasing the employment of single mothers. Welfare reform had the good fortune of being implemented shortly after major expansions of the Earned Income Tax Credit (EITC) and at the beginning of an incredibly strong labor market that reached unemployment rates as low as 4 percent. These factors, along with the work supports welfare reform provided, made it possible for many single mothers to find work.

A large number of econometric studies have tried to establish a causal link between welfare policy reforms and various outcome variables such as welfare use, employment, earnings, income, poverty, hardship, marriage, childbearing, and child outcomes. The econometric studies generally found that welfare reform had an impact both on declines in welfare participation and on increases in work effort, although the magnitude of this effect varies across studies. As summarized by Grogger and Karoly's meta-analysis (2005), most econometric studies found that welfare reform as a whole was responsible for about a 20 percent decline in welfare caseloads and a 4 percent increase in the employment of single mothers.

However, only a handful of studies (Meyer & Rosenbaum, 2001; Grogger, 2003; Fang & Keane, 2004; Looney, 2005; Noonan, Smith & Corcoran, 2007) have tried to explicitly compare the impact of welfare reform on single mother employment relative to the impact of the economy and other policy reforms such as the EITC. This paper aims to contribute to that string of the literature.

Meyer and Rosenbaum (2001) found that during 1984-1996, the EITC accounted for 61 percent of the overall change in annual employment of single mothers relative to single women without children. Meyer and Rosenbaum also analyzed the 1992-1996 period and found that the EITC accounted for a smaller share of the change (35 percent), but still had the largest effect on annual employment of single mothers during this period compared to other policy variables. Welfare waivers (any time limits and whether the state had terminated any cases under a waiver provision) accounted for approximately 15-20 percent of the employment increase during both periods. The maximum welfare benefit accounted for 11-25 percent of the employment increase depending on the measure and time period. Meyer and Rosenbaum used data from the March CPS (1985-1997) and the CPS Outgoing Rotation Group File (1984-1996). Their sample included all single women ages 19-44 who were not in school.

Jeffrey Grogger (2003) found that welfare reform accounted for just 13 percent of the total rise in employment among single mothers in the 1990s. The EITC (which was expanded in 1990 and 1993) and the strong economy were much bigger factors, accounting for 34 percent and 21 percent of the increase, respectively. Grogger (2003) used data from the March CPS that covers the period 1978 to 1999.

Fang and Keane (2004) found that the economy was the most important factor behind the 1993-2000 employment increase. It contributed 40 percent to the increase. The implementation of TANF work requirements and time limits contributed 13 percent and 6 percent, respectively, and the EITC contributed 20 percent to the increase. When looking at the employment increase between 1993 and 2002, they found that the EITC was the most important factor contributing 33 percent to the increase while the economy contributed 25 percent. This study used data from the March CPS 1981-2003.

Looney (2005) finds that welfare reform made the largest contribution (26 percent) to the increase in single mothers' employment between 1993 and 1999, but the impact of taxes was only slightly smaller (22 percent). The economy contributed 17 percent to the increase and declining welfare benefit generosity contributed 11 percent. Looney used monthly data on all single mothers from the 1990 and 1996 SIPP.

Noonan, Smith, and Corcoran (2007) found that the EITC accounted for the largest portion of the employment increase for both black and white single mothers. For all single mothers combined, the EITC accounted for 19-25 percent of the employment increase from 1991 to 2000, and TANF, unemployment, and AFDC/TANF benefit generosity accounted for 6-12 percent each. The size of each factor's impact is slightly different across black and white single mothers, but the same overall patterns hold for both groups. The unemployment rate was the only factor that contributed to the change in employment between 2000 and 2003. The study used March CPS data from 1991 to 2003, and included all white and black single mothers ages 18-54 that lived in a Metropolitan Statistical Area.

The latest year of analysis for any of these papers was 2003. This paper contributes to the literature by incorporating data that extends until 2012. In addition to having newer data, this paper contributes to the literature by providing a more detailed analysis of how welfare reform and other factors impact different subgroups of single mothers. This is important given that single mothers are a fairly heterogeneous group. I analyze how policies have impacted single mothers differently depending on their educational attainment and the age of their youngest child. Most previous research papers have focused on the impact of AFDC/TANF and the EITC on employment. An important contribution of this paper is that I compare the impact of TANF and the EITC with the impact of the Supplemental Nutrition Assistance Program (SNAP, formerly food stamps). Using a consistent methodology, I create a measure for TANF, SNAP, and the EITC that captures in dollar terms how access and benefit levels have changed over time by state and by family size. The fact that I use the same methodology to create the measures for the three programs allows me to compare how TANF, SNAP, and EITC policies have impacted the employment of single mothers in a more consistent and easier to understand way than previous research. The first chapter of my dissertation explained the development of these measures.

2.3 Methodology

Choice of Data Set

Like many previous researchers, I have chosen to use the Annual Social & Economic Supplement (ASEC) from the Current Population Survey (CPS), commonly known as the March CPS. The CPS microdata which is publicly available provides information on labor market participation, family structure, demographics, receipt of government benefits, and many other variables. The March CPS sample size currently stands at about 100,000 households per year. (U.S. Census Bureau, 2010). This paper uses March CPS data covering the years 1980-2012.

Level of Analysis & Sample

In order to be able to compare the impact of individual level and macro level variables, I have decided to conduct my analysis at the individual level. Doing the analysis at the individual level also allows me to more easily take into account individual characteristics such as the age and education level of the person. I limit the sample to all single women between the ages of 18 and 54. Similarly to Hoynes and Patel (2015), I drop from the sample women who did not work during the previous year because of illness, disability or school enrollment because these women have visibly different incentives entering the work decision. All women except those who are married and have a spouse present in the household are counted as single women. Under this definition single women include the never married, separated, widowed, divorced and those who are married but their spouse is not present in the household. This definition of single women matches the one used by Census to identify female family heads. I define as a mother someone living with an own child younger than 18.

Choice of Dependent Variable

My dependent variable is whether someone worked during the year. The March CPS asks respondents how many weeks they worked during the prior calendar year. My dependent variable has a value of 0 if someone did not work during the prior year and a value of 1 if someone did work during the prior year.

Measurement of Safety Net Policies

The observational econometric studies analyzing the impact of welfare reform make use of the variation that exists between states and over time in their implementation of welfare policies.

Under TANF states have a significant amount of flexibility in how they design their TANF programs. States have great flexibility in their choice of benefit levels, entry and work participation requirements, sanctions, time limits, family caps, earning disregards, exemptions, and other policies. The Urban Institute has collected and coded a number of these state policy choices in their Welfare Rules Database. Prior to welfare reform many states applied for waivers that allowed them to implement some of these policies before the implementation of TANF in 1996. Many previous studies use dummy variables to differentiate between years before and after TANF, and years before and after a state implemented a waiver.

Using a dummy variable like many previous researches seems unwise in my case because my goal is to analyze the impact of welfare reform policies in the 2000s and states have implemented various additional reforms to those they implemented during the 1990s. Therefore, I need to use a measurement of welfare policies that is able to capture additional policy reforms states implemented since 1996 and is able to better capture the differences between state policies.

My measurement approach starts with the premise that a program's benefit levels and accessibility matter the most in terms of influencing the behavior of individuals and impacting their incomes. A program's benefit levels and its accessibility to people with earnings below the poverty line can largely determine how much a program reduces poverty. One would also expect that if a program is to influence behavior such as whether to enter the paid labor market, then the size and availability of benefits would play a very important role.

In chapter 1 of this dissertation I discussed six potential metrics to measure how access and benefit levels of AFDC/TANF changed after the 1996 welfare law. The regressions in this paper use the simulated annual benefits adjusted by the TANF-to-Poverty ratio measure. I adapt that methodology to created similar measures for SNAP and the EITC.

Some researchers have included a number of additional policy variables beyond the three that I've included. Fang and Keane (2004) were the most comprehensive in their approach. In addition to variables for TANF, SNAP and the EITC, they included variables for the minimum wage, child care subsidies, Medicaid, child support enforcement, and the federal income tax rate for the lowest bracket. Looney (2005) included policy variables for AFDC/TANF, Medicaid, the EITC and other taxes. Grogger (2003) included variables for TANF, the EITC, and the minimum wage. Hoynes and Patel (2015) included variables for TANF, the EITC and other taxes. Noonan, Smith and Corcoran (2007) included policy variables for just TANF and the EITC.

Many previous researchers did not include SNAP, but I think the inclusion of SNAP in my model is important given its growth over the last decade. The fact that my model has only three policy variables has the advantage that it makes interpretation and presentation easier compared to more complex models. As discussed below, my model adequately fits the data and produces results that are in line with previous research. However, in future research, I would like to investigate how including additional policy variables will impact the fit of my model and results.

Economic Variables

Almost all studies control for macroeconomic factors using state unemployment rates, which is what I do in this paper. Some studies went further by also controlling for state GDP, state median income, and state wages at the 25th percentile. In future research, I plan to test whether controlling for these variables improves the fit of the model.

2.4 Descriptive Statistics

Table 2.1 provides employment rates for single women between the ages of 18 and 54 by various characteristics. The first two columns show what percent of my sample belongs to each category. Data for single mothers and single women without children are provided separately given their different characteristics. The remaining columns compare 1992 and 2000 employment rates, the period over which employment levels increased the most for single mothers. The first row of data shows that between 1992 and 2000 employment for single mothers increased by 15 percentage points while employment for single women without children remained flat. This pattern of single mothers increasing their employment more than single women without children holds true across all characteristics. Another general pattern is that those single mothers with the lowest employment levels in 1992 increased their employment the most between 1992 and 2000.

Table 2.1: Employment Rates of Single Women Age 18-54 by Various Characteristics, 1992-2000

	Percent of all in 1992-2000		Employment Rates					
			Single Mothers			Single women with no children		
	Single mothers	Single, no children	1992	2000	Difference 1992-2000	1992	2000	Difference 1992-2000
All	100%	100%	74%	89%	15%	93%	94%	0%
Number of children and their age								
one child, youngest is 0-3	14%	n.a	69%	85%	16%	n.a	n.a	n.a
one child, youngest is 4-7	11%	n.a	83%	92%	9%	n.a	n.a	n.a
one child, youngest is 8-17	26%	n.a	87%	95%	9%	n.a	n.a	n.a
2+ children, youngest is 0-3	17%	n.a	49%	79%	29%	n.a	n.a	n.a
2+ children, youngest is 4-7	14%	n.a	72%	87%	16%	n.a	n.a	n.a
2+ children, youngest is 8-17	18%	n.a	81%	92%	12%	n.a	n.a	n.a
Own Age								
18-24	17%	37%	59%	81%	22%	95%	95%	0%
25-34	37%	24%	72%	88%	17%	93%	94%	1%
35-44	36%	18%	81%	92%	11%	92%	92%	0%
45-54	10%	21%	82%	95%	13%	91%	92%	1%
Educational Attainment								
No high school degree	20%	12%	47%	74%	27%	76%	81%	5%
High school degree only	38%	28%	75%	89%	14%	91%	92%	1%
Some college	31%	36%	87%	94%	7%	97%	97%	-1%
BA degree or more	11%	24%	93%	97%	4%	98%	97%	-1%
Race/Ethnicity								
White	51%	71%	82%	92%	11%	96%	96%	0%
Black	31%	15%	66%	89%	22%	87%	92%	5%
Hispanic	15%	9%	61%	80%	19%	84%	87%	3%
Other	3%	5%	67%	90%	22%	92%	92%	0%
Marital Status								
Divorced	37%	21%	85%	94%	9%	94%	94%	0%
Never married	40%	70%	63%	85%	23%	94%	94%	0%
Other, spouse absent	23%	9%	71%	87%	16%	86%	88%	2%

Notes for Table 2.1: "Other, spouse absent" consists of separated, married but spouse absent and widowed. Women who did not work during the previous year because of illness, disability or school enrollment are not included in the analysis.
Source: Author's analysis of Current Population Survey.

Mothers of very young children are less likely to be employed than mothers of older children or women without children. For example, the employment rate of single mothers with one child who is under the age of four was 82 percent in 2000 compared to 94 percent for those with a youngest child over the age 7, and 94 percent for single women without any children. However, between 1992 and 2000, single mothers with a youngest child under the age of four increased their employment rate more than other single women.

Single mothers in the 18-24 age group are less likely to be employed than single mothers in the 25-34, 35-44, or 45-54 age groups. However, single mothers in the 18-24 age group increased their employment the most between 1992 and 2000. The employment levels of single women without children vary less by age group, but younger women have slightly higher employment levels. The employment levels of single women without children stayed fairly flat regardless of their age group.

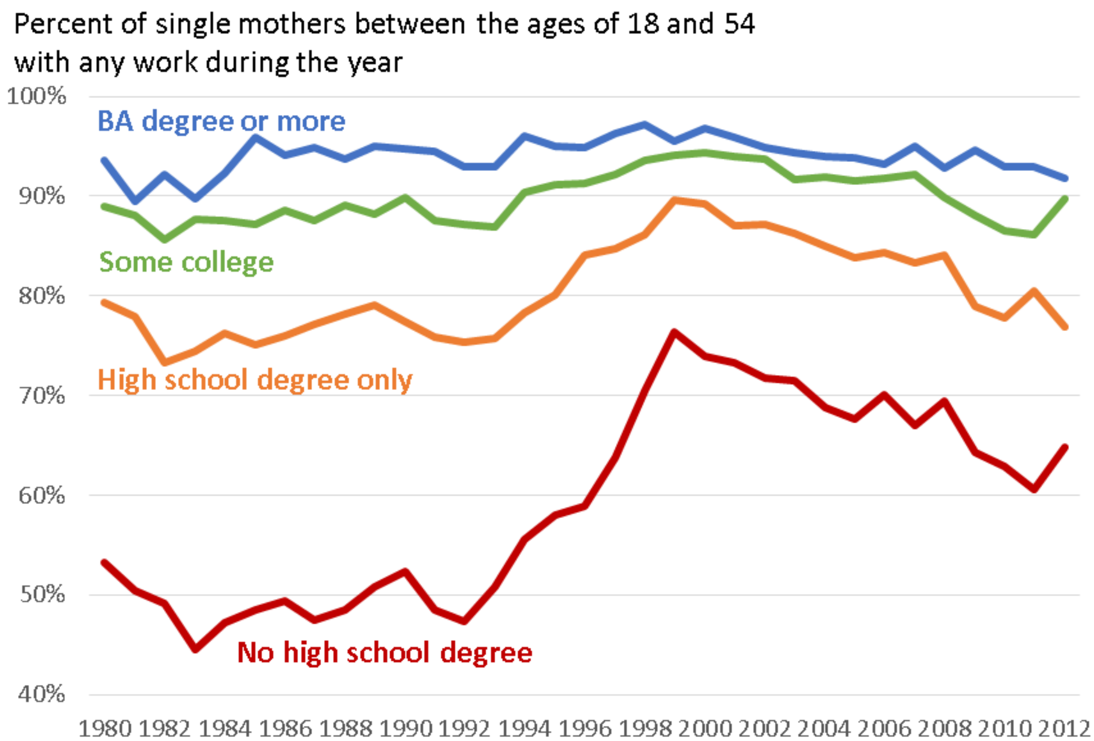
Single women who did not graduate from high school are less likely to work than women who have a high school degree. In 2000, the employment rate of single mothers who did not finish high school was 74 percent compared to 89 percent for mothers with only a high school degree. Similarly, the employment rate for single women with no children without a high school degree was 81 percent compared to 92 percent for those with only a high school degree. However, women without a high school degree were the ones that increased their work the most between 1992 and 2000. Single mothers without a high school degree increased their employment level by 27 percentage points.

Employment rates for non-white single mothers were lower than employment rates of white single mothers in 1992. However, non-white mothers saw the biggest increase in employment levels between 1992 and 2000. Employment rates of single women without children varied less by race and ethnicity, but black and Hispanic women increased their employment the most between 1992 and 2000.

Never-married mothers and other types of single mothers have lower employment rates than divorced women. However, these two groups increased their employment rates by a lot more than divorced mothers between 1992 and 2000.

Figure 2.2 shows the employment rates for single mothers by educational attainment. This makes clear how the biggest increase in employment between 1992 and 2000 was among those single mothers that did not graduate high school.

Figure 2.2: Employment rates for single mothers by educational attainment, 1980-2012

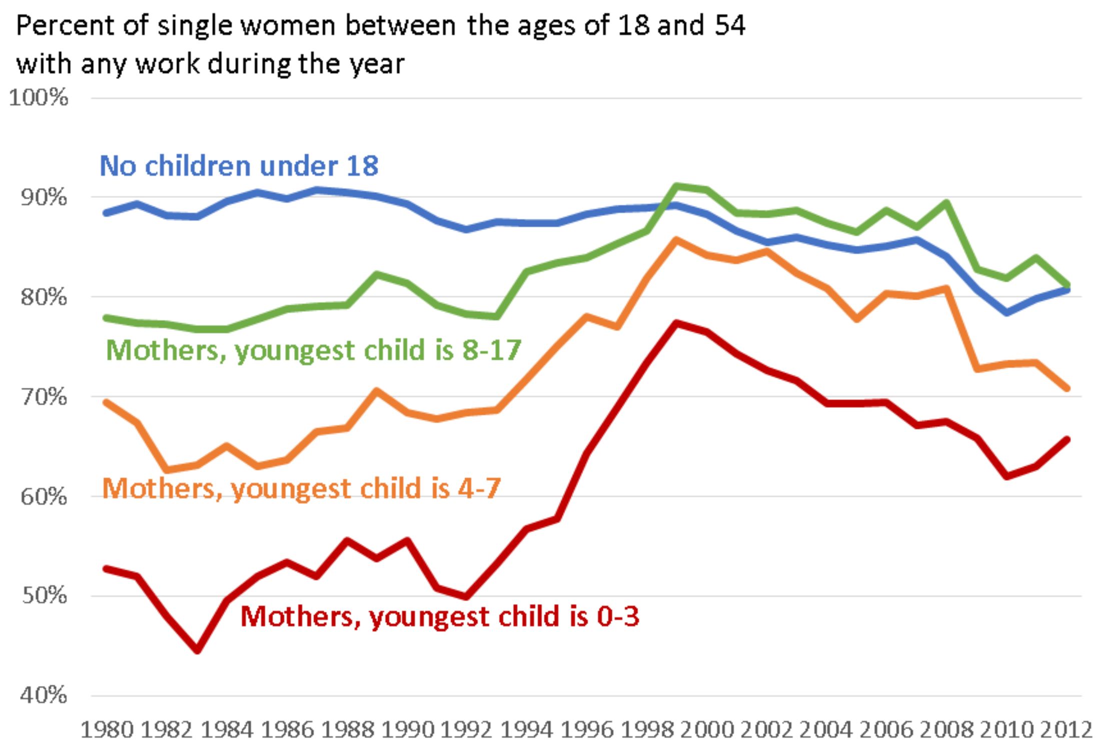


Note: Women who did not work during the previous year because of illness, disability or school enrollment are not included in the analysis.
Source: Author's analysis of March Current Population Survey.

Figure 2.3 shows the employment rates for single women with a high school education or less by whether they have children and the age of their youngest child. These data show how mothers with the youngest children increased their employment the most over the 1992-2000 period. Mothers with children who were at least 8 years old already had employment levels of close to 80 percent before 1992. This means that most of the employment increase among single mothers during the 1990s was due to single mothers entering the workforce earlier than they used to. the effect of the 1990s

Since 2000, the employment rate has fallen for all single women with a high school education or less regardless of whether they have children. This suggests that at least part of the reason for the decline in employment is due to the economy and the labor market for people with a high school education or less as opposed to safety net benefits that are mostly only available to families with children.

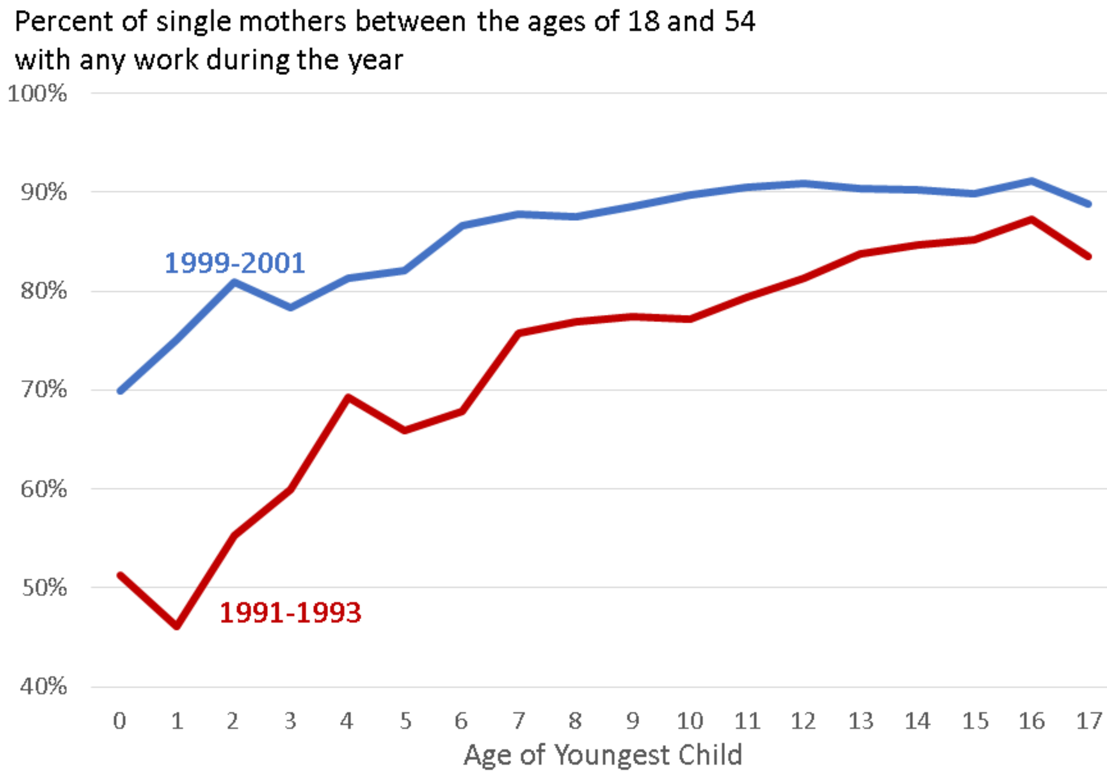
Figure 2.3: Employment rates for single women with a high school education or less by presence and age of children, 1980-2012



Note: Women who did not work during the previous year because of illness, disability or school enrollment are not included in the analysis.
Source: Author's analysis of March Current Population Survey.

Another way to analyze the relationship between employment and age of youngest child is to look at the employment levels in a given year for single mothers grouped by the age of their youngest child. Figure 2.4 does this for 1991-1993 and 1999-2001 for single mothers with a high school education or less. I combined three years of data in order to have more sample size and improve reliability. Across both time periods the general pattern emerges that single mothers with older children have higher employment rates than single mothers with very young children.

Figure 2.4: Employment rates for single mothers with a high school education or less by age of youngest child



Note: Women who did not work during the previous year because of illness, disability or school enrollment are not included in the analysis.
Source: Author's analysis of March Current Population Survey.

Comparing the red line (1991-1993) to the blue line (1999-2001) in Figure 2.4 shows how much employment increased between those years among single mothers with a youngest child of the same age. It's striking how much of that increase was among single mothers with very young children.

