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ESSAYS ON TRANSFER-PROGRAM INTERACTIONS AMONG LOW-INCOME HOUSEHOLDS

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DISSERTATION

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fulfillment of the requirements for
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By
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ABSTRACT OF DISSERTATION

ESSAYS ON TRANSFER-PROGRAM INTERACTIONS AMONG LOW-INCOME HOUSEHOLDS

This dissertation consists of three essays examining the role of transfer-program interactions for families and households who participate in the social safety net. The safety net is comprised of many different programs, run by different agencies, governed by different rules, and often administered by disparate and secluded entities. However, many households participate in multiple programs, subjecting them to the milieu of administrative hurdles. In this dissertation, I try to untangle some of the intended and unintended effects of program participation that may be experienced by these households.

In Essay 1, I examine the effect of the Patient Protection and Affordable Care Act of 2010 (ACA) on food hardship in US households, utilizing food security information from the Food Security Supplement of the Current Population Survey. Because states adopted the Medicaid expansions provided under the ACA at different times beginning in 2014, the cross-state, over time variation allows me to separate the impact of the ACA on food hardship using triple difference specifications. The richness of questions in the Food Security Supplement allows me to examine the effect of the ACA across different measures of food hardship, and also examine differential response for households participating in the Supplemental Nutrition Assistance Program (SNAP). Examining the mechanisms through which the ACA could affect food insecurity, I find the ACA not only increased average weekly food expenditure, but also the probability a household participates in SNAP. I employ a two-stage, control function approach to address reverse causality between SNAP and food insecurity. I find that the ACA reduced the probability that a household participating in SNAP falls into the two lowest food security categories by 6.5 percentage points and reduced the probability of being food insecure by 14.2 percentage points. Across specifications, I find strong evidence for increasing returns to program participation, and evidence of a differential impact of the ACA across the distribution of food hardship.

In Essay 2, I examine how grant funding and fiscal structure affect program response over the business cycle. I compare child enrollment in Medicaid, a matching grant funding program, with enrollment the State Children's Health Insurance Program, a block grant funded program, utilizing the similarities in beneficiaries, program benefits, and administration to isolate the impact of fiscal structure. I utilize administrative enrollment records, along with individual level participation data, and find a one percentage point increase in the unemployment rate leads to a 7.6% decrease in the number of beneficiaries per person enrolled in block grant funded programs, and a 10% decrease in state expenditure per person decreases the probability of enrollment in a block grant program by 0.58 percentage points. I also find that enrollment is much more persistent among matching grant funded programs, and being enrolled in a block grant funded program the previous period increases the probability of enrolling in a matching grant program this period 75% more than remaining enrolled in the block grant funded program.

Finally, in Essay 3 I explore the effect of the minimum wage on the self-reported value of public assistance program benefits, and the joint effect of the minimum wage and public assistance programs on the income to poverty ratio using data from the 1995-2016 Current Population Survey Annual Social and Economic Supplement. In the first stage, I estimate a Tobit model controlling for the censoring of received benefits from below at zero, and examine the effect of changes in the minimum wage on the self-reported dollar value of benefits received for food stamps/ the Supplemental Nutrition Assistance Program (SNAP), Aid to Families with Dependent Children (AFDC)/Temporary Assistance to Needy Families (TANF), Supplemental Security Income (SSI), and the Earned Income Tax Credit (EITC), as well as the total sum of benefits. I find that the minimum wage reduces the value of means-tested benefits, but that this effect is strongest for programs with strong work requirements. Utilizing the residuals from the first stage, I employ a control function approach to estimate the joint effect of the minimum wage and program benefits on the income to poverty ratio. I find the own-effect of the minimum wage provides a small increase in the income to poverty ratio, but that the total effect, accounting for changes in benefits, attenuates by approximately 30%.

KEYWORDS: Transfer Programs; Safety Net; Program Evaluation; Program Participation; Poverty; Welfare

Author's signature: Nicholas S. Moellman

Date: July 19, 2018

ESSAYS ON TRANSFER-PROGRAM INTERACTIONS AMONG LOW-INCOME HOUSEHOLDS

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Date: July 19, 2018

For my daughter, Laurel, and my wife, Nicole

In loving memory of Laura Francis Skates, 1943-2018

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Chapter 1: Introduction

The social safety net is a complex web of rules, regulations, eligibility requirements, benefits, agencies, and exceptions that often makes analysis, even from policy experts, difficult. These programs are run by different institutions with different policy objectives, and which may or may not communicate and coordinate among the separate program administrators. Individuals, families, and households participating in the safety net are often not experts, and are constrained by more than a lack of information or estimation techniques. These low-income individuals face financial burdens that make navigating the tangle of programs difficult even in the best circumstances. If policy experts and researchers struggle to understand the multiple facets of the safety net, how are those individuals who receive safety net benefits supposed to understand how to best utilize these programs to meet their needs?

There are many stories told in public debates about the role of transfer program policy. With the passage and attempted repeal of the Patient Protection and Affordable Care Act of 2010 (ACA), policy makers and pundits on one side extol the virtues of expanded healthcare coverage, while those on the other side lament the growing burden of the "welfare state" and the negative consequences program participation has on households and communities. In Congress, serious discussion has been given to the role of programs like the Supplemental Nutrition Assistance Program (SNAP) and Medicaid, how these programs are funded, and how they should be administered moving forward.

The following essays attempt to disentangle some of these connections between programs and policy objectives, analyzing not only the own effect of programs on given outcomes, but also how the interactions between the programs may bolster or curb their effectiveness, or produce unintended consequences for policy makers or participants. Transfer program interaction, the unifying concept of this dissertation, is often not fully explored in the broader literature, perhaps due to the difficulty of identifying further effects outside of the direct effects of typical program evaluation. However, the policy implications of this program interaction can be significant in the design, reformulation, and implementation of safety net policy.

In Essay 1, I examine the effect of the Patient Protection and Affordable Care Act of 2010 on food hardship in US households. Much of the debate surrounding the ACA has, justifiably, concerned its effect on health insurance coverage in the US. Very little has been done to examine the effect of the ACA on other policy goals. SNAP, the largest food assistance program in the US, primarily occupies the conversation surrounding food insecurity. However, both the lack of healthcare coverage present before the implementation of the ACA, as well as the persistently high rates of food insecurity after the Great Recession of the late 2000s, are public health issues. Thus, I examine any potential spillovers from the ACA, the largest expansion of public health benefits in recent years, into food insecurity.

Using food security information from the Food Security Supplement of the Current Population Survey from 2001-2016, I find that the ACA reduced the probability a household participating in SNAP falls into the two lowest food security categories by 6.5 percentage points, and reduced the probability of being food insecure by 14.2 percentage points. I find no effects for households not participating in SNAP, suggesting these positive spillovers are largely due to increasing returns to program participation. Moreover, I find that these gains are concentrated in the high end of the food hardship distribution, suggesting that the ACA affected individuals differentially based on their food security status. These results warrant more research into both the outside consequences of the ACA, as well as the role of healthcare in addressing food insecurity.

In Essay 2, I examine how the method in which programs are funded affects the provision of program benefits. Many transfer programs are funded either through a matching grant, where state funds are matched at some rate by the federal government, or through a block grant, where the federal government appropriates a specified amount of funding for a state, and does not provide any additional resources. These separate fiscal structures promote very different incentives to states providing transfer program benefits, especially during recessionary periods where there may be both increased demand for program benefits and lower levels of state resources.

I examine the role of fiscal structure and program response over the business cycle by examining how enrollment in Medicaid, a matching grant funded program, and enrollment in the State Children's Health Insurance Program, a block grant funded program, changed from 1999 to 2015. Using both administrative enrollment records, as well as individual level two-year matched panels from the Current Population Survey, I find that enrollment in block grant funded programs is much more volatile over the business cycle than enrollment in matching grant funded programs. I also find that enrollment is much more persistent among matching grant funded programs, and being enrolled in a block grant funded program last period increases the probability of enrolling in a matching grant program this period 75% more than remaining enrolled in the block grant funded program.

Lastly, in Essay 3, I explore the effect of the minimum wage on the value of public assistance programs, and the joint effect of the minimum wage and public assistance programs on the income to poverty ratio. Much of the literature on the minimum wage has examined its influence on employment and poverty, finding ambiguous effects on both. However, a mechanical relationship exists between the minimum wage and means-tested transfer programs, which has been relatively understudied. Any increase in the wages of low-income families directly reduces the value of means tested benefits. This, coupled with ambiguously negative employment effects of the minimum wage, may complicate the minimum wage's role as an antipoverty tool.

Using data from the 1995-2016 Current Population Survey Annual Social and

Economic Supplement, I estimate the effect of changes in the minimum wage on the self-reported value of transfer program benefits for food stamps or SNAP, Aid to Families with Dependent Children (AFDC)/Temporary Assistance to Needy Families (TANF), Supplemental Security Income (SSI), and Earned Income Tax Credit (EITC) benefits, as well as the total sum of benefits. I find that the minimum wage reduces the value of means-tested benefits, but that this effect is strongest for programs with strong work requirements. I then use these results to estimate the joint effect of the minimum wage and program benefits on the income to poverty ratio. I find the own effect of the minimum wage provides a small increase in the income to poverty ratio, but that the total effect, accounting for changes in benefits, attenuates by approximately 30%.

Chapter 2: Healthcare and Hunger: Impacts of the Affordable Care Act on Food Insecurity in America

2.1 Introduction

The Patient Protection and Affordable Care Act (ACA) of 2010 enacted broad reform for healthcare in the United States. The number of Americans lacking health insurance has been a public health issue for policy makers, with 17.5% of non-elderly individuals uninsured in 2009. The ACA implemented large expansions in Medicaid that provided subsidized health insurance coverage for individuals less than 133% of the federal poverty line. However, 19 states chose not to expand Medicaid, leaving residents who did not qualify for Medicaid under previous rules ineligible for increased benefits provided by the ACA.

Alongside the lack of health insurance, food insecurity has emerged as a persistent public health concern facing the nation. From 2008 through 2016, between 12% and 15% of households were food insecure. While food insecurity has been declining in recent years, in 2016 12.3% percent of US households were still defined as food insecure by the U.S. Department of Agriculture, implying 15.6 million households did not have adequate access to the quantity nor quality of food necessary for a healthy lifestyle. Moreover, 6.1 million households experienced very low food security, a severe category of food insecurity that often results in families not eating for entire days (Coleman-Jensen et al., 2017).

The health consequences of food insecurity can be dire. Food insecurity has detrimental effects on adult health, and is associated with poor nutritional outcomes, both obesity and low body mass index, less healthy diets, poor mental health outcomes, and various other serious conditions (Cook et al., 2013; Heflin and Ziliak, 2008; Bhattacharya et al., 2004). Children living in food insecure households have also been shown to be negatively affected by food insecurity, being more likely to have poor health (Gundersen et al., 2011; Meyerhoefer and Yang, 2011; Almond et al., 2011; Gundersen and Kreider, 2009; Cook et al., 2004), have poor BMI (Gundersen and Kreider, 2009), experience behavioral issues (Howard, 2011), and experience a host of specific health problems (Chi et al., 2014; Gundersen and Ziliak, 2014). Gundersen and Ziliak (2015) show that these poor outcomes are evident across studies, countries, data sets, and time periods.

Policy makers have many traditional methods of combating food insecurity such as the Supplemental Nutrition Assistance Program (SNAP), one of the largest public assistance programs in the US (5th by expenditure, 3rd by recipients), the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), and school breakfast and lunch programs. As noted by Moffitt (2015), nearly 80% of SNAP recipients also receive Medicaid benefits, however, we know little about how healthcare policy, acting alone or in concert with other food programs, may affect food insecurity. Despite the proliferation of literature on both food insecurity and the ACA, few studies, if any, have yet examined potential links between public healthcare and food insecurity. Public healthcare provides in-kind benefits to at-risk individuals, and while these benefits do not directly address food insecurity, they may free up household income to be redirected toward alleviating food hardship.

I fill this gap in the literature using data from the Current Population Survey (CPS) Food Security Supplement for years 2001-2016 to present the first evidence on the effect of the ACA on food insecurity in America. I contribute to the literature examining the effect of non-food programs on food insecurity, and I extend these studies by analyzing the interaction between the traditional food support system (SNAP) and Medicaid. For my purposes, I limit the impact of the ACA to families with incomes less than 185% of the federal poverty line, capturing not only the population most served by Medicaid expansion, but also households who are likely to receive food benefits. I utilize variation across time in the roll-out of Medicaid expansion through the ACA, as well as cross-state variation in Medicaid expansion, to identify the effect of the ACA. This allows me to employ a quasi-experimental design, examining the impact of the ACA across many food insecurity thresholds and varying definitions of food hardship. As many studies have shown (Gregory et al., 2015; Gundersen et al., 2011), reverse causality between SNAP and food insecurity results in the endogeneity of SNAP benefits. Thus, I use a two stage control function approach to address the endogeneity of SNAP and its interaction with Medicaid expansions. I find that the ACA had the largest impact for households already participating in SNAP, reducing the probability that these households fall into the two lowest categories of food security by 6.5 percentage points. I also find the ACA reduced the probability households participating in SNAP are food insecure by 14.2 percentage points. I find the ACA increased average household weekly food expenditure, as well as the probability the household participates in SNAP, providing two avenues through which the ACA could influence food hardship.

These results suggest that while the safety net does affect food insecurity, it does not do so uniformly across the distribution of food hardship. I show that the largest mitigating factor for those experiencing very low, low, or marginal food security is SNAP. However, spillovers from the ACA increase gains in food security by roughly 50% at all thresholds, with larger total gains at the low end of the food security spectrum. I show large, increasing returns to program participation, of particular importance for policy makers and researchers studying safety net programs. By ignoring the positive spillovers from the ACA and SNAP, we risk drastically understating the efficacy of both programs in addressing food insecurity.

2.2 Background and Motivation

Official food insecurity statistics are reported by the United States Department of Agriculture (USDA) and come from the Food Security Supplement (FSS) in the December Current Population Survey (CPS). Coleman-Jensen et al. (2017) categorize food security as all individuals in a household having enough food for an active, healthy lifestyle. Households are placed into categories of food hardship based on their responses to 18 questions in the FSS, with affirmative responses indicating increased food hardship for the family. The module includes three questions about food conditions of the entire household, seven questions about food security conditions of adults in the household, and eight questions about food conditions of children if they are present.

I use the nomenclature of the USDA and consider four categories of food security—fully food secure, marginally food secure, low food secure, and very low food secure. Households are fully food secure if they report no food insecure conditions, marginally food secure if they report one or two food insecure conditions, low food secure if they report three to five food insecure conditions with no children (three to seven with children), and very low food secure if they report six or more food insecure conditions (8 or more with children). For some of my analyses, I instead focus on the nonmutually exclusive categories of marginally food insecure, food insecure, and very low food secure. Households are marginally food insecure if they report at least one food insecure condition, food insecure if they report at least three food insecure conditions, and are very low food secure if they report six or more food insecure conditions (eight or more if children are present in the household). Note that all households that are very low food secure will also be food insecure and marginally food insecure, and all households that are food insecure will also be marginally food insecure.

The questions that characterize food hardship are summarized in table 2.1. Examples of questions include “We worried whether our food would run out before we got money to buy more.” (the least severe); “In the last 12 months, did you lose weight because there wasn’t enough money for food?”; or the most severe, “In the last 12 months did any of the children ever not eat for a whole day because there wasn’t enough money for food?” These questions are designed to assess a spectrum of food hardship ranging from stress about the adequacy of food, to monetary concerns associated with food costs, to the lack of meals for members of the family. Each of these questions is also qualified by the stipulation that the food insecure condition be a result of lack of funds, rather than some other reason for the reported hardship. The questions are designed to assess the impact of household financial conditions on the general adequacy of food.

Figure 2.1 shows response rates to these questions over time. What is immediately apparent is that response rates to questions indicating food hardship for adults are much higher than those indicating food hardship among children. The first panel of figure 2.1 demonstrates that many households worried about their ability to maintain adequate food in the household (questions 1-3). From 2008 onward, between 16-20 percent of households worried they would run out of money for food, while roughly 15% of households ran out of money for food or could not afford to eat balanced meals. A smaller portion of households had to reduce their food intake due to lack of sufficient funds for food (questions 4-10).

The second panel of figure 2.1 shows that less than 1% of households with children were forced to reduce food intake for children (questions 14-18). However, children were not completely insulated from food hardship, with around 4-6% of households with children forced to reduce the quality of meals for children, and 3-4% of households with children unable to feed the children balanced meals. Taken together, these questions show that many households experience many different kinds of food hardship.

The reforms of the ACA were not designed to directly address food hardship, rather, they focused on decreasing the population of uninsured individuals through the expansion of Medicaid to those below 133% of the federal poverty line (FPL), decreasing the cost of healthcare through additional subsidies, and improving the continuity and quality of care received through new regulations. Health insurance exchanges were established in order to provide a statewide marketplace where consumers could compare competing health plans. Individual mandates required that all individuals obtain a minimum standard of health insurance, and employer mandates required employers with more than 50 employees offer insurance coverage that meets minimum requirements. New regulations were put into place that addressed the price and types of services insurance plans covered, as well as changing how insurance companies delivered and charged for care.

States that expanded Medicaid coverage received additional subsidies from the federal government for doing so, and also had more control over the operation of the state-run health exchanges. Prior to the ACA, the income limit for Medicaid eligibility was 100% FPL. The ACA mandated that those less than 133% FPL[1] be eligible for Medicaid, expanding the population of potential beneficiaries. However, the Supreme Court ruled in National Federation of Independent Business v. Sebelius in 2012 that mandated Medicaid expansions were unconstitutional, and allowed states to opt out of the expansions. Twenty four states and the District of Columbia enacted Medicaid expansion on January 1, 2014. Subsequently, 7 states expanded Medicaid

[1] The law also proposes a 5% income disregard, making the effective income eligibility limit 138% FPL. The Centers for Medicare and Medicaid Services classify the limit as 133% FPL, which I will follow in this paper.

in later years.[2] Figure 2.2 shows the cross-state and over time variation in Medicaid expansion. Many states on the East and West Coast, as well as Midwestern states, chose to expand Medicaid, while many Southern states did not. However, some Southern states like Kentucky, West Virginia, Arkansas, and Louisiana did choose to expand Medicaid, while some coastal states, like Maine, chose not to, showing the expansion decision was not exclusively regional. These reforms all attempt to reduce the burden of healthcare costs by moderating the price of healthcare and increasing healthcare coverage.

Evidence suggests that the ACA has increased coverage, and benefited individuals who were targeted by the ACA. Black and Cohen (2015) find that not only has the number of uninsured decreased after the implementation of the ACA, but also states that expanded Medicaid saw larger decreases in the uninsured population. Courtemanche et al. (2017) also find that the ACA increased coverage, and note that coverage increased through both public and private markets. Some evidence suggests that the expansion of Medicaid may have crowded out private insurance (Wagner, 2015). Still, the broad impact seems to be that the ACA increased coverage across the population, not only amongst low-income individuals, with overall improvements in health and access (Antwi et al., 2015; Sommers et al., 2012). Hu et al. (2016) have shown the ACA contributed to the financial security of individuals in Medicaid expansion states, decreasing levels of debt and enabling individuals to meet other financial obligations. With evidence suggesting small (if any) negative impacts on employment (Garrett and Kaestner, 2014), and overall decreases in the amount of resources individuals need to devote to healthcare, the ACA could have a potentially large impact on food insecurity by changing the consumer's budget set.

[2] Michigan (4/1/2014), New Hampshire (8/15/2014), Pennsylvania (1/1/2015), Indiana (2/1/2015), Alaska (9/1/2015), Montana (1/1/2016), and Louisiana (7/1/2016). The election of Matt Bevin as governor of Kentucky has prompted the state to discuss dismantling the Medicaid expansion in place.

Figure 2.3 shows average food insecurity across states in 2012-2013 and 2014-2015, immediately before and after the ACA Medicaid expansions. In 2013, no states had expanded Medicaid, while by 2015, all but two states that ultimately expanded Medicaid had done so. After expanding Medicaid, four states worsened with regard to food insecurity (Alaska, Indiana, New Jersey, and New Mexico), while many others improved. Many states that did not expand Medicaid saw improvements in food insecurity; however, states like Alabama, Nebraska, Maine, and South Carolina saw increases in food insecurity, while others such as Louisiana (which did not expand Medicaid until 2016), Mississippi, and Georgia, saw no change in food insecurity, leaving many residents without access to sufficient food. While the maps are far from definitive regarding the relationship between public healthcare and food insecurity, they do provide some context for further analysis of how healthcare subsidies may affect food insecurity.