So far my analysis has looked at employment rates defined as whether someone worked at all during the year. To some, that might seem like too low of a threshold to focus on. Table 2.2 shows the percent of single women that worked during the year at least 500, 1,000, 1,500 and 2,000 hours. These thresholds of hours worked can be roughly interpreted as working at least 25 percent, 50 percent, 75 percent and 100 percent of the year. If someone works 40 hours per week for 52 weeks that adds up to 2,080 hours worked during the year[5].

[5] At least 2,000 hours worked is probably too strict of a definition of full-time year-around work. The Census Bureau defines full-time year-round workers as those who usually worked 35 hours or more per week for 50-52 weeks a year. That definition adds up to at least 1,750 hours worked during the year. See Census Bureau website: https://www.census.gov/hhes/www/laborfor/faq.html#Q7

Table 2.2: Employment rates for single women with a high school education or less by amount of hours worked, 1980-2012

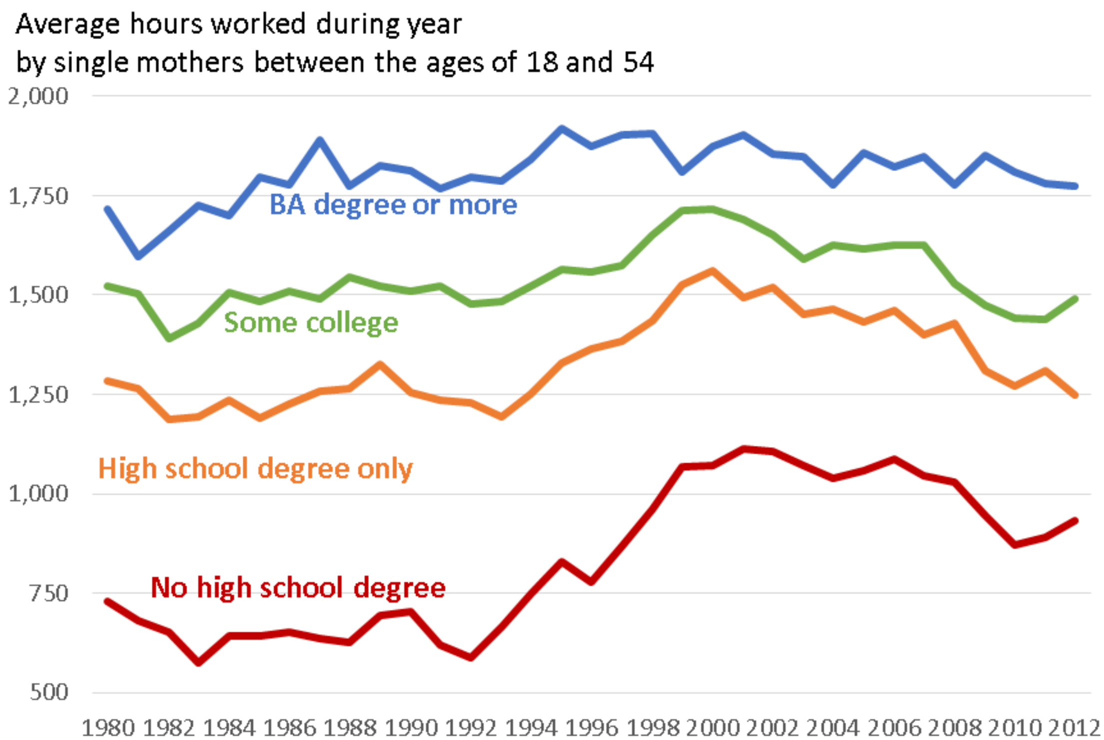
	1992	2000	Difference
Percent that worked during year			
Single women with no children	87%	88%	2%
Single mothers	65%	84%	19%
Youngest child is 0-3	50%	76%	27%
Youngest child is 4-7	68%	84%	16%
Youngest child is 8-17	78%	91%	13%
Percent that worked at least 500 hours during year			
Single women with no children	76%	77%	1%
Single mothers	55%	76%	20%
Youngest child is 0-3	37%	63%	26%
Youngest child is 4-7	60%	79%	19%
Youngest child is 8-17	71%	85%	14%
Percent that worked at least 1,000 hours during year			
Single women with no children	67%	68%	1%
Single mothers	48%	68%	20%
Youngest child is 0-3	29%	53%	24%
Youngest child is 4-7	53%	72%	19%
Youngest child is 8-17	65%	79%	14%
Percent that worked at least 1,500 hours during year			
Single women with no children	57%	59%	1%
Single mothers	40%	59%	19%
Youngest child is 0-3	20%	42%	22%
Youngest child is 4-7	43%	63%	20%
Youngest child is 8-17	57%	71%	14%
Percent that worked at least 2,000 hours during year			
Single women with no children	42%	46%	4%
Single mothers	28%	43%	14%
Youngest child is 0-3	13%	27%	14%
Youngest child is 4-7	31%	47%	16%
Youngest child is 8-17	42%	54%	12%

Table 2.2 shows that the finding that single mothers increased their employment over the 1992 to 2000 period relative to single women with no children is robust regardless of the threshold of hours worked that one uses to define someone as employed. In 1992 there was a large gap in the employment levels of single

mothers and single women not raising children, but gap narrowed dramatically regardless of the threshold of hours worked used. It’s also true that across various definitions of employment, single mothers with the youngest children increased their employment the most.

Another way to analyze the labor market participation of individuals is to examine the average hours worked in a year. Figure 2.5 shows this for single mothers grouped by their educational attainment. This measure averages together the hours of non-workers (those with zero hours) and workers. The advantage of this metric is that it captures both people moving from no work to work and those moving from part-time to full-time work. Between 1992 and 2000, single mothers without a high school degree increased their average hours worked per year by 485 hours. Single mothers with a high school degree and no further education increased their annual work by 333 hours. This compares to an increase of 239 hours by those with some college education and no BA degree, and an increase of 76 hours by those with a BA degree. This pattern is very similar to the pattern in Figure 2.2 that showed that single mothers with no college education increased their employment levels more than single mothers with at least some college education.

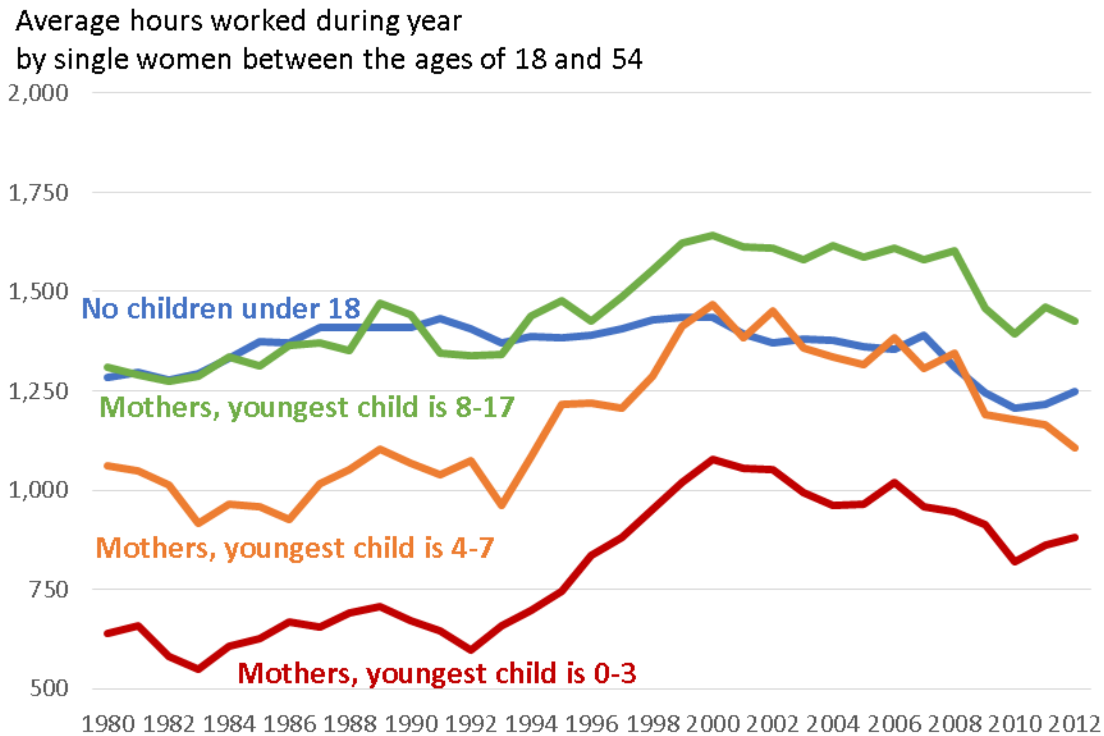
Figure 2.5: Average hours worked by single mothers by educational attainment, 1980-2012



Note: Women who did not work during the previous year because of illness, disability or school enrollment are not included in the analysis.
Source: Author's analysis of March Current Population Survey.

Figure 2.6 shows the average hours worked in a year for single mothers by the presence and age of their youngest child. It is striking how single mothers on average are able to work just as much or even more hours than single women without children with comparable education levels given that in order to work single mothers have the extra challenge of figuring out child care arrangements. Since the mid-1990s single mothers with a high school degree or less and a youngest child between the ages of 8 and 17 years old have worked more hours per year than single women without children. Since 2000, single mothers with a high school degree or less education and a youngest child who is 4-7 years old have worked just as many hours as single women without children.

Figure 2.6: Average hours worked by single women with a high school education or less by presence and age of children, 1980-2012



Note: Women who did not work during the previous year because of illness, disability or school enrollment are not included in the analysis.
Source: Author's analysis of March Current Population Survey.

Most research studies on the effect of safety net programs on employment outcomes analyze whether someone works as opposed to how much someone works. Therefore, in this paper, the dependent variable in my regression analysis is whether someone worked during the year. In future research, I'm interested in investigating whether safety net programs and other factors have a similar effect on the amount of hours worked or on whether someone obtains at least part-time or full-time work.

Table 2.3 provides mean values for the safety net and economic variables I include in my analysis. The table shows how, between 1992 and 2000, the unemployment rate declined and the EITC became more generous, especially for adults with two or more children. During the same period, TANF and SNAP declined. Between 2000 and 2010, state unemployment rates increased substantially, while the EITC remained fairly flat. TANF further declined between 2000 and 2010 while SNAP increased.

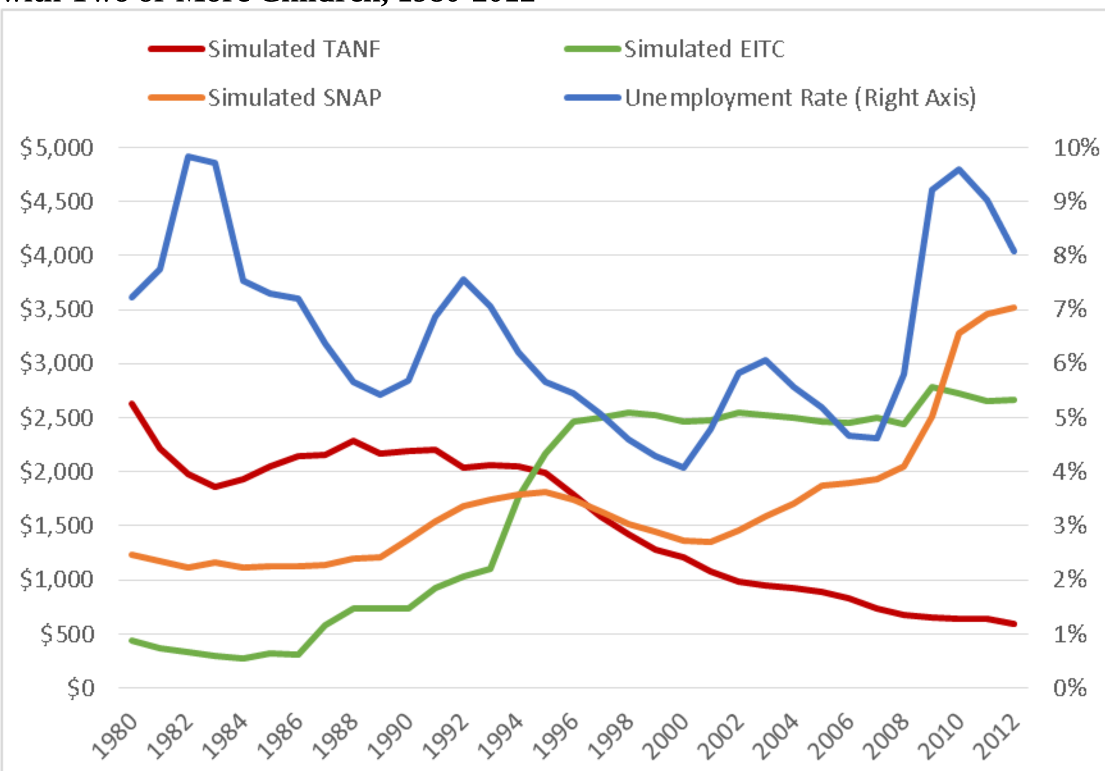
Table 2.3: Mean Values for Policy and Economic Variables, 1980-2012

	Mean values (All dollar figures are in 2012 dollars)							
	1980	1992	1995	2000	2002	2007	2010	2012
Simulated mean EITC								
no children	$0	$0	$55	$55	$56	$56	$58	$56
1 child	$385	$896	$1,358	$1,360	$1,413	$1,379	$1,424	$1,388
2+ children	$440	$1,028	$2,166	$2,467	$2,552	$2,501	$2,723	$2,666
Simulated mean AFDC/TANF								
no children	$0	$0	$0	$0	$0	$0	$0	$0
1 child	$1,416	$1,104	$1,013	$649	$537	$404	$354	$308
2+ children	$2,630	$2,034	$1,986	$1,210	$989	$737	$640	$594
Simulated mean SNAP								
no children	$110	$152	$163	$124	$130	$175	$311	$334
1 child	$528	$701	$757	$578	$599	$805	$1,395	$1,499
2+ children	$1,238	$1,678	$1,816	$1,369	$1,456	$1,937	$3,284	$3,523
State unemployment rate	7.2	7.6	5.7	4.0	5.8	4.6	9.7	8.1

Figure 2.7 graphs the mean values of the policy and economic variables for single mothers with two children between 1980 and 2012. This makes it easier to see how during the 1990s, TANF, SNAP and the unemployment rate declined, while the EITC increased. One can also observe the impact of the Great Recession when unemployment increased dramatically starting in 2008. SNAP increased during that

period both because of an increase in access (participation among the eligible population increased) and because of a temporary increase in monthly SNAP benefits enacted as part of the Recovery Act which became effective on April 1, 2009 and expired in November 2013. The Recovery Act increased monthly SNAP benefits by an average of 15 percent[6]. The EITC also increased in 2009 due to an increase in EITC benefits included in the Recovery Act. That expansion has now been made permanent.

Figure 2.7 Mean Values for Policy and Economic Variables for Single Mothers with Two or More Children, 1980-2012



[6] For more information on the Recovery Act's effect on SNAP, see United States Department of Agriculture Economic Research website: http://www.ers.usda.gov/topics/food-nutrition-assistance/supplemental-nutrition-assistance-program-(snap)/arra.aspx

2.5 Empirical Specification

I use a logistic regression model to predict the odds of an individual being employed. The main regression model consists of the dependent variable, whether someone worked during the year, regressed on individual-level demographic variables, individual-level policy variables, and the state-level unemployment rate. The main model also includes interactions of the three policy variables and unemployment with all the demographic variables, state and year fixed effects, and the following six interactions: TANF*SNAP, TANF*EITC, SNAP*EITC, unemployment*TANF, unemployment*EITC, and unemployment*SNAP. See Table 2.4 for a list of all the variables included in my analysis.

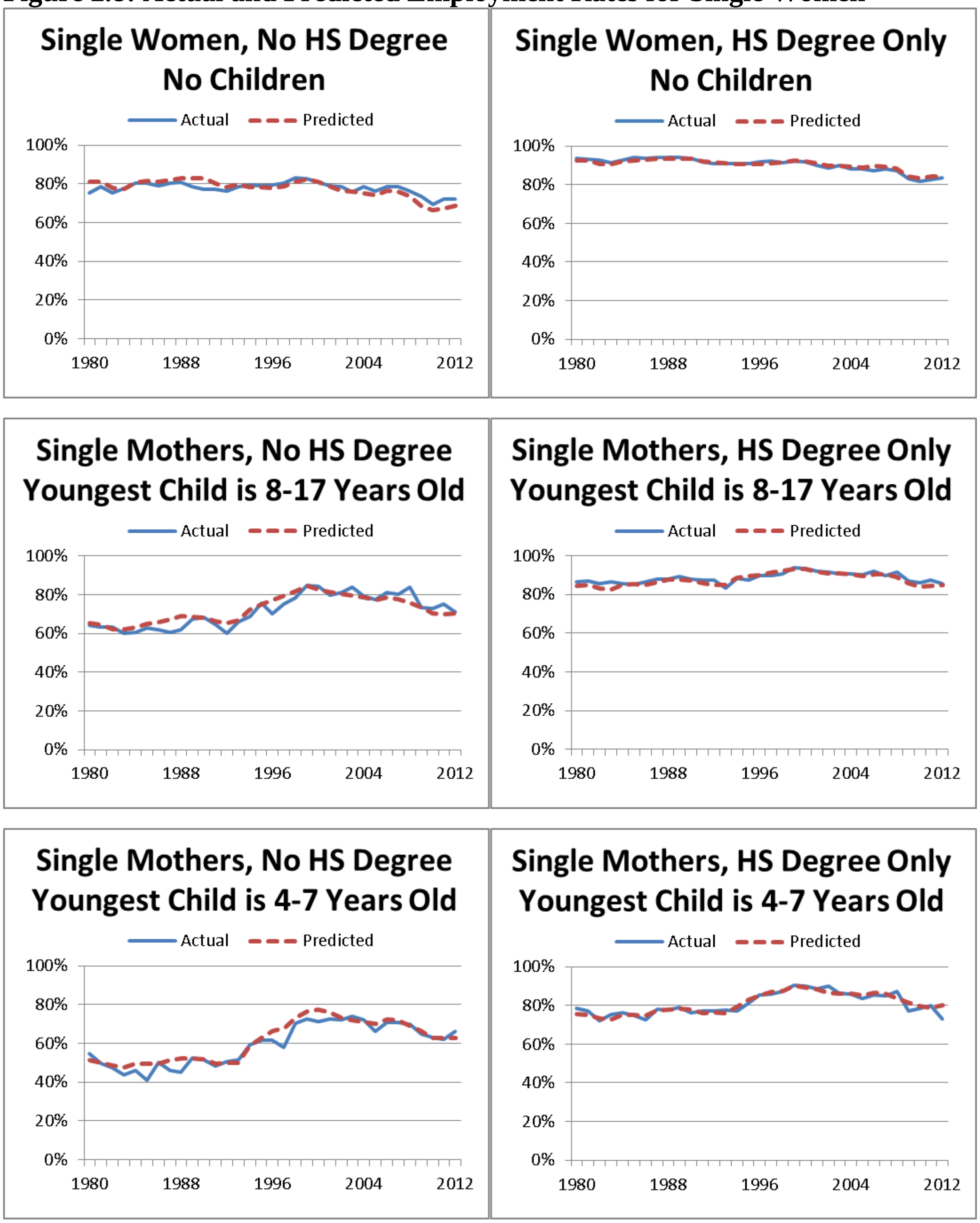
Similarly to Fang and Keane (2004), my specification was not chosen as the result of a specification search. I did not choose a specific set of demographic, policy, economic variables and interaction terms based on whether they reached significance. Instead, I specified a set of demographic, policy, and economic variables, and a full set of interaction terms, a priori. The main rational for including interaction terms was the notion that policy variables should have different effects on individuals with different characteristics. For example, the fixed cost to working is different for a mother with a young child, while the labor market opportunities for a woman with less than a high school degree is different than for a woman with some college education. Therefore, the availability of safety net benefits might impact the decision of these women join the labor force in a differently. The reason for including state and year fixed effects is to control for unobserved variables that vary by state or by year.

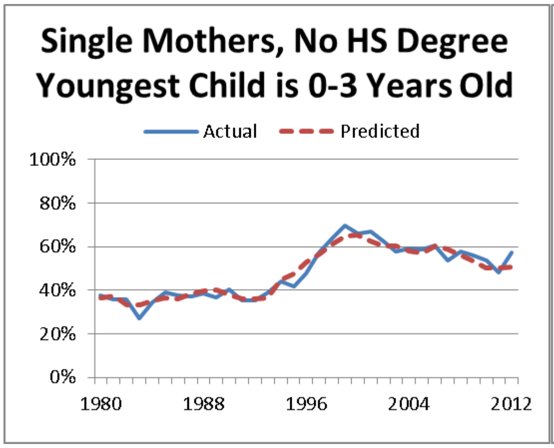
Table 2.4: Description of Variables Used in the Analysis

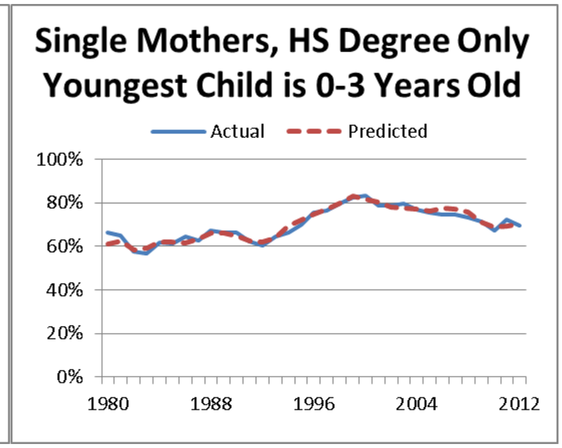
Variable	Description
Dependent variable	
WORK	Categorical variable indicating whether woman worked during the year
Individual-level demographic variables	
AGE	Categorical variable indicating age of woman (18-24, 35-44 or 45-54 years old)
EDU	Categorical variable indicating educational attainment (less than high school, finished high school, some college, or finished college)
KIDS	Categorical variable indicating number of own children and age of youngest child of woman (no children, one child 0-3 years old, one child 4-7 years old, one child 8-17 years old, two children and youngest is 0-3, two children and youngest is 4-7, or two children and youngest is 8-17)
RACE	Categorical variable indicating race/ethnicity of woman (white non-Hispanic, black non-Hispanic, Hispanic, or other)
MARITAL	Categorical variable indicating marital status of woman (never married, divorced, or other) "Other" includes separated, widowed, and married but spouse absent. Married women with husband present are not included in the sample.
State-level economic variable	
UNEMP	State unemployment rate
Individual-level policy variables	
EITC	Simulated EITC benefit, varies by number of own children, and year. (EITC benefits don't vary by state. Due to lack of available data, a constant participation rate is assumed across all states and years.)
TANF	Simulated TANF benefit, varies by number of own children, state, and year. (State variation is due to both benefit levels and accessibility.)
SNAP	Simulated SNAP benefit, varies by number of own children, state, and year. (State variation is due to both benefit levels and accessibility. Note state SNAP benefits are the same for all states except Alaska and Hawaii.)
Interaction terms	
UNEMP#AGE, UNEMP#EDU, UNEMP#KIDS, UNEMP#RACE, UNEMP#MARITAL, EITC#AGE, EITC#EDU, EITC#KIDS, EITC#RACE, EITC#MARITAL, TANF#AGE, TANF#EDU, TANF#KIDS, TANF#RACE, TANF#MARITAL, SNAP#AGE, SNAP#EDU, SNAP#KIDS, SNAP#RACE, SNAP#MARITAL, UNEMP#EITC, UNEMP#TANF, UNEMP#SNAP, EITC#TANF, EITC#SNAP, TANF#SNAP	

The graphs in the following pages plot actual employment rates for different groups in my sample compared to the employment rates predicted by my model over the 1980-2012 period.

Figure 2.8: Actual and Predicted Employment Rates for Single Women







The graphs in the previous pages generally give me confidence that my model is adequately fitting the data and has fairly strong predictive powers across different groups of single women in my sample. The inclusion of state and year fixed effects did not make much of a difference for the fit of my model. However, my model did seem to fit the data better when using the full set of interaction terms.

Due to the large number of interaction terms in my model, the regression coefficients it produces for each variable are difficult to interpret. One would need to calculate through all the interactions in order to know what a given variable predicts. Therefore, I prefer to present the results of my model showing how different variables predict changes in the probability of being employed. Appendix table

Table 2.5 shows what my model predicts in terms of employment levels for women with different characteristics. Changes in the probability of being employed are expressed in relation to the baseline scenario of a 25-34 year old white never-married woman with a high school degree and no further education.

Table 2.5 Changes in Probability of Being Employed Due to Various Characteristics

Changes in probabilities are expressed in relation to the baseline scenario of a 25-34 year old white never-married woman with a high school degree and no further education.

	Single mothers with one child			Single mothers with two or more children			Single women with no children
Age of Youngest Child:	0-3	4-7	8-17	0-3	4-7	8-17	
Baseline Employment	79%	86%	90%	66%	76%	83%	92%
Change in probability of being employed:							
Own Age							
18-24	0.2%	0.1%	0.1%	-4.4%	-3.6%	-2.9%	1.7%
35-44	0.2%	0.2%	0.1%	0.4%	0.3%	0.3%	0.0%
45-54	-2.3%	-1.7%	-1.3%	-3.8%	-3.1%	-2.4%	-0.6%
Educational Attainment							
No high school degree	-17.2%	-13.6%	-10.4%	-19.8%	-17.5%	-14.7%	-9.9%
Some college	10.1%	7.0%	5.0%	12.9%	9.7%	7.4%	4.7%
BA degree or more	12.8%	8.9%	6.3%	18.3%	13.5%	10.1%	5.8%
Race/Ethnicity							
Black	-6.6%	-4.9%	-3.7%	-2.8%	-2.3%	-1.8%	-5.5%
Hispanic	-6.7%	-5.0%	-3.7%	-4.4%	-3.6%	-2.9%	-5.9%
Other	-8.5%	-6.4%	-4.8%	-6.9%	-5.7%	-4.5%	-5.3%
Marital Status							
Divorced	5.5%	3.9%	2.8%	10.9%	8.3%	6.3%	1.7%
Other, spouse absent	-4.1%	-3.0%	-2.2%	1.1%	0.9%	0.7%	-4.5%

2.6 Analysis of Policy and Economic Variables

One of main ways that scholars have analyzed the effect of policy changes on single mother employment rates is by using the results of their regression models to simulate what would have happened if certain policy and economic variables had not changed. For example, one can use a model's regression coefficients to simulate what the employment rate for a given group would be in 1999 if EITC policies would have stayed constant at 1992 levels. Under such a simulation, the difference between what was originally predicted by the model using actual data and what is predicted by holding EITC policies at 1992 levels provides an estimate of how much of the change in employment was due to EITC policy changes.

I ran simulations for two time periods; 1992-1999 and 1999-2007. I chose to do 1992-1999 because employment for single mothers with a high school degree or less education increased by 20.2 percentage points during that period and peaked in 1999. Understanding whether that rise in employment was due to EITC expansions, AFDC/TANF changes or the economy continues to be policy relevant today. Many policy makers who propose TANF-like reforms for other safety net programs cite the rise of single mother employment rates during the 1990s as a reason to do them. I chose to analyze 1999-2007 because single mothers with a high school degree or less education decreased their employment by 7.3 percentage points during that period. I ended my simulation in 2007 because I wanted to look at the period before the Great Recession. It’s well established that employment rates across the entire labor force dropped due to the Great Recession, but it’s less understood what led to the drop in single mother employment between 1999 and 2007.

In order to interpret my simulation results, it’s important to know what the levels of the policy and economic variables were at the beginning and end of the periods covered by the simulations. Table 2.6 shows the employment rates, and the levels of the policy and economic variables faced by single mothers with a high school degree or less education in 1992, 1999, and 2007 and how they changed between 1992-1999 and 1999-2007. Between 1992 and 1999 mean simulated EITC increased by $1,008, simulated AFDC/TANF declined by $635, and state unemployment rates declined by 3.3 percentage points. All three of these reflect pretty substantial changes over that period. In contrast, the simulated SNAP variable declined by only $184 between 1992 and 1999.

Table 2.6: Employment Rates, Safety Net Policies and State Unemployment Rates Faced by Single Mothers with a High School Degree or Less Education, 1992-2007

	Mean values			Differences	
	1992	**1999**	**2007**	**1992-1999**	**1999-2007**
Percent Employed	65.1%	85.3%	78.0%	20.2%	-7.3%
Simulated mean EITC	$967	$1,975	$1,966	$1,008	-$9
Simulated mean AFDC/TANF	1598	963	583	-$635	-$380
Simulated mean SNAP	$1,231	$1,047	$1,420	-$184	$373
State unemployment rate	7.6	4.3	4.6	-3.3	0.3

The CPS data shows that between 1992 and 1999 employment rates for single mothers with a high school degree or less education increased by 20.2 percent. That compares to a 19.3 percentage point increase predicted by my model. Table 2.7 provides the simulation results from using my model to predict employment levels under different policy and economic scenarios.

Table 2.7: Simulation Results of Employment Levels for Single Mothers, High School Degree or Less Education, 1992-1999

Predicted Employment in 1999 if the following stayed at 1992 levels:	1992	1999	Difference 1992-1999	Difference with baseline	Percent Explained
State unemployment	65.4%	80.7%	15.3%	3.9%	20%
Mean simulated EITC	65.4%	77.6%	12.2%	7.0%	36%
Mean simulated TANF	65.4%	82.6%	17.3%	2.0%	10%
Mean simulated SNAP	65.4%	84.0%	18.6%	0.7%	4%
All of above stayed at 1992 levels	65.4%	70.8%	5.5%	13.8%	72%
Baseline Scenario predicted by model: None of above stayed at 1992 levels	65.4%	84.6%	19.3%		
Actual CPS employment trend:	65.1%	85.3%	20.2%		

For example, table 2.7 shows that if state unemployment rates had stayed at 1992 levels, single mothers with a high school education or less education would have increased their employment level by 15.3 percentage points. (See top line, 4th column in table 2.7.) Instead, they increased their employment level by 19.3 percentage points. This means that changes in state unemployment rates were responsible for a 3.9 percentage point increase in single mother employment.[7] This 3.9 percentage point increase accounts for 20 percent of the total 19.3 percentage point increase in employment predicted by my model between 1992 and 1999.

In terms of policy variables, changes in the EITC between 1992 and 1999 seem to be the most important. They account for 36 percent of the 1992-1999 increase in employment levels. TANF policy changes account for 10 percent of the employment increase and SNAP policy changes account for 4 percent. Together, changes in state unemployment rates and the three policy variables explain 72 percent of the total variation captured by the model. I chose 1999 as the end point of these

[7] 19.3-15.3 = 3.9 when using unrounded figures.

simulations because 1999 was the peak employment year for single mothers with a high school degree or less education.

As I discussed in my literature review, only a handful of studies (Meyer & Rosenbaum, 2001; Grogger, 2003; Fang & Keane, 2004; Looney, 2005; Noonan, Smith & Corcoran, 2007) have tried to explicitly compare the impact of welfare reform on single mother employment relative to the impact of the economy and other policy reforms such as changes to the EITC and AFDC/TANF. In order to test the accuracy of my model simulations, it is instructive to compare my results to previous scholars. Table 2.8 shows that my simulation results for the 1992-1999 period are broadly consistent with the findings from the literature.

Table 2.8: Comparison to Earlier Literature: Percent of Single Mother Employment Change Explained by Various Factors

	Years	Economy	AFDC/TANF	EITC	Other
Grogger 2003	1993-1999	21	20	34	26
Fang and Keane 2004	1993-2000	40	19	20	21
Looney 2005	1993-1999	17	37	22	24
Noonan et al. 2007	1991-2000	7	14	19	60
Average of four above:		**21**	**24**	**24**	**33**
My Results	1992-1999	20	10	36	33

The biggest difference is that my model seems to attribute more responsibility to EITC changes and less responsibility to AFDC/TANF changes than the four earlier studies. Table 2.9 provides a summary of how my analysis differs from the four earlier studies. These methodological differences can provide some clues to why estimates differed across studies.

The main difference between Looney (2005) and the rest of the analyses, including my own, is that Looney (2005) used monthly data from the Survey of

Income and Program Participation (SIPP) instead of annual data from the March Current Population Survey (CPS). Relative to my analysis and the other three studies, Looney (2005) finds less of an effect of the economy and more of an effect of welfare reform policies on the employment of single mothers. Looney (2005) argues that studies examining annual data may overestimate the effects of the economy and underestimate the effects of Welfare Reform policies.

My model found that the economy accounted for 20 percent of the employment increase of single mothers with a high school degree or less education. This came very close to the 21 percent found by Grogger and the 17 percent found by Looney. In contrast, Fang and Keane found that the economy accounted for 40 percent and Noonan et al. found that it accounted for 7 percent of the employment increase. Like Grogger, I only used the state unemployment rates to measure the economy. However, the other three papers used some additional variables to measure the economy such as wage levels, and the share of low skill jobs. When available, Looney and Noonan used unemployment rates of smaller geographic areas, Metropolitan Statistical Areas, instead of states. It’s surprising that Looney attributes close to the same amount of responsibility to the economy as Grogger and I do even though he used a fairly different approach to measuring the economy. (See Table 2.9) Therefore, it seems like the differences across the papers in how much is attributed to the economy are likely driven by other methodological decisions besides how the economy was measured.

Table 2.9: Comparison of My Regression Variables to Earlier Literature

	Trisi 2016	Grogger 2003	Fang and Keane 2004	Looney 2005	Noonan et al. 2007
Data set	March CPS data for 1980-2012	March CPS data for 1978-1999	March CPS data for 1981-2003	SIPP data for 1989 to 2000 (monthly data)	March CPS data for 1991-2003
Economy variables	State unemployment rates	State unemployment rates	State unemployment rates; hourly wage at 20th percentile.	State or MSA (metropolitan statistical area) unemployment rates; wages at the 25th percentile; state employment to population ratio	MSA (metropolitan statistical area) unemployment rates; share of low-skill jobs in a state.
EITC variables	Simulated EITC that varies by year and number of children.	Maximum EITC amount as function of number of children; subsidy rate to the lowest-income workers	Maximum EITC amount as function of number of children; EITC phase-in rate	Calculates an “average net of tax rate” that includes state and federal taxes/credits. Mathematically: (Earnings – Taxes)/Earnings	Maximum EITC amount as function of number of children
AFDC/TANF variables	Simulated TANF that varies by state-level benefits and accessibility, year and family size	Maximum monthly benefits; dummy variables for when states implemented welfare reform and time limits.	Maximum monthly benefits; dummy variables for when states implemented time limits, work requirements, sanctions, and diversion programs; variables measuring whether family is subject to work requirements and time-limits; length of state time limit; fixed income disregard; benefit reduction rate.	Maximum monthly benefits; dummy variables for when states implemented waivers and TANF; benefit reduction rate; months of transitional child care and Medicaid; sanction policies; work requirement and time limit exemptions; value of diversion payments.	Maximum monthly benefits; dummy variables for when states implemented waivers and TANF; severity of sanction policy (Low, Moderate, High)
Other policy variables included	Simulated SNAP that varies by state-level benefits and accessibility, year and family size	State minimum wages	SNAP benefits; personal exemption for income tax; lowest bracket federal tax rate; Medicaid eligibility; state child support enforcement expenditure; state child care subsidy expenditure.	Medicaid/SCHIP eligibility; net federal tax rate; state minimum wage; state child support enforcement expenditure; state child care subsidy expenditure.	none
Interaction terms	Include full set of interaction terms	Interact welfare reform variables and state policy and economic variables with age of the youngest child in the family.	Include full set of interaction terms	Some interactions between policies and age of children.	Welfare with education, welfare with marital status, welfare with severity of sanctions, share of low-skill jobs with education, share of low-skill jobs with central city, EITC with education.

In terms of measuring the EITC, my analysis and most of the papers followed a similar approach that accounted for the amount of EITC that families with different numbers of children were eligible for. Like when trying to measure the effects of the economy, my simulations of the effect of the EITC seemed to match Grogger the best. I found that the EITC accounted for 36 percent of the employment increase of single mothers while Grogger found that the EITC accounted for 34 percent. The other three studies found that the EITC accounted for 19-22 percent of the employment increase. Given that the EITC was measured in a similar way across studies, I think the differences found in how much the EITC affected single mother employment were likely due to other methodological decisions besides the creation of the EITC variables.

My analysis differed the most from the other four studies in how I measured AFDC/TANF changes. As I explained in Chapter 1, I believe that my measure of AFDC/TANF changes that is based on a simulated variable that captures changes in benefit levels and accessibility across states and time is superior to approaches that use dummy variables to mark the implementation of policy changes. The other four papers do include the maximum state AFDC/TANF benefit in their models, but they do not make any adjustments for differences in how accessibility to TANF changed across states or time. As I discussed in Chapter 1, there is a lot of variation by state and time in accessibility as revealed by the TANF-to-Poverty ratio. Using my AFDC/TANF variable, my simulations find that AFDC/TANF changes were responsible for 10 percent of the increase in single mother employment. This comes closest to the 14 percent found by Noonan et al. In contrast, Looney found that

AFDC/TANF changes accounted for 37 percent. Grogger found that AFDC/TANF changes accounted for 20 percent while Fang and Keane found that they accounted for 19 percent of the increase in single mother employment. I need to do additional research to determine whether the differences between my results and those of the other papers were due to how I measured AFDC/TANF or because of other methodological differences between our models. As shown in Table 2.9, my model differed considerably from the other models in terms of what other policy variables and interaction terms were included. In order to test whether my AFDC/TANF made the difference, I would need to recreate the AFDC/TANF measures used in the other papers, apply them to my model, and see how they change my AFDC/TANF predictions. It would also be instructive to do a more complete replication study and go step-by-step through each of the other methodological differences between my paper and the other papers and observe what drives differences in the predictions.

Table 2.10 provides the simulation calculations from my model for the 1999-2007 period. My model explains much less of the 1999-2007 decline of single mother employment compared to how much my model explained the 1992-1999 employment increase. Changes in my state unemployment and three policy variables only explain 15 percent of the 1999-2007 drop in employment. My EITC variable and state unemployment rates account for almost no change in the employment rate of single mothers with a high school education or less between 1999 and 2007. That's not surprising given that state unemployment rates and the EITC were almost the same in 2007 compared with 1999. TANF continued to decline between 1999-2007, but not as much as it did during the 1992-1999 period. (See Table 2.6). My SNAP variable increased during the 1999-2007 period, but only accounted for a 1.7 percentage point decline in the employment rate of single mothers with a high school education or less.

Table 2.10: Simulation Results of Employment Levels for Single Mothers, High School Degree or Less Education, 1999-2007

Predicted Employment in 2007 if the following stayed at 1999 levels:	1999	2007	Difference 1999-2007	Difference with baseline	Percent Explained
State unemployment	84.6%	78.7%	-5.9%	-0.4%	6%
Mean simulated EITC	84.6%	78.5%	-6.1%	-0.2%	4%
Mean simulated TANF	84.6%	77.0%	-7.7%	1.3%	-21%
Mean simulated SNAP	84.6%	80.0%	-4.6%	-1.7%	27%
All of above stayed at 1999 levels	84.6%	79.3%	-5.4%	-1.0%	15%
Baseline Scenario predicted by model: None of above stayed at 1999 levels	84.6%	78.3%	-6.3%		
Actual CPS employment trend:	85.3%	78.0%	-7.3%		

It's not that surprising that my model doesn't explain much of the single mother employment decline over the 1999-2007 period given that there was a secular decline in employment among various groups during that period. The causes behind that secular decline in employment are still not well understood by scholars. Relevant to this discussion is the fact that the employment rate for single women between the ages of 25 and 45 not raising children and with a high school education or less declined by 3.7 percentage points between 1999 and 2007. That compares to the 5.9 percentage point drop in employment for single mothers with the same education level and within the same age group[8]. Single women not raising children is a group that relies very little on safety net benefits. Therefore, this leads me to think that there is something about the economy that is driving at least half of this downward

[8] I restricted this comparison to single women between the ages of 25 and 45 to make the single women without children group more comparable to single women with children group in terms of their age composition.

employment trend for both single women raising and not raising children. My model could benefit from adding more variables to better measure the characteristics of a changing labor market such as wage levels and the share of low skill jobs. In addition, I could structure my analysis to focus on the difference in employment rates between single women raising and not raising children. Such a difference-in-difference approach could help to isolate the effects of changes in the safety net from other changes in the economy.

2.9 Conclusion

Many policy makers point to the increase in employment of single mothers during the 1990s as one of the major achievements of the 1996 welfare law. This paper first looked into how employment changes differed between single women with various characteristics using descriptive analysis. Secondly, it looked at how policy and economic factors affected the employment increase of single mothers between 1992 and 1999 and the employment decline between 1999 and 2007 using econometric techniques.

The descriptive analysis shows that employment among single mothers 18-54 years old increased by 15 percentage points from 1992 to 2000 while the employment rate of 18-54 year old single women without children stayed flat. Single mothers increased their employment more than comparable single women without children between 1992-2000 across all ages, race/ethnicity, education level, and marital status groups. However, since 2000, both single mothers and single women without children have decreased their employment levels. Another pattern that can be observed from the descriptive analysis is that those single mothers with the lowest employment levels in 1992 increased their employment the most between 1992 and 2000. Single mothers with the least educational attainment and those with the youngest children increased their employment the most between 1992 and 2000.

The econometric analysis confirmed previous research showing that EITC policy changes and the great economy during the 1990s combined to be more important for the increase in employment of single mothers than the changes in AFDC/TANF assistance. It finds that the EITC accounted for 42 percent of the employment increase among single mothers with a high school education or less between 1992 and 2000. The economy accounted for 25 percent, changes in cash assistance accounted for 13 percent, and SNAP changes accounted for 6 percent. This confirmation of the findings of previous research is notable given that the econometric analysis in this paper used more years of data and measures for TANF, SNAP and the EITC that differ from previous researchers. This paper used a measure of TANF, SNAP, and EITC policies that capture in dollar terms using a consistent methodology how access and benefit levels have changed over time by state and by family size.

In future research, I would like to further improve my model and my policy variables. I would like to test out whether including additional policy or economic variables will improve my model. Based on my descriptive data analysis showing how single mother employment trends differed by the age of the youngest child, the availability of child care subsidies seems important to include as a policy variable. In terms of economic variables, I would like to investigate whether controlling for state median income and state wages at the 25^{th} percentile like other studies have done would make a difference in my model. There a number of refinements that I could make to the creation of my TANF and SNAP policy variables. These improvements include simulating benefits in a more detailed way such as taking into account earnings disregards when simulating TANF benefits. I would also like to test out whether my results would be different if I used one of the other six measures I developed in my first chapter.

An important caveat of my findings so far is that I have only analyzed whether someone worked during the year and not how many hours they worked or at what wage. It would be important to know, for example, whether the increase in employment among single mothers with very young children consisted of just a few hours at low pay or enough to greatly improve their economic well-being. The next chapter tries to address the question of how economic well-being changed for families with children over the 1993-2012 period.

My long term research goal is to use the policy variables I developed and the econometric techniques I used in this paper to try to also explain income, poverty and deep poverty trends. The end goal would be to construct a set of models that could illustrate for policymakers using historical data the potential tradeoffs that exist when adopting new safety net policies. For example, the models could try to show in numerical terms what the effect of a decline in SNAP would be in terms of potentially increasing single mother employment and also potentially increasing deep poverty rates for children.

Appendix Table 2.1: Regression Coefficients for Logistic Model Predicting Any Employment During the Year

Number of observations	571,887
Pseudo R2	0.1804

This table reports standard errors clustered at the state level.