Figures 2.5-2.7 present a simple budget constraint analysis to provide intuition about the effect of Medicaid subsidies on food consumption, and how participation in SNAP may affect these outcomes. I assume convex preferences that can be well represented by a generic utility curve. Figure 2.5 shows how consumption of both food and all other goods (which includes medical care) responds to Medicaid benefits. In the absence of subsidized medical care, a representative consumer would consume some mix of both food and other goods, here represented by (F_0, G_0). The introduction of public health insurance guarantees some base level of medical care, creating a kink in the budget set represented by point D. This causes an outward shift in the budget set, resulting in an increase in consumption of both food and other goods. Figure 2.6 shows the analogous shift in the budget set from the introduction of SNAP benefits. Once again, we see that the SNAP subsidy increases consumption of both food and other goods.

Figure 2.7 depicts an individual receiving both Medicaid and SNAP subsidies.

In the depicted scenario, consumption of both food and other goods increase from (F_0, G_0) to (F_3, G_3). These three figures show how the introduction of Medicaid benefits may increase consumption of food, thereby reducing food insecurity. However, I also show that the increase in consumption may not be the same for all Medicaid beneficiaries. If an individual does not receive SNAP benefits, they consume the bundle (F_1, G_1) after the expansion of benefits. Individuals participating in SNAP consume $(F_3, G3)$, which is not necessarily, or likely, equal to (F_1, G_1).

In each of these scenarios, it may be possible that the subsidies do not increase the consumption of either other goods or food. For example, Medicaid or SNAP subsidies may simply result in an increase in other goods consumed, with no change in food consumption. If subsidies do not increase food consumption, this suggests that the individual does not desire additional food, and that the individual in unlikely to be food insecure. This is unlikely to be the case for SNAP recipients; Hoynes et al. (2015) show that, in the case of SNAP, most consumers are inframarginal, consuming more than the cash value of benefits, indicating consumption at any point $F_j < F_0$ (including point E) unlikely after receiving the SNAP subsidy. Moreover, Beatty and Tuttle (2014) show that increases in SNAP benefits from the American Recovery and Reinvestment Act of 2009 resulted in more spending than even typical theory suggests. Medicaid subsidies have been shown to increase the consumption of medical care (Wherry and Miller, 2016), however, the link between Medicaid and food consumption is not as clear, thus, I will explore whether the ACA has increased the consumption of food. Finally, it may be the case that the addition of subsidies changes preferences for food or other goods, resulting in a change in the marginal rate of substitution and the shape of the indifference curves, which could also result in no increase in food consumption.

The goal of this paper is to disentangle the effect of ACA Medicaid expansion alone and the effect of ACA Medicaid expansion for individuals also participating in

SNAP. This paper fits into the small literature examining the issues associated with the interaction of non-food programs and food insecurity, alongside Borjas (2004) who examines the impact of welfare reform on food insecurity, and Schmidt et al. (2015), who simulate eligibility for many programs, including Medicaid, to determine the effect of cash benefits on food insecurity. Identifying this interaction is difficult. There is a large literature on the effect of nutrition programs on food insecurity; however, reverse causality between SNAP and food insecurity can often severely bias estimates. Overall, after controlling for the endogeneity associated with reverse causality, results suggest that SNAP reduces food insecurity and improves the health outcomes of recipients (Hoynes et al., 2016; Gregory et al., 2015; Hoynes and Schanzenbach, 2015; Gundersen and Ziliak, 2014; Yen, 2010). To understand how the ACA interacts with traditional food programs, I control for the the endogeneity of SNAP. Similar to Borjas (2004), I employ a two stage control function strategy that accounts for the endogeneity of all interactions of the ACA and SNAP.

2.3 Model

2.3.1 Ordered Probit

Most studies that examine food hardship consider only the most widely reported category, food insecurity. However, it is not immediately apparent that the ACA should have similar effects across the distribution of food insecure households. Moreover, figure 2.3 suggests differential food insecurity rates across states that expanded Medicaid, with some states showing much larger decreases in food insecurity than others. Thus, I begin by analyzing how the ACA affected the probability a household falls within the mutually exclusive categories of marginally food secure, low food secure, and very low food secure. By establishing an ordering, I'm able to see how the ACA might move families along the distribution of food insecurity.

These categories represent increased levels of food hardship, with very low food security being more severe than low food security, both of which are more severe than being marginally food secure. I employ an ordered probit model that uses these categories as thresholds. My primary specification is

$$\begin{aligned} \text{Food Rank}^*_{ijt} &= \beta_1 \text{ACA}_{jt} + \beta_2 \text{SNAP}_{ijt} + \beta_3 (\text{ACA} \times \text{SNAP})_{ijt} \\ &+ X'_{ijt}\beta_4 + \delta_t + \delta_j + \eta_{ijt} \end{aligned} \tag{2.1}$$

where, Food Rank$^*_{ijt}$ is a latent variable representing where a household falls on the food security spectrum. As Food Rank$^*_{ijt}$ crosses some unknown thresholds α_l, food hardship increases such that for Food Rank$^*_{ijt} < \alpha_0$ the household is fully food secure, $\alpha_0 <$ Food Rank$^*_{ijt} \leq \alpha_1$ the household is marginally food secure, and so on. I let Food Rank$^*_{ijt} \in \{0, 1, 2, 3\}$, and define Food Rank$^*_{ijt}$ below.

$$\text{Food Rank}^*_{ijt} = \begin{cases} 0 & \text{if Fully Food Secure} \\ 1 & \text{if Marginally Food Secure} \\ 2 & \text{if Low Food Secure} \\ 3 & \text{if Very Low Food Secure} \end{cases} \tag{2.2}$$

Thus, Food Rank$^*_{ijt}$ describes household i's food security status in state j at time t, δ_j, δ_t are state and year fixed effects, and X_{ijt} is a vector of state and household demographic characteristics shown to impact food insecurity, including gender, household size, number of children, marital status, age, age squared, disability status, race, education, urban/rural status, number of Medicaid beneficiaries in the state, governor party affiliation, the natural log of the 50/10 income ratio, the 25th percentile of income, and the unemployment rate (Ziliak, 2015; Gundersen and Ribar, 2011; Bartfeld and Dunifon, 2006; Bhattacharya et al., 2004).

Since implementation of the ACA took place at different times across different states, I estimate a continuous measure of the proportion of the year a state had Medicaid reform implemented (ACA$_{jt}$). This variable holds at zero for states such as

South Carolina which never implement Medicaid reform, is a 1 for 2014 onward for states such as Kentucky who implement Medicaid reform at the beginning of 2014, and is some positive fraction for the remaining states. To more accurately capture the treatment population, I limit the impact of the ACA to only those less than 185% of the federal poverty line (FPL). While the ACA extends coverage to those less than 133% of the FPL, special SNAP eligibility requirements for the elderly and disabled, along with provisions for broad based categorical eligibility, make this threshold less clear.[3] This results in an intention to treat estimate, with identification coming from cross-state and over time variation of Medicaid expansion, framed as a triple difference specification.

SNAP_{ijt} is a dichotomous measure of SNAP participation, equal to one if the household participates in SNAP and zero otherwise. Reverse causality between SNAP and food insecurity is a significant issue. Bitler (2015) notes that SNAP use is correlated with observable characteristics regarding health, but also unobserved characteristics such as innate health, health habits, and general self-care that researchers may not observe in the data. Prima facie evidence often seems to suggest that SNAP actually *increases* food insecurity, a result of significantly biased estimates. It is highly unlikely that there is some underlying propensity for food insecurity amongst SNAP recipients, rather, it is more likely that those with strong needs seek food assistance. There have been a variety of approaches to control for this reverse causality (Gregory et al., 2015; Schmeiser, 2012; Gundersen et al., 2011; Meyerhoefer and Yang, 2011; Yen, 2010; Borjas, 2004). Any method employing matching estimators relies crucially on matching on only observed characteristics, which does not address unobserved health conditions. Moreover, the health stock evolves dynamically. This

[3]The binned income data of the December CPS also makes identifying the 133% FPL threshold difficult. 185% of the FPL corresponds to the variable hrpoor in the CPS data, and is a more precise threshold.

presents challenges in panel settings when trying to account for unobserved selection via a fixed effects approach, which will be insufficient for addressing time variant unobserved heterogeneity.

To address the endogeneity of SNAP as a result of this reverse causality, I use measures of SNAP access and state level measures of benefit generosity to exogenously identify SNAP participation, employing a control function approach. I use measures of broad based categorical eligibility, fingerprinting requirements, the presence of online applications (and the ability to sign these applications online), the presence of vehicle exclusions, non-citizen eligibility requirements, the family specific SNAP benefit, and the log of the prevailing minimum wage as exogenous identifying variation. Ziliak (2015) discusses many of these state level SNAP eligibility and policy parameters, and how they influence SNAP take-up, while Gregory et al. (2015) and Borjas (2004) use many of these variables (specifically the eligibility of non-citizens) as key identifying parameters. Letting Z_{jt} be the set of exogenous variables, the requirements for the validity of this control function strategy are that $\mathbb{E}[Z_{jt}\eta_{ijt}] = 0$ and $\mathbb{E}[Z_{jt}\text{SNAP}_{ijt}] \neq 0$, or that the policy instruments are both orthogonal to individual level health investment decisions and correlated with participation in SNAP. Since these policy variables are set at the state level, it is unlikely that they are determined by individual level health based decisions, lending credence to the exogeneity of the policy variables.

I include the interaction of the ACA and SNAP to examine whether the impact of the marginal benefit dollar will differentially affect SNAP beneficiaries vs non-participants. In this model, $(\text{ACA} \times \text{SNAP})_{ijt}$ will be endogenous through the endogeneity of SNAP. I instrument for this interaction with the product of the exogenous variables and the measure of the ACA. Thus, my first stage regressions take the form

$$\text{SNAP}_{ijt} = \gamma_1 \text{ACA}_{jt} + Z'_{jt}\Theta_1 + \text{ACA}_{jt} Z'_{jt}\Gamma_1 + X'_{ijt}\Omega_1 + \delta_{1t} + \delta_{1j} + a_{ijt} \tag{2.3}$$

$$\text{ACA}_{jt} \times \text{SNAP}_{ijt} = \gamma_2 \text{ACA}_{jt} + Z'_{jt}\Theta_2 + \text{ACA}_{jt} Z'_{jt}\Gamma_2 + X'_{ijt}\Omega_2 + \delta_{2t} + \delta_{2j} + e_{ijt} \tag{2.4}$$

where all variables are defined as above. As noted by Heckman and Robb Jr (1985); Wooldridge (2002), and Blundell and Powell (2004), to consistently estimate β_1, β_2, and β_3 in the second stage, the control function methodology also requires the independence of Z_{jt} and the first stage error terms, or $Z_{jt} \perp a_{ijt}$ and $Z_{jt} \perp e_{ijt}$. While the conditions for the consistency of the control function approach are less well established for my model, they are likely to follow through. I then save the residuals, $\widehat{a_{ijt}}, \widehat{e_{ijt}}$, and include them in my second stage specification. Thus, the final functional form of the ordered probit model is

$$\begin{aligned} \text{Food Rank}^*_{ijt} &= \beta_1 \text{ACA}_{jt} + \beta_2 \text{SNAP}_{ijt} + \beta_3 (\text{ACA} \times \text{SNAP})_{ijt} \\ &\quad + X'_{ijt}\beta_4 + \widehat{a_{ijt}} + \widehat{e_{ijt}} + \delta_t + \delta_j + \eta_{ijt} \\ &= \widetilde{X}\psi + \eta_{ijt} \end{aligned} \tag{2.5}$$

where the model is simplified to $\widetilde{X}\psi + \eta_{ijt}$ for notational convenience. The functional form of the ordered probit model implies that the probability a household falls into food security category l is defined by

$$\begin{aligned} Pr[\text{Food Rank}_{ijt} = l] &= Pr[\alpha_{l-1} < \text{Food Rank}^*_{ijt} \leq \alpha_l] \\ &= \Phi(\alpha_l - \widetilde{X}\psi) - \Phi(\alpha_{l-1} - \widetilde{X}\psi) \end{aligned}$$

where $\Phi()$ is the standard normal cumulative distribution function. The regression parameters are obtained by maximizing the likelihood for the ordered probit, which involves maximizing the product of the probabilities associated with each discrete outcome. The marginal effects for each associated outcome are defined by

$$\frac{\partial Pr[\text{Food Rank}_{ijt} = l]}{\partial \widetilde{X}} = [\phi(\alpha_{l-1} - \widetilde{X}\psi) - \phi(\alpha_l - \widetilde{X}\psi)]\psi \tag{2.6}$$

where $\phi() = \Phi'()$.

There may be additional concern about the endogeneity of Medicaid expansion through the ACA in equation (2.5), however, this concern should be of second order importance. First, by controlling for governor party affiliation as well as state and year fixed effects, the endogeneity must enter through time varying, state specific means that remain un-captured by the changing political climate as controlled for by gubernatorial party. Next, the large literature on food insecurity establishes the large biases associated with the endogeneity of SNAP, requiring that addressing this endogeneity be of primary importance for any estimates of policy on food insecurity. Since I already instrument $\text{ACA}_{jt} \times \text{SNAP}_{ijt}$ with $\text{ACA}_{jt} \times Z_{jt}$, β_3 is biased only if $\mathbb{E}[(\text{ACA}_{jt} \times Z_{jt})\eta_{ijt}] \neq 0$, or the interaction of state level SNAP eligibility parameters and Medicaid expansion must be correlated with both some unobserved propensity for healthcare expansion and food insecurity. Food insecurity was not the primary concern of the ACA; the topic is not even mentioned in the text of the bill. For β_1 to be biased, Medicaid expansion must be correlated with some unobserved heterogeneity that is also correlated with food insecurity. By the arguments above, food insecurity was not only not a driving force in Medicaid expansion, but any political characteristics that might affect both expansion and food insecurity would be captured through controls for governor party affiliation as well as the control function approach taken with food policy. Finally, the intention-to-treat framework mitigates endogeneity through Medicaid take-up since all individuals in Medicaid expansion states are given the same "treatment" value, regardless of actual participation. Thus, bias in β_1 and β_3 resulting from the endogeneity of Medicaid expansion is likely to be small.

2.3.2 Linear Probability Difference-in-Difference-in-Differences

While the ordered probit model is useful in determining how a household moves from one mutually exclusive food security category to another, a large portion of the literature examines the non-mutually exclusive categories of marginally food insecure, food insecure, and very low food secure. Thus, I also employ linear probability triple difference (difference-in-difference-in-differences) models, which have the benefit of relaxing the functional form assumptions of the ordered probit framework. Similar to the models above, I establish

$$\begin{aligned} \text{food insecure}_{ijt} = {} & \tau_1 \text{ACA}_{jt} + \tau_2 \text{SNAP}_{ijt} + \tau_3 (\text{ACA}_{jt} \times \text{SNAP}_{ijt}) \\ & + X'_{ijt}\beta + \mu_t + \mu_j + \nu_{ijt} \end{aligned} \tag{2.7}$$

where food insecure$_{ijt}$ $\in$\{food marginally food insecure, food insecure, very low food secure\} is an indicator measure of household i's food insecurity status in state j at time t, μ_t is a state fixed effect, μ_j is a time fixed effect, and all other variables are defined as above.

The same caveats about the reverse causality between SNAP and food insecurity hold in this model. Thus, I employ an analogous IV approach as above, instrumenting for both SNAP$_{ijt}$ and ACA$_{jt}$ $\times$ SNAP$_{ijt}$. Triple difference specifications also allow me to examine the effect of the ACA across the distribution of food insecurity, and allow me to directly interpret the effect of the ACA on falling in to a given food insecurity category. However, they do not take into account the inherent ordering of food insecurity outcomes. For example, suppose the marginal effect of the ACA on marginal food insecurity in a triple difference model is $\kappa > 0$. This tells us that individuals living in states that enacted Medicaid reform are κ percentage points more likely to be marginally food insecure.

This result could have two possible interpretations. The first is that the ACA actually *increased* food hardship, resulting in more families describing at least one food insecure condition. The other possibility is that the ACA increased the probability a household is marginally food insecure by reducing more severe food deprivation conditions, but not completely alleviating food hardship all together. Thus, care must be employed when interpreting the coefficients in the linear probability models.

2.3.3 Mechanisms

I will consider two separate mechanisms through which the ACA could influence food hardship. The first, as discussed previously, is increased food expenditure. If the ACA allows households to reallocate food away from medical expenditure, toward food expenditure, then households may be able to reduce their degree of food hardship. To estimate this mechanism, I will employ the same instrumental variable strategy as before, with

$$\begin{aligned}\text{Food Expend.}_{ijt} = \psi_1 \text{ACA}_{jt} + \psi_2 \text{SNAP}_{ijt} + \psi_3 (\text{ACA} \times \text{SNAP})_{ijt} \\ + X'_{ijt}\psi_4 + \rho_{1t} + \rho_{1j} + \zeta_{ijt}\end{aligned} \tag{2.8}$$

where Food Expend.$_{ijt}$ is weekly food expenditure, in dollars, for household i in state j at time t, ρ_{1t} and ρ_{1j} are the year and state fixed effects, and all other variables are defined as before. Here, the one exception will be the addition of the bin of household income in X_{ijt}. Since I am estimating a model of expenditure in (2.8), failing to control for income could greatly bias results. This model allows me to directly estimate the change in expenditure due to both Medicaid expansion in the ACA as well as the receipt of SNAP benefits.

The second mechanism I will consider is the influence of the ACA on SNAP take-up. Moffitt (2015) notes a large degree of multiple program participation in SNAP and

Medicaid. Furthermore, Keane and Moffitt (1998) show that there are many costs associated with participating in safety-net programs. The expansions of Medicaid through the ACA may induce households to pay some of these costs, such as stigma and information costs, thereby making participation in SNAP less costly. The receipt of SNAP benefits, in turn, could reduce food hardship. Thus, I will estimate

$$\text{SNAP}_{ijt} = \iota_1 \text{ACA}_{jt} + X'_{ijt}\iota_2 + \rho_{2t} + \rho_{2j} + \vartheta_{ijt} \tag{2.9}$$

through both a probit and linear probability models, where all variables are defined as before. Since SNAP_{ijt} enters on the left hand side of the equation, I do not have to employ an instrumental variables strategy, and equation (2.9) takes the form of a simple difference in differences model where ACA_{jt} is identified through cross state, over time variation in Medicaid expansion.

2.3.4 Alternative Measures of Food Hardship

All previously described measures of food insecurity estimate the probability a household falls into a certain category of food insecurity, but fail to take into account the variability of food deprivation within a given category, and fail to fully utilize the richness of the 18 question food security supplement. Dutta and Gundersen (2007) propose new measures that more strongly weight households that experience severe food deprivation. I consider two measures the authors propose—the food insecurity gap and the square of the food insecurity gap, which are based on similar measures utilized in the income poverty literature. These measures are also utilized in Gundersen (2008).

To compute the food insecurity gap, affirmative answers to the 18 question food security supplement are converted into a single indicator by the Rasch scoring method, which measures the probability a household answers in the affirmative depending on the degree of food insecurity experienced by the household and the extent of food insecurity captured by the question. Using this Rasch score, one can create an index that measures how far a food insecure household is from the food security threshold relative to the maximum distance from the food security threshold (i.e. answering in the affirmative to all 18 questions in the food security supplement.) Letting d_{ijt} be the normalized distance from the food security threshold, the normalized food insecurity gap is measured as:

$$d_{ijt} = \begin{cases} \frac{s_{ijt}-e}{z-e} & \text{if } s_i > e \\ 0 & \text{if } s_i \leq e \end{cases} \tag{2.10}$$

where s_{ijt} is the Rasch scoring indicator, which depends not only on the number of questions an individual answers affirmatively, but also on family structure. The maxima of the Rasch scores are represented by z, and are 13.03 for a household with children, and 11.05 for a household without children. e is the minimum value for a household to be food insecure, and is 3.10 for a household with children, and 2.56 for a household without children. Thus, all food secure households obtain a value of zero, and all food insecure households obtain a value between zero and one based on the severity of their food insecurity. The food insecurity gap squared is simply d^2_{ijt}.

Since the food insecurity gap measure is directly dependent on the number of children, including IVs that are dependent on the number of children (EITC rates and the family specific SNAP benefit), along with the number of children directly, violates exclusion restrictions. Thus, when modeling the food insecurity gap, I do not include the number of children in the household as an independent variable. The regression framework takes the form

$$\begin{aligned} d_{ijt} &= \pi_1 \text{ACA}_{jt} + \pi_2 \text{SNAP}_{ijt} + \pi_3 (\text{ACA} \times \text{SNAP})_{ijt} \\ &+ X'_{ijt}\pi_4 + \omega_{1t} + \omega_{1j} + \varepsilon_{ijt} \end{aligned} \tag{2.11}$$

where ω_{1t}, ω_{1j} are year and state fixed effects, ε_{ijt} is the error term, and all other variables are defined as above. I also address the endogeneity of SNAP in the same manner as before.

The final measure of food deprivation that I consider is the additional amount of money a household would need to spend each week to purchase enough food to meet household needs, which I term the income gap. This measure directly monetizes the severity of food deprivation, providing a continuous scale of income to needs. However, this is also a subjective measure, requiring both accurate assessment and reporting of the money needed to meet food needs. I model the income gap as

$$\begin{aligned} I_{ijt} = {} & \lambda_1 \text{ACA}_{jt} + \lambda_2 \text{SNAP}_{ijt} + \lambda_3 (\text{ACA} \times \text{SNAP})_{ijt} \\ & + X'_{ijt}\lambda_4 + \omega_{2t} + \omega_{2j} + \xi_{ijt} \end{aligned} \tag{2.12}$$

where ξ_{ijt} is the error term, and the definition of variables and the description of the endogeneity of SNAP are defined as before.

2.4 Data

Individual characteristics, along with food security information, come from the 2001-2016 waves of the Current Population Survey Food Security Supplement, also known as the December CPS. The December CPS asks all 18 questions in the food security module, which determines the household's food security status, with households placed into varying categories of food hardship depending on the number of affirmative responses to the questionnaire. These categories are defined above, and represent a spectrum of food hardship, with marginal food security being the least severe, and having very low food security being the most severe.

Figure 2.8 depicts rates of food security statistics over time, including marginal food security, low food security, and very low food security. In 2007, coinciding with the Great Recession, we see a large uptick in all categories of food hardship.

All categories of food hardship remain persistently high until approximately 2013, with around 8.5% of households experiencing marginal food security, 8.5% of households experiencing low food security, and 5% of households experiencing very low food security. These rates begin to trend downward after 2013, coinciding with the implementation of the ACA. Figure A.1 in the appendix details the commonly reported, nonmutually exclusive categories of food insecurity over time, showing similar patterns as figure 2.8.

Figure 2.9 shows rates of food security by Medicaid expansion status. One of the requirements for a difference in differences methodology is the parallel trend assumption for both treatment and comparison groups. Figure 2.9 shows generally uniform trends for both Medicaid expansion and non-expansion states, validating the assumption of parallel trends. While it seems that food hardship is generally higher in non-expansion states, there does seem to be some divergence, especially in low and very low food security, between the groups in later years.

The December CPS reports the household's Rasch score, which I use to construct the food insecurity gap (and squared gap) as defined in equation (2.11). The mean of the food insecurity gap (squared food insecurity gap) is 0.13 (0.98) for the population as a whole. Figure 2.10 depicts the mean of the food insecurity gap for different subsets of households. We see that poorer households have larger gaps, and that households receiving SNAP benefits and households headed by single mothers have larger gaps than average. Interestingly, households in Medicaid expansion states have slightly lower gaps than the national average.

The December CPS also asks questions about average weekly food expenditure, and about how much more income a household would need to spend each week to purchase enough food to meet household needs, which I term the income gap. Prior to 2011, average weekly food expenditure was top-coded at $1,000, while from 2011 onward, the top values range from $400-530. To account for such a large discrepancy, I use only the years from 2011 onward for average weekly expenditure. While this limits the scope of the analysis, the time frame accounts for a sizable "pre" period prior to ACA Medicaid expansions, as well as the years post expansion. The income gap changes top-coding more frequently than average weekly food expenditure, however, I top-code the entire series at \$200 for consistency. In each year, the dollar amounts range from \$1 to the top value. The mean of the income gap is \$3.99 per week for the population as a whole. Figure 2.11 breaks out the income gap by sub-category. Here, we see SNAP recipients have large income gaps, around \$17 per week, with poorer households and single mothers also experiencing larger income gaps.

Table 2.2 presents weighted summary statistics from the December CPS by Medicaid expansion status as well as SNAP receipt. Medicaid expansion states are similar to states that did not expand Medicaid with regard to poverty, age, education, and household composition. Individuals in Medicaid expansion states are more likely to be black, live in a metro area, and experience higher unemployment rates. They also have higher 50/10 income ratios and the 25th percentile of earnings is higher, suggesting that middle-income inequality is greater in Medicaid expansion states. Individuals receiving SNAP are more likely to be black or Hispanic, female, and unmarried. SNAP recipients are also younger, have more children, and have lower levels of education on average.

To address endogeneity in equation (2.7), I identify SNAP participation with measures of SNAP access and generosity from the USDA Economic Research Service SNAP policy database, along with other state level measures of benefit generosity. The SNAP policy database documents state policy options for SNAP, and provides these data at a monthly level. While the majority of the data are up to date, the most recent version of the SNAP policy database contains missing data for some variables for 2013-2016. I assume missing values take on the value in the previous year, and if the policy was in effect for a portion of the year, that fraction is represented in the policy variable. Means for these instruments are presented in table 2.3. Data from the University of Kentucky Center for Poverty Research are used for state level economic data, and data on SNAP benefits. SNAP benefits are calculated at the national level and adjusted for family size and income, resulting in family size specific SNAP benefits. I use weighted estimates from the Current Population Survey Annual Social and Economic Supplement (CPS ASEC) to construct the 50/10 income ratio and the 25th percentile of income for each state and year.

2.5 Results

I begin by presenting the ordered probit results examining the mutually exclusive categories of food security, using a two stage control function approach to control for the endogeneity of SNAP. I then present linear probability specifications for the non-mutually exclusive food insecurity categories while instrumenting for the endogeneity of SNAP. Next, I present evidence for the mechanisms through which the ACA might influence food hardship, including both expenditure and SNAP take-up. Finally, I present other measures of food hardship to assess the robustness of the impact of the ACA on food insecurity. All models control for state and year fixed effects, individual characteristics, and all standard errors are clustered at the state level.

2.5.1 Main Results

Table 2.4 presents first stage results from the two stage ordered probit model. Not all of the exogenous, state level policy variables are statistically significant individually, but the policy variables are strongly jointly significant, with large F statistics and p-values for F statistics of 0. Moreover, these policy variables have been shown to be predictive in other contexts, as noted in Ziliak (2015).[4] This suggests the policy variables have predictive power for SNAP receipt.

Table 2.5 presents the ordered probit results from estimating equation (2.5), employing a control function approach. I present coefficients, as well as marginal effects (at means) for the three mutually exclusive categories of households experiencing food hardship. Using an ordered probit framework allows me to examine how both SNAP and the ACA move households from more severe food insecurity categories to less severe categories. The primary benefit from this framework is that there is no ambiguity in the transition from threshold to threshold, with each cut point representing transition from less severe food insecurity to more severe food insecurity. While not presented in the table, the coefficients on the first stage residuals are strongly significant, with p-values <0.001, confirming the validity of the control function approach.

Column (1) from table 2.5 presents the coefficients from the model. Here, we see that SNAP reduced food hardship in U.S. households, however, the own effect of the ACA is positive, small in magnitude, and statistically insignificant, suggesting relatively little impact from the ACA alone. If individuals live in ACA expansion states, but do not meet the criteria for subsidies, they will be required to pay some form of premium. This could result in the positive, but small and insignificant own-effects in the first row. While magnitudes are not directly interpretable from coefficients, we are able to see that not only did SNAP reduce the probability a household experienced food hardship, but also that this reduction in probability increased for families living in Medicaid expansion states. This suggests some positive spillover from the ACA, with households participating in both programs experiencing more gains than

[4] While these state level policy variables have been used extensively in other contexts, I am also able to examine them one by one for the validity of their inclusion in the instrument set. For example, the p-values for the C-statistic for the natural log of the minimum wage are above 0.05 for all triple difference models except those marginal food insecurity, suggesting it's inclusion in the set of exogenous policy variables is valid.

households treated by SNAP or the ACA alone.

Columns (2)-(4) show the marginal effects at each threshold of food security. These marginal effects have the same implications as above. SNAP reduced the probability a household was very low food secure by 15 percentage points, the probability a household was low food secure by 16 percentage points, and the probability a household was marginally food secure by 6.4 percentage points (all statistically significant at the 1% level). These results also suggest that the impact of SNAP is strongest for those households experiencing more severe food insecurity, but further suggest that SNAP alleviates all levels of food hardship, moving households towards full food security. However, households in each of these food secure categories saw additional gains from the ACA. The marginal effects of the interaction between the ACA and SNAP suggest that households participating in SNAP and in Medicaid expansion states saw an additional reduction of 6.4 percentage points in the probability of being very low food secure, an additional 6.8 percentage point reduction in the probability of being low food secure, and an additional reduction in the probability of being marginally food secure of 2.7 percentage points. All marginal effects for SNAP and the interaction of the ACA and SNAP are statistically significant at the 1% level, and while the marginal effects at the low food secure and very low food secure levels are not statistically different from one another, both are statistically different from the marginal effect at the marginally food secure level.

These results suggest large, increasing returns to program participation. Schmidt et al. (2015) found that $1,000 in additional non-food benefits reduced the incidence of food insecurity by roughly 0.9 percentage points. While low food security and food insecurity measure slightly different types of food hardship, a 6.5 percentage point reduction in the probability of being low food secure is roughly equivalent to $6,500 in additional non-food benefits. The average spending per enrollee in Medicaid was

\$5,736[5] in 2014, suggesting that the Medicaid expansions more than doubled the value of the benefit for SNAP recipients.

Table A.1 in the appendix shows results from a standard ordered probit for reference. The ordered probit results that do not control for reverse causality with SNAP show large, negative values for the impact of the ACA, but also large positive values for the impact of SNAP on food hardship. The two stage control function approach presented in table 2.5 removes the bias stemming from economic circumstances and participation in SNAP.

Table 2.6 presents the results of estimating equation (2.7) at different, nonmutually exclusive food insecurity thresholds. For reference, I present results from OLS regressions that estimate the impact of the ACA where the endogeneity of SNAP is not accounted for in table A.2 in the appendix, once again demonstrating the reverse causality associated with SNAP.

Column (1) shows the impact of the ACA on the commonly reported summary category of food insecurity. Here, we see no statistical relationship between Medicaid expansion alone and food insecurity. However, for households who also participate in SNAP, the ACA further reduced the probability they are food insecure by 14.2 percentage points. In my sample, 53% of households participating in SNAP are food insecure. This 14.2 percentage point reduction translates into a 26.8% decrease in the probability a household is food insecure. Thus, program interaction matters, with increasing returns to program participation for reductions in food insecurity.

Column (2) examines the effect of the ACA on marginal food insecurity. Here, we still see the impact of multiple program participation as well as increasing returns to program participation, with SNAP households seeing a reduction in the probability

[5]http://www.kff.org/medicaid/state-indicator/medicaid-spending-per-enrollee/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D

of being marginally food insecure of 28 percentage points on a basis of 74%, or a 38% reduction in the probability of being marginally food insecure.

This is strongly contrasted with results in column (3), where we see no impact of the ACA on the probability of experiencing very low food security, regardless of SNAP participation. However, we see the own effect from SNAP reduces the probability a household experiences very low food security by 74 percentage points. The large coefficient suggests that SNAP strongly reduces the probability individuals experience extreme food hardship, although individuals who leave this category may still be food insecure. This suggests that at the low end of the food security distribution, SNAP does most of the work in alleviating food hardship, with little effect from healthcare programs. These results suggest that the ACA and SNAP assist those at different ends of the food insecurity spectrum, and also present the first IV estimates of SNAP on very low food security of which I am aware.

I also report first stage statistics to assess the performance of the instruments. The Kleibergen under-identification statistics reject the null hypothesis that the SNAP access measures and state policy variables are only weakly correlated with SNAP participation. Since I have more instruments than endogenous regressors, I also report the Hansen J statistic as a test of overidentifying restrictions. Here, the large p-values result in failing to reject the null hypothesis that the instruments are uncorrelated with the error term at any standard threshold, giving greater confidence in the validity of the instrument set.

While the results in column (1) coincide with the notions of program interaction, some of the results from columns (2) and (3), specifically the coefficients on SNAP, are surprising in sign and magnitude. Taken at face value, the coefficient on SNAP in column (2) suggests participating in SNAP *increases* the probability an individual is marginally food insecure by 33.2 percentage points, even when instrumenting for SNAP participation. In column (3), the large, negative coefficient on SNAP suggests a surprisingly large decrease in very low food insecurity. However, the findings in table 2.5 provide the needed context. Here, it seems that SNAP reduces food hardship at all levels, but does not completely alleviate it, suggesting SNAP increases the probability of being higher on the food security distribution (more food secure), and decreases the probability of being lower on the food insecurity distribution (less food secure).

The key finding of this paper is that the ACA reduces the probability a household experiences food insecurity, but that these reductions are not uniform across the distribution of food insecurity, nor are they uniform across the SNAP benefit population. Tables 2.5 and 2.6 together show the interplay of Medicaid expansion through the ACA and SNAP. The ACA complemented the traditional food support system, further reducing food insecurity for those already receiving SNAP benefits. Furthermore, I show that SNAP moves people up the food security distribution at all levels.

2.5.2 Evidence on Mechanisms

Previously, I discussed the intuition behind how the ACA might influence food hardship. In this section, I provide evidence detailing two mechanisms through which the ACA might increase household access to food. In the background section, I presented budget constraint analysis that graphically depicts the income effect of receiving both Medicaid and SNAP subsidies, with the general idea being that receiving subsidized public health care allows households to reallocate resources away from medical expenditure and towards food expenditure. Thus, I directly estimate the effect of the ACA on food expenditure.

When estimating food expenditure models, I limit the analysis to the years 2011-2016. The reason for this is twofold. First, as discussed previously, the wide discrepancy in the top-coding of food expenditure in the CPS makes comparison with earlier years difficult. Second, this provides a tighter window around Medicaid expansion to analyze expenditure. When estimating food expenditure, I also further control for the income bin provided by the CPS. While I do not have exact data on household income, attempting to estimate expenditure without controlling for income in some fashion could bias estimates. Column (1) of table 2.7 shows instrumental variables results examining how both SNAP and the ACA influence average real average weekly food expenditure using the same instrument set described above.

Here, we see that participation in SNAP increases weekly food expenditure by \$164.32, which I consider to be an upper bound on the effect of SNAP on food expenditure. From 2011-2016, the nominal value of the maximum weekly benefit for a family of four is approximately \$160, which is roughly equivalent to the estimate presented above. The average family size for SNAP recipients in my sample is 3, with an average maximum weekly benefit of \$105.34. Average weekly food expenditure is \$115.93. Thus, the estimated return to SNAP participation is large compared with sample baselines. However, the instrumental variables strategy results in a local average treatment effect, meaning the effect may be larger than otherwise estimated. Beatty and Tuttle (2014) find that the actual food share of the budget changes in response to changes in SNAP benefits, resulting in greater increases in food expenditure than otherwise predicted, consistent with the results presented here.

Column (1) also shows that households in Medicaid expansion states see larger increases than other households. I find that average weekly food expenditure is \$21.63 lower in ACA states on average, however, for households that reside in expansion states and participate in SNAP, food expenditure is \$38.24 higher. This is once again consistent with requiring premiums for those who do not meet Medicaid income cutoffs. These individuals may reduce food expenditure to cover premiums (which will be required for all due to the individual mandate). For those who also receive SNAP benefits, any income lost due to income will be mitigated through food subsidies. The increase in food expenditure for SNAP recipients in Medicaid expansion states is direct evidence for the mechanism described previously—households residing in Medicaid expansion states see an additional return to program participation, once again detailing the complementarities between Medicaid and SNAP. Thus, it seems that subsidized public healthcare does act as an income shock for SNAP households, increasing their access to food.

Another potential avenue for the ACA to influence food hardship comes through the reduction in information and/or stigma costs associated with participating in the safety net. Columns (2) and (3) of table 2.7 examine whether the Medicaid expansions through the ACA brought new households into the safety net. For these households, participation in SNAP (if they were not already participating) may become easier. Perhaps by participating in public healthcare, these households have learned something about navigating the safety net, making it subsequently easier to apply for, and obtain, SNAP benefits. These households might also pay some fixed portion of the stigma costs, as noted by Keane and Moffitt (1998), making it less costly for them to participate in SNAP. Columns (2) and (3) show that the ACA increased SNAP take-up, regardless of using a linear probability or probit model to estimate the impact on take-up. Together with the evidence from spending, I show two means by which the ACA might cause the results presented above.

2.5.3 Additional Measures of Food Hardship

I now turn to other measures of food hardship. Table 2.8 presents IV results estimating the impact of the ACA on the food insecurity gap, the square of the food insecurity gap, and the income gap as defined in equations (2.11) and (2.12). OLS results are available in table A.3 in the appendix. Here, I attempt to more fully utilize the entirety of the food security supplement in the December CPS. Regardless of whether we consider only the food insecurity gap (d_{ijt}) in column (1), or the square of the gap (d_{ijt}^2) in column (2), the results are the same. I find that the own effect of the ACA is positive, suggesting that households in Medicaid expansion states are more likely to be farther from the food security threshold. However, for households participating in SNAP, the ACA reduces the distance to the food security threshold by 9.2-10.1 percentage points. I also show that SNAP participation greatly reduces the distance to the food security threshold by approximately 33-42 percentage points in both columns (1) and (2). While less conclusive than the results from tables 2.5 and 2.6, these results still suggest there are increasing returns to program participation, with the ACA and SNAP acting in concert to reduce food hardship.

The income gap provides the benefit of directly monetizing the amount of food hardship experienced by the household, at the expense of potential increases in measurement error. The question as posed by the CPS asks individuals to opine on the amount of money that they would require to meet food needs. The hypothetical nature of the question inherently poses uncertainty in the measure. However, in column (3) I (imprecisely) estimate that the ACA reduces the amount of money a household needs to meet food needs by approximately $5 per week. I once again show increasing returns to program participation, with the magnitude of the effect larger for households participating in SNAP. The coefficient on SNAP is positive. Taken at face value, this suggests SNAP increases the amount of money a household needs to meet food requirements; however, the coefficients on the ACA suggest beneficial effects of Medicaid expansion.

These additional measures are less commonly reported in both the food insecurity literature and policy debates. However, they still suggest that the Medicaid expansions from the ACA and SNAP work together to reduce food insecurity, and are more effective as a pair than either alone. While precise identification of these parameters is difficult, they compliment earlier, more ubiquitous measures of food insecurity.

2.6 Conclusion

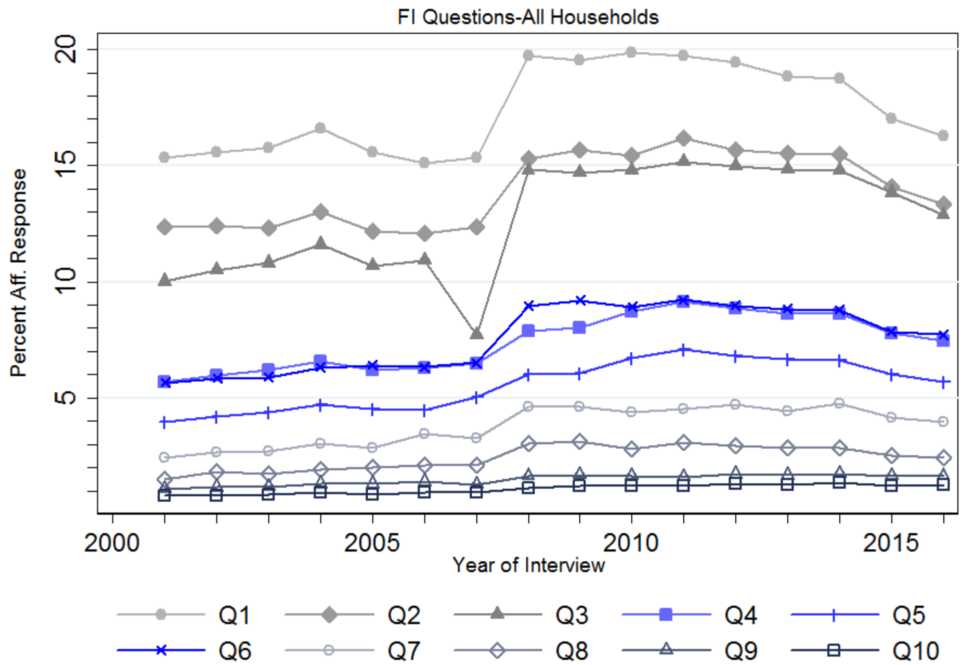
The focus of the Affordable Care Act was to overhaul the American healthcare system through mandated coverage, subsidized private coverage, reforms in Medicare taxes and spending, and significant expansions in the Medicaid program to low income populations. Gruber (2011) provides an overview of the aims and predicted consequences of the ACA, documenting many of the challenges associated with assessing the impact of the law. However, he does not consider the impact that expanded Medicaid coverage might have on food insecurity, one of the largest public health concerns facing the nation.