Variable	Coefficient	Std. Error	t	P>t
Number of children and their age				
No children (Omitted)				
one child, 0-3 years old	-1.6077	0.1540	-10.44	0.000
one child, 4-7 years old	-0.9240	0.1713	-5.39	0.000
one child, 8-17 years old	-0.4124	0.1816	-2.27	0.023
2+ children, youngest is 0-3	-1.7190	0.1778	-9.67	0.000
2+ children, youngest is 4-7	-1.0322	0.1971	-5.24	0.000
2+ children, youngest is 8-17	-0.5423	0.2171	-2.50	0.012
Own Age				
18-24 (Omitted)				
25-34	-0.4607	0.0753	-6.12	0.000
35-44	-0.3785	0.0727	-5.21	0.000
45-54	-0.4617	0.1179	-3.92	0.000
Educational Attainment				
Less than a high school degree (Omitted)				
High school degree only	0.8886	0.0755	11.77	0.000
Some college, No BA degree	1.7998	0.0776	23.21	0.000
BA degree or more	2.2028	0.1354	16.27	0.000
Race/Ethnicity				
White (Omitted)				
Black	-0.3753	0.0697	-5.38	0.000
Hispanic	-1.0301	0.0890	-11.57	0.000
Other	-0.8243	0.1149	-7.17	0.000
Marital Status				
Divorced (Omitted)				
Never married	-0.2532	0.0734	-3.45	0.001
Other, spouse absent	-0.8905	0.0573	-15.55	0.000
Economy				
State unemployment	-0.1196	0.0163	-7.33	0.000

Policy				
Simulated EITC	-0.0049	0.0017	-2.84	0.005
Simulated TANF	-0.0003	0.0001	-4.54	0.000
Simulated SNAP	-0.0014	0.0004	-3.86	0.000
Unemployment#Children				
one child, 0-3 years old	0.0294	0.0155	1.90	0.057
one child, 4-7 years old	0.0354	0.0193	1.83	0.067
one child, 8-17 years old	0.0187	0.0174	1.08	0.281
2+ children, youngest is 0-3	0.0561	0.0218	2.57	0.010
2+ children, youngest is 4-7	0.0469	0.0244	1.93	0.054
2+ children, youngest is 8-17	0.0552	0.0247	2.24	0.025
Unemployment#Age				
25-34	0.0300	0.0127	2.37	0.018
35-44	0.0176	0.0130	1.35	0.177
45-54	0.0173	0.0179	0.97	0.333
Unemployment#Education				
High school degree only	0.0041	0.0116	0.35	0.725
Some college, No BA degree	0.0057	0.0100	0.57	0.569
BA degree or more	0.0039	0.0228	0.17	0.864
Unemployment#Race				
Black	-0.0363	0.0076	-4.77	0.000
Hispanic	0.0638	0.0102	6.27	0.000
Other	0.0364	0.0159	2.28	0.022
Unemployment#Marital				
Never married	0.0032	0.0100	0.32	0.746
Other, spouse absent	0.0223	0.0074	3.03	0.002
EITC#Children				
one child, 0-3 years old	0.0053	0.0016	3.29	0.001
one child, 4-7 years old	0.0054	0.0016	3.35	0.001
one child, 8-17 years old	0.0053	0.0016	3.32	0.001
2+ children, youngest is 0-3	0.0053	0.0017	3.16	0.002
2+ children, youngest is 4-7	0.0052	0.0017	3.16	0.002
2+ children, youngest is 8-17	0.0052	0.0017	3.12	0.002
EITC#Age				
25-34	0.0001	0.0000	3.38	0.001

35-44	0.0001	0.0001	2.71	0.007
45-54	0.0001	0.0001	1.00	0.315
EITC#Education				
High school degree only	-0.0001	0.0000	-2.20	0.028
Some college, No BA degree	-0.0002	0.0000	-4.96	0.000
BA degree or more	-0.0003	0.0001	-4.36	0.000
EITC#Race				
Black	0.0001	0.0000	4.10	0.000
Hispanic	0.0002	0.0001	2.64	0.008
Other	0.0000	0.0001	0.76	0.445
EITC#Marital				
Never married	0.0000	0.0000	0.51	0.612
Other, spouse absent	0.0001	0.0000	1.87	0.062
TANF#Children				
one child, 0-3 years old	0.0001	0.0001	1.97	0.049
one child, 4-7 years old	0.0000	0.0000	-0.36	0.719
one child, 8-17 years old	0.0000	0.0000	1.37	0.169
2+ children, youngest is 0-3	0.0000	0.0000	-0.02	0.987
2+ children, youngest is 4-7	0.0000	0.0000	-0.66	0.509
2+ children, youngest is 8-17 (Omitted)				
TANF#Age				
25-34	0.0001	0.0000	5.58	0.000
35-44	0.0001	0.0000	6.12	0.000
45-54	0.0001	0.0000	3.31	0.001
TANF#Education				
High school degree only	0.0000	0.0000	1.90	0.057
Some college, No BA degree	0.0000	0.0000	1.30	0.193
BA degree or more	0.0000	0.0000	-0.42	0.672
TANF#Race				
Black	0.0000	0.0000	-0.01	0.993
Hispanic	0.0000	0.0001	0.46	0.646
Other	0.0000	0.0000	-1.00	0.318
TANF#Marital				
Never married	-0.0001	0.0000	-5.83	0.000
Other, spouse absent	0.0001	0.0000	3.75	0.000

SNAP#Children				
one child, 0-3 years old	0.0009	0.0003	3.19	0.001
one child, 4-7 years old	0.0006	0.0003	1.96	0.050
one child, 8-17 years old	0.0007	0.0003	2.61	0.009
2+ children, youngest is 0-3	0.0007	0.0003	2.20	0.028
2+ children, youngest is 4-7	0.0007	0.0003	2.08	0.038
2+ children, youngest is 8-17	0.0006	0.0003	2.02	0.043
SNAP#Age				
25-34	0.0000	0.0000	0.49	0.627
35-44	0.0000	0.0000	0.19	0.852
45-54	0.0000	0.0001	0.57	0.569
SNAP#Education				
High school degree only	0.0000	0.0000	0.12	0.905
Some college, No BA degree	-0.0001	0.0000	-2.29	0.022
BA degree or more	0.0001	0.0001	0.98	0.325
SNAP#Race				
Black	0.0001	0.0000	5.04	0.000
Hispanic	0.0000	0.0001	0.05	0.958
Other	0.0002	0.0001	2.27	0.023
SNAP#Marital				
Never married	-0.0001	0.0000	-2.69	0.007
Other, spouse absent	0.0000	0.0000	1.24	0.215
Unemployment#EITC	0.0000	0.0000	-2.36	0.019
Unemployment#TANF	0.0000	0.0000	-2.05	0.040
Unemployment#SNAP	0.0000	0.0000	1.93	0.054
EITC#TANF	0.0000	0.0000	-1.28	0.200
EITC#SNAP	0.0000	0.0000	3.35	0.001
TANF#SNAP	0.0000	0.0000	2.36	0.018
Year				
1980 (Omitted)				
1981	0.0150	0.0354	0.42	0.672

1982	0.0101	0.0543	0.19	0.852
1983	-0.0383	0.0464	-0.83	0.409
1984	-0.0460	0.0442	-1.04	0.298
1985	-0.0470	0.0437	-1.07	0.283
1986	-0.0403	0.0411	-0.98	0.326
1987	-0.0513	0.0389	-1.32	0.188
1988	-0.0779	0.0465	-1.67	0.094
1989	-0.0906	0.0526	-1.72	0.085
1990	-0.0575	0.0511	-1.13	0.260
1991	-0.0672	0.0456	-1.47	0.140
1992	-0.0829	0.0523	-1.59	0.113
1993	-0.0795	0.0590	-1.35	0.178
1994	-0.0010	0.1015	-0.01	0.992
1995	-0.0258	0.1233	-0.21	0.834
1996	-0.0349	0.1301	-0.27	0.789
1997	-0.0392	0.1235	-0.32	0.751
1998	-0.0030	0.1313	-0.02	0.982
1999	0.1341	0.1314	1.02	0.307
2000	0.0269	0.1313	0.21	0.838
2001	-0.0905	0.1212	-0.75	0.455
2002	-0.0881	0.1228	-0.72	0.473
2003	-0.0657	0.1087	-0.60	0.545
2004	-0.1402	0.1177	-1.19	0.234
2005	-0.2043	0.1127	-1.81	0.070
2006	-0.1706	0.1188	-1.44	0.151
2007	-0.1890	0.1276	-1.48	0.138
2008	-0.1409	0.1196	-1.18	0.239
2009	-0.1093	0.1264	-0.87	0.387
2010	-0.0935	0.1238	-0.76	0.450
2011	-0.0610	0.1231	-0.50	0.620
2012	-0.0712	0.1169	-0.61	0.542
State				
Alabama (Omitted)				
Alaska	0.8337	0.0497	16.77	0.000
Arizona	0.0100	0.0214	0.47	0.641
Arkansas	0.0988	0.0127	7.76	0.000
California	0.2310	0.0727	3.18	0.001
Colorado	0.2981	0.0230	12.98	0.000
Connecticut	0.4570	0.0577	7.92	0.000
Delaware	0.4616	0.0197	23.43	0.000
District Of Columbia	0.5880	0.0321	18.32	0.000
Florida	0.1668	0.0130	12.79	0.000

Georgia	0.2276	0.0091	24.91	0.000
Hawaii	0.4667	0.0909	5.14	0.000
Idaho	0.1393	0.0327	4.26	0.000
Illinois	0.1848	0.0146	12.66	0.000
Indiana	0.1611	0.0201	8.02	0.000
Iowa	0.4547	0.0309	14.72	0.000
Kansas	0.4142	0.0312	13.25	0.000
Kentucky	0.0552	0.0182	3.04	0.002
Louisiana	-0.0472	0.0075	-6.30	0.000
Maine	0.2154	0.0296	7.27	0.000
Maryland	0.3828	0.0181	21.19	0.000
Massachusetts	0.2121	0.0379	5.59	0.000
Michigan	0.3349	0.0225	14.86	0.000
Minnesota	0.5494	0.0321	17.12	0.000
Mississippi	0.1540	0.0148	10.43	0.000
Missouri	0.3690	0.0161	22.97	0.000
Montana	0.0688	0.0312	2.20	0.028
Nebraska	0.3762	0.0352	10.69	0.000
Nevada	0.2479	0.0270	9.19	0.000
New Hampshire	0.3515	0.0369	9.51	0.000
New Jersey	0.1271	0.0276	4.60	0.000
New Mexico	0.1117	0.0275	4.05	0.000
New York	-0.0440	0.0426	-1.03	0.302
North Carolina	0.2853	0.0128	22.25	0.000
North Dakota	0.2210	0.0398	5.55	0.000
Ohio	0.2781	0.0157	17.74	0.000
Oklahoma	0.1463	0.0198	7.39	0.000
Oregon	0.2954	0.0252	11.71	0.000
Pennsylvania	0.1630	0.0186	8.78	0.000
Rhode Island	0.4098	0.0380	10.77	0.000
South Carolina	0.2872	0.0054	52.73	0.000
South Dakota	0.3520	0.0357	9.86	0.000
Tennessee	0.2173	0.0063	34.61	0.000
Texas	0.3024	0.0136	22.27	0.000
Utah	0.1585	0.0339	4.68	0.000
Vermont	0.3171	0.0397	7.98	0.000
Virginia	0.3227	0.0198	16.29	0.000
Washington	0.3320	0.0265	12.55	0.000
West Virginia	-0.3164	0.0274	-11.56	0.000
Wisconsin	0.6572	0.0331	19.83	0.000
Wyoming	0.4276	0.0307	13.91	0.000
_cons	3.0156	0.1242	24.29	0.000

Chapter 3: From Welfare Reform to the Great Recession: How has the level and composition of income changed for families with children?

3.1 Introduction

Over the last two decades the safety net for families with children has gone through some significant changes. During the early 1990s the Earned Income Tax Credit (EITC) was expanded. The maximum EITC that a working single mother with two children could receive increased from $1,511 in 1993 to a $3,556 in 1996. Later legislation and automatic adjustments by inflation increased the maximum available EITC for a working single mother of two to $5,236 in 2012. The Child Tax Credit (CTC) was enacted in 1997 and during its first year a family could receive a $400 per child annual credit. Subsequent legislation made it so that starting in 2003 a family could receive a credit of up to $1,000 per child. The Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996 made major changes to safety net programs. The act replaced the Aid to Families with Dependent Children (AFDC) program with a block grant program called the Temporary Assistance for Needy Families (TANF). The law ended the entitlement of poor families to assistance from the federal government, instituted a five-year time limit on federal cash benefits, imposed stronger work requirements on recipients and devolved most details of welfare policy making to the fifty states. Along with other changes, it also restricted the eligibility of legal residents to safety net benefits and modified the benefits and eligibility requirements in the Food Stamp Program. Between, 1997 and 2012, the TANF caseload declined by 50 percent. The Supplemental Nutrition Program (SNAP, formerly called the Food Stamp Program) caseload declined between 1996 and 2000 by 33 percent. Between 2000 and 2007 the SNAP caseload increased by 53 percent due to the weakening of the economy and bipartisan efforts at the federal and state level to streamline paperwork requirements and change eligibility rules so that families could still qualify for aid if they owned a certain amount of assets such as a modest car for commuting to work. From 2007 and 2012 the SNAP caseload increased by 77 percent due to the impact of the Great Recession and increased participation among the eligible population.

The 1996 welfare reform law generated a great number of research studies. Rebecca Blank wrote a review of the literature in 2002 and in 2009. Jeffrey Grogger and Lynn A. Karoly did a synthesis of the literature in 2002 and a meta-analysis in 2005. In total, these four publications reviewed over 70 non-experimental econometric studies that aimed to establish a causal link between welfare policy reforms and various outcome variables such as welfare use, employment, earnings, income, poverty, hardship, marriage, childbearing, and child outcomes. About half of the studies focused on understanding changes in welfare use and one fourth focused on employment outcomes. Surprisingly, only four of all of the studies reviewed by these publications used poverty as a dependent variable and six used total family income.

These econometric studies generally found that welfare reform had an impact both on declines in welfare participation and on increases in work effort, although the magnitude of this effect varies across studies. As summarized by Grogger and Karoly's meta-analysis (2005), most studies found that welfare reform as a whole was responsible for a 20 percent decline in welfare caseloads and a 4 percent increase in the employment of single mothers. On average, the increase in employment led to an increase in earnings that outweighed the loss of TANF benefits, and therefore poverty rates went down.

Grogger and Karoly lament that most of these studies considered only family income before taxes and exclusive of non-cash benefits such as SNAP and housing assistance. They also pointed out that underreporting of benefits may bias results. One of the key contributions of this paper is to use an income measure that counts the impact of taxes, non-cash benefits, and corrects for the underreporting of SNAP, TANF, and SSI benefits.

One of the weaknesses of many of these studies is that they focus on average effects, and do not account for the possibility that welfare reform policies could have heterogeneous effects. Using random assignment data from Connecticut's Jobs First waiver, Bitler et al. (2006) found that average effects miss a great deal of variation that exists between different parts of the income distribution. They concluded that welfare reform's effects are likely both more varied and more extensive than has been recognized. The possibility of heterogeneous effects is further supported by researchers that have found that after 1996 some families increased their income to put them above the poverty line, yet another group of families saw their income drop below half the poverty (also known as deep poverty). Yonatan Ben-Shalom, Robert A. Moffitt, and John Karl Scholz (2011) analyzed poverty trends using the Survey of Program Participation (SIPP) and a poverty measure that counts non-cash public benefits like SNAP and tax provisions like the EITC. They found that while the poverty rate declined from 15.3 percent in 1984 to 13.5 percent in 2004, the deep poverty rate rose from 4.5 percent to 6.6 percent. Ben-Shalom et al. (2011) attribute at least part of the increase of deep poverty to a decline in cash assistance for the very poor and a general shifting of the safety net away from those with the lowest incomes to those with incomes closer to the poverty line. Sherman and Trisi (2015) reached a similar conclusion using Current Population Survey (CPS) data from 1995-2010 and a more comprehensive measure of poverty that included non-cash and tax benefits, and deducted medical and work expenses such as child care, and made corrections for underreported benefit income. They found that although poverty rates fell from 1995 to 2005, deep poverty rose due to a weakening of the safety net, particularly TANF. They found that in 1995, AFDC lifted 61 percent of children who would otherwise have been below half of the poverty line out of deep poverty. By 2005, this figure for TANF was just 22 percent.

Primus et al. (1999) were one of the few studies that analyzed the impact of welfare reform at various points in the income distribution. They examined changes in the income of female-headed households in the periods 1993-1995 and 1995-1997. Using an income measure that counts food stamps, housing subsidies, the Earned Income Tax Credit and other such benefits as income, they found that between 1993 and 1995 the disposable income of single mother families rose broadly and substantially. However, they found that between 1995 and 1997, the average disposable income of the poorest fifth and poorest 10th of single mother families fell mainly due to a drop in cash-assistance and food stamp benefits that substantially exceeded the decline in need.

Bollinger, Gonzalez, and Ziliak (2009) improved on many of the previous studies by analyzing the impact of welfare reform on the incomes of single mothers not only at the mean, but at various quintiles. They found that TANF raised disposable incomes an average of eight percent among higher skilled mothers, and raised earnings among low skilled mothers in the lower half of the distribution by as much as 20 percent, but that it also resulted in a significant equal-size loss of after-tax total income among the low-skilled. They conclude that "the earnings gains among the low skilled a decade after the implementation of TANF and expansions of the EITC have been more than offset by losses in transfer income and have left the most vulnerable single mothers either running in place or falling behind."

This paper aims to contribute to this string of the literature by dividing children into twenty equal groups (ventiles) ranked by their family's private income. The paper will analyze how the level and composition of income of children in each ventile changed between 1993 and 2012. Being able to cover the Great Recession, which officially lasted from December 2007 to June 2009, and its aftermath is another important contribution of this paper. A number of studies have shown how spending on most major social programs increased significantly during the Great Recession to help families make up the loss in earnings. (Ziliak 2011; Burtless and Gordon 2011; Moffitt 2013; Bitler and Hoynes 2016). The Congressional Budget Office (2016) recently published the latest version of their report on the distribution of household income and federal taxes which uses a comprehensive income measure that includes government transfers. However, none of these studies break down the increases of safety net spending by ventiles of families with children. This paper will demonstrate how important it is to look at ventiles instead of quintiles because of how different trends can be for the bottom 5 percent of children compared to the next 5 percent. The ventiles analysis allows one to see how economic wellbeing and the reach of safety net programs have changed within the bottom quintile of the income distribution. In addition, this paper will analyze the characteristics of children and their families at different points of the income distribution in 2012.

3.3 Data and Methodology

Like many previous researchers, I have chosen to use the Annual Social & Economic Supplement (ASEC) from the Current Population Survey (CPS), commonly known as the March CPS. The CPS microdata which is publicly available provides information on labor market participation, family structure, demographics, receipt of government benefits, and many other variables. The March CPS sample size currently stands at about 100,000 households per year. (U.S. Census Bureau, 2010).

Similarly to other household surveys, the CPS suffers from some underreporting of income and benefits. The total amount of government benefits that people report receiving in the CPS falls short of the actual figures according to administrative data. Changes in the degree of underreporting over time could be particularly problematic for time series analyses. (Wheaton, 2007) One way to address this issue is to augment CPS data using a microsimulation model that corrects for underreporting. Sherman and Trisi (2015) use this approach, and that’s also my approach here. I correct for the tendency of CPS data to underreport income from three government assistance programs: Temporary Assistance for Needy Families

(TANF), Supplemental Security Income (SSI), and the Supplemental Nutrition Assistance Program (SNAP, formerly food stamps). To make these corrections, I use baseline data from the Transfer Income Model Version III (TRIM III) policy micro-simulation model developed by the Urban Institute under contract with the U.S. Department of Health and Human Office of the Assistant Secretary for Planning and Evaluation. TRIM starts with Census survey data but uses a different method of filling in questions skipped by survey respondents regarding program participation and benefit income, in order to closely match actual numbers and characteristics of benefit recipients shown in administrative records. The problem of underreporting of AFDC/TANF cash assistance has gotten worse over time. The CPS data captured 77 percent of AFDC spending in 1993 but only 48 percent of TANF spending in 2012. However, TRIM corrections can help fix this problem. The CPS data augmented by TRIM captures 93 percent of AFDC spending in 1993 and 91 percent of TANF spending in 2012. This analysis ends with 2012 because that's the latest year for which TRIM underreporting corrections are available for SNAP, TANF and SSI.

Instead of analyzing poverty rates and deep poverty rates of children, this paper will analyze the mean family income of ventiles of children. Ventiles are created by ranking all children by their family's size adjusted private income and dividing them into 20 equal groups. I adjusted for family size using the same methodology that the Congressional Budget Office uses in their studies of household income. (See CBO 2016). I adjust for family size by dividing family income by the square root of the number of people in the family, counting adults and children equally. This adjustment implies that each additional person increases a family's needs but does so at a decreasing rate. This is done to take into account for the fact that larger families need more total income but less per capita income than smaller families because they can share resources and take advantage of economies of scale. All the mean income figures that I present in this paper are equivalent to a family of four.

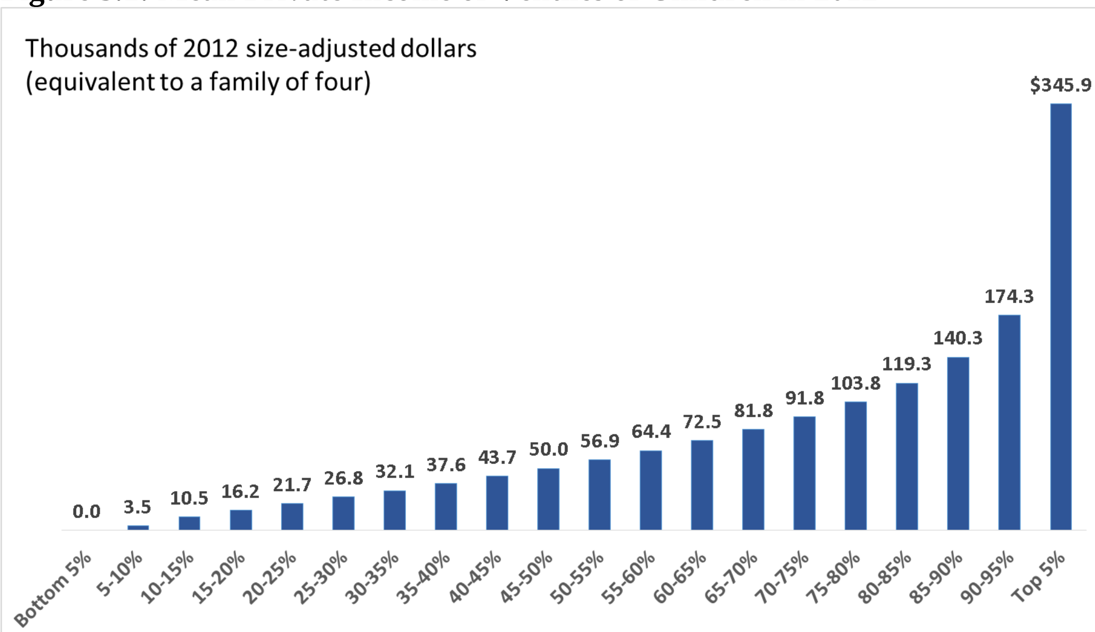
Private income consists of labor income, business income, and other non-government sources of income such as private pensions, interest income, and rental income. In this paper, I use private income and pre-government income interchangeably. For children in the bottom half of the family private income distribution, earnings made up 94 percent of the total private income in 1993-2012. Therefore, in this paper I use the private income distribution, the pre-government income distribution and the earnings distribution interchangeably. The CBO uses the term market income instead of private income in its household income study. For the next iteration of this paper, I'm going to consider whether I should use market income instead of private income to be consistent with their terminology.

Families are defined using the same methodology that the Census Bureau uses to calculate the official poverty measure. A family is defined as two or more people living together and related to each other by birth, marriage or adoption. Under this definition unmarried partners are not considered part of the same family unit. All mean income figures presented are in 2012 dollars adjusted by the Bureau of Labor Statistics' Consumer Price Index for All Urban Consumers Research Series (CPI-U-RS). This is the same series that the Census Bureau uses to adjust for inflation in its annual poverty and income reports.

3.4 Results and Discussion

The first step in my analysis is to rank all children by their family's size adjusted private income and divide them into 20 equal groups (ventiles). Figure 3.1 shows the mean private income of each ventile. Each ventile consists of roughly about 3.6 million children.

Figure 3.1: Mean Private Income of Ventiles of Children in 2012

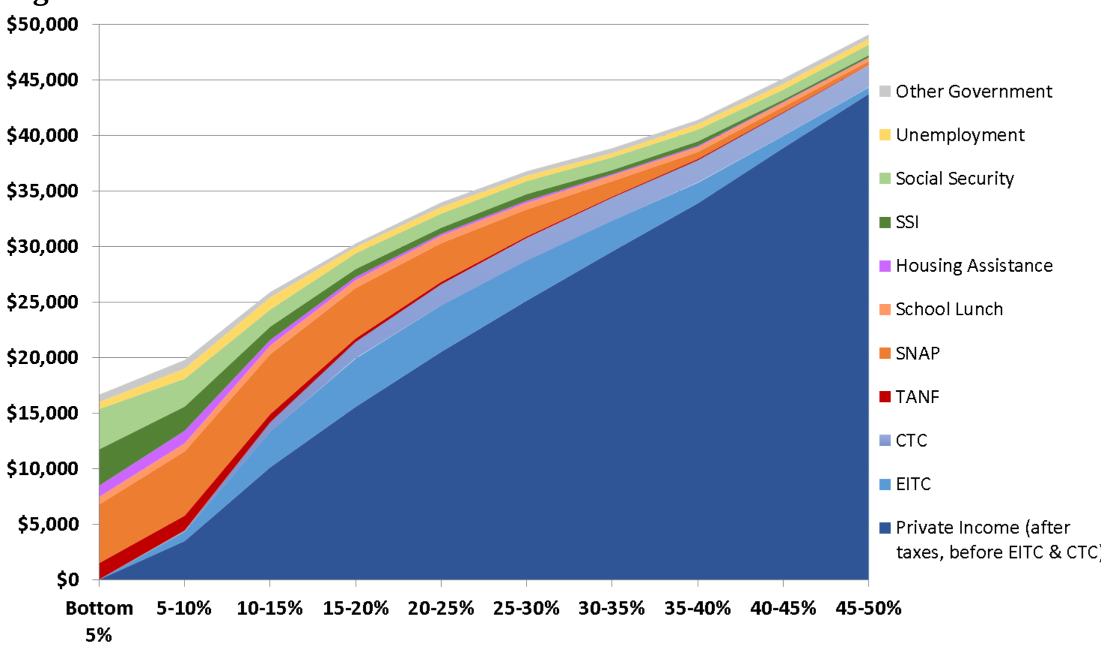


Note: Figures are in 2012 dollars and equivalent to a family of four. Ventiles of children are created by ranking children by their family's pre-government size-adjusted income.