Participating in multiple safety net programs is one way households may increase total resources available to alleviate food hardship. This paper examines the effect of the Affordable Care Act, one of the largest increases in Medicaid coverage, on food insecurity. While the primary goal of Medicaid expansion through the ACA was to increase healthcare coverage across America, I find strong evidence that the ACA also reduced food hardship across the spectrum of food security, but that these gains were concentrated among those who also participated in SNAP. I find the ACA reduced the probability a household participating in SNAP falls into the two lowest food security categories by about 6.5 percentage points, and reduced the probability these households were classified as food insecure by 14.2 percentage points.

One consistent implication of the results implies that the ACA had a differential impact depending on whether the household received SNAP benefits. Despite the reverse causality between SNAP and food security, demonstrated in this work and elsewhere, I show that households that both reside in Medicaid expansion states and receive SNAP benefits experience larger gains in food security than households benefiting from either program alone. Households in Medicaid expansion states see a 45% greater reduction in the probability of being very low food secure or low food secure than households participating in SNAP alone. Households that participate in SNAP and live in Medicaid expansion states see a decrease in the probability of being food insecure, nearly doubling the impact from SNAP alone. Even under alternative measures of food hardship, I consistently find evidence for increasing returns to food security from program participation; living in a Medicaid expansion state and participating in SNAP have larger benefits for food security than either program alone.

Increasing returns to program participation shows that by analyzing these programs separately, we risk mischaracterizing the benefits of the safety net. Rarely do families participate in only one safety net program. By receiving multiple types of benefits, households may be able to redirect resources in ways that compound gains in resources from a single program. As this study shows, by including multiple benefit types in our analyses, we may be able to get a more complete picture of where policy actually bites. This is especially relevant for researchers studying the impact of the safety net on poverty related issues. By limiting the scope of analysis for safety net issues, researchers narrow the spectrum of results that might otherwise be present. Ultimately, this paper shows that public health insurance has benefits beyond health-care coverage. While access to quality medical care is crucial for the health of all families, so too is access to food. As many studies have shown, food insecurity can have large, detrimental effects on health. I show that public healthcare can make large strides in alleviating health risks posed by food insecurity.

Figure 2.1: Response Rates to FI Questions



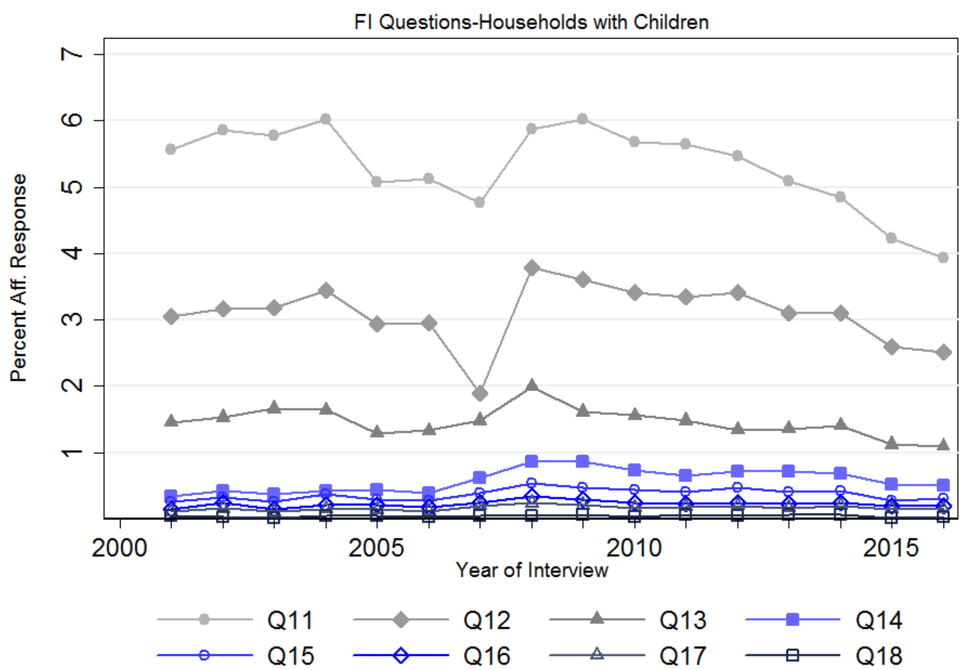


Figure 2.2: State Medicaid Expansion

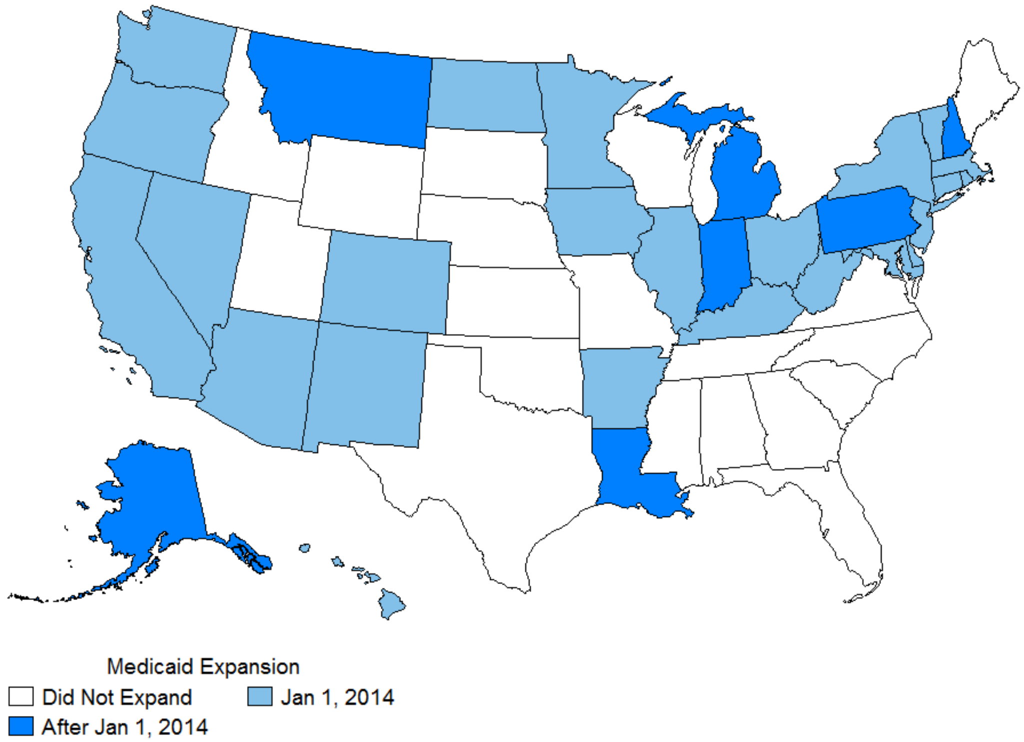


Figure 2.3: Food Insecurity Rates: 2013

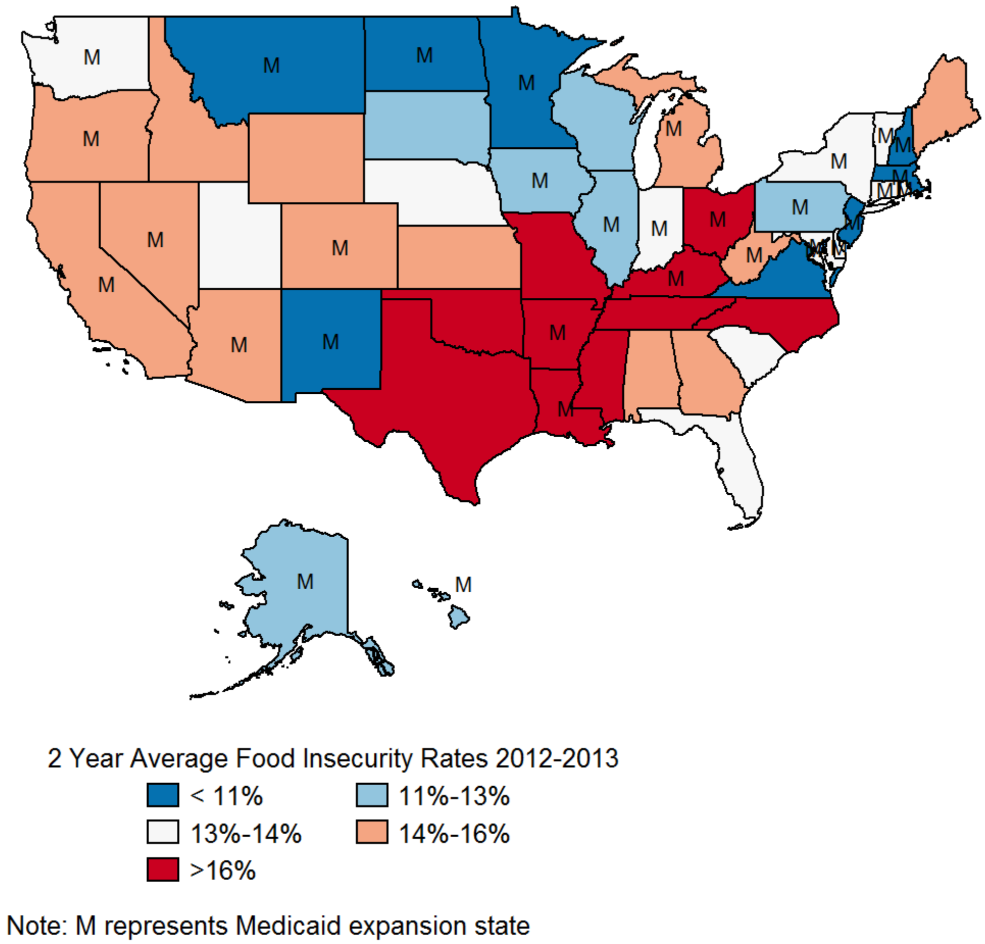


Figure 2.4: Food Insecurity Rates: 2015

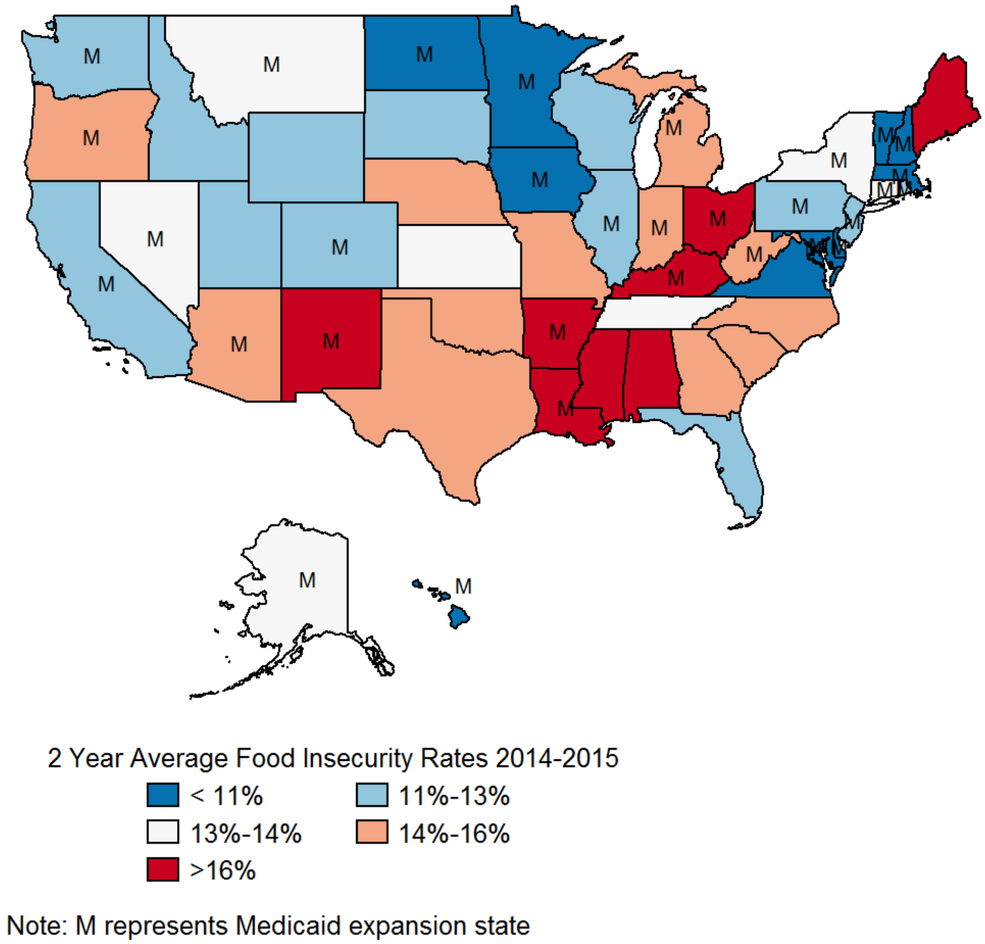


Figure 2.5: Medicaid Subsidy

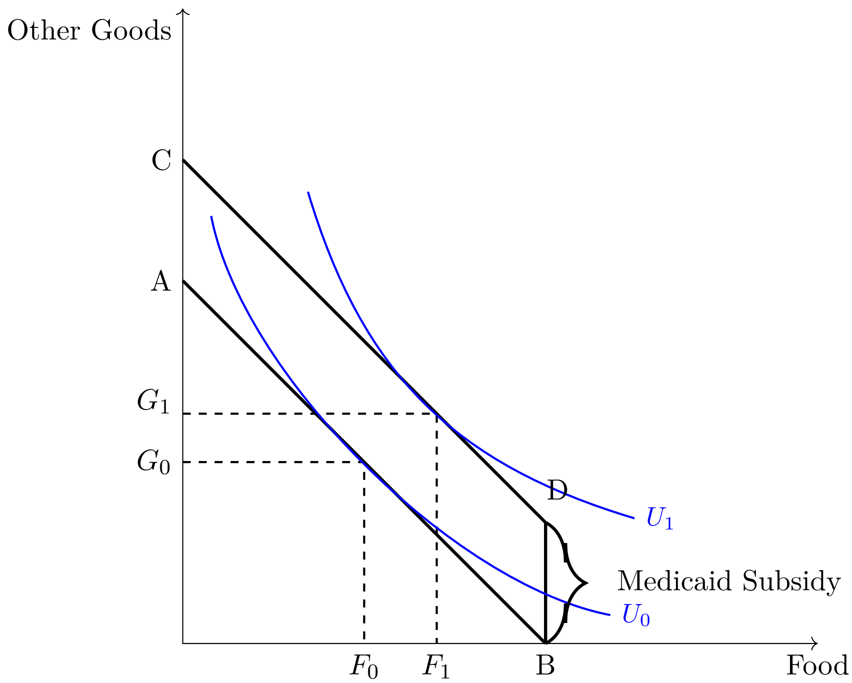


Figure 2.6: SNAP Subsidy

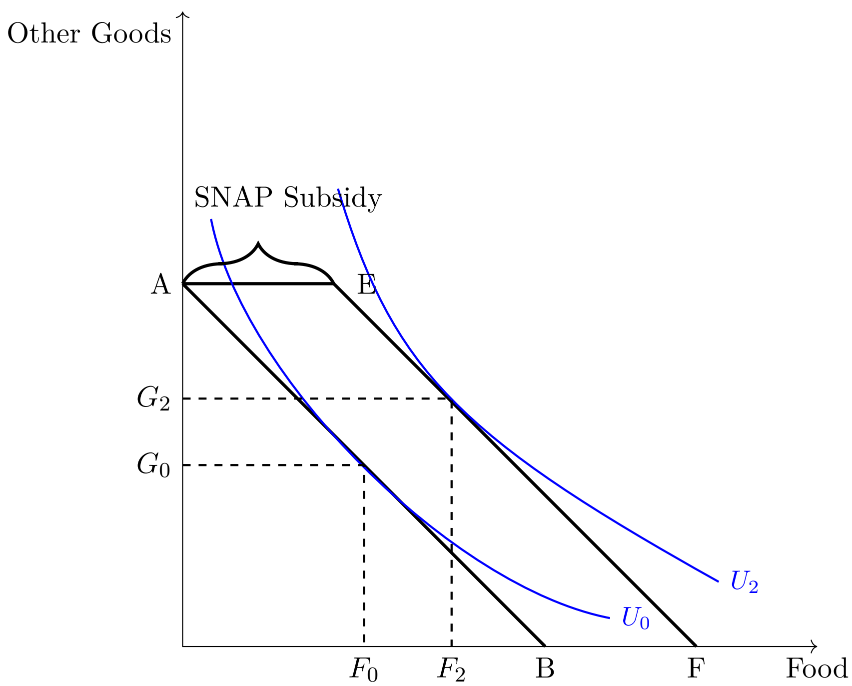


Figure 2.7: SNAP & Medicaid Subsidies

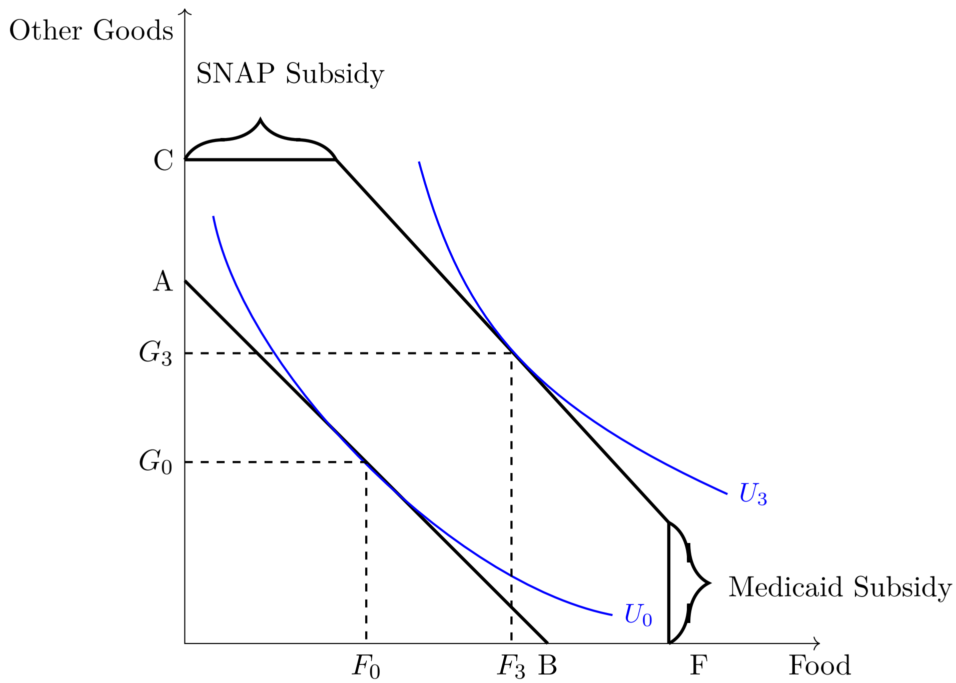


Figure 2.8: Household Food Security

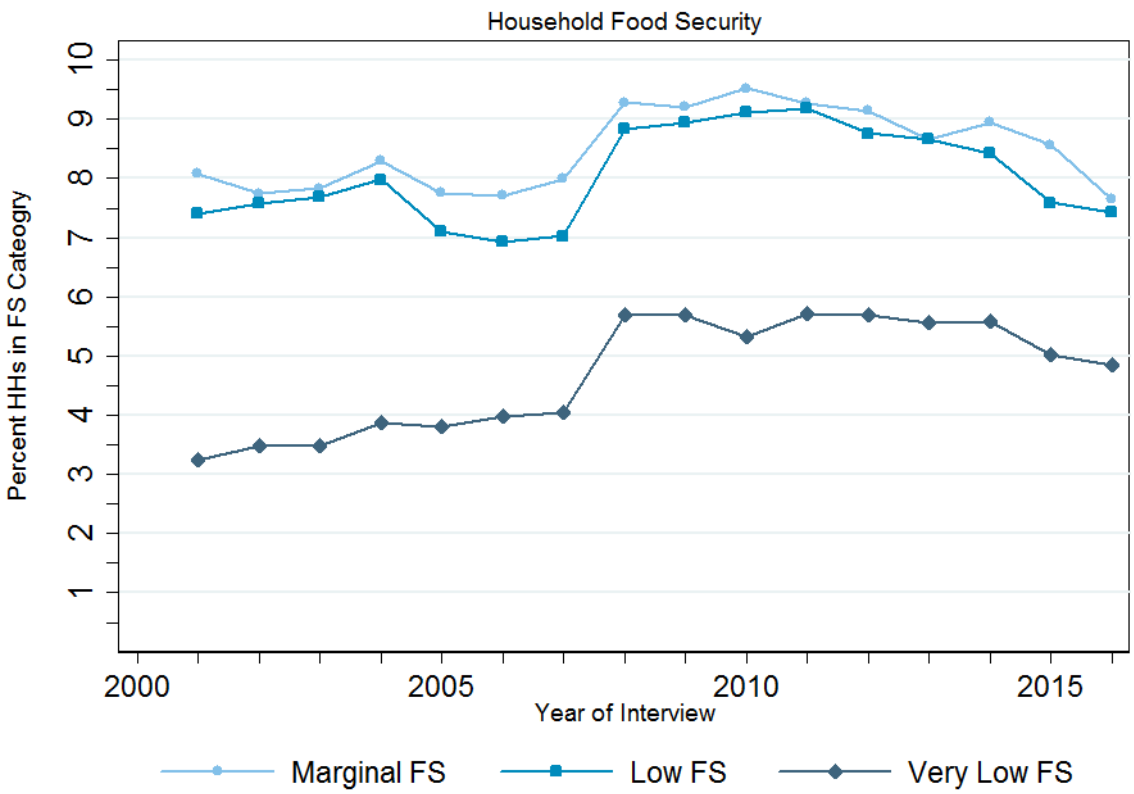


Figure 2.9: Household Food Security by Medicaid Expansion

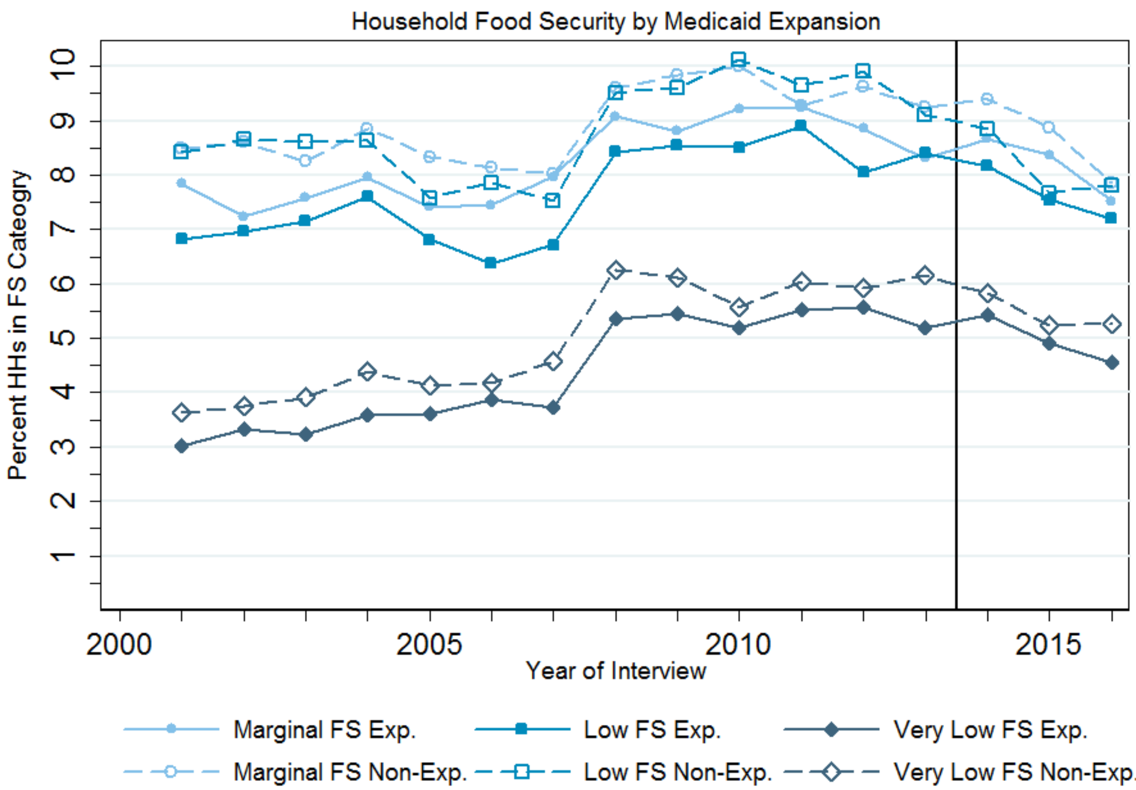


Figure 2.10: Mean of FI Gap

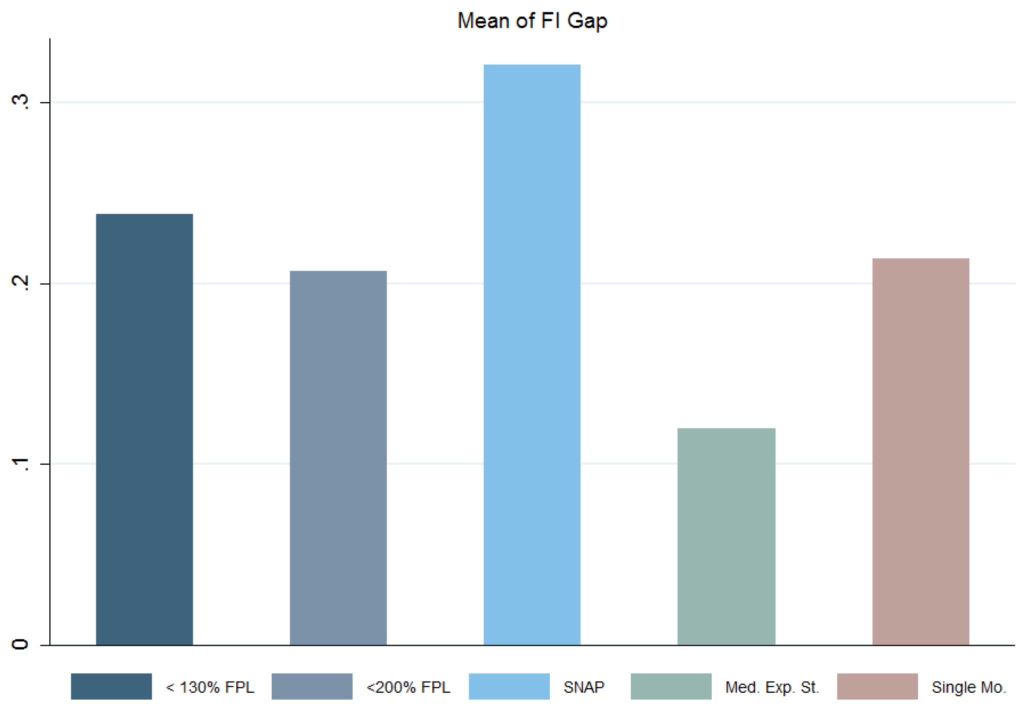


Figure 2.11: Mean of Income Gap

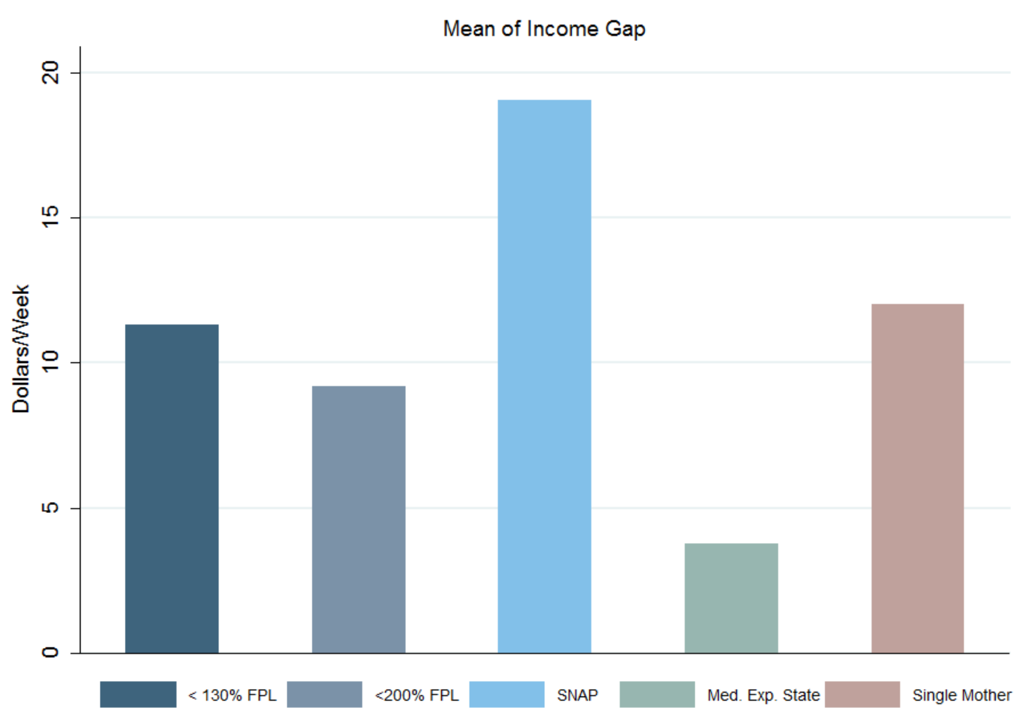


Table 2.1: Food Insecurity Questions

1	"We worried whether our food would run out before we got money to buy more." Was that often, sometimes, or never true for you in the last 12 months?
2	"The food that we bought just didn't last and we didn't have money to get more." Was that often, sometimes, or never true for you in the last 12 months?
3	"We couldn't afford to eat balanced meals." Was that often, sometimes, or never true for you in the last 12 months?
4	In the last 12 months, did you or other adults in the household ever cut the size of your meals or skip meals because there wasn't enough money for food? (Yes/No)
5	(If yes to question 4) How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?
6	In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money for food? (Yes/No)
7	In the last 12 months, were you ever hungry, but didn't eat, because there wasn't enough money for food? (Yes/No)
8	In the last 12 months, did you lose weight because there wasn't enough money for food? (Yes/No)
9	In the last 12 months did you or other adults in your household ever not eat for a whole day because there wasn't enough money for food? (Yes/No)
10	(If yes to question 9) How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?
	Questions 11-18 were asked only if the household included children age 0-17
11	"We relied on only a few kinds of low-cost food to feed our children because we were running out of money to buy food." Was that often, sometimes, or never true for you in the last 12 months?
12	"We couldn't feed our children a balanced meal, because we couldn't afford that." Was that often, sometimes, or never true for you in the last 12 months?
13	"The children were not eating enough because we just couldn't afford enough food." Was that often, sometimes, or never true for you in the last 12 months?
14	In the last 12 months, did you ever cut the size of any of the children's meals because there wasn't enough money for food? (Yes/No)
15	In the last 12 months, were the children ever hungry but you just couldn't afford more food? (Yes/No)
16	In the last 12 months, did any of the children ever skip a meal because there wasn't enough money for food? (Yes/No)
17	(If yes to question 16) How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?
18	In the last 12 months did any of the children ever not eat for a whole day because there wasn't enough money for food? (Yes/No)

Table 2.2: Summary Statistics by Medicaid Expansion and SNAP Receipt

	ACA		No ACA	
	SNAP	No SNAP	SNAP	No SNAP
<130% Pov. Line	0.75	0.13	0.76	0.15
<185% Pov. Line	0.85	0.22	0.87	0.26
<200% Pov. Line	0.88	0.24	0.90	0.28
WIC	0.29	0.08	0.27	0.08
Free Lunch	0.82	0.36	0.83	0.36
Free Break.	0.81	0.69	0.87	0.77
Age	44.15	50.44	43.99	49.95
High School	0.36	0.28	0.36	0.29
Some College	0.27	0.28	0.26	0.29
College	0.06	0.34	0.05	0.30
Hisp	0.21	0.11	0.19	0.11
White	0.67	0.83	0.61	0.82
Black	0.26	0.10	0.35	0.14
Unemp.	6.86	6.55	6.43	6.05
ln(50/10)	1.63	1.65	1.53	1.54
25th pctile	17010.58	17153.87	16145.02	16252.44
Emp./Pop.	0.46	0.47	0.46	0.46
Num. in HH	3.04	2.48	3.07	2.43
Num. Child	1.06	0.52	1.05	0.50
Female	0.68	0.48	0.69	0.47
Married	0.26	0.53	0.27	0.54
Metro	0.82	0.87	0.74	0.80
Obs.	34,057	422,632	21,365	231,340

Note: Household survey weights used.

Table 2.3: IV Summary by Medicaid Expansion

	Medicaid Expansion	Non-Expansion
Broad Based Categorical Eligibility	0.56	0.50
	(0.49)	(0.49)
Excl. All Vehicles	0.72	0.57
	(0.43)	(0.49)
Higher Vehicle Exemption	0.03	0.29
	(0.15)	(0.45)
Requires Fingerprinting	0.23	0.13
	(0.42)	(0.33)
Child Non-Cit. Elig	0.89	0.86
	(0.30)	(0.33)
Adult Non-Cit. Elig	0.27	0.06
	(0.44)	(0.23)
Online Application	0.57	0.55
	(0.48)	(0.48)
Digital Signiture	0.41	0.49
	(0.48)	(0.49)
Max SNAP Benefit	3.60	3.56
	(1.55)	(1.50)
ln(Min. Wage)	1.95	1.87
	(0.12)	(0.09)

Note: Household survey weights used.

Table 2.4: First Stage Results, Food Rank Second Stage Dependent Variable

	SNAP (1)	ACA × SNAP (2)
Broad Based Categorical Eligibility	0.008	−0.004**
	(0.006)	(0.002)
Excl. All Vehicles	0.002	−0.001
	(0.006)	(0.002)
Higher Vehicle Exemption	−0.002	0.001
	(0.012)	(0.002)
Requires Fingerprinting	−0.003	0.009
	(0.008)	(0.006)
Child Non-Cit. Elig	0.012	−0.003
	(0.012)	(0.002)
Adult Non-Cit. Elig	−0.002	0.001
	(0.014)	(0.002)
Online Application	−0.001	−0.003*
	(0.006)	(0.002)
Digital Signiture	0.007	0.001
	(0.007)	(0.002)
Max SNAP Benefit	0.017***	−0.003***
	(0.003)	(0.000)
ln(Min. Wage)	−0.032	−0.008
	(0.027)	(0.011)
ACA × BBCE	−0.004	0.042*
	(0.010)	(0.021)
ACA × Excl. All Vehicles	0.003	−0.016
	(0.014)	(0.021)
ACA × Fingerprint	0.004	−0.053***
	(0.013)	(0.012)
ACA × Online App.	0.024	−0.083
	(0.048)	(0.068)
ACA × Adult Non-Cit. Elig	0.051**	−0.084**
	(0.021)	(0.033)
ACA × Digital Sig.	0.005	0.024
	(0.016)	(0.019)
ACA × Max SNAP Benefit	−0.026***	0.030***
	(0.002)	(0.005)
ACA × ln(Min. Wage)	−0.039	0.212***
	(0.052)	(0.066)
F Stat.	75.4488	3,145.5295
	(0.0000)	(0.0000)
Obs.	290,707	290,707

Note: standard errors clustered at the state level, * p <0.10, ** p <0.05, *** p <0.01. Household survey weights used. Controls include gender, household size, number of children, marital status, age, age squared, disability status, race, education, urban/rural status, number of medicaid beneficiaries in the state, governor party affiliation, the 50/10 income ratio, the 25th percentile of income, and the unemployment rate. F statistic p-value in parentheses.

Table 2.5: Ordered Probit Coefficients and Marginal Effects: Two-Stage

	Coeffs. (1)	Marginal FS (2)	Low FS (3)	Very Low FS (4)
ACA	0.082	0.006	0.014	0.013
	(0.051)	(0.003)	(0.009)	(0.008)
SNAP	-0.940^{***}	-0.064^{***}	-0.160^{***}	-0.150^{***}
	(0.230)	(0.016)	(0.039)	(0.037)
ACA × SNAP	-0.481^{***}	-0.033^{***}	-0.082^{***}	-0.077^{***}
	(0.165)	(0.011)	(0.028)	(0.026)
Obs.	284,804	284,804	284,804	284,804

Note: standard errors clustered at the state level, * p <0.10, ** p <0.05, *** p <0.01. Ordering for probit is 0—fully food secure, 1—marginal food security, 2—low food security, 3—very low food security. Household survey weights used. Controls include gender, household size, number of children, marital status, age, age squared, disability status, race, education, urban/rural status, number of medicaid beneficiaries in the state, governor party affiliation, the 50/10 income ratio, the 25th percentile of income, and the unemployment rate

Table 2.6: Triple Difference LPM: IV

	Food Insecure (1)	Marginal FI (2)	Very Low FI (3)
ACA	0.030	−0.015	0.058
	(0.038)	(0.035)	(0.038)
SNAP	-0.184^{***}	0.332^{***}	-0.743^{***}
	(0.055)	(0.081)	(0.079)
ACA × SNAP	-0.172^{**}	-0.265^{***}	−0.044
	(0.086)	(0.088)	(0.103)
Under ID Kleibergen	27.4528	27.4528	27.4528
	(0.0518)	(0.0518)	(0.0518)
Hansen J	20.9529	23.7661	14.8943
	(0.1803)	(0.0947)	(0.5324)
Obs.	284,804	284,804	284,804

Note: standard errors clustered at the state level, * p <0.10, ** p <0.05, *** p <0.01. P-values in parentheses for first stage statistics. Household survey weights used. Controls include gender, household size, number of children, marital status, age, age squared, disability status, race, education, urban/rural status, number of medicaid beneficiaries in the state, governor party affiliation, the 50/10 income ratio, the 25th percentile of income, and the unemployment rate

Table 2.7: ACA Mechanisms

	Avg. Weekly Spending (1)	SNAP Take-Up LPM (2)	SNAP Take-Up Probit (3)
ACA	-21.628^{**}	0.078^{***}	0.276^{***}
	(10.144)	(0.009)	(0.033)
SNAP	164.315^{***}		
	(26.972)		
ACA × SNAP	59.863^{*}		
	(31.171)		
Obs.	96,522	290,707	290,707

Note: standard errors clustered at the state level, * p <0.10, ** p <0.05, *** p <0.01. Household survey weights used. Controls include gender, household size, number of children, marital status, age, age squared, disability status, race, education, urban/rural status, number of medicaid beneficiaries in the state, governor party affiliation, family income (spending), the 50/10 income ration, the 25th percentile of income, and the unemployment rate. Years for spending 2011-2016.

Table 2.8: Alternative Measures of Food Hardship

	FI Gap (1)	FI Gap Squared (2)	Inc. Gap (3)
ACA	0.069^{**}	0.072^{***}	0.181
	(0.030)	(0.027)	(1.596)
SNAP	-0.423^{***}	-0.327^{***}	16.683^{**}
	(0.060)	(0.052)	(7.995)
ACA × SNAP	-0.161^{**}	-0.173^{**}	-6.921
	(0.079)	(0.074)	(5.005)
Under ID Kleibergen	28.0890	28.0890	27.7125
	(0.0439)	(0.0439)	(0.0484)
Hansen J	17.8778	17.3594	13.6181
	(0.3311)	(0.3627)	(0.6271)
Obs.	194,565	194,565	264,521

Note: standard errors clustered at the state level, * p <0.10, ** p <0.05, *** p <0.01. P-values in parentheses for first stage statistics. Household survey weights used. Controls include gender, household size, number of children, marital status, age, age squared, disability status, race, education, urban/rural status, number of medicaid beneficiaries in the state, governor party affiliation, the 50/10 income ratio, the 25th percentile of income, and the unemployment rate

Chapter 3: Fiscal Structure and Program Response Over the Business Cycle

3.1 Introduction

The funding and administration of the social safety net requires the coordination and cooperation of many layers of government. The structure of this decentralized federal system is rarely a topic of popular concern. However, there has been a large resurgence in interest in how both states and the federal government fund programs like Medicaid, SNAP (the Supplemental Nutrition Assistance Program, also known as food stamps), and SSDI (Social Security Disability Insurance). While ultimately not adopted, President Donald Trump's proposed budget for 2018 included massive redesigns of the funding mechanisms for both Medicaid and SNAP, converting open-ended matching grants, where each dollar of state spending is matched by federal spending, into fixed federal allotments to states, known as block grants. This desire to change fiscal structure is reiterated in the Welfare Reform and Upward Mobility Act proposed by Congressman Jim Jordan and Senator Mike Lee. These large scale funding reforms echo back to the Clinton era welfare reforms of the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA), where cash welfare was reformulated from the matching grant entitlement program, Aid to Families with Dependent Children (AFDC) to the block grant program, Temporary Assistance for Needy Families (TANF).