Figure 3.1 is dominated by the relatively high income of the top 5 percent ventile ($345,900). The mean income of the top 5 percent would be even higher if I used another data set that fully captured the income of that group. The CPS data used here does not include information about earnings over $1,099,999 in any given job, and some earnings below that threshold are suppressed in the public use file in order to preserve confidentiality.

This paper will focus on the bottom 50 percent of the income distribution (the bottom 10 ventiles). The CPS does a much better job at capturing the private income of that group compared to the top 5 percent. Figure 3.2 shows the level and composition of post-tax post-transfer income for the bottom 10 ventiles of children. The blue area here indicates the average amount of private income after taxes, but before the EITC and CTC are taken into account. The remaining colors indicate the mean amount of income received through different government programs. For example, the light blue areas show the mean amount of EITC and CTC benefits received by the families of these children.

Figure 3.2: Mean Post-Tax Post-Transfer Income of Ventiles of Children in 2012



Note: Figures are in 2012 dollars and equivalent to a family of four. Ventiles of children are created by ranking children by their family's pre-government size-adjusted income.

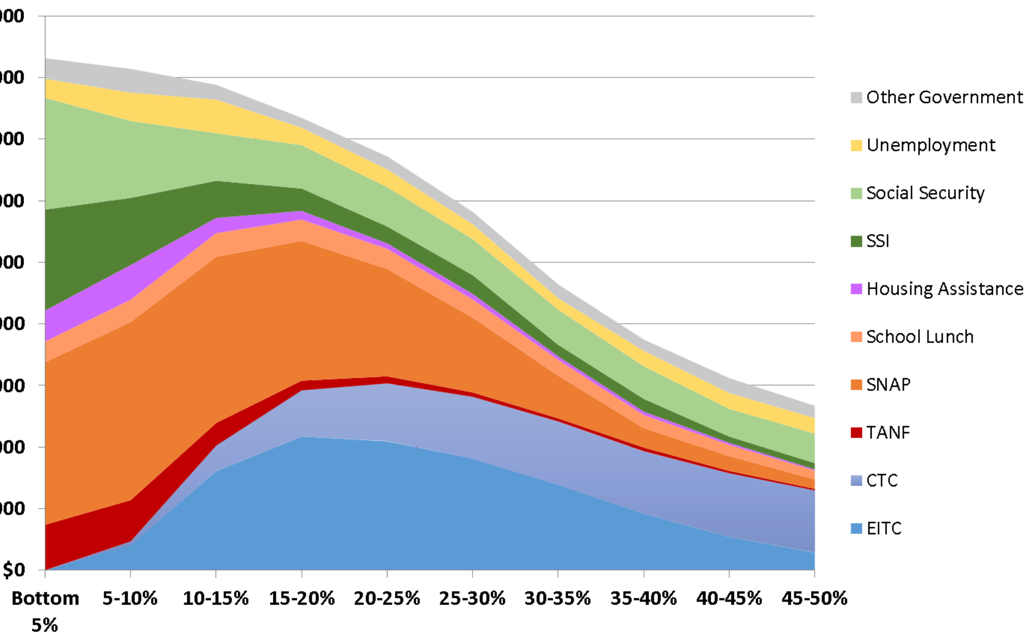
The first take-away of Figure 3.2 is that the safety net does a lot to increase the income of children at the bottom of the family earnings distribution. Without the safety net, the bottom 5 percent of children would have access to zero income. The safety net also increases the income of children in the next couple of ventiles by a large amount, but most safety net benefits are phased-out by the ninth (40-45%) ventile.

The second take-away is that safety net is designed so that the more a family earns, the more their total income rises. The upward slope for total income in Figure 3.2 shows how much total income increases as one moves from the ventiles with the lowest family earnings to the ventiles with higher earnings. If you want to increase the economic well-being of your children, it pays to work more and earn more.

The color coding in Figure 3.2 allows us to see how different programs phase-in and phase-out at different earnings levels. For example, the EITC (light blue) peaks around the fourth (15-20%) and fifth (20-25%) ventiles and phases out after that. SNAP (orange) helps a lot of children in families with zero earnings but also provides a pretty large work-support to families further up the earnings distribution.

Figure 3.3 shows the same data as Figure 3.2 but removes private income. This allows one to more clearly see how different safety net programs phase out and play a different role at different points in the family earnings distribution.

Figure 3.3: Mean Safety Net Benefits for Ventiles of Children in 2012

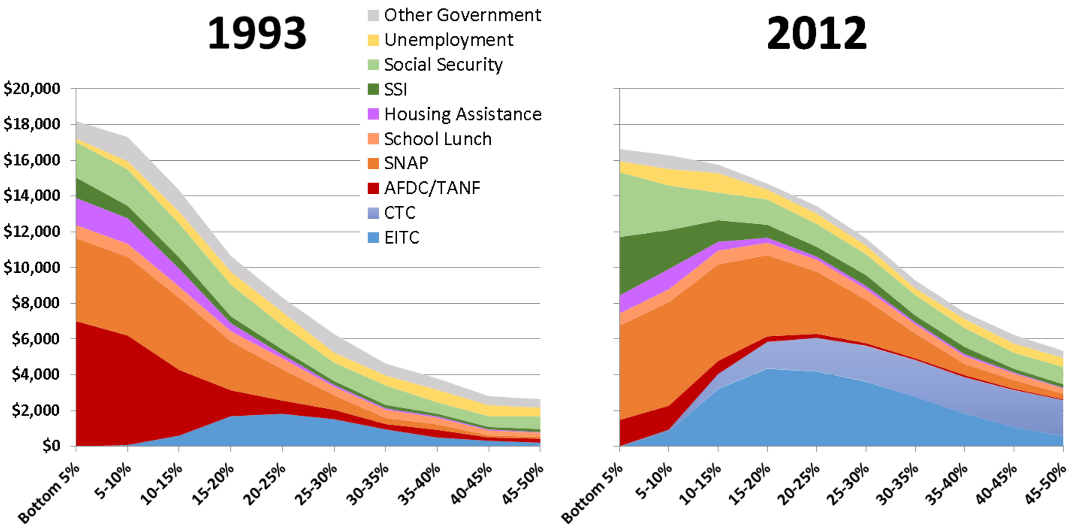


Note: Figures are in 2012 dollars and equivalent to a family of four. Ventiles of children are created by ranking children by their family's pre-government size-adjusted income.

3.4.2 How Has the Safety Net Changed Between 1993 and 2012?

The expansion of tax credits for working families and the 1996 welfare reform law have made the safety net look much different in 2012 compared to 1993. Figure 3.4 shows mean safety net benefits for ventiles of children in 1993 and 2012.

Figure 3.4: Mean Safety Net Benefits for Ventiles of Children in 1993 and 2012

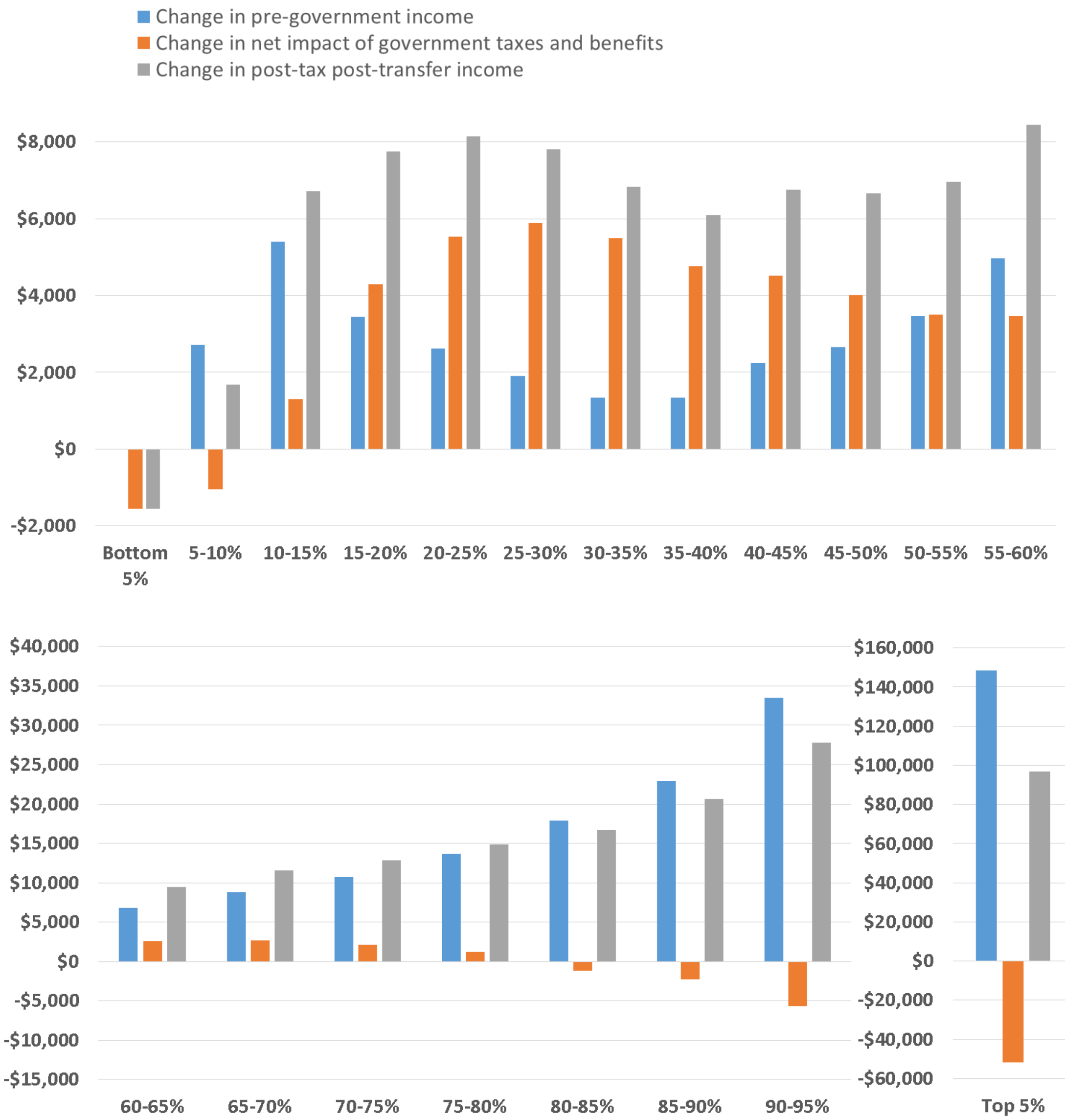


Note: Figures are in 2012 dollars and equivalent to a family of four. Ventiles of children are created by ranking children by their family's pre-government size-adjusted income.

The decline of AFDC/TANF and the increase of the EITC and CTC is quite striking. It's also remarkable how SNAP has become a much bigger support for both families at the bottom and families with higher earnings. The fact that the 2012 graph has more of a rounded belly shape compared to the 1993 graph is a visual representation of how the safety net has become more "work focused" and therefore provides more benefits to working families. A higher reliance on Social Security for the bottom ventiles is likely due to more children living with grandparents or other adults receiving Social Security benefits as opposed to an expansion of Social Security benefits for children.

Between 1993 and 2012 the mean post-tax post-transfer income of all child ventiles increased, except for the bottom ventile. Figure 3.4 shows changes in income between 1993 and 2012 for all ventiles. The post-tax post-transfer income changes (grey bars) are the sum of changes in pre-government income (blue bars) and changes in the net impact of government taxes and benefits (orange bars).

Figure 3.5: Change in the Mean Income of Child Ventiles, 1993-2012

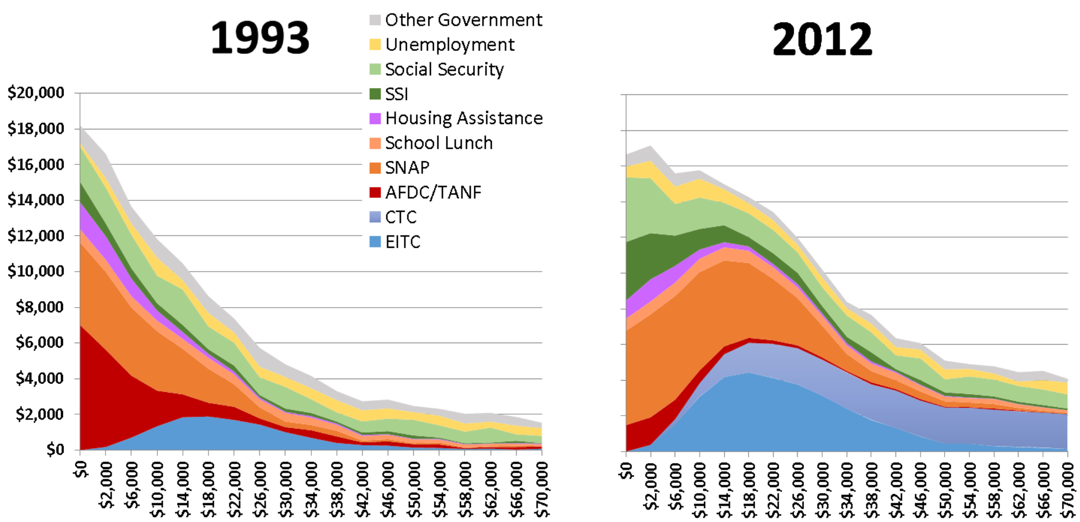


Note: Figures are in 2012 dollars and equivalent to a family of four. Ventiles of children are created by ranking children by their family's pre-government size-adjusted income.

Between 1993 and 2012 the bottom ventile saw no change in pre-government income, therefore the drop in post-tax post-transfer income was driven entirely by changes in the net impact of government taxes and benefits. In the case of the second ventile (5%-10% of the distribution), the increase in pre-government income of $2,700 was offset by a decline in the net impact of government taxes and benefits of

$1,000, which resulted in a $1,700 increase in post-tax post-transfer income. Given that safety net benefits generally phase-out as earnings increase, that decline in safety net benefits could be both due to the increases in earnings of that ventile and due to changes in the benefit levels of safety net programs. A more direct way to observe how safety net programs have changed is to compare children with similar levels of family private income across years. Figure 3.6 does this for children with family private income up to $70,000 per year.

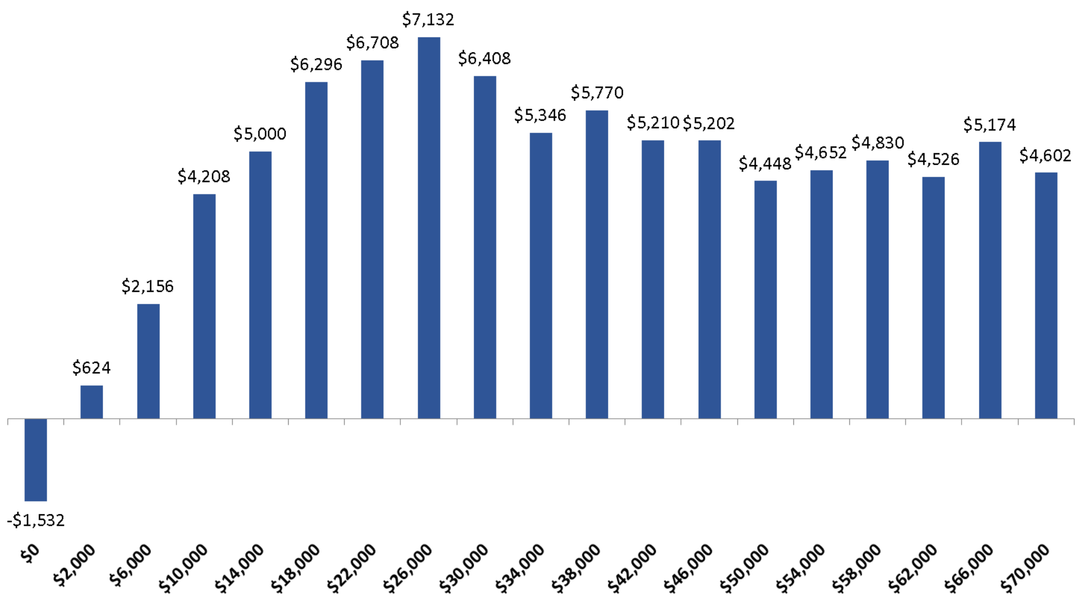
Figure 3.6: Mean Safety Net Benefits for Children in 1993 and 2012 by family private income groups



Note: Figures are in 2012 dollars and equivalent to a family of four.

The similarity between Figure 3.6 and 3.4 provides evidence that the differences observed between 1993 and 2012 are largely due to changes in the benefit structure and availability of safety net benefits as opposed to changes in the mean private income of ventiles. To get a clearer picture of how the net impact of taxes and benefits have changed for families at different points in the earnings distribution one can subtract the total amount of government assistance in 2012 from the total amount of government assistance in 1993 for each family earnings group. Those differences are presented in Figure 3.7.

Figure 3.7: Change in the impact of taxes and benefits by family private income group, 1993 to 2012

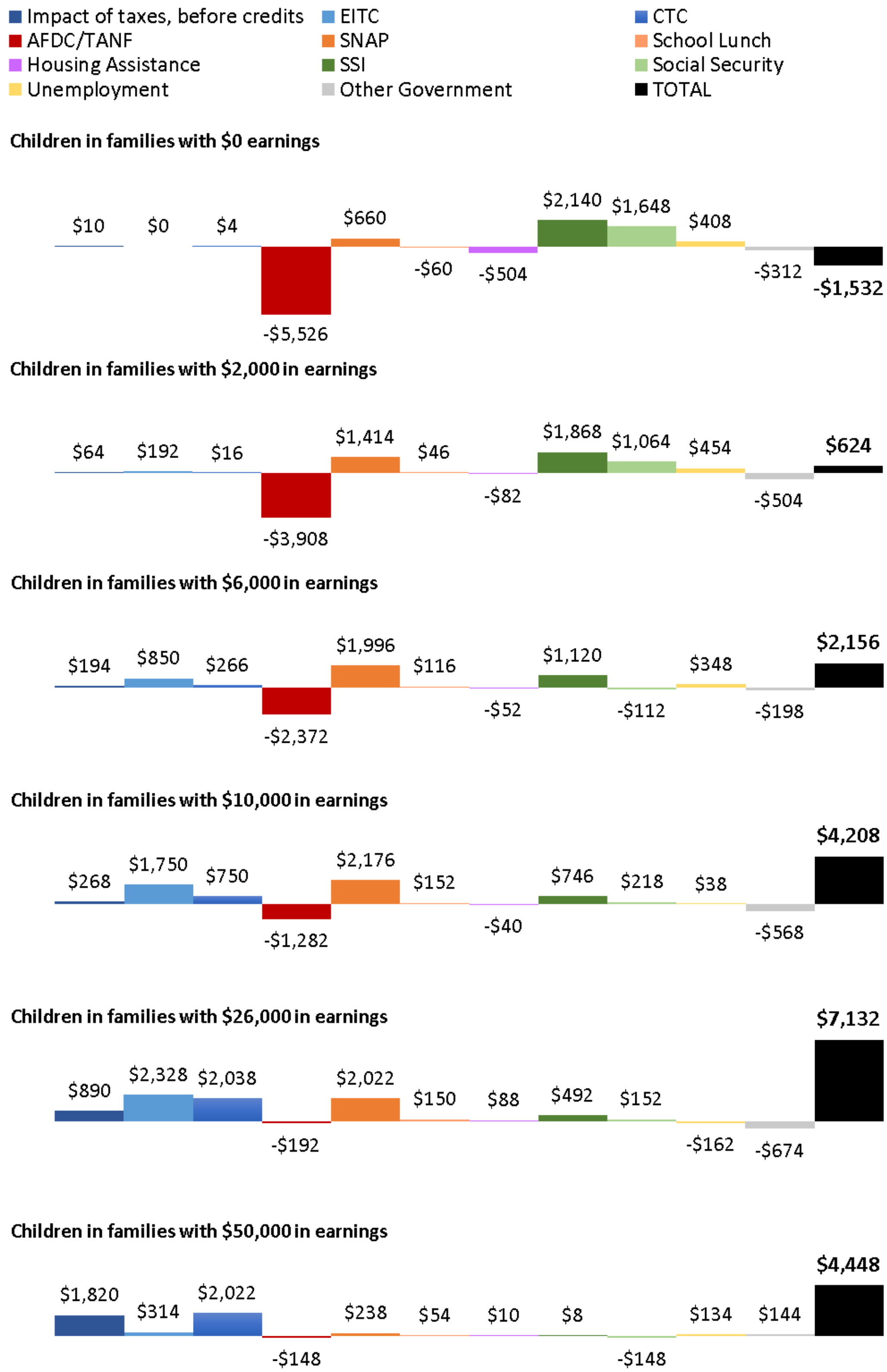


Note: Figures are in 2012 dollars and equivalent to a family of four.

For children in families with zero private income, taxes and transfers provided $1,500 less in support in 2012 than in 1993. In contrast, figure 3.7 shows how the taxes and transfers system provided more support for all families with $2,000-$70,000 in pre-government income in 2012 than in 1993. Children in families with pre-government income between $18,000-$30,000 saw the biggest boost, but even children in families with pre-government income between $50,000 and $70,000 had an increase in the impact of government taxes and assistance of over $4,000.

Figure 3.8 shows what income sources drove the changes of the impact of the tax and benefits system for families with children at different points in the private income distribution.

Figure 3.8: Change in the Impact of Safety Net by Income Source, 1993 to 2012



Note: Figures are in 2012 dollars and equivalent to a family of four.

For families at the bottom of the earnings distribution, the decline in AFDC/TANF drove down the impact of government benefits and taxes. Families have mitigated that loss by relying more on Social Security and Supplemental Security Income (SSI). The increase in Social Security income suggests that these families responded to the decline in other income sources by doubling up with a family member who receives Social Security such as a grandparent.

For families higher in the pre-government income distribution, the increase of the EITC and CTC drove the boost in the positive impact of taxes and transfers. The SNAP program also provided much more support for families with earnings in 2012 than in 1993.