Fiscal structure is a crucial component of program design, and has a direct impact on the provision of benefits. Safety net programs provide support to low-income families, and act as a buffer against the consequences of economic downturns. The Great Recession of 2008 put unprecedented strain on the modern safety net, with the national unemployment rate reaching double digits, and millions of jobs lost. These lost jobs cost many families their access to medical care and caused enrollment in publicly provided health insurance and other programs to greatly increase. Cawley et al. (2015) note that enrollment in Medicaid, which is funded through a matching grant, increased by 12.6 million, or 33.1% between 2005 and 2011. For SNAP, a federally funded program with administrative costs shared equally at the state and federal level, the increase was 9.8 million caseloads, or approximately 88%.[1] The total number of families enrolled in TANF actually decreased by 152,488 families, or about 7%, showing large differences in the responsiveness of programs to business cycles.

In this paper, I explain these disparities in responsiveness by analyzing the role of fiscal structure. I examine two programs—Medicaid, a matching grant funded program, and the State Children's Health Insurance Program (SCHIP), a block grant funded program. I examine two specific types of program response. The first is the overall change in the number of beneficiaries due to a change in economic conditions. The second is the degree of cross-program substitution due to a change in business cycle indicators. The first type of response is relatively straightforward. If economic conditions worsen, demand for program benefits may increase. Moreover, in economic downturns, states may face pressure to decrease expenditure due to diminished funding. Block grants provide a set amount for program funding, with a marginal price of 1 to states for every dollar spent above some pre-specified allotment. If the increase in demand for benefits is enough for states to exceed this allotment, or if states are trying to reduce overall expenditure, it becomes more expensive to provide benefits to the marginal beneficiary in a block grant funded program.

The second type of response is a direct consequence of the first type. If providing benefits through the block grant funded program is more expensive, states may substitute generosity toward relatively cheaper programs, i.e. matching grant funded

[1]https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap

programs. Since the number of beneficiaries can be affected not only through the amount of funds provided for benefits, but also from increased demand for benefits due to poor economic conditions, I estimate both the impact of state expenditure and the impact of economic conditions (through the unemployment rate) on the probability an individual receives benefits.

First, I use administrative enrollment data at the state-year level for fiscal years 1999 to 2015 to examine effect of business cycles on program Medicaid and SCHIP enrollment. I find that block grant funding decreases the ability of public assistance programs to respond to economic downturns. A one percentage point increase in the unemployment rate leads to an 8% decrease in the number of beneficiaries per person enrolled in block grant funded programs, and no change in the number of beneficiaries per person enrolled in a matching grant program.

Next, I use two-year matched panels from the 2000-2015 Current Population Survey Annual Social and Economic Supplement (ASEC) to examine how business cycles and state funding affect the probability of enrollment for a given individual. I find a one percentage point increase in the unemployment rate leads to a 0.4 percentage point increase in the overall probability of being enrolled in a matching grant funded program, with no change in enrollment probability for block grant funded programs. I find that a 10% decrease in state expenditure per person decreases the probability of enrollment in a block grant program by 0.5 percentage points, and decreases the probability of remaining enrolled in the block grant program by 1.4 percentage points. I find little evidence for cross-program substitution due to increased demand for program benefits, with the unemployment rate not increasing the probability of transitioning from a block grant program to a matching grant program. However, I find that enrollment is much more persistent among matching grant funded programs, and being enrolled in a block grant funded program last period increases the probability of enrolling in a matching grant program this period 70% more than remaining enrolled in the block grant funded program.

These two data sources jointly suggest an important role to be played by fiscal structure. I find evidence that block grant funded programs struggle to respond in economic downturns, and that decreases in state expenditure lead to large decreases in enrollment. I also find that enrollment in block grant programs is uniformly more variable than enrollment in matching grant programs. This suggests that funding structure can play an important role in the accessibility and stability of the safety net over the business cycle.

3.2 Background

I focus on Medicaid and SCHIP as the exemplary cases of fiscal structure. In 2016, federal Medicaid spending was $350 billion, state spending was $200 billion, with total spending ($550 billion) equivalent to 3% of national GDP. As of April 2017, 75 million individuals were enrolled in Medicaid and SCHIP. These programs play enormous roles in the financing of state governments and the provision of benefits to low income individuals. Medicaid and SCHIP provide subsidized health insurance to low income adults and children, especially in times of economic distress. Moreover, Republican policy makers have been increasingly calling for the reformulation of Medicaid into a block grant funded program.

Recent policy proposals have placed Medicaid benefits and expenditure in the public spotlight. While these proposals have called for the reformulation of Medicaid into a block grant, the idea is far from new. Lambrew (2005) notes that the first call for reformulation came in 1981 during the Reagan administration, and was re-proposed by then Speaker of the House Newt Gingrich in 1995, and again by President George W. Bush in 2003. The primary concern during current and previous debates centers on the need for guaranteed provision of healthcare to needy populations, such as low income children, pregnant mothers, the disabled, and the elderly. Lambrew (2005) notes two primary reasons for the support of block grant funding, the first being the federalist structure of block grants, which gives states greater control in program administration. The second is the ability of block grants to limit the "uncontrollable" aspects of entitlement programs.

Medicaid is currently jointly financed by federal and state governments through the Federal Medical Assistance Percentage (FMAP), which is defined as

$$FMAP = 1 - [\frac{(\text{State Per Capita Income})^2}{(\text{National Per Capita Income})^2} \times 0.45] \tag{3.1}$$

where income is calculated as a lagged 3 year moving average. Through this matching grant structure, the federal government finances a minimum of 50% of Medicaid expenditures, with some states having matching rates of near 3:1.[2] If the state has a severe income shock (as during a recession) relative to the rest of the nation, the matching rate will increase in response, acting as counter-cyclical funding mechanism. However, the moving average of income often makes this response slow.

While there have been calls to reformulate Medicaid into a block grant program, the State Children's Health Insurance Program was designed with a block grant structure. SCHIP was created as part of the Balanced Budget Act of 1997; the program can act independently or as a form of Medicaid expansion, and covers low income children whose family income puts their family over the income limit for Medicaid eligibility. State funds spent on SCHIP are matched by federal funds at a higher rate than Medicaid through a formula known as the Enhanced Federal Medical Assistance Percentage (EFMAP), which is a monotonic transformation of the FMAP.[3] In 2015, 8 states, 5 territories, and the District of Columbia operated Medicaid expansion

[2]While the legislated ceiling is 83%, matching rates have stayed well below this threshold in recent years.

[3]The EFMAP covers an additional 30 percent of the gap between the FMAP reimbursement rate and a 100 percent reimbursement rate, but may not exceed 85 percent. $EFMAP = FMAP + .3(1 - FMAP)$

SCHIP programs, 29 states operated combination standalone and Medicaid expansion programs which combine SCHIP and Medicaid funds, and 13 states operated standalone programs.[4]

However, unlike Medicaid, the total funds available for SCHIP are capped through a block grant, with funding set at only $5 billion per year until 2009. While a redistribution formula exists to reallocate funds from low spending states to high spending states, once funds are exhausted, new funds can only be raised through new legislative action. Thus, while SCHIP is not a standard block grant due to its matching component, the low level of capped funding coupled with the overall level of state expenditure guarantees that, at least in recent years, states hit the federal allotment. For example, in 2016, the federal budget allotment was $14,426 million for SCHIP,[5] but federal spending was $14,445.1 million,[6] requiring the federal government to utilize the Child Enrollment Contingency Fund, a fund created to address funding shortfalls for SCHIP.

Much of the literature on SCHIP has focused on how the introduction of SCHIP, or SCHIP expansions, have affected healthcare coverage. Lo Sasso and Buchmueller (2004) find that SCHIP expansions increase coverage, at the expense of private crowd out. Crowd out is corroborated by Buchmueller et al. (2005). Leininger et al. (2010) find that, although there may be crowd out, SCHIP improves material well-being of near-poor households.

The program parameters are similar between Medicaid and SCHIP, with income limits and fiscal federalism playing a large role. Table 3.1 shows income eligibility levels for all states in 2016. Income limits for SCHIP were lowest in North Dakota at 170% of the federal poverty line (FPL), and highest in New York at 400% FPL. In

[4]https://www.medicaid.gov/chip/downloads/chip-map.pdf

[5]https://www.hhs.gov/about/budget/fy2017/budget-in-brief/cms/chip/index.html

[6]https://www.macpac.gov/wp-content/uploads/2015/01/EXHIBIT-32.-CHIP-Spending-by-State-FY-2016-millions.pdf

comparison, Medicaid has a mandated minimum eligibility of 133% FPL, and Iowa had the highest income limits at 375% FPL. Some states have very similar thresholds for Medicaid and SCHIP, such as Louisiana where the Medicaid threshold is 212% FPL for all children, and 250% FPL for separate SCHIP coverage. Some states have a wide gap in coverage thresholds, such as New Jersey, where the Medicaid threshold is 142% FPL for children above 1 year of age, and 350% for SCHIP.

Cawley and Simon (2005) and Cawley et al. (2015) study how insurance, both public and private, respond to business cycles, finding children were actually more likely to enroll in Medicaid as the unemployment rate increased during the Great Recession, and that Medicaid provided a buffer against declining employer coverage during a contraction. Buchmueller et al. (2014) find that insurance coverage stability plays a large part in healthcare utilization among children, and that those children who transition to public insurance have higher rates of utilization than those who transition to no insurance, suggesting the counter cyclicality of Medicaid provides much needed stability for children.

Determining the cause of responsiveness (or lack thereof) can be difficult. Many have noted that some programs are more responsive to business cycles than others. Bitler and Hoynes (2015) and Bitler and Hoynes (2010) both note that non-cash programs are more responsive than cash programs like AFDC/TANF. McGuire and Merriman (2006), Ziliak et al. (2000), and Figlio and Ziliak (1999) all examine the role of business cycles and various policies that might impact the responsiveness of AFDC/TANF. These papers note that some components of program administration determine sensitivity to business cycles, but the large differences that exist across these programs make it difficult to pin down the exact mechanism driving responsiveness.

Fiscal structure could potentially explain a large degree of the disparity in program response, with the difference in fiscal structure between Medicaid and SCHIP creating two important differences in the way programs respond to business cycles. The first is the difference in the provision of benefits during economic downturn. Ribar and Wilhelm (1999) examine the implications of block grants for cash benefits, and find only small changes in the overall level of benefits. In contrast, Marton and Wildasin (2007a) and Chernick (1998) predict large changes in overall benefits resulting from fiscal structure. Chernick (1998) estimates that the change in fiscal structure could reduce overall benefits from 15-30%.

States can change Medicaid and SCHIP benefits in a few ways. States are federally required to cover "mandatory benefits" to qualify for federal support, with some leeway in the type, amount, duration, and scope of services.[7] Cardwell et al. (2014) provide an overview of different state SCHIP programs, and note that 38 states and the District of Columbia provided similar benefits to Medicaid. States can change the types of services that are covered and rates of publicly provided coinsurance to alter the bundle of medical goods recipients consume.

States can also change the level of benefits by adjusting the number of beneficiaries through program parameters. For SCHIP, states can limit the number of recipients by introducing waiting periods for benefits, enrollment caps, or requiring premiums. While waiting periods have become increasingly uncommon, 37 states imposed waiting periods for SCHIP benefits in 2013.[8] Hill et al. (2007) note that seven states introduced enrollment caps during the recession of the early 2000s, but maintenance of effort requirements do not allow the implementation of new SCHIP enrollment caps. While waiting periods and enrollment caps are not permitted in Medicaid without a waiver, states can limit the number of recipients through restrictions in the eligibility thresholds (states can do this for SCHIP as well). However,

[7] https://www.medicaid.gov/medicaid-chip-program-information/by-topics/benefits/medicaid-benefits.html

[8] https://www.macpac.gov/subtopic/key-design-features/

this makes it more difficult for states to directly impact the number of Medicaid recipients. States cannot require premiums in Medicaid without a waiver, however, in 2013, 33 states required SCHIP premiums, often tied to family income, ranging from around $10-$30 per month.[9] Recently, states have been permitted to request waivers for work requirements for Medicaid benefits. CMS has approved a work requirement waiver for Kentucky, with nine other states submitting work requirement proposals.[10]

The second difference in the way provision of program benefits could change due to fiscal structure and business cycle pressure is cross-program substitution. Marton and Wildasin (2007b) predict that the additional constraints placed on states by block grant funding might give rise to cross-program substitution, substituting toward greater generosity in programs funded through a matching component. Schmidt and Sevak (2004) find empirical evidence of cross-program substitution for cash welfare and Supplemental Security Income due to the reformulation of cash welfare. Calsamiglia et al. (2013) suggest that the way states respond to fixed levels of federal funding could have a large impact on overall social welfare.

Cross-program substitution has already been shown with Medicaid and SCHIP in other contexts. Kenney et al. (2006) and Marton (2007) thoroughly document how the introduction of premiums in SCHIP programs not only reduced enrollment in SCHIP, but also encouraged transition into Medicaid. The introduction of premiums in SCHIP increased the probability of subsequent Medicaid take-up ranging from 0.68% to 7% (Kenney et al., 2007; Marton and Talbert, 2010; Marton et al., 2010).

Clemens and Ippolito (2017) provide a modern exploration of the effect of fiscal structure on the state financing of Medicaid, explicitly examining how block grant funding might impact public health insurance. The authors compare the current

[9] https://www.macpac.gov/subtopic/key-design-features/

[10] AR, AZ, IN, KS, ME, NH, UT, and WI. https://www.kff.org/medicaid/issue-brief/medicaid-and-work-requirements-new-guidance-state-waiver-details-and-key-issues/

matching grant fiscal structure with three different block grant style financing structures: a status-quo block grant, a uniform need-based grant, and per-beneficiary allotments. The latter two differ from traditional block grants by incorporating mechanisms to increase program responsiveness during recessions. With the uniform need-based grant, funds can be redistributed across states based on a need-based income scaling factor (this is similar to the redistribution formula used in SCHIP). The per-beneficiary allotment has a counter-cyclical mechanism by its very nature; the level of funding increases as the number of beneficiaries increases. The authors simulate Medicaid responsiveness to business cycles across regimes, and even incorporate additional federal intervention to provide additional counter-cyclical support in the form of a scaling factor based on deviations from the natural rate of unemployment. They find that without additional counter-cyclical mechanisms, many states would require large increases in state expenditure to maintain current levels of overall spending. Even with the additional scaling factor, overall federal funding decreases, requiring additional state level expenditure.

Clemens and Ippolito (2017) make two especially relevant points about the implications of switching Medicaid from a matching grant to a block grant. (1) The overall level of federal funding decreases, and (2) that many states face large funding shortfalls that must be made up from own-revenue sources. The authors, however, place relatively little emphasis on the impact on beneficiaries, leaving the question of the effect on overall benefits unanswered. Moreover, much of their analysis hinges on the idea that the federal government would consider additional counter-cyclical mechanisms to support Medicaid. If 20 years of evidence from TANF financing is any indication, not only is additional support highly unlikely (although funding did increase during the Great Recession), even inflation-adjusted increases in expenditure are off the table. Taken together, these facts suggest that there might be large, negative consequences for beneficiaries, especially in states where budgetary pressures are strongest.

This paper then answers the other question suggested by Clemens and Ippolito (2017); if state budgets are sensitive to the fiscal structure of assistance programs, what is the overall impact for beneficiaries? This question builds on the literature describing the effect of business cycles on the safety net by examining a specific mechanism that determines program responsiveness—fiscal structure. Thus, it also contributes to the literature examining the role of fiscal structure for safety net programs, and provides one of only a few modern empirical assessments. Finally, by utilizing public health insurance as the demonstrative programs, this paper also contributes to the literature describing the implications surrounding the provision of public health insurance during recessions.

3.3 Model

3.3.1 A Simple Model of State Health Care Expenditures

I examine the differential response of block grant and matching grant programs by comparing SCHIP and Medicaid. Ideally, I would be able to compare all safety net programs while controlling for funding structure, or look within a given program for quasi-experimental variation that would allow me to identify the impact of funding. Practically, the large differences in program benefits, administration, and benefit populations make this comparison infeasible. The second alternative is to compare individuals across programs with differing funding structures, which has been done in some theoretical applications. Empirically, the difficulty in identifying the impact is much the same as looking within a program. Vast differences exist not only in the type of benefits provided by different programs, but also among recipients and the reasons they apply for assistance in the first place. Thus, an empirical comparison of a block grant funded program like TANF with a matching grant funded program like Medicaid would fail to adequately control for these differences. Utilizing SCHIP and

Medicaid allows me to mitigate some of these concerns due to the similarity of the programs.

I present a simple model to provide intuition for differential response, derived from Gramlich et al. (1982). The state chooses taxes and expenditure on Medicaid and SCHIP to maximize the utility of the representative voter subject to the state's budget constraint.

$$\max_{t,E_m,E_s} U((1-t)y, \alpha(E_m+E_s)) \tag{3.2}$$

$$\text{s.t.}$$

$$G_s + tY = (1-FMAP)E_m + E_s \tag{3.3}$$

Where the voter derives utility from disposable income, $(1-t)y$, and the overall level of benefits provided for public healthcare, represented by total expenditure on Medicaid and SCHIP, (E_m+E_s) (with utility weight α). The state's budget constraint is defined by Y, state income, t, a proportional tax rate encompassing federal and state taxes, and G_s, a block grant for SCHIP benefits. Here, I simplify the model so that the state pays some fixed fraction of healthcare costs E_i for both Medicaid and SCHIP recipients. Taxpayers pay the unmatched portion of expenditure on Medicaid, $(1-FMAP)E_m$, but also finance the federal share through taxes t.

Rather than explicitly modeling the nature of program benefits, I simplify the model with the state choosing program expenditure, which approximates how states allocate resources across programs. This term should be viewed as average expenditure across program beneficiaries. Ultimately, the state chooses some average level of expenditure as a function of benefits and recipients and pays the unmatched portion. This expenditure term captures not only average expenditure, but average generosity as well. In this formulation, the state has no incentive to spend less than the block grant on SCHIP since $U(\cdot)_{E_s} > 0$, thus $E_s \geq G_s$. After the state has reached the block grant allotment, the state will spend the marginal dollar on SCHIP if

$$\begin{aligned} &U((1-t)y, \alpha(E_m + E_s + \epsilon)) - (1 - FMAP)E_m - \epsilon > \\ &U((1-t)y, \alpha(E_m + \epsilon + E_s)) - (1 - FMAP)(E_m + \epsilon) \end{aligned} \tag{3.4}$$

meaning the utility, less costs for additional expenditure, ϵ, on SCHIP outweighs the utility, less costs, for expenditure on Medicaid. Since the utility weights are the same for both SCHIP and Medicaid in (3.2), (3.4) simplifies to

$$-(1 - FMAP)E_m - \epsilon > -(1 - FMAP)(E_m + \epsilon)$$

implying

$$FMAP < 0 \tag{3.5}$$

or that the federal government charges states to provide Medicaid benefits rather than subsidizing them. Thus, the state ends up at a corner solution, where the full allotment of the block grant for SCHIP is spent, and each additional dollar the state spends is directed toward Medicaid rather than SCHIP.

Suppose then that the state receives an economic shock, such that the demand for public health care benefits increases. As the block grant for SCHIP financing is exhausted, the state has the incentive to reduce expenditure on SCHIP such that $E_s = G_s$. This implies that there is increased pressure to reduce the number of enrollees in SCHIP, and increase the number of enrollees in Medicaid, with potential for cross-program substitution, where children leave SCHIP rolls for Medicaid rolls. This result is the key theoretical prediction of this paper. Since the marginal cost of providing benefits is lower for matching grant programs (assuming block grant programs have exhausted the pre-allotted funding), states prefer to provide benefits through matching grant programs during tough economic conditions.