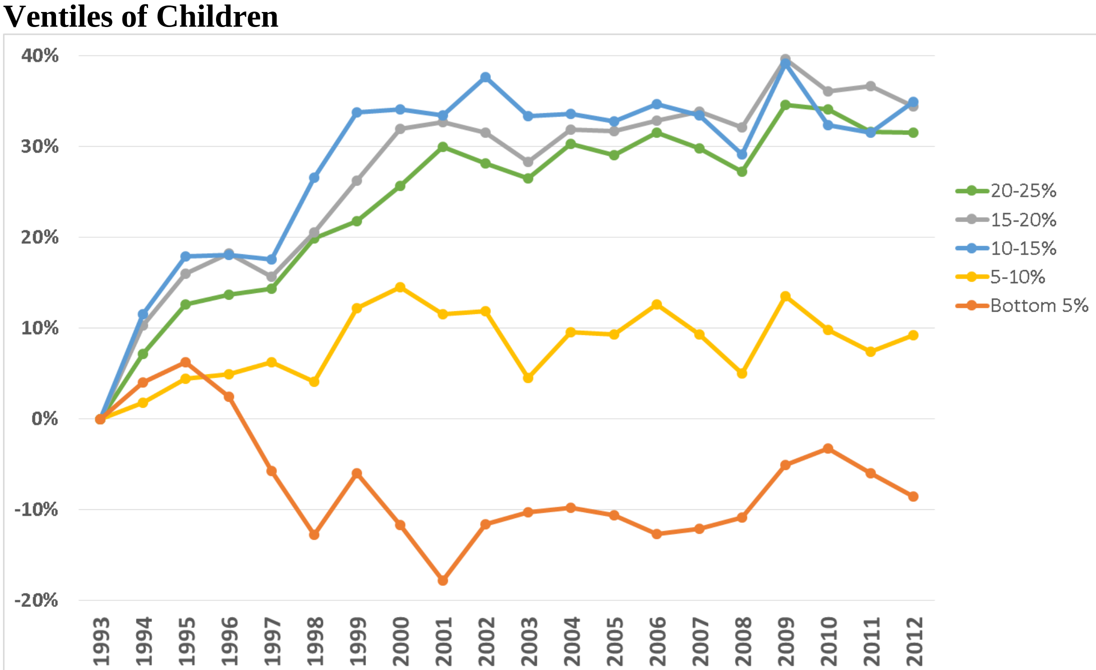
The boost in the net impact of government transfers and taxes for families with children with $50,000 in pre-government income was driven by the CTC and other changes in tax policy such as tax rate and marriage penalty reductions. (See the $2,022 increase of the impact of the CTC and the $1,820 increase in the impact of taxes before credits in Figure 3.8.)

3.4.3 How Has the Level and Composition of Income Changed for Different Ventiles Between 1993 and 2012?

Changes in the tax and transfer system have impacted the mean post-tax and post-transfer incomes of families with children. Between 1993 and 2012, the post-tax and post-transfer income of the bottom ventile of children in the private family income distribution dropped by 9 percent or $1,600 dollars. Most of that decline occurred between 1995 and 2001 when post-tax post-transfer income dropped by 23 percent or $4,400.

The mean post-tax post-transfer income of the second ventile (children with family pre-government income between 5-10% of the distribution) increased by 9 percent between 1993 and 2012. The total income of the next three ventiles increased by 32-35 percent. See figure 3.9.

Figure 3.9: Percent Change Since 1993 in Post-Tax Post-Transfer Income of Ventiles of Children



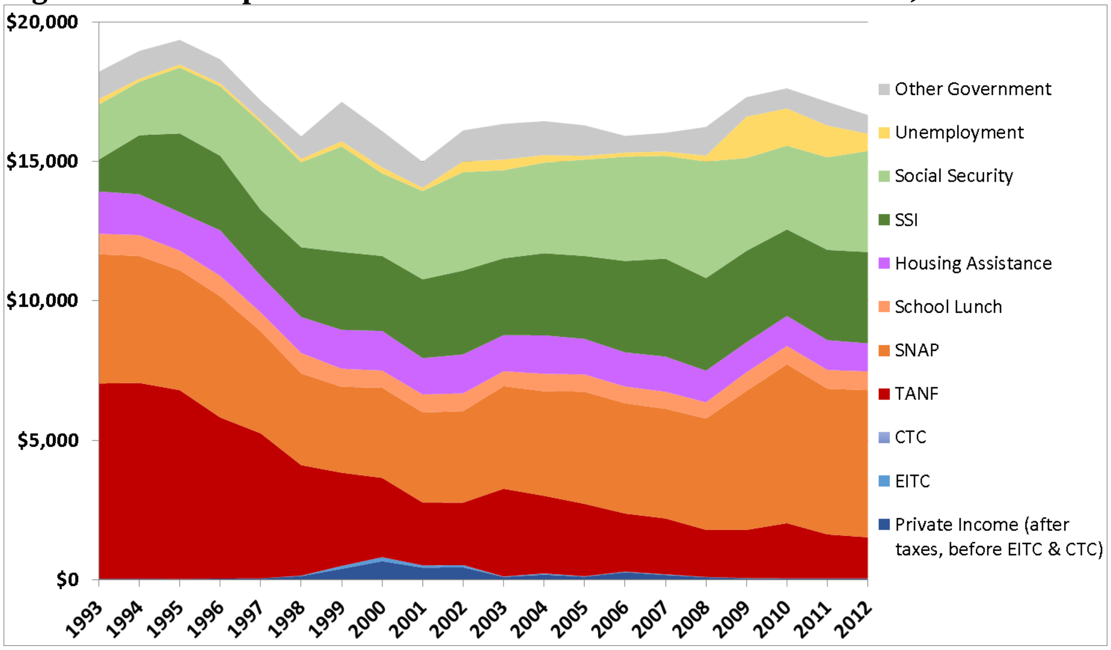
Note: Figures are in 2012 dollars and equivalent to a family of four. Ventiles of children are created by ranking children by their family's pre-government size-adjusted income.

Figure 3.10 explains why the mean post-tax post-transfer income of the bottom ventile fell. Between 1995 and 2005 the post-tax post-transfer income of the bottom ventile of children dropped by 16 percent or $3,100. Comparing 1995 to 2005 provides an especially revealing look because 1995 was the year before the enactment of the 1996 welfare law while 2005 was a year with comparable economic conditions. The percent of adults employed stood at 62.7 percent in 2005 compared to 62.9 percent in 1995. The unemployment rate in 2005 (5.1 percent) was similar to the rate in 1995 (5.6 percent).

The drop in post-tax post-transfer income of the bottom ventile was driven by a decline in AFDC/TANF income. The mean amount of AFDC/TANF assistance received by the bottom ventile of children dropped by 62 percent ($4,200) from 1995 to 2005. Some families responded to this drop by moving in with a family member who received Social Security. In 1995, 20 percent of children in the bottom ventile lived with a family member who received Social Security compared to 24 percent in 2005. That contributed to a 46 percent ($1,100) increase in Social Security benefits received by the bottom ventile of children.

The average amount of SNAP assistance received by the bottom ventile of children increased from 2007 to 2010 by 45 percent ($1,800). This was partly due to an increase in the participation rate of eligible families and a temporary increase in monthly SNAP benefits included in the 2009 Recovery Act. This was one of various measures enacted to support the struggling economy during the Great Recession. The temporary boost in SNAP benefits ended in November 2013.

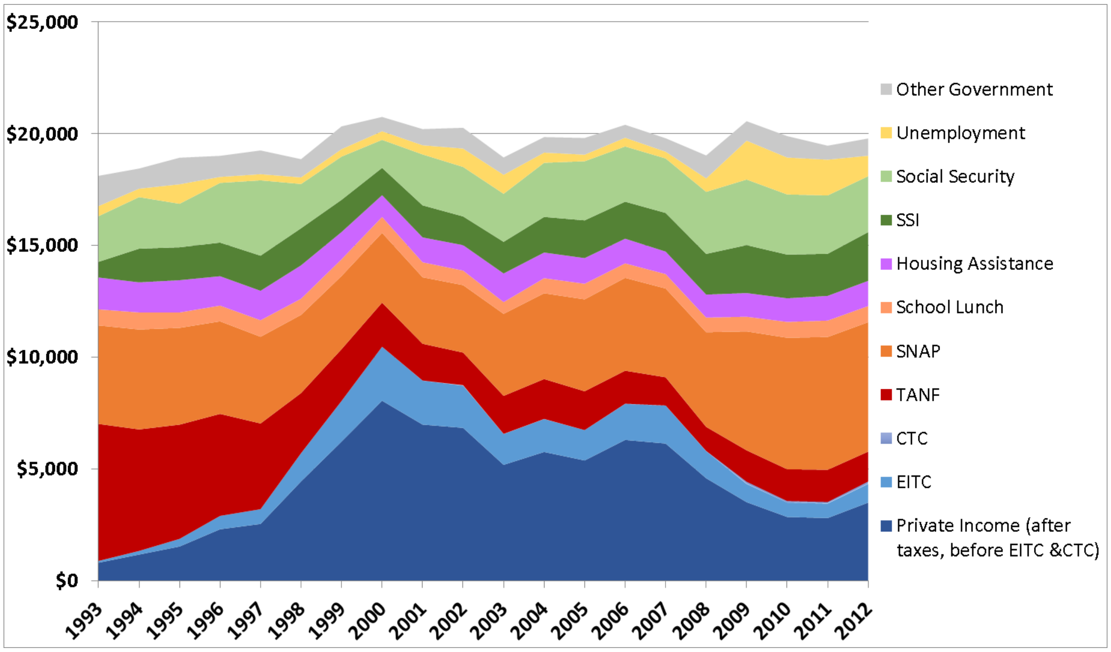
Figure 3.10: Composition of Income of Bottom Ventile of Children, 1993-2012



Note: Figures are in 2012 dollars and equivalent to a family of four. Ventiles of children are created by ranking children by their family's pre-government size-adjusted income.

Figure 3.11 shows the post-tax post-transfer income trends of the 2nd ventile. Those are children with private family income between 5 and 10 percent of the distribution. The total income of children in this ventile stayed flat during the economic boom of 1995 because the increase in family earnings and the EITC were offset by receiving less SNAP and TANF benefits.

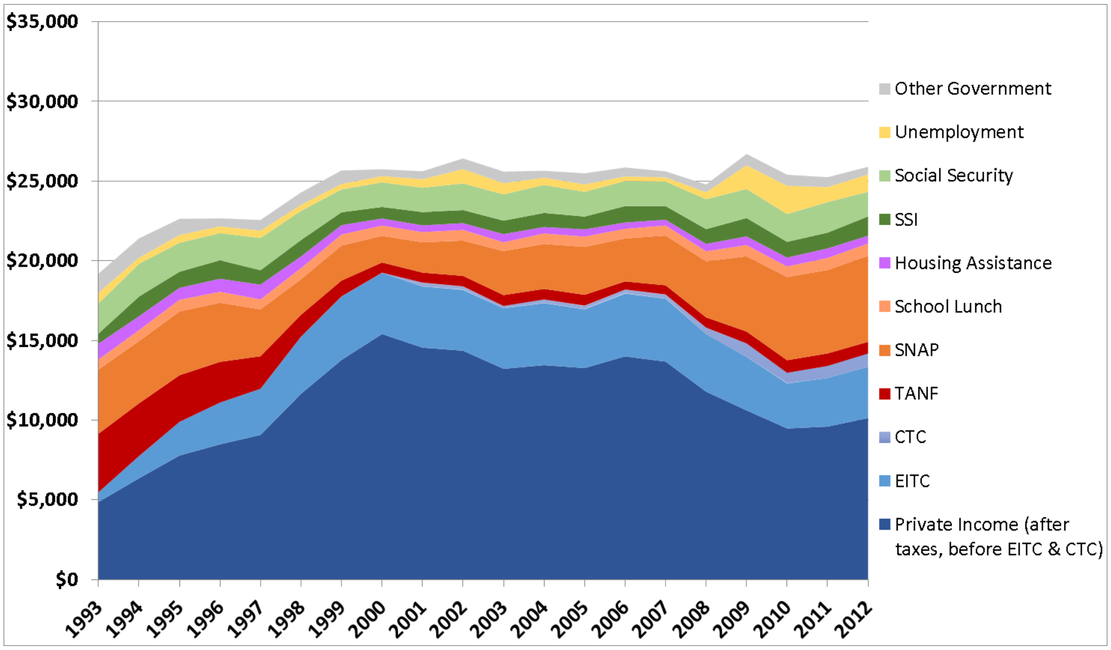
Figure 3.11: Composition of Income of 2nd Ventile (5-10%) of Children, 1993-2012



Note: Figures are in 2012 dollars and equivalent to a family of four. Ventiles of children are created by ranking children by their family's pre-government size-adjusted income.

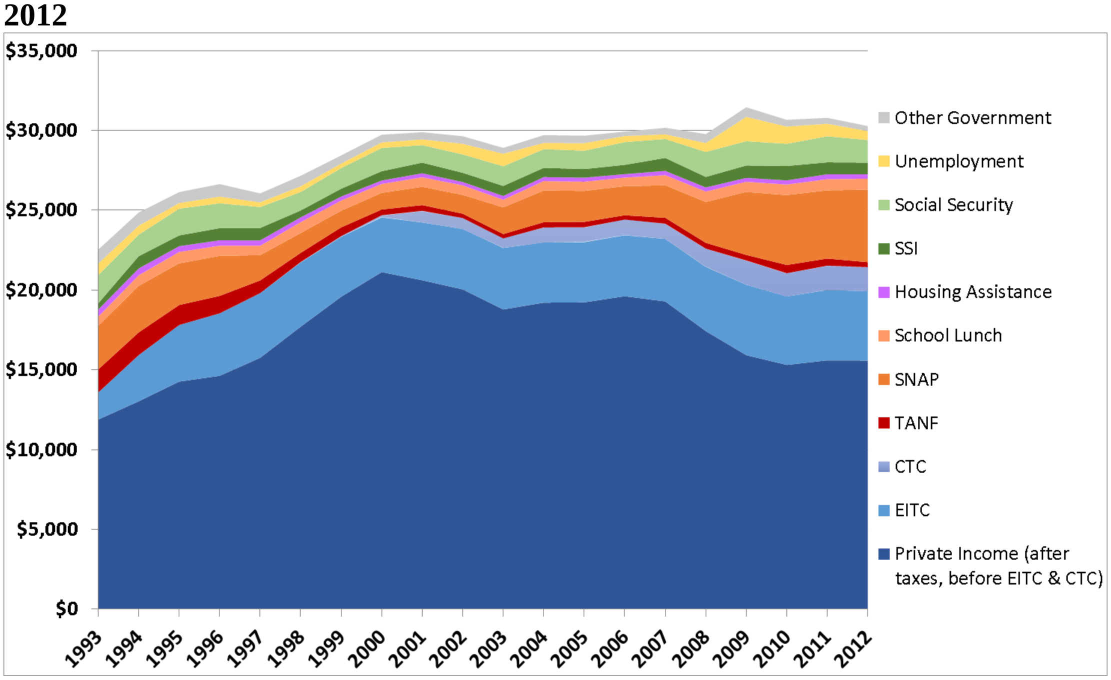
Figures 3.12-3.15 show mean income trends for the 3rd, 4th, and 5th ventiles of children. Together these figures show how as one moves up the private income distribution the role of TANF and SNAP decrease substantially. These families are the ones that saw an increase in total income during the 1990s which drove the decline in child poverty rates. These figures show how the rise of total income for these three ventiles was driven by gains in earnings, which more than made up for TANF and SNAP losses during that period. Expansions of the EITC and CTC also contributed to increasing family's post-tax post-transfer incomes. Earnings declined for a few years after 2000, and declined more after the Great Recession started in 2007. Rising SNAP income helped maintain the level of total income throughout the 2000s and particularly during the Great Recession for these three ventiles.

Figure 3.12: Composition of Income of 3rd Ventile (10-15%) of Children, 1993-2012



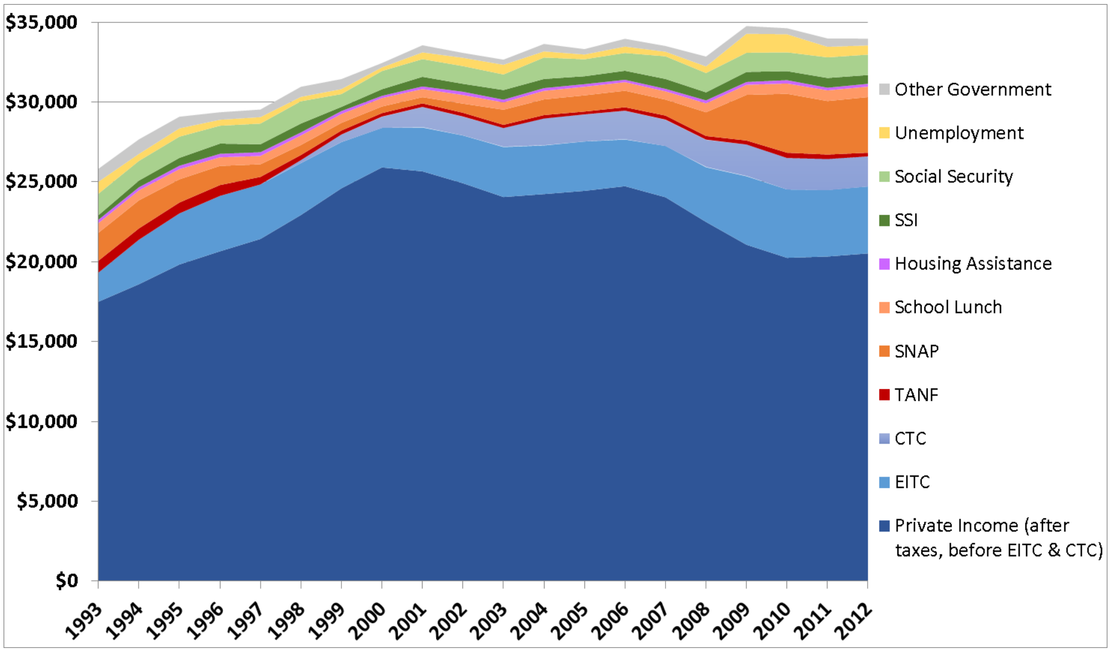
Note: Figures are in 2012 dollars and equivalent to a family of four. Ventiles of children are created by ranking children by their family's pre-government size-adjusted income.

Figure 3.13: Composition of Income of 4th Ventile (15-20%) of Children, 1993-2012



Note: Figures are in 2012 dollars and equivalent to a family of four. Ventiles of children are created by ranking children by their family's pre-government size-adjusted income.

Figure 3.14: Composition of Income of 5th Ventile (20-25%) of Children, 1993-2012



Note: Figures are in 2012 dollars and equivalent to a family of four. Ventiles of children are created by ranking children by their family's pre-government size-adjusted income.

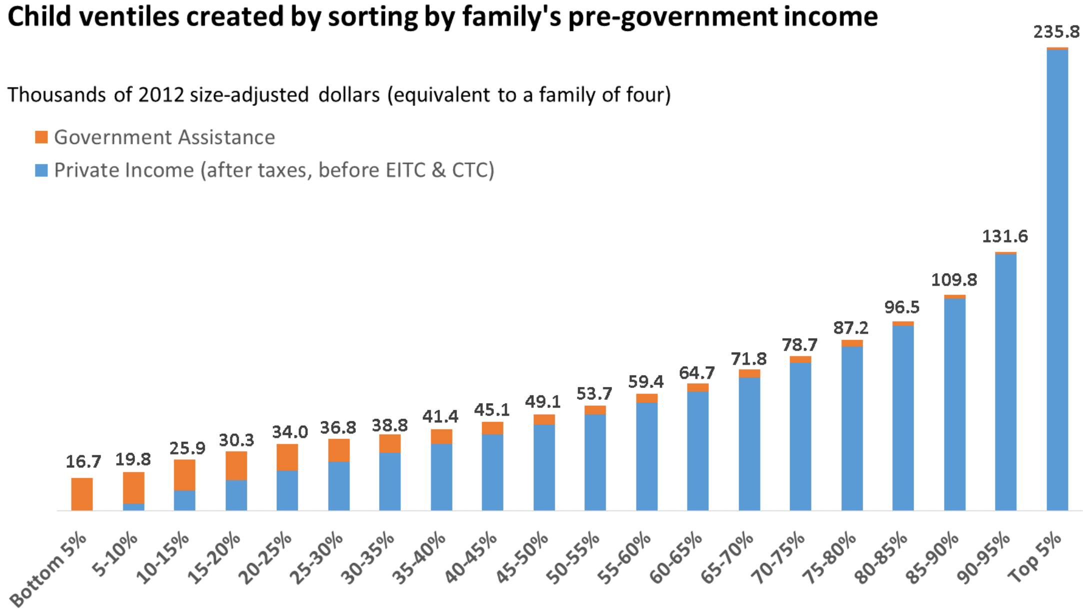
Figures 3.12-3.14 show how even after recent expansions, the CTC helps the 5th ventile more than the 3rd and 4th ventiles. Therefore, it seems like an in increase in the phase-in rate of the CTC (currently at 15 percent) and starting CTC benefits at the first dollar of earnings instead of at $3,000 would make the CTC much more beneficial to children in the 3rd and 4th ventiles.

3.4.4 Demographic and Other Characteristics of Child Ventiles in 2012

Instead of analyzing trends over time like previous sections, this section focuses on the characteristics of children in different ventiles in 2012. The graphs in this section show the share of children in each ventile that fit a given characteristic. The ventiles for these graphs were created by ranking children by their family's post-tax and post-transfer income. That income measure was chosen since it includes the impact of all government benefits and taxes and therefore provides a better measure of the economic well-being of children. Previous sections ranked children by their family's pre-government income in order to analyze how the safety net impacts the income of children at different points in the family earnings/private income distribution.

Figure 3.15 shows the mean post-tax post-transfer income of ventiles created by both sorting children by their family's pre-government income and sorting children by their family's post-tax and post-transfer income. The graphs separate out private income (after taxes, before EITC & CTC) and government assistance. Here, government assistance includes all the government income sources shown separately in previous graphs. (EITC, CTC, TANF, SNAP, school lunch, housing assistance, SSI, social security, unemployment insurance, and "other government.") For most families, private income sources make up almost all of their total income. Therefore, sorting by post-tax post-transfer income doesn't make that much difference to the overall picture of income distribution. However, the sorting does make a difference to the mean income at the very bottom of the distribution. The mean post-tax post-transfer income of the bottom 5 percent of children drops from $16,700 to $11,300 when sorting by post-tax post-transfer income instead of sorting by pre-government income. That's because access to safety net benefits is not universal. Some families with little earnings get enough safety net benefits to substantially boost their income while some families with little earnings get very little assistance. By ranking by post-tax post-transfer income, all those families with little earnings *and* little assistance get grouped together in a bottom ventile. Therefore, that bottom ventile ends up with lower mean post-tax post-transfer income than the bottom ventile that was created by ranking by pre-government income. In future research, I plan to look more closely at which families with little earnings get assistance and which families don't. I'd like to see whether this varies by state and whether this variation has increased since 1996 due to the flexibility given to states in the 1996 welfare law. It's important to note that the 1995-2005 decline in post-tax post-transfer income of the bottom 5 percent of children previously discussed is similar if one ranks children by their family's pre-government income (16 percent decline) or post-government income (14 percent decline).