3.3.2 Empirical Model

I will utilize two classes of models to analyze fiscal structure. The first set examine outcomes at the state level, looking at overall levels of enrollment across states. These models have the benefit of analyzing aggregate trends, and avoid attenuation bias that may result from individual under-reporting. However, I am limited in the number of factors I am able to control for that might determine benefit take-up. I examine the responsiveness of SCHIP and Medicaid to the unemployment rate. Here, an increase in the unemployment rate represents a negative economic shock, and has been shown to be predictive of insurance status (Cawley and Simon, 2005). I estimate two equations of the form

$$ln\left(\frac{\text{Medicaid}_{jt}}{\text{Population}_{jt}}\right) = \beta_1 \text{Unemp}_{jt} + X\beta_2 + \mu_{1j} + \mu_{1t} + \eta_{jt} \tag{3.6}$$

$$ln\left(\frac{\text{SCHIP}_{jt}}{\text{Population}_{jt}}\right) = \delta_1 \text{Unemp}_{jt} + X\delta_2 + \mu_{2j} + \mu_{2t} + \varepsilon_{jt} \tag{3.7}$$

where Medicaid_{jt} is child enrollment in Medicaid in state j at time t, SCHIP_{jt} is enrollment in SCHIP in state j at time t, Unemp_{jt} is the unemployment rate, and X is a vector of state characteristics, including the FMAP, governor party affiliation, and the growth rate of employment per capita, μ_j is a state fixed effect, and μ_t is a time fixed effect. I also include the number of National School Lunch Program (NSLP) and National School Breakfast Program (NSBP) recipients per person in X. Many states use NSLP and NSBP rolls to reach out to families about potential eligibility for either SCHIP or Medicaid benefits. The state fixed effect controls for time invariant differences in states such as economic infrastructure that affects program participation, while the time effect controls for macroeconomic and policy changes that affect all states equally, such as changes to federal SCHIP or Medicaid policy. This analysis is similar to estimates on the cyclicality of safety net programs

(Figlio and Ziliak, 1999; Ziliak et al., 2000; Blank, 2001; Bitler and Hoynes, 2010, 2016).

Where this analysis differs from previous estimates is in the interpretation of the comparison of the coefficients on the unemployment rate. Equation (3.4) suggests that the level of benefits for Medicaid should increase relative to the benefits of SCHIP, implying $\beta_1 > \delta_1$ as a direct result of the fiscal structure of these programs. By using a logarithmic transformation, these coefficients are interpretable as the percent change in enrollment per capita resulting from a one percentage point change in the unemployment rate.

The second set of models I consider examine how individuals respond to state level macroeconomic shocks. These models allow me not only to control for more covariates, but also allow me to examine the transition patterns of individuals after they are exposed to these shocks. While equation (3.4) suggests that enrollment in block grant programs should decrease relative to enrollment in matching grant program, it is agnostic about whether these individuals will lose benefits all together, or whether they will transfer from the block grant program to the matching grant program. However, there is theoretical and empirical evidence suggesting that some form of cross-program substitution could result from changing fiscal structure. As mentioned previously, Marton and Wildasin (2007b) suggest, specifically in the context of public health care, that a change from a matching grant structure to a block grant structure could result in increased generosity and participation in a matching grant program. Schmidt and Sevak (2004) examine the impact of welfare reform, and find that mothers in states that implemented major waivers as part of welfare reform (which included reformulation into a block grant structure) were more likely than other mothers to receive SSI benefits. While Schmidt and Sevak (2004) are unable to directly attribute this increase to fiscal structure, their results suggest that cross-program substitution may be a result of the way programs are funded. I adapt this approach to an analogous difference-in-differences style framework.

$$\begin{aligned}\text{Medicaid}_{ijt} &= \kappa_1 \text{SCHIP}_{ij(t-1)} + \phi_1 \text{Econ Ind}_{jt} \\ &\quad + \rho_1 \text{SCHIP}_{ij(t-1)} \times \text{Econ Ind}_{jt} + X\xi_1 + \mu_{3j} + \mu_{3t} + \nu_{1ijt}\end{aligned} \tag{3.8}$$

$$\begin{aligned}\text{SCHIP}_{ijt} &= \kappa_2 \text{SCHIP}_{ij(t-1)} + \phi_2 \text{Econ Ind}_{jt} \\ &\quad + \rho_2 \text{SCHIP}_{ij(t-1)} \times \text{Econ Ind}_{jt} + X\xi_2 + \mu_{4j} + \mu_{4t} + \nu_{2ijt}\end{aligned} \tag{3.9}$$

$$\begin{aligned}\text{Uninsurance}_{ijt} &= \kappa_3 \text{SCHIP}_{ij(t-1)} + \phi_3 \text{Econ Ind}_{jt} \\ &\quad + \rho_3 \text{SCHIP}_{ij(t-1)} \times \text{Econ Ind}_{jt} + X\xi_3 + \mu_{5j} + \mu_{5t} + \nu_{3ijt}\end{aligned} \tag{3.10}$$

$$\begin{aligned}\text{Medicaid}_{ijt} &= \omega_1 \text{Medicaid}_{ij(t-1)} + \psi_1 \text{Econ Ind}_{jt} \\ &\quad + \gamma_1 \text{Medicaid}_{ij(t-1)} \times \text{Econ Ind}_{jt} + X\zeta_1 + \mu_{6j} + \mu_{6t} + e_{1ijt}\end{aligned} \tag{3.11}$$

$$\begin{aligned}\text{SCHIP}_{ijt} &= \omega_2 \text{Medicaid}_{ij(t-1)} + \psi_2 \text{Econ Ind}_{jt} \\ &\quad + \gamma_2 \text{Medicaid}_{ij(t-1)} \times \text{Econ Ind}_{jt} + X\zeta_2 + \mu_{7j} + \mu_{7t} + e_{2ijt}\end{aligned} \tag{3.12}$$

$$\begin{aligned}\text{Uninsurance}_{ijt} &= \omega_3 \text{Medicaid}_{ij(t-1)} + \psi_3 \text{Econ Ind}_{jt} \\ &\quad + \gamma_3 \text{Medicaid}_{ij(t-1)} \times \text{Econ Ind}_{jt} + X\zeta_3 + \mu_{8j} + \mu_{8t} + e_{3ijt}\end{aligned} \tag{3.13}$$

In equations (8)-(13), I consider transitions between three insurance states, being enrolled in Medicaid, being enrolled in SCHIP, and being uninsured. Since I am no longer estimating the impact of the economy on overall enrollment, I am able to use the negative of the natural log of state expenditure per capita (-ln(Exp/Pop)) as an additional measure of economic hardship,[11] as well as the unemployment rate. Using the negative of ln(Exp/Pop) allows for direct comparison of the coefficient on the unemployment rate, describing what happens to the probability a child is enrolled in

[11]In equations (3.6) and (3.7), enrollment is essentially price×quantity, and state expenditure is essentially price, using expenditure would result in endogeneity issues.

a given insurance scheme due to a negative economic shock. This analysis extends on the framework utilized by Schmidt and Sevak (2004).

A priori, the signs of κ_2 and ω_1 are unclear. These coefficients are measures of program persistence. If the cost of switching programs is high, one would expect these coefficients to be positive. κ_1 and ω_2 are measures of churn. While the direction of these is indeterminate as well, if one thinks block grant funding might make participation more tenuous regardless of economic conditions, one might expect the magnitude of κ_1 to be significantly higher than the magnitude of ω_2, suggesting significantly more churn associated with block grant funding. Program churn has been shown to not only be costly for states, but also stressful for families that are unable to rely on the stability of benefits (Mills et al., 2014).

Equation (3.4), along with results from Marton and Wildasin (2007b) and Schmidt and Sevak (2004), provide predictions about the directions of ϕ_1, ϕ_2, ψ_1, ψ_2, ρ_1, ρ_2, γ_1 and γ_2. From equation (3.4), a negative economic shock should reduce enrollment SCHIP relative to Medicaid. Thus $\phi_1 > \phi_2$ and $\psi_1 > \psi_2$. If cross-program substitution exists, ρ_1 and γ_2 should be less than zero, and ρ_2 and γ_1 should be greater than zero.

Cawley and Simon (2005) and Cawley et al. (2015) show that enrollment in public health insurance should buffer a child from economic hardship. This suggests that κ_3, ρ_3, ω_3, and γ_3 should all be negative. As economic conditions worsen, individuals already receiving public health insurance should be relatively insulated with regard to healthcare. Thus, while direction of the coefficients on the direct impact of business cycles, ϕ_3 and ψ_3 are indeterminate, the coefficients should play a small role in the probability of being uninsured.

Finally, I simplify the transitions framework into a switching model, which examines only how children switch between Medicaid and SCHIP in times of economic hardship.

$$\begin{aligned}\Delta P_{ijt} = {} & \pi_1 \text{Medicaid}_{ij(t-1)} + \pi_2 \text{SCHIP}_{ij(t-1)} + \pi_3 \text{Econ Ind}_{jt} \\ & + \pi_4 \text{Medicaid}_{ij(t-1)} \times \text{Econ Ind}_{jt} + \pi_5 \text{SCHIP}_{ij(t-1)} \times \text{Econ Ind}_{jt} \\ & + X\pi_6 + \mu_{9j} + \mu_{9t} + \omega_{ijt}\end{aligned} \tag{3.14}$$

The switching model defines the dependent variable, ΔP_{ijt}, as 1 for an individual who is in Medicaid in year 1 and SCHIP in year 2, or vice versa. ω_{ijt} is the error term, and all other variables are defined as above. This framework is similar to Ziliak and Gundersen (2016).

The switching model directly analyzes cross-program substitution due to macroeconomic shocks. Similar to the transitions models above, the simple theory and previous literature on cross-program substitution predicts $\pi_4 < 0$ and $\pi_5 > 0$, with the sign of π_1 and π_2 dependent on the innate variability of Medicaid and SCHIP. The sign of π_3 will be dependent on how the macroeconomy affects public health insurance as a whole.

The models presented above are useful in that I am able to test aspects of theory previously inaccessible empirically. I am able to provide a direct comparison between the implications of block grant funding, which is important due to the difficulty in isolating the impact of funding empirically. Moreover, by using both the unemployment rate and state expenditure, I am able to distinguish between increased demand for benefits due to poor economic conditions, and reduced supply of benefits resulting from lower expenditure during economic downturns.

3.4 Data

I utilize two primary data sources in this paper. The first is state level administrative data. Administrative data has the benefit of being the most reliable reporting of child Medicaid and SCHIP enrollment. While measurement error certainly exists in enrollment numbers, they are the official data used by CMS, and have been thoroughly vetted. The drawback to these data are that they are aggregated to the state year level, which does not allow me to control for individual characteristics. Thus, I also use individual level, self-reported enrollment data. These data are much more likely to suffer from measurement error, but include demographic characteristics that allow me to control for variables that might influence enrollment. Moreover, these data allow me to examine individual transitions into and out of programs.

State level administrative enrollment data for SCHIP and Medicaid come from the SCHIP Statistical Enrollment Data Systems (SEDS), collected through the Medicaid Budget and Expenditure System (MBES), the Medicaid Statistical Information System (MSIS), and various reports through CMS. These data characterize the number of children ever enrolled in either SCHIP or Medicaid for fiscal years 1999-2015 for all 50 states and the District of Columbia. CMS compiles these data from reports issued by individual states on forms CMS-21E, CMS-64, and CMS-64.EC. Some states report either no enrollment in SCHIP or no children enrolled in Medicaid. For example, in 2003, Tennessee eliminated its Medicaid-expansion SCHIP program, and re-implemented the program as a Medicaid-expansion standalone combination program in 2006. In other cases, the state may have just failed to report enrollment through SEDS. Some states also fail to report child Medicaid enrollment. States where either child Medicaid or SCHIP enrollment are not reported are available in table A.6 in the appendix.

To examine the role of business cycles, I collect monthly, seasonally adjusted unemployment data, as well as employment and population data, from the Bureau of Labor Statistics Local Area Unemployment Statistics collapsed to the fiscal year level. This allows me to match the timing of reporting from CMS to concurrent economic and labor market conditions in the state. In all specifications, I control for FMAP rates, which come from the U.S. Department of Health and Human Services, and vary annually by state. By controlling for the FMAP, I isolate the impact of the macroeconomy separate from the level of funding. I use data on the number of NSLP and NSBP participants per capita, as well as party affiliation of the state's governor from the University of Kentucky Center for Poverty Research National Welfare Database to adjust for any program characteristics that might be associated with state level political climate, ensuring I am not simply capturing the effect of overall state level generosity over and above a fixed effect.

These state level, administrative data provide the most reliable estimates of enrollment. Figure 3.2 shows trends in child enrollment for both Medicaid and SCHIP over a 16 year period. The early years of SCHIP are characterized by low enrollment, however, by the early 2000s, increased program demand coupled with the state redistribution formula saw a gradual increase in enrollment, with overall enrollment stable from 2008 onward.

The series for Medicaid seems more dynamic. The early 2000s demonstrate a strong upward trend in enrollment for children, flattening prior to the Great Recession (indicated by the vertical line), with the upward trend resuming in the late 2000s. However, much of the disparity in trend may be explained by the large difference in the levels of program participation. Figure 3.3 shows that the growth rate of SCHIP exceeded that of Medicaid prior to the Great Recession, with only a slightly larger growth rate for Medicaid after the Great Recession.

Figure 3.4 examines raw correlations between the unemployment rate and enrollment in SCHIP and Medicaid. The vertical axis represents the number of children enrolled in the program as a fraction of the state's population, while states are ordered on the horizontal axis by the unemployment rate. Correlations are presented for fiscal years 2004, 2007, and 2010 in order to demonstrate the lead up to, and peak of, the Great Recession. No attempt is made to discern cause and effect, with the correlations intended to motivate and anchor further estimates. As noted by McGuire and

Merriman (2006), examining the variation in macroeconomic conditions will help to identify the overall impact of block grant funding. The U.S. unemployment rate was roughly 5.5% during 2004. While December 2007 marks the beginning of the great recession, the national unemployment rate was roughly 5%, comparable to the early 2000s. February 2010 marks the end of the Great Recession, where the unemployment rate hovered around 10%.

The top left panel of figure 3.4 shows a strong positive correlation between child Medicaid enrollment and the unemployment rate in 2004. This suggests that the matching structure of Medicaid allowed states to meet the demand for public health insurance in states facing tougher economic climates. The bottom left panel suggests that SCHIP enrollment was also positively correlated with the unemployment rate, however, here the relationship is much weaker. The middle panels show a similar relationship between program enrollment and the unemployment rate in 2007 at the onset of the Great Recession.

The final two panels show the relationship during the height of the economic downturn. Here, we can see that the correlation for both Medicaid and SCHIP has attenuated somewhat. However, while there is still a discernible positive relationship between the matching grant funded program, Medicaid, the same cannot be said of the block grant funded program, SCHIP. The final panel seems to suggest that SCHIP was unresponsive to business cycles during the height of the great recession, where demand for benefits would arguably be strongest.

Figures 3.5 and 3.6 examine rates of change of enrollment as a fraction of the population. What is immediately apparent is that SCHIP is, overall, more variable than Medicaid. This could be a result of the relative youth of the SCHIP program, which had only been operating since the late 1990s, and had only firmly established rules for the redistribution of funds in 2000. While figures 3.5 and 3.6 do not speak to the causes of this variability, large changes in enrollment in SCHIP, both positive and negative, occur much more frequently than large changes in Medicaid enrollment. However, while states experiencing low unemployment relative to others have multiple instances of large increases and decreases in SCHIP enrollment, states with high unemployment rates show very few large increases in SCHIP enrollment. The final panel of figure 3.6 demonstrates this well. For the 10 states with the highest levels of unemployment (AZ-NV), 9 saw increases in the number of child Medicaid enrollees, while only 2 saw increases in the number of SCHIP enrollees.

The second primary data source I use is the 2000-2015 Current Population Survey (CPS) Annual Social and Economic Supplement, also known as the ASEC. The ASEC is also one of the few data sources to distinguish SCHIP enrollment from Medicaid enrollment. I limit my sample to only children, comparing only those 18 years of age or younger, since enrollment in SCHIP is limited to children. The ASEC provides information on age, sex, race, the marital status of adults in the family, the educational attainment of adults in the family, family size, and family structure. In 2002, the ASEC incorporated a large expansion in the sample in order to better gauge SCHIP enrollment. In 2014, the ASEC redesigned income and health insurance questions or more accurately measure household income and healthcare coverage, breaking the sample into a traditional representative sub-sample and a redesigned representative sub-sample. Based on CPS recommendations, for any weighted estimates, such as levels of enrollment or summary statistics, I only include the sample asked the redesigned questions to provide continuity with future estimates.

The sample design of the ASEC also allows for some individuals to be tracked over time. Madrian and Lefgren (2000) document the panel structure of the ASEC. Households are divided into 8 representative rotation groups, where they are interviewed for 4 consecutive months, followed by an 8 month break, and then interviewed again for 4 consecutive months. Since the ASEC is fielded every March, it is possible to match households interviewed in their first four months in sample in the subsequent year.

Following the recommended Census procedure, I first match individuals on the basis of month in sample (months 1-4 for year 1, months 5-8 for year 2), sex, household identifier, household number, and line number of the individual in the household. I then check for consistency in race, age, and state of residence. If the race or state of residence changes, or the age attributed to the record changes by more than two years (as a result of the staggered timing of the initial and final interviews) I consider those records unique individuals. This procedure is also used in Hardy et al. (2017), Burns and Ziliak (2017), Ziliak and Gundersen (2016), and others. This results in approximately one-half of individuals being observed in multiple years. By observing individuals across time, I am able to analyze cross-program substitution and continuity of enrollment in either SCHIP or Medicaid. I drop all children from the sample who have imputed values for either SCHIP or Medicaid enrollment.

Table 3.2 describes simple transition probabilities across different insurance states from the matched CPS panels. The rows of the table show what type of insurance a child had in their first year of the survey, while the columns show the type of insurance in year two conditional on year one. This means the probabilities in each row sum to one.

The diagonal of table 3.2 shows a large degree of persistence in all types of insurance, with private insurance being the most persistent. Given that they were enrolled in private insurance in year 1, children have a 92% probability of being enrolled in private insurance in year two. The Medicaid-Medicaid and SCHIP-SCHIP probabilities are 66% and 43% respectively, with Medicaid being the second most stable insurance state after private insurance. What is striking is that SCHIP is not only the least stable insurance state, but SCHIP-Medicaid transitions occur with a probability of 34%, more than any other type of cross insurance type transition. This suggests that the block grant program is highly variable, and that transitions from the block grant program to the matching grant program happen with regularity.

Figure 3.8 shows the weighted number of child recipients for both SCHIP and Medicaid by year. The weighted number of Medicaid child recipients in the ASEC is consistently lower than administrative records by approximately 10 million children per year. This suggests significant under-reporting of Medicaid receipt throughout the sample frame. This under-reporting is also demonstrated in SCHIP receipt prior to 2007. In 2007, reported enrollment increases to levels that match administrative records, but reporting decreases again in 2013. Davern et al. (2009) note that in 2007, the CPS changed the survey skip pattern for Medicaid and SCHIP questions. Prior to 2007, people who indicated they were enrolled in Medicaid were not asked about their enrollment in SCHIP. Beginning in 2007, individuals were allowed to answer both the Medicaid and SCHIP question. Census documentation seems to suggest that this skip pattern was re-introduced following the redesign in survey year 2014 (calendar year 2013)[12]. The nature of the survey questions likely accounts for the increase in SCHIP response from 2007-2013. This misclassification could potentially attenuate any results derived from the ASEC (Meyer and Mittag, 2017; Bollinger and David, 1997).

Table 3.3 presents summary statistics from the entire sample of children in the ASEC, separated by insurance type. The impetus behind using Medicaid and SCHIP as the reference example for examining fiscal structure relies on the similarity of recipients. Columns (1) and (2) of table 4.1 show that children receiving SCHIP are quite similar to children receiving Medicaid in terms of age, race, ethnicity, sex, and health status. However, children enrolled in SCHIP are more likely to be in a family where a family member is married or has a college degree, and are more likely to be slightly higher in the income distribution. These facts are not surprising, since the income thresholds for SCHIP are slightly higher than those for Medicaid. Children

[12]https://www.census.gov/content/dam/Census/topics/health/health-insurance/guidance/hlthinsseq.pdf

enrolled in either public health program are much more similar than children who are uninsured or insured through some other program, such as private health insurance or military health insurance. Uninsured children are, on average, older, more likely to be Hispanic, less likely to live in a family where an adult has a college degree, and less likely to be below 130% or 200% FPL. Children insured through other means are more likely to be white, live in a family with an adult who has a college degree, and live in a lower unemployment state.