Figure 3.15: Mean Post Tax & Transfer Income of Child Ventiles sorted by pre-government and post-government income, 2012



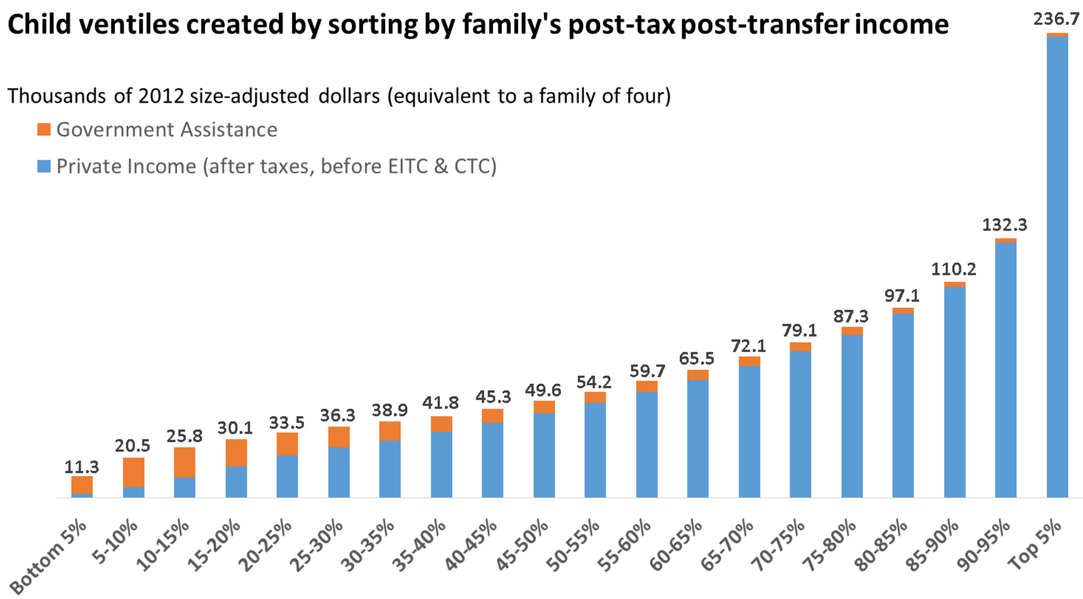
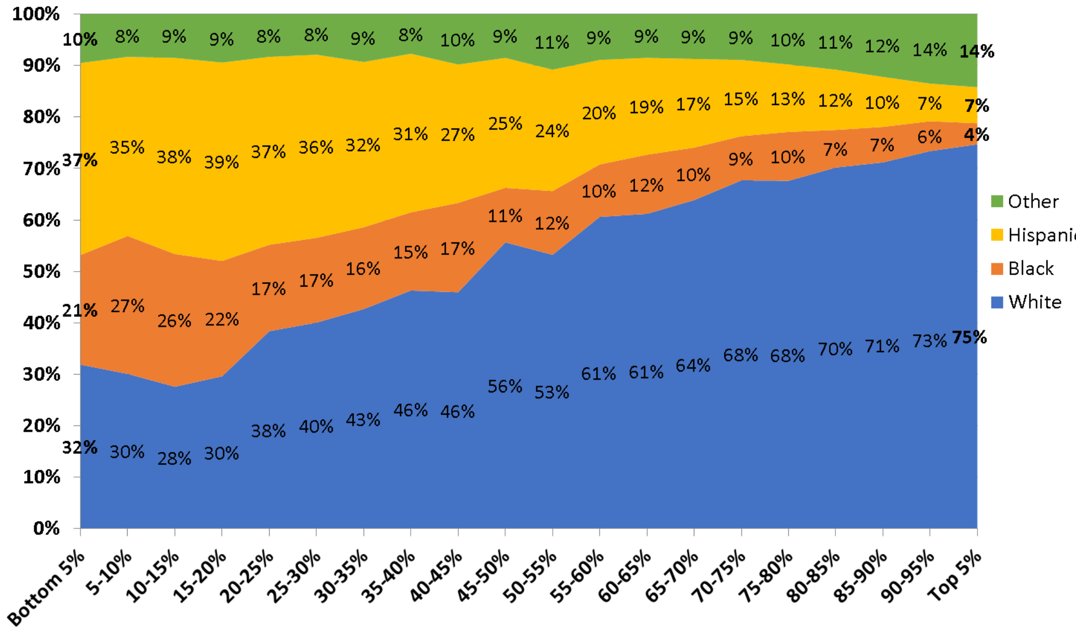


Figure 3.16 shows the percent of children in each post-tax and transfer ventile by their race and ethnicity. White non-Hispanic children made up 32 percent of children in the bottom ventile, but 75 percent of children in the top ventile. Black and Hispanic children make up the majority of children in the bottom six ventiles, but

their share declines as one moves up the income distribution. Only 11 percent of children in the top ventile are either Hispanic or Black.

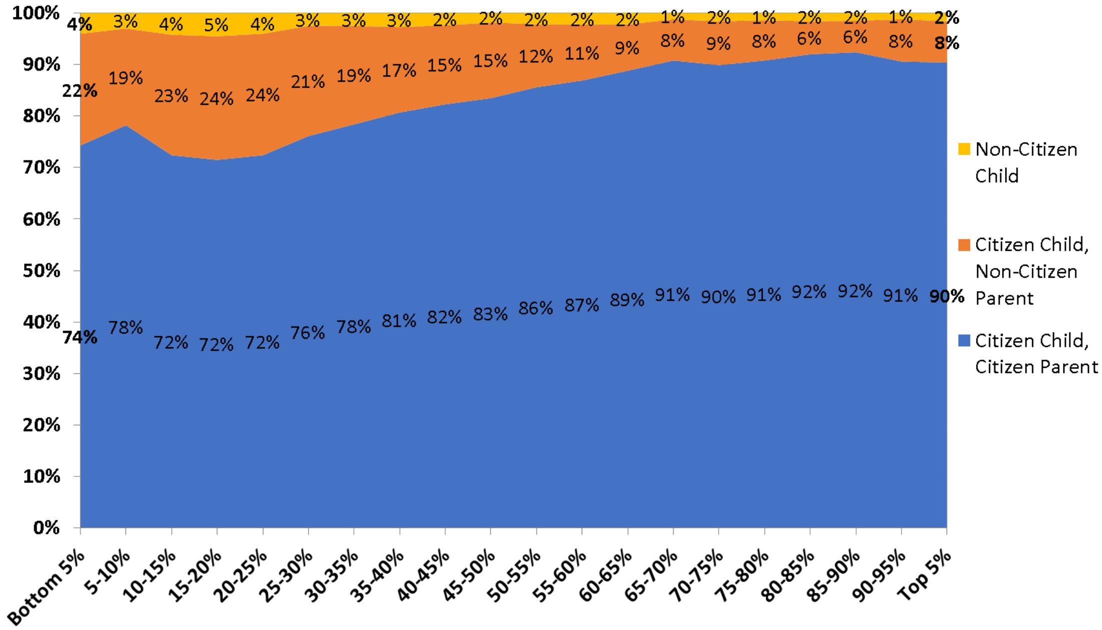
Figure 3.16: Race Composition of Post Tax & Transfer Child Ventiles, 2012



Ventiles of children are created by ranking children by their family's post-taxes post-transfers size-adjusted income.

Figure 3.17 show the share of children in different ventiles by their own and their parents' citizenship status. The share of children who are citizens does not vary a lot by ventiles; 96 percent of children in the bottom ventile are U.S. citizens while 98 percent of children in the top ventile are U.S. citizens. What varies more is the citizenship status of their parents. Over 20 percent of children in the bottom six ventiles are citizens themselves, but have a parent (or primary caretaker) who is a non-citizen. Meanwhile, on average, 8 percent of children in the top six ventiles are citizens themselves, but have a parent (or primary caretaker) who is a non-citizen.

Figure 3.17: Citizenship Status Composition of Post Tax & Transfer Child Ventiles, 2012



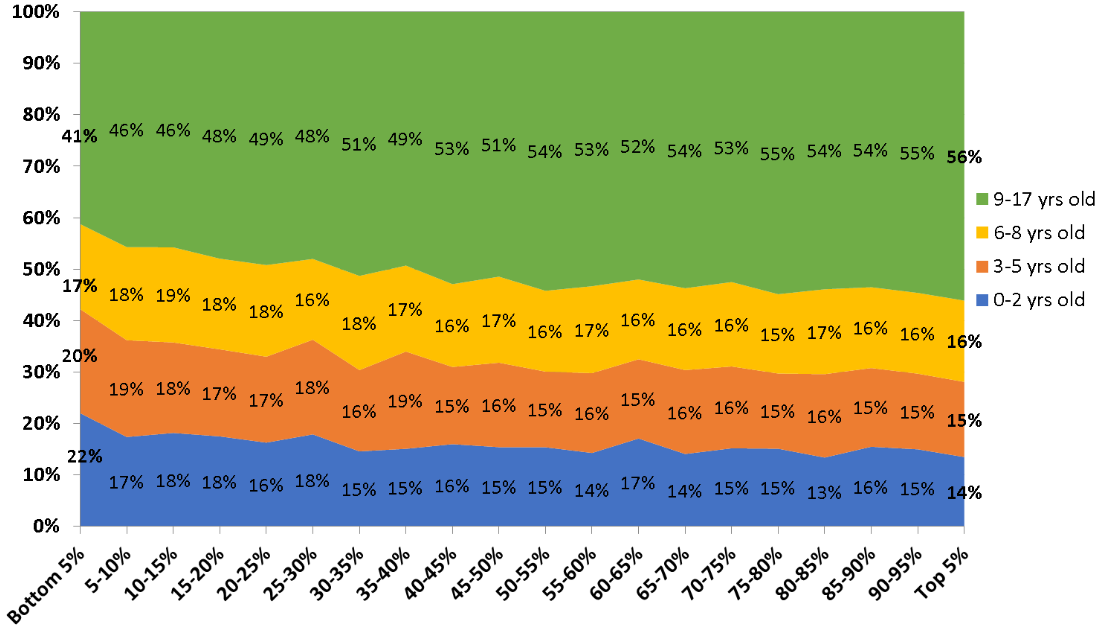
Ventiles of children are created by ranking children by their family's post-taxes post-transfers size-adjusted income.

A growing body of research finds that exposure to poverty in early childhood can impact brain development, school performance, and can have a cumulative toll on a person's longer term physical and mental health[9]. Therefore, it seems important to look at the distribution of children by ventiles by their age. Figure 3.18 shows how children in the bottom ventile tend to be younger than children further up the income distribution. For example, 42 percent of children in the bottom ventile are under age 6 compared to 28 percent of children in the top ventile.

---

[9] See March 2016 Policy Statement by the American Academy of Pediatrics. http://pediatrics.aappublications.org/content/pediatrics/early/2016/03/07/peds.2016-0339.full.pdf

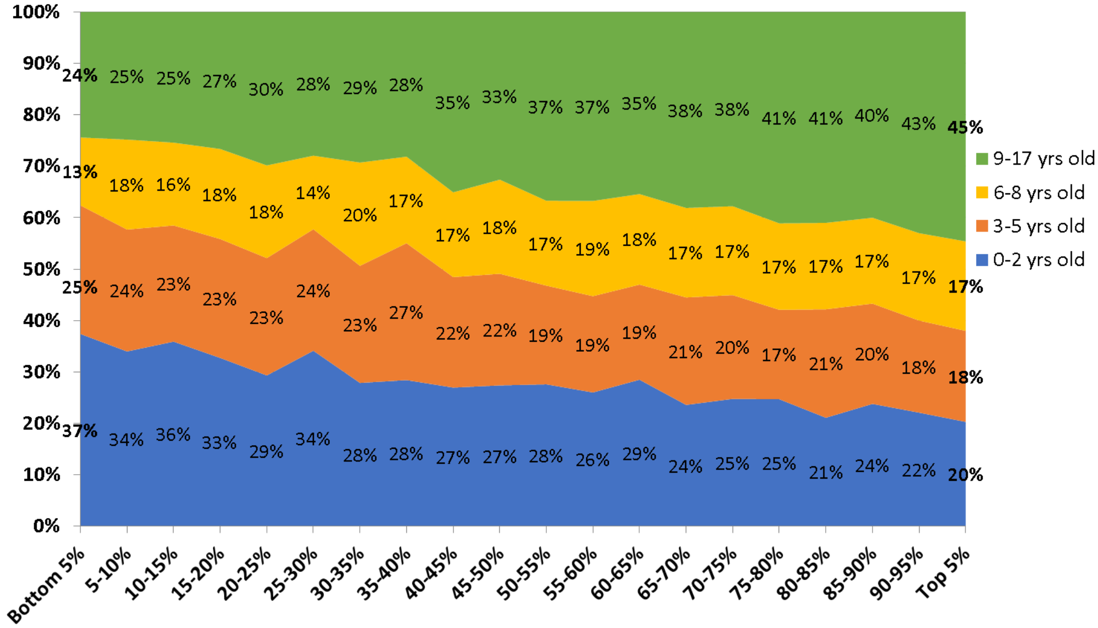
Figure 3.18: Age of Child Composition of Post Tax & Transfer Child Ventiles, 2012



Ventiles of children are created by ranking children by their family's post-taxes post-transfers size-adjusted income.

A likely reason for younger children to be found in the bottom ventiles is due to parents working less while their children are young. To test that theory, figure 3.19 looks at ventiles of children, but not by each child's age, but the age of the youngest child in their family. Using that measure, one finds that 62 percent of children in the bottom ventile live in a family whose youngest child is 5 years old or younger compared to 48 percent in the middle two ventiles and 38 percent of children in the top ventile. That provides some evidence on how children might not be in the same ventile during their whole childhood. As they and/or their siblings get older, they're more likely to be in a higher income ventile.

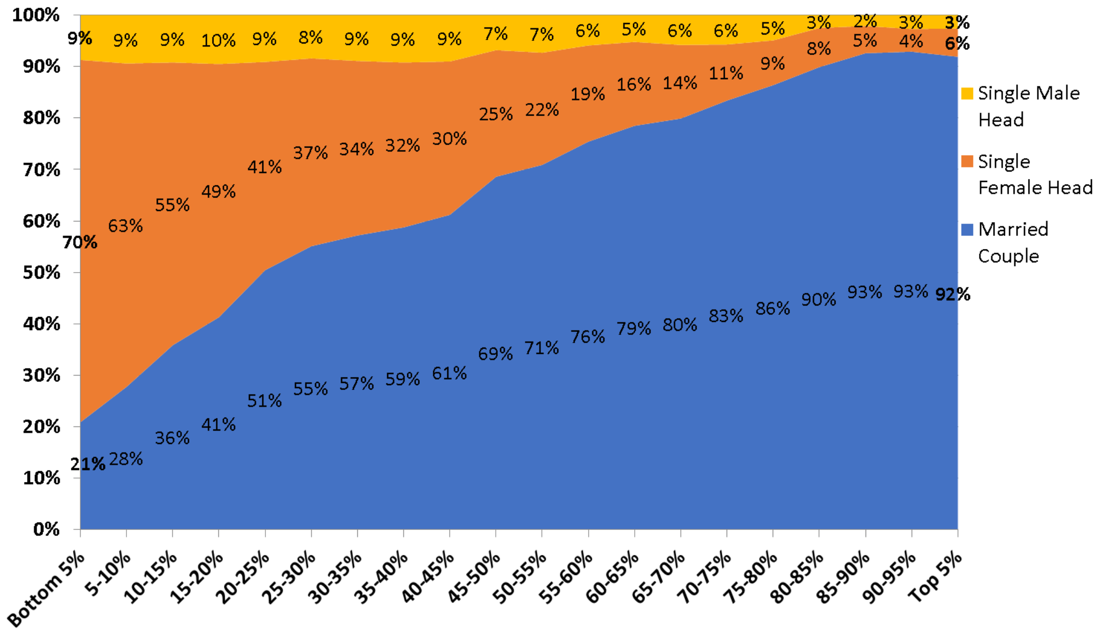
Figure 3.19: Age of Youngest Child Composition of Post Tax & Transfer Child Ventiles, 2012



Ventiles of children are created by ranking children by their family's post-taxes post-transfers size-adjusted income.

Figure 3.20 presents data on family composition. Approximately 70 percent of children in the bottom ventile live in a single female headed family. The percent of children who live in a single female headed family drops as one moves up the income distribution. Only 6 percent of children in the top ventile live in a single female headed family. About 9 percent of children in the bottom half of the income distribution live in a single male headed family. That percentage also declines as one moves further up the income distribution. For this chapter I used the official poverty family unit which groups together those related by marriage, birth or adoption. In future research, I would like to analyze how this graph and other findings in this paper would change if I included the income of unmarried partners into my family unit.

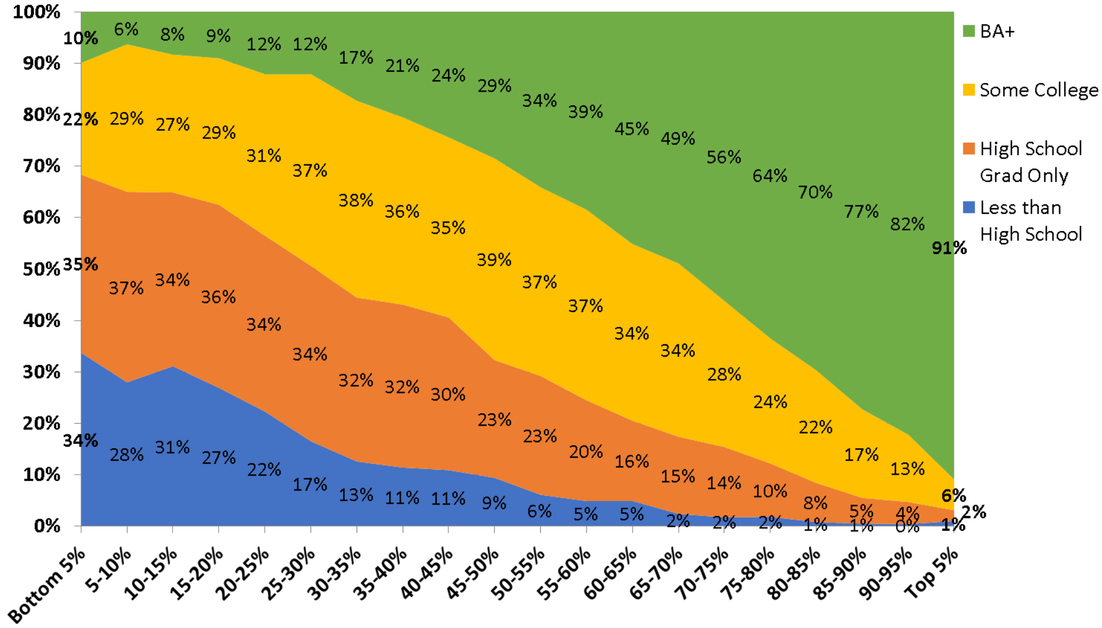
Figure 3.20: Family Type Composition of Post Tax & Transfer Child Ventiles, 2012



Ventiles of children are created by ranking children by their family's post-taxes post-transfers size-adjusted income.

Figure 3.21 shows the share of children in each ventile by their parent's educational attainment. If a child lives with both parents, then the educational attainment of the parent with the most education is used for these calculations. The bottom ventile is about equally split into thirds. A third of children live with parents whose highest educational attainment is less than high school, a third have parents with just a high school degree, and another third have a parent with at least some college education. The share of children who have a parent (or primary caretaker) with a college education or more increases as one moves up the income distribution.

Figure 3.21: Education of Parent Composition of Post Tax & Transfer Child Ventiles, 2012



Ventiles of children are created by ranking children by their family's post-taxes post-transfers size-adjusted income.

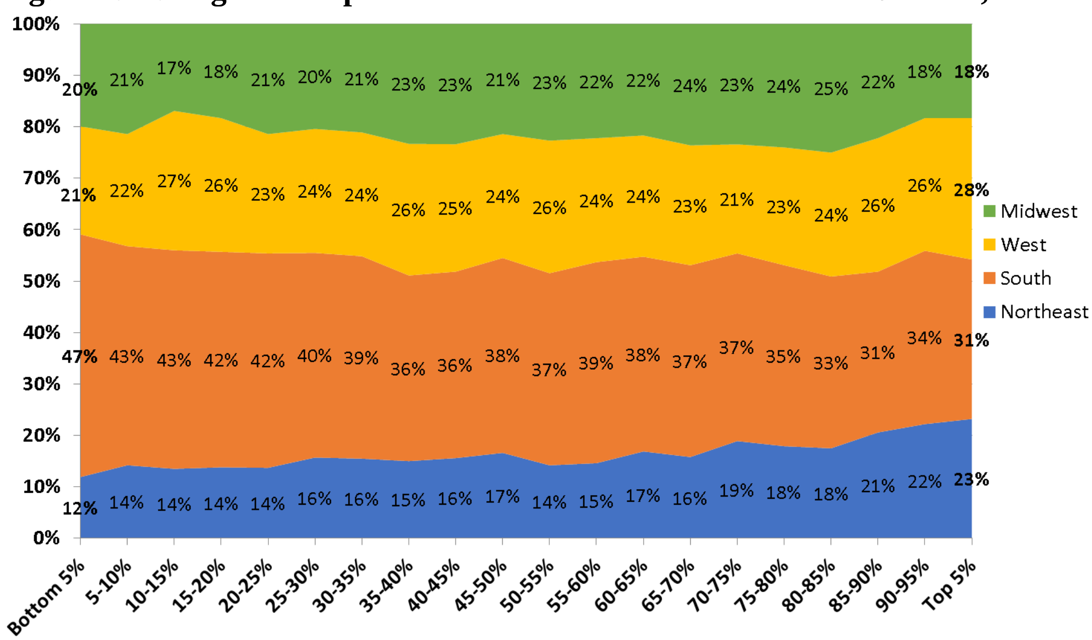
Figure 3.22 shows the share of children in each ventile by what region of the country they live[10]. The South and Northeast provide contrasting stories in terms of the distribution of children by ventiles. Almost half (47 percent) of children in the bottom ventile live in the South compared to 31 percent of children in the top ventile. Meanwhile, 12 percent of children in the bottom ventile live in the Northeast compared to 23 percent of children in the top ventile. Some factors that could be

[10] States are grouped by region using the Census Bureau's definition of regions. The Northeast Census region consists of Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island and Vermont. The Midwest region is defined as Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota and Wisconsin. The South region is defined as Alabama, Arkansas, Delaware, District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia and West Virginia. The West region is defined as Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington and Wyoming.

driving those differences could be differences in the availability of jobs, wage levels, and safety net benefits between those two regions.

The share of children who live in the Midwest is fairly constant across ventiles going from 20 percent in the bottom ventile to 18 percent in the top ventile. The West has a higher proportion of children in the top ventile (28 percent) than in the bottom ventile (21 percent), but a more constant distribution across some of the intermediate ventiles. For example, 26 percent of children in the 4th, 8th, 11th, 18th, and 19th ventiles live in the West. All these figures by region would likely be different if some sort of geographic adjustment was done to take into account differences across regions in living costs such as housing.

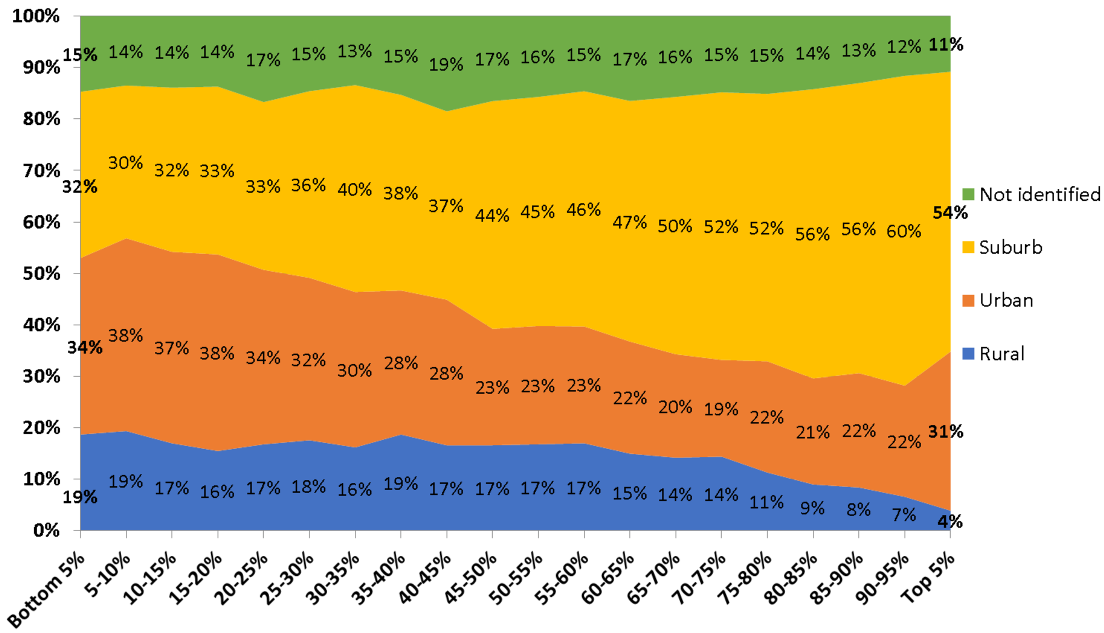
Figure 3.22: Region Composition of Post Tax & Transfer Child Ventiles, 2012



Ventiles of children are created by ranking children by their family's post-taxes post-transfers size-adjusted income.

The CPS data also provides information on whether someone lives in an urban, rural or suburban setting. Due to privacy reasons, the location for some households are not identified. Figure 3.23 shows the share of children in each ventile by where they live. Almost a fifth (19 percent) of children in the bottom ventile live in a rural area compared to only 4 percent of children in the top ventile. The proportion of children in urban areas is highest in the 2nd ventile (38 percent) and that percentage mostly declines as one moves up to higher income ventiles, except for the top ventile.

Figure 3.23: Rural vs Urban vs Suburbs Composition of Post Tax & Transfer Child Ventiles, 2012

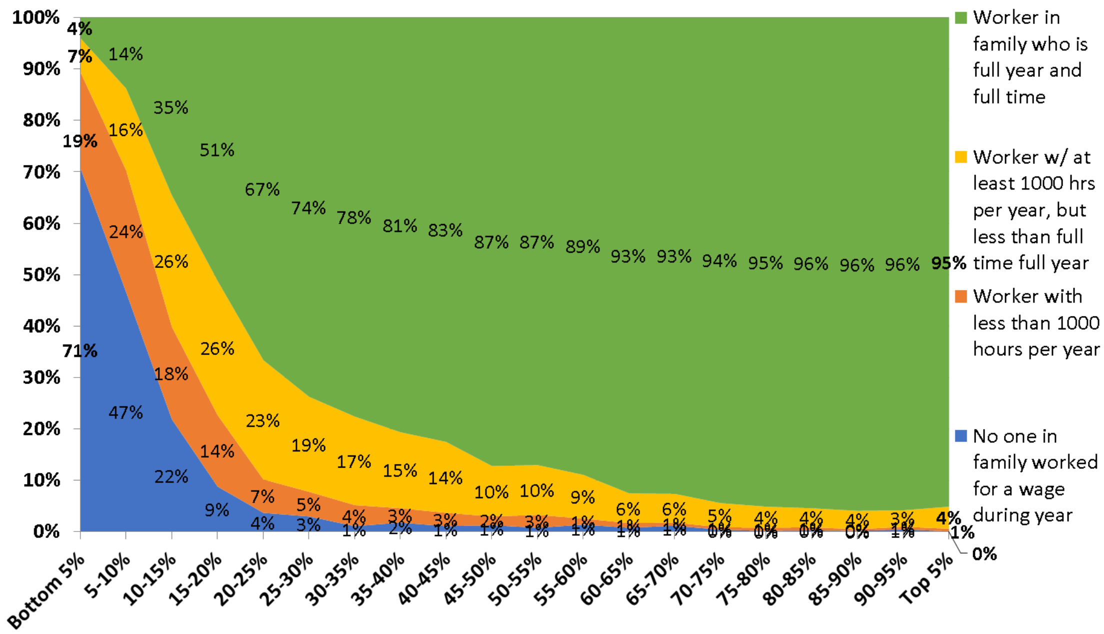


Ventiles of children are created by ranking children by their family's post-taxes post-transfers size-adjusted income.

Figure 3.24 shows the composition of child ventiles by the labor status of their family members. Given their very low pre-government income, it's not surprising that 71 percent of children in the bottom ventile live in a family where no one worked during the year.

The CPS asks respondents for the reason for not having worked during the year. Out of the parents who did not work in 2012, 57 percent reported taking care of home or family, 19 percent reported being ill or disabled, 11 percent reported not being able to find a job and 8 percent reported going to school.

Figure 3.24: Work Status Composition of Post Tax & Transfer Child Ventiles, 2012

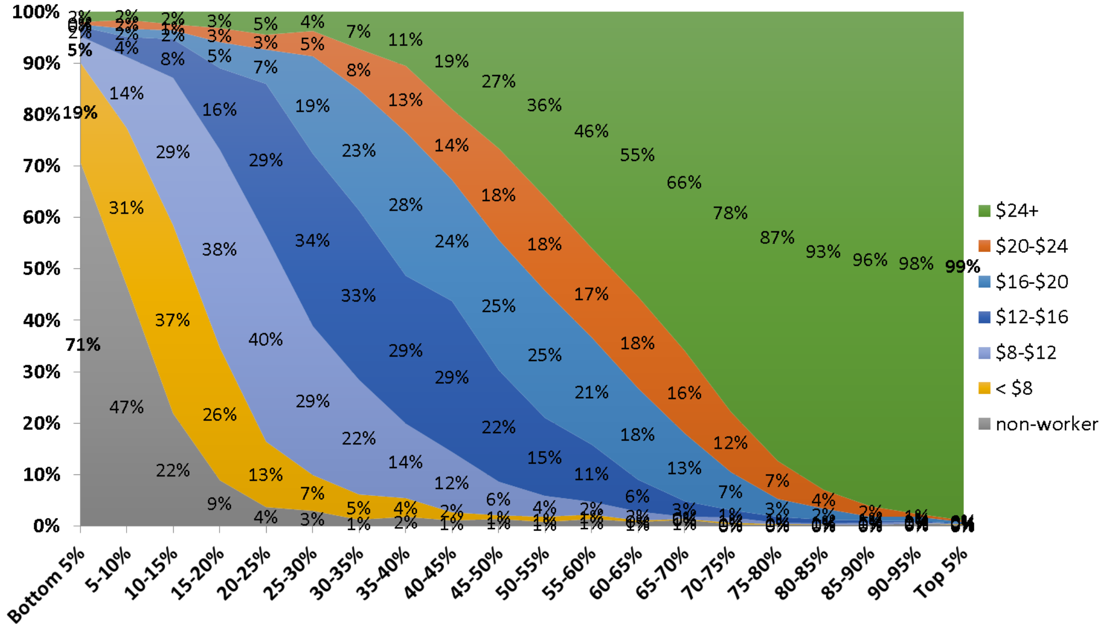


Ventiles of children are created by ranking children by their family's post-taxes post-transfers size-adjusted income.

Some of the characteristics already discussed also provide some evidence to why so many parents in the bottom ventile did not work in 2012. A lot of them are single mothers with young children and therefore the lack of affordable and safe child care could be a barrier to full-time work. Many of these single mothers will work once their kids are older. The employment rate for single mothers with a child younger than 3 was 65 percent in 2012 compared to 80 percent for single mothers with a youngest child who is at least 10 years old. Most children in the bottom ventile have parents who don't have more than a high school education which adds to the difficulty of finding work. Nationwide, in 2012, the employment rate for 25-54 year olds with a high school degree or less was 72 percent compared to 85 percent for those with at least some college education. Differences in the labor market across the country could also play a role. As figures 3.22 and 3.23 showed, children in the bottom ventiles are more likely to live in the South and in rural areas compared to children further up the income distribution. When more recent data becomes available, it will be interesting to see what this graph would look like in 2016 when the national unemployment rate fell below 5 percent. In 2012, the labor market was still recovering from the Great Recession and monthly national unemployment rates averaged 8.1 percent.

Nevertheless, starting with the 2nd ventile, a majority of children in 2012 lived in a family with at least one worker. In the 3rd ventile, 60 percent of children lived in a family with someone who worked at least half-time (1,000 hours during the year.). In the 4th ventile, 51 percent of children live in a family with someone who worked full-time full year. The mean post-tax post-transfer income (equivalent to a family of four) for these three ventiles are $20,500 $25,800 and $30,100 respectively. Given that a majority of children in these three ventiles lived in a family where someone worked, the path for these families towards higher incomes seems to be one of not only additional hours worked, but one of higher paying jobs. This is further demonstrated by figure 3.25 which shows the composition of child ventiles by the pre-tax hourly wage of their family member with the highest hourly wage. More than two-thirds of children in the third and fourth ventiles (10-20 percent of the income distribution) lived in a family whose highest hourly wage worker earns less than $12 per hour.

Figure 3.25: Maximum Hourly Wage of Family Member Composition of Post Tax & Transfer Child Ventiles, 2012



3.5 Conclusion

The safety net does a lot to support the income of children at various points of the family earnings distribution. In 2012, it provided $16,700 to children in the bottom 5 percent of the family earnings distribution and $14,000 to children in the fourth ventile (15-20% of the distribution). Nonetheless, for children in the poorest families, this support became weaker in the decade after 1995. For children in families with zero private income, taxes and transfers provided $1,500 less in support in 2012 than in 1993. In contrast, the taxes and transfers system provided $7,100 more in support for families earning $26,000 and provided $4,500 more in support for families earning $50,000. These trends were driven by the decline of cash assistance after the 1996 welfare law, the expansions of the EITC and CTC, and by SNAP becoming a much more important income support for working families. During the Great Recession additional SNAP, EITC, and CTC income helped maintain the income level of families with children even though earnings were declining due to the weakness in the economy.

Changes in the tax and transfer system have impacted the mean post-tax and post-transfer incomes of families with children. Between 1993 and 2012 the mean post-tax post-transfer income of all child ventiles increased, except for the bottom ventile. This paper demonstrated how important it is to look at ventiles instead of quintiles of children because of how different trends can be for the four ventiles of children within the bottom quintile. The post-tax and post-transfer income of the bottom ventile of children in the private family income distribution dropped by 9 percent between 1993 and 2012. The mean post-tax post-transfer income of the second ventile (5-10% of the distribution) increased by 9 percent between 1993 and 2012. The post-tax post-transfer income of the next two ventiles (10-20% of the distribution) increased by 34-35 percent.

The mean post-tax post-transfer income of the bottom ventile fell because of the reduction in cash assistance that followed the passing of the 1996 welfare law. Between 1995 and 2005 the post-tax post-transfer income of the bottom ventile of children dropped by 16 percent or $3,100. Comparing 1995 to 2005 provides an especially revealing look because 1995 was the year before the enactment of the 1996 welfare law while 2005 was a year with comparable economic conditions. The drop in post-tax post-transfer income of the bottom ventile was driven by a decline in AFDC/TANF income. The mean amount of AFDC/TANF assistance received by the bottom ventile of children dropped by 62 percent ($4,200) from 1995 to 2005. This finding is important for understanding the impact of the 1996 welfare law and informing policy debates about the future of the safety net. Some policy makers are proposing TANF-like reforms to the SNAP program. If those reforms have the same impact of reducing access to assistance, then the income of the bottom 5 percent of children could further decline.

The analysis of the characteristics of children and their families in different ventiles provides some clues to the challenges faced by these families. Children in the bottom ventiles are more likely to live in a single mother family and have siblings who are two years old or younger. They are also more likely to live in a family where no one has a postsecondary education. Children in the bottom ventiles are more likely to live in the South and live in a rural area. They are also more likely to live in a family where no one works or someone works for less than $8 per hour. The fact that Hispanic and Black children make up 59 percent of children in the bottom ventile, but 11 percent of children in the top ventile shows that the United States is still far from providing equality of opportunity for children regardless of their race and ethnicity. Public policies need to focus on supporting these families so that these children can have an equal shot at fulfilling their potential.

Bibliography

American Academy of Pediatrics Council on Community Pediatrics. 2016 "Poverty and Child Health in the United States," Pediatrics. 137(4):e20160339. Accessible at: http://pediatrics.aappublications.org/content/pediatrics/early/2016/03/07/peds.2016-0339.full.pdf

Ben-Shalom, Yonatan, Robert A. Moffitt, and John Karl Scholz. 2011 "An Assessment of the Effectiveness of Anti-Poverty Programs in the United States," NBER Working Paper no. 17042, May.

Bennett, Neil G, Hsien-Hen Lu, and Younghwan Song. 2004. "Welfare Reform and Changes in Economic Well-Being of Children." Population Research and Policy Review, 23:671-699.

Bitler, Marianne P., Jonah B. Gelbach, and Hilary W. Hoynes. 2002. "The Impact of Welfare Reform on Living Arrangements." National Bureau of Economic Research Working Paper no. 8784. Cambridge, Mass. February.

Bitler, Marianne P., Jonah B. Gelbach, and Hilary W. Hoynes. 2006 "What Mean Impacts Miss: Distributional Effects of Welfare Reform Experiments." The American Economic Review, Vol. 96, No. 4, pp. 988-1012. September.

Bitler, Marianne P., and Hilary W. Hoynes. 2013. "The More Things Change, the More They Stay the Same: The Safety Net, Living Arrangements, and Poverty in the Great Recession." National Bureau of Economic Research Working Paper 19449. Cambridge, MA: NBER.

Blank, Rebecca M. 2002. "Evaluating Welfare Reform in the United States." Journal of Economic Literature. Vol 40(4):1105-1166. December.

Blank, Rebecca M.. 2009. "What We Know, What We Don't Know, and What We Need to Know about Welfare Reform." In Welfare Reform and its Long-Term

Consequences for America's Poor, James P. Ziliak, ed, Cambridge, UK: Cambridge University Press, 22-58.

Blank, Rebecca M., and Brian Kovak. 2008. "The Growing Problem of Disconnected Single Mothers" National Poverty Center Working Paper #07-82. Ann Arbor, MI.

Bollinger, Christopher, Luis Gonzalez, and James P. Ziliak. 2009. "Welfare Reform and the Level and Composition of Income." In Welfare Reform and its Long-Term Consequences for America's Poor, James P. Ziliak, ed, Cambridge, UK: Cambridge University Press, 59-103.

Burtless, G. and T. Gordon. 2011. "The Federal Stimulus Program and Their Effects." In The Great Recession, eds. David B. Grusky, Bruce Western, and Christopher Wimer. New York: Russell Sage Foundation.

Cancian, Maria, Robert Haveman, Daniel R. Meyer, and Barbara Wolfe. 2000. Before and After TANF: The Economic Well-Being of Women Leaving Welfare. IRP Discussion Paper No. 1244-02. Madison, WI: University of Wisconsin Institute for Research on Poverty. February.

Cancian, Maria and Daniel R. Meyer. 2004. "Alternative Measures of Economic Success Among TANF Participants: Avoiding Poverty, Hardship, and Dependence on Public Assistance." Journal of Policy Analysis and Management, 23:531-548.

Council of Economic Advisers (CEA). 1999. *The Effects of Welfare Policy and the Economic Expansion on Welfare Caseloads: An Update.* Washington, D.C. August.

Congressional Budget Office (CBO). 2016. "The Distribution of Household Income and Federal Taxes, 2013." June. https://www.cbo.gov/publication/51361

Congressional Budget Office (CBO). 2011. "Trends in the Distribution of Household Income Between 1979 and 2007." October. https://www.cbo.gov/publication/42729

Ellwood, David T. 2000. “The Impact of the Earned Income Tax Credit and Social Policy Reforms on Work, Marriage, and Living Arrangements.” National Tax Journal. Vol 53(4, part 2):1063-1105. December.

Fang, Hanming and Michael Keane. 2004. “Assessing the Impact of Welfare Reform on Single Mothers.” Washington, DC: Brookings Papers on Economic Activity.

Floyd, Ife and LaDonna Pavetti and Liz Schott. 2015. “TANF Continues to Weaken as a Safety Net.” Washington, DC. Center on Budget and Policy Priorities. October.

Grogger, Jeffrey. 2003. “The Effect of Time Limits, the EITC, and Other Policy Changes on Welfare Use, Work, and Income Among Female-Headed Families.” Review of Economics and Statistics 85(2): 394-408.

Grogger, Jeffrey. 2004. “Welfare Transitions in the 1990s: The Economy, Welfare Policy, and the EITC.” Journal of Policy Analysis and Management 23(4): 671-695. (this is an updated version of the Grogger 2003b paper below)

Grogger, Jeffrey and Lynn A. Karoly. 2005. Welfare Reform: Effects of a Decade of Change. Cambridge, MA: Harvard University Press.

Grogger, Jeffrey, Lynn Karoly, and Jacob Klerman. 2002. Consequences of Welfare Reform: A Research Synthesis. Document DRU-2676-DHHS, Prepared by RAND for the Agency for Children and Families, Department of Health and Human Services. Santa Monica, CA: RAND.

Gunderson, Craig and James P. Ziliak. 2003. “Poverty and Macroeconomic Performance Across Space, Race, and Family Structure.” Unpublished manuscript. January

Hoynes, Hilary 2007. “The Earned Income Tax Credit, Welfare Reform, and the Employment of Low-Skilled Single Mothers.” Paper prepared for Chicago Federal Reserve Bank of Chicago Conference on "Strategies for Improving

Economic Mobility of Workers," November 15-16, 2007. Revised Draft, August 22, 2008

Hoynes, Hilary W. and Erzo F.P. Luttmer 2011. “The insurance value of state tax-and-transfer programs.” Journal of Public Economics. Vol 95(11-12): 1466-1484.

Hoynes, Hilary W. and Ankur J. Patel. 2015. “Effective Policy for Reducing Inequality? The Earned Income Tax Credit and the Distribution of Income.” Working Paper 21340, National Bureau of Economic Research, July.

Looney, Adam. 2005. “The Effects of Welfare Reform and Related Policies on Single Mothers’ Welfare Use and Employment.” Federal Reserve Board of Governors, Finance and Economics Discussion Series 2004-45, Washington, DC: Federal Reserve Board.

Loprest, Pamela. 2001. How Are Families that Left Welfare Doing? A Comparison of Early and Recent Welfare Leavers. Series B, No B-36, Assessing the New Federalism Project. Washington, D.C.: Urban Institute. April.

Matsudaira, Jordan D. and Rebecca M. Blank. 2014 “The Impact of Earnings Disregards on the Behavior of Low Income Families.” Journal of Policy Analysis and Management. Vol 33(1):7-35. Winter.

McKernan, Signe-Mary and Caroline Ratcliffe. 2006. “The Effect of Specific Welfare Policies on Poverty” Washington, DC. The Urban Institute.

Meyer, Bruce D. and Dan T. Rosenbaum. 2001. “Welfare, the Earned Income Tax Credit, and the Labor Supply of Single Mothers.” The Quarterly Journal of Economics. Vol 116(3): 1063-1114. August.

Meyer, Bruce D. and James X. Sullivan. 2004. “The Effects of Welfare and Tax Reform: The Material Well-Being of Single Mothers in the 1980s and 1990s.” Journal of Public Economics. Vol 88(7-8): 1387-1420. July.

Moffitt, Robert A. 1999. “The Effects of Pre-PRWORA Waivers on AFDC Caseloads and Female Earnings, Income, and Labor Force Behavior,” In Economic

Conditions and Welfare Reform, Sheldon H. Danziger, ed. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Noonan, Mary C., Sandra S. Smith, and Mary E. Corcoran. 2007. "Examining the Impact of Welfare Reform, Labor Market Conditions, and the Earned Income Tax Credit on the Employment of Black and Single Mothers." Social Science Research. Vol 36(1): 95-130.

Pavetti, LaDonna and Liz Schott. 2016. "TANF at 20: Time to Create a Program that Supports Work and Helps Families Meet Their Basic Needs." Washington, D.C. Center on Budget and Policy Priorities. August.

Primus, Wendell, Lynette Rawlings, Kathy Larin, and Kathryn Porter. 1999. "The Initial Impacts of Welfare Reform on the Incomes of Single-Mother Families." Washington, D.C.: Center on Budget and Policy Priorities.

Schoeni, Robert F. and Rebecca M. Blank. 2000. "What Has Welfare Reform Accomplished? Impacts on Welfare Participation, Employment, Income, Poverty, and Family Structure." National Bureau of Economic Research Working Paper 7627. Cambridge, MA: NBER.

Schott, Liz and LaDonna Pavetti. 2011. "Many States Cutting TANF Benefits Harshly Despite High Unemployment and Unprecedented Need." Washington, DC. Center on Budget and Policy Priorities. October.

Schott, Liz and LaDonna Pavetti and Ife Floyd. 2015. "How States Use Federal and State Funds Under the TANF Block Grant." Washington, DC. Center on Budget and Policy Priorities. October.

Shaefer, H. Luke and Kathryn Edin. 2013. "Rising Extreme Poverty in the United States and the Response of Federal Means-Tested Transfer Programs," National Poverty Center Working Paper 13-06. http://www.npc.umich.edu/publications/working_papers/?publication_id=255

Sherman, Arloc. 2009. “Safety Net Effective at Fighting Poverty But Has Weakened for the Very Poorest.” Washington, DC. Center on Budget and Policy Priorities.

Sherman, Arloc and Danilo Trisi. 2015. “Safety Net More Effective Against Poverty Than Previously Thought.” Washington, DC. Center on Budget and Policy Priorities. May.

Sherman, Arloc and Danilo Trisi. 2015b. “Safety Net for Poorest Weakened After Welfare Law But Regained Strength in Great Recession, at Least Temporarily.” Washington, DC. Center on Budget and Policy Priorities. May.

Trisi, Danilo and LaDonna Pavetti. 2012. “TANF Weakening as a Safety Net for Poor Families.” Washington, DC. Center on Budget and Policy Priorities.

Urban Institute. "The Welfare Rules Database." http://anfdata.urban.org/WRD .

Urban Institute. "Transfer Income Model, Version 3 (TRIM3)" http://trim3.urban.org

U.S. Census Bureau. 2006. “Overview of the Survey of Income and Program Participation.” http://www.census.gov/sipp/overview.html

U.S. Census Bureau. 2012. “Fact Sheet – Differences Between CPS ASEC and ACS” http://www.census.gov/hhes/www/poverty/about/datasources/factsheet.html

U.S. Department of Health and Human Services. 1998. “Aid to Families with Dependent Children, the Baseline.” ASPE Report. June. https://aspe.hhs.gov/basic-report/aid-families-dependent-children-baseline

U.S. Department of Health and Human Services. 2015. “Welfare Indicators and Risk Factors: Fourteenth Report to Congress.” ASPE Report. September. https://aspe.hhs.gov/basic-report/indicators-welfare-dependence-annual-report-congress

Wheaton, Laura. 2007. “Underreporting of Means-Tested Transfer Programs in the CPS and SIPP,” 2007 Proceedings of the American Statistical Association, Social Statistics Section, Alexandria, VA: American Statistical Association: 3622-3629.

Weinberg, Daniel H. 2006. "Income Data Quality Issues in the CPS." Monthly Labor Review. June.

Ziliak, James P. 2011. "Recent Developments in Antipoverty Policies in the United States." Institute for Research on Poverty. Discussion Paper no. 1396-11. September.