One striking difference in Table 4.1 is the disparity in the number of children who participate in both SCHIP and Medicaid. Children currently enrolled in Medicaid are 20 percentage points less likely to receive both SCHIP and Medicaid during the sample frame than children currently enrolled in SCHIP. Figure 3.9 shows this relationship is consistent across years, with only 3% of children enrolled in Medicaid in 2014 switching between programs, compared with 16% of children enrolled in SCHIP. Thus, while the samples seem to be relatively similar between the two health insurance programs, the program dynamics are very different.

3.5 Results

In presenting results, I begin with administrative caseload analysis, and then expand the scope to include individual level participation decisions. I establish a differential relationship between each program (SCHIP, Medicaid) and the macroeconomy. I then establish both unconditional enrollment patterns, as well as transition patterns between the programs in order to discuss the implications of cross-program substitution. I also examine individual enrollment decisions in the context of both the unemployment rate, which serves to measure increased demand for program benefits due to economic downturns, as well as state level expenditure, which measures the decreased supply of benefits due to state budget constraints. All models include state and year fixed effects, and all standard errors for all models are clustered at the state level.

3.5.1 Administrative Data

I begin by using administrative data to estimate equations (3.6) and (3.7), with results presented in table 3.4. Columns (1) and (2) are the year over year correlations between Medicaid child enrollment (MC) and SCHIP enrollment (SC), similar to the results in figure 3.4. These correlations show a positive relationship between both Medicaid and SCHIP enrollment, with a one percentage point increase in the unemployment rate increasing the number of Medicaid child beneficiaries per person by 6% and the number of SCHIP beneficiaries per person by 10%. As these coefficients are not statistically different from one another, this suggests that block grant funding has no negative consequences for program responsiveness.

However, the inclusion of state and year fixed effects demonstrates a very different relationship. The fixed effects estimate for Medicaid in column (2) is 0.008 (se=0.010), and the fixed effect estimate for SCHIP in column (3) is -0.079 (se=0.032), meaning that if the unemployment rate increases by one percentage point, enrollment in Medicaid is stable, but the number of SCHIP beneficiaries per person decreases by approximately 8% (column (4)). The inclusion of control variables, including the FMAP, governor party affiliation, the percent change in employment per person, NSLP recipients per capita, and NSBP recipients per capita in columns (5) and (6) does little to change these estimates.

These results are consistent with the implications from equation (3.4). Here, during economic downturn, there is no response in Medicaid child enrollment, but a decrease in enrollment in SCHIP. These results are economically significant, although only one half the magnitude predicted by Chernick (1998). If I consider SCHIP as the missing counterfactual for Medicaid child enrollment, I can back out the number of children that would lose health insurance from converting Medicaid to a block grant during times of economic distress. In 2010, approximately 33 million children were enrolled in Medicaid. An 8% decrease in enrollment resulting from a one percentage point change in the unemployment rate would result in approximately 500 thousand children losing Medicaid coverage. Table A.7 in the appendix demonstrates the sensitivity of these estimates to the inclusion of varying combinations of fixed effects. Year fixed effects seem to negate all counter-cyclical properties of SCHIP, while leaving Medicaid strongly counter-cyclical.

3.5.2 Individual Probabilities and Transitions

While administrative data are the most accurate measure of enrollment, they do not directly address the characteristics of benefit populations for the two programs, nor do they allow me to characterize the path individuals might take in enrollment patterns. For example, with administrative data, I cannot differentiate changes in enrollment from cross-program substitution. Thus, I utilize matched person level data from the CPS ASEC. All models include controls for race, education, and family structure, as well as state level variables such as the FMAP, population, minimum wage, and governor party affiliation, and are evaluated only for children 18 years of age or less.

Table 3.5 estimates the analog of equations (3.6) and (3.7) at the individual level, examining the effect of the unemployment rate on the probability a child is enrolled in Medicaid or SCHIP. Columns (1) and (2) include the entire sample of individuals, utilizing the data as a repeated cross section and evaluating pooled linear probability models.

The coefficient on the unemployment rate is 0.004 (se=0.002) for Medicaid, and 0.002 (se=0.003) for SCHIP, meaning that a one percentage point increase in the unemployment rate increases the probability a child enrolls in Medicaid by 0.4 percentage points, and has no statistically significant impact on the probability a child enrolls in SCHIP. I consider table 3.5 the individual analog to the results in table 3.4, showing higher levels of responsiveness for the matching grant program.

To examine the economic impact of fiscal structure, it is useful to contextualize these estimates. In 2010, 44.5% of all children received Medicaid. This implies the 0.4 percentage point change in Medicaid enrollment translates to a 9% increase in the number of children enrolled in Medicaid, or 2.97 million children. Thus, the opportunity cost of block grant funding is approximately 3 million children. Once again, these results are approximately half the magnitude predicted by Chernick (1998), but closely mirror the results from the administrative analysis, and confirm the implications of equation (3.4). These results also provide nuance to the results of Cawley et al. (2015) and Cawley and Simon (2005), suggesting that the responsiveness of public health insurance for children to the unemployment rate is driven primarily by Medicaid, the matching grant program.

Next, I estimate equations (8)-(13) to assess the extent of cross-program substitution. Here, I use the unemployment rate as the economic indicator, with results presented in table 3.6. Using the unemployment rate measures the increased demand for public health insurance benefits from economic downturns. Table 3.6 employs a framework similar to that of Schmidt and Sevak (2004); in columns (1)-(3), enrollment transitions are analyzed *from* SCHIP, the block grant program, to either Medicaid, the matching grant program, or uninsurance, representing the loss of benefits. The variable $\text{SCHIP}_{ij(t-1)}$ represents the baseline probability of enrollment churn (in column (1)) or stability (in column (2)), with $\text{SCHIP}_{ij(t-1)}\times$ Unemp representing the differential impact of the unemployment rate based on previous enrollment, or cross-program substitution.

The coefficient on $\text{SCHIP}_{ij(t-1)}\times$ Unemp is -0.002 (se=0.003) for Medicaid, and 0.014 (se=0.005) for SCHIP. This means that a one percentage point increase in the unemployment rate increases the probability a child remains enrolled in SCHIP by 1.4

percentage points, and has no effect on the probability a child switches from SCHIP to Medicaid. Columns (4) and (5) support this conclusion, showing analogous results for previous enrollment in Medicaid, with a one percentage point increase in the unemployment rate increasing the probability of transition from Medicaid to SCHIP. Thus, contrary to the predictions in Marton and Wildasin (2007b), I find no evidence of cross-program substitution from block grant programs to matching grant programs as a result of higher levels of unemployment. If anything, I show increased demand for benefits improves the stability of block grant programs.

However, while I do not find evidence of cross-program substitution, I do find evidence that the matching grant program is much more stable than the block grant program, with SCHIP experiencing much higher levels of churn than Medicaid. The coefficient on $\text{SCHIP}_{ij(t-1)}$ in columns (1) and (2) suggests that being enrolled in SCHIP last year increases the probability a child is enrolled in Medicaid this year by 48 percentage points compared to other children (such as children receiving private insurance, uninsured children, and children on Medicaid). Compare this to the coefficient in column (2) which suggests a child enrolled in SCHIP last period is only 28 percentage points more likely to be enrolled in SCHIP this period compared with other children. This implies being enrolled in a block grant funded program last period increases the probability of enrolling in a matching grant program this period 75% more than remaining enrolled in the block grant funded program.

The unemployment rate is the primary metric used in caseload analysis (Figlio and Ziliak, 1999; Ziliak et al., 2000; Blank, 2001; Bitler and Hoynes, 2010, 2015, 2016; Clemens and Ippolito, 2017), as well as analysis examining how the macroeconomy affects participation (Schmidt and Sevak, 2004; Cawley and Simon, 2005; Cawley et al., 2015). The unemployment rate represents a demand side shock; as the unemployment rate rises, individuals will pursue more safety net benefits to compensate for lost income. Other demand side shocks include shocks to per capita income and the poverty rate. Supply side shocks capture the impact the macroeconomy has on the ability of states to fund and supply benefits. To measure the effect of state finances, I re-estimate equations (3.6), (3.7), and (8)-(13) using the (negative) natural log of state expenditure per person as my economic indicator. I use the negative of the natural log to facilitate comparisons with the unemployment rate—both sets of coefficients measure the response to a negative macroeconomic shock.

Table 3.7 shows the impact of both expenditure and the unemployment rate on the probability a child is enrolled in Medicaid or SCHIP. In column (1), the coefficient for -ln(Exp/Pop) is -0.028 (se=0.026) and the coefficient for the unemployment rate is 0.005 (0.002), meaning the probability of enrollment in Medicaid is relatively insensitive to changes in expenditure, but increases by 0.5 percentage points for a 1 percentage point increase in the unemployment rate. Column (2) shows a very different relationship for SCHIP. The coefficient for -ln(Exp/Pop) is -0.058 (0.022), while the coefficient on the unemployment rate is 0.003 (0.003). This implies a 10% decrease in expenditure per person decreases the probability an individual is enrolled in SCHIP by 0.5 percentage points.

Comparing these results with those in table 3.5 suggests that Medicaid has counter-cyclical response to increases in demand for benefits, while SCHIP has a comparable pro-cyclical response to changes in state expenditure. Thus, not only do block grant programs fail to respond to increased demand for program benefits, they are also much more sensitive to changes in funding.

Table 3.8 examines cross-program substitution as a result of changing state expenditure. Similar to the results in 3.6, the coefficient on $\text{SCHIP}_{ij(t-1)}$ in column (1) and the coefficient on $\text{Medicaid}_{ij(t-1)}$ in column (5) suggests a high level of churn from SCHIP to Medicaid, implying higher levels of volatility for block grant programs. Enrollment in Medicaid is highly persistent and comparable to previous results.

The real distinction between demand and supply side shocks come through the coefficients on $\text{SCHIP}_{ij(t-1)} \times$ -ln(Exp/Pop) and $\text{Medicaid}_{ij(t-1)} \times$ -ln(Exp/Pop). In columns (1)-(3), we see a 10% decrease in expenditure per person decreases the probability a child enrolled in SCHIP last period is enrolled in SCHIP this period by 1.4 percentage points with no change in the probability a child enrolls in Medicaid, but increases the probability a child is uninsured by 0.4 percentage points. While this still does not provide evidence of cross-program substitution, it does imply larger decreases in enrollment for block grant funded programs vs. matching grant programs. It also does not rule out the possibility that these benefits are being substituted for program benefits outside the model. Columns (4)-(6) suggest a 10% decrease in state expenditure also decreases the probability a child remains enrolled in Medicaid by 0.6 percentage points, decreases the probability they enroll in SCHIP by 2.0 percentage points, and increases the probability they are uninsured by 0.3 percentage points.

To address the misclassification bias from the survey skip pattern of the CPS, I present adjusted estimates for tables 3.5, 3.7, 3.6, and 3.8 in the appendix. The adjustment process, which controls for the probability of false positives and false negatives when responding to public health insurance questions, is also detailed in the appendix. While the adjusted estimates suggest that the results in the main specification might be slightly attenuated, any bias is likely to be small.

Tables 3.9 and 3.10 estimate the switching regressions from equation (3.14). These switching regressions are looking only at children who transition between (or remain enrolled in) Medicaid and SCHIP for two years. Table 3.9 estimates the impact of the unemployment rate on the probability of switching. These results are similar to the results above; we see that SCHIP is drastically more variable than Medicaid, with the probability of transitioning out of SCHIP three times greater than the probability of transitioning out of Medicaid. I once again find no evidence of cross-program substitution from demand side shocks.

Table 3.10 does show some evidence of cross-program substitution, and re-affirms the volatile nature of SCHIP enrollment. Column (1) shows that the probability of switching decreases by 20 percentage points for children previously enrolled in Medicaid, and further decreases by 2.6 percentage points for a 10% decrease in state expenditure per person. Column (2) suggests that while SCHIP enrollment is more volatile than Medicaid enrollment, negative expenditure shocks stabilize the program. However, when I combine the measures into a single regression in column (3), this increased stability disappears, suggesting that for negative macroeconomic supply shocks, Medicaid provides much more stability for children than SCHIP. These results suggest that block grant funding increases the sensitivity of benefits to state funding. This follows exactly from the theory. If the marginal cost of benefits is $1 for block grant funded programs, a loss of funds will result in the decrease of block grant benefits, especially if the states can provide benefits through a matching grant program where the marginal cost of benefits is less than $1.

3.6 Conclusion

Recent proposals by policymakers have put a strong emphasis on the desire to reform the fiscal structure of many programs, most prominently Medicaid, by converting them from matching grant funded programs to block grant funded programs. This desire seems to be a potential answer to increases in program expenditure experienced in recent years, however, it often fails to account for the effect of this reform on beneficiaries. I present new estimates of the impact of fiscal structure on beneficiary enrollment, utilizing the similarities in benefits and beneficiaries between SCHIP and Medicaid to empirically isolate the effect of fiscal structure, something not typically achievable in previous studies. I present both state-level enrollment analysis, as well as individual level analysis to examine the transition patterns among beneficiaries.

I find that matching grant funding is associated with much stronger counter cyclical response than block grant funding. Enrollment level analysis suggests that a one percentage point increase in the unemployment rate is associated with an 7.6% decrease in enrollment for block grant programs. From fiscal year 2007 to fiscal year 2010, child enrollment in Medicaid increased by about 4 million children. During the same time period, the unemployment rate increased by approximately 5 percentage points. Were Medicaid funded through a block grant, this suggests enrollment would have decreased by approximately 6 million children over this time period, a stark difference. Individual level analysis suggests a one percentage point increase in the unemployment rate results in a 0.4 percentage point increase in the probability a child is enrolled in matching grant funded programs, implying matching grant funded programs provide strong counter-cyclical support against economic downturns. I find that block grant funded programs have significantly more churn, and are inherently more volatile than matching grant funded programs.

I also find that block grant funded programs are highly sensitive to changes in state expenditure, with a 10% decrease in state expenditure per person resulting in a 0.58 percentage point decrease in the probability an individual is enrolled in a block grant program. Using estimates from Clemens and Ippolito (2017), switching Medicaid from a matching grant program to a block grant program would likely result in a 4% revenue shortfall for states. This would imply a 0.23 percentage point decrease in the probability a child is enrolled in Medicaid. In 2011, 46% of children were enrolled in Medicaid (34 million). If Medicaid were converted to a block grant, enrollment would decrease to 45.77% of children, resulting in approximately 170,000 children losing Medicaid coverage.

It is also important to contextualize these results within overall policy proposals. Many of the bills introduced that would convert Medicaid funding to block grant funding are also packaged with decreases in the overall level of funding for Medicaid.[13] The results in this paper speak only to the impact of the change in fiscal structure, thus, accompanied by large budget decreases, one should expect the overall impact of this policy to be much larger in magnitude.

Implicit in the discussion of fiscal structure reform is the desire to curtail spending on public assistance. While block grant funding mechanically limits federal spending, it also limits the ability of the safety net to respond to business cycle fluctuations. The question then is whether, after fiscal structure reform, the safety net is flexible enough to accommodate potential enrollees during economic downturns, or able to adjust to decreases in expenditure from state level fiscal shocks. This analysis makes clear that the discussion around program reform needs to be broadened to consider *how* programs are funded, not only overall funding levels.

[13] Recent proposals by the Trump administration propose cutting Medicaid spending by $800 billion over the next 10 years (http://www.cnn.com/2017/05/22/politics/medicaid-budget-cuts/index.html)

Figure 3.1: Public Healthcare Funding

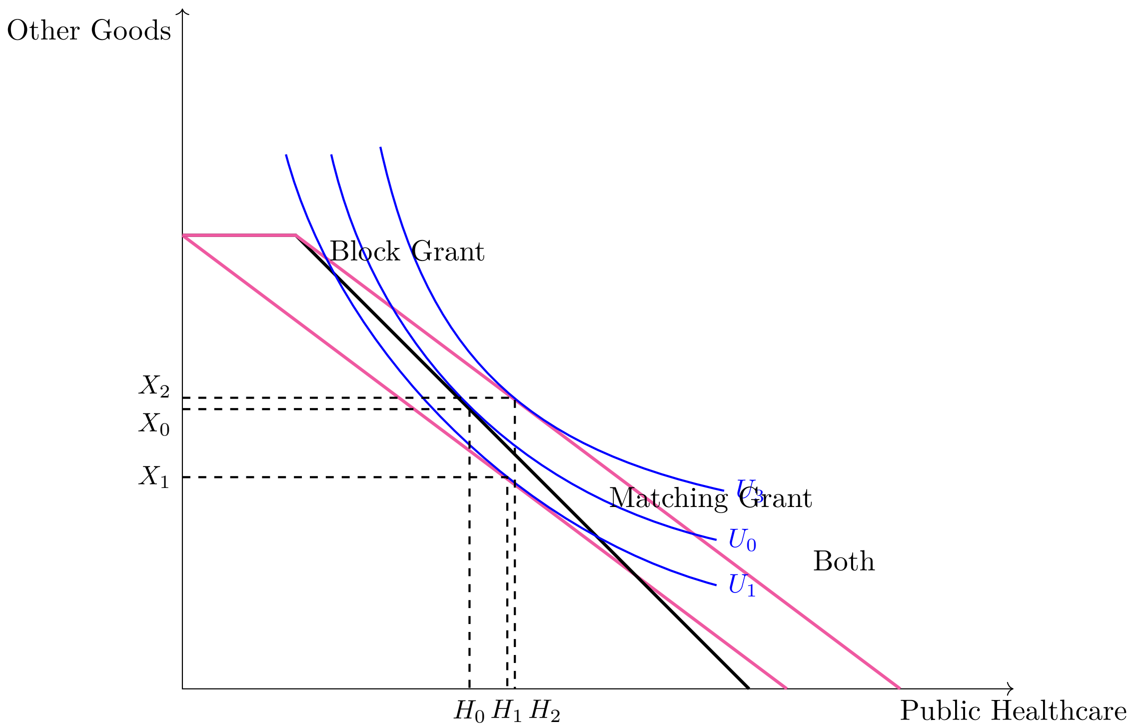


Figure 3.2: Administrative Enrollment by Year

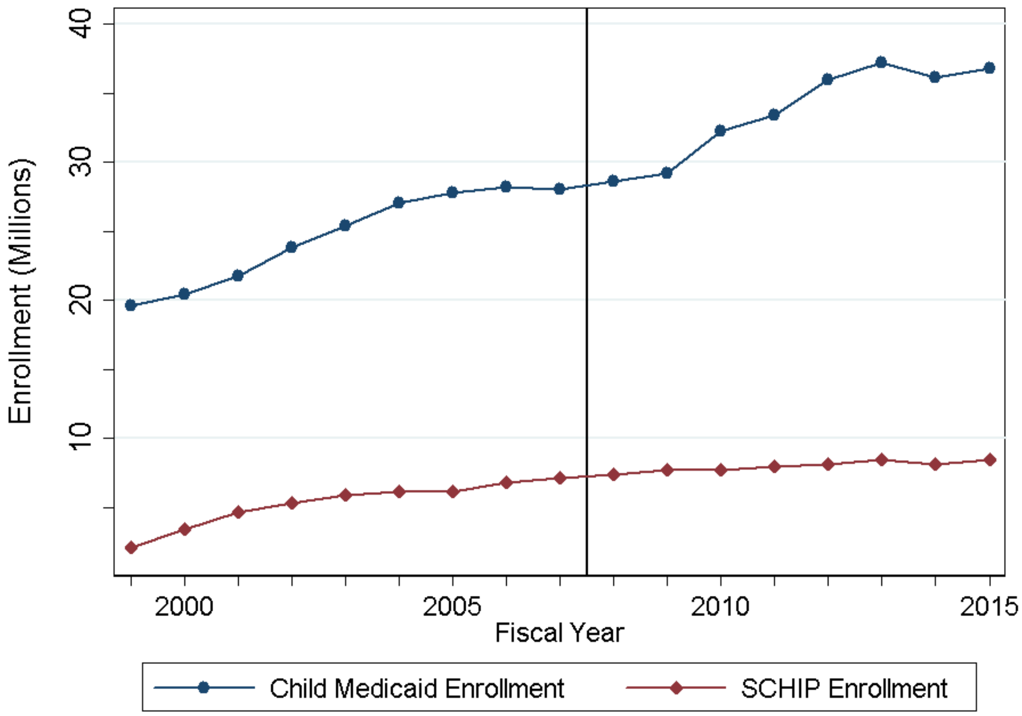


Figure 3.3: Percent Change in Enrollment by Year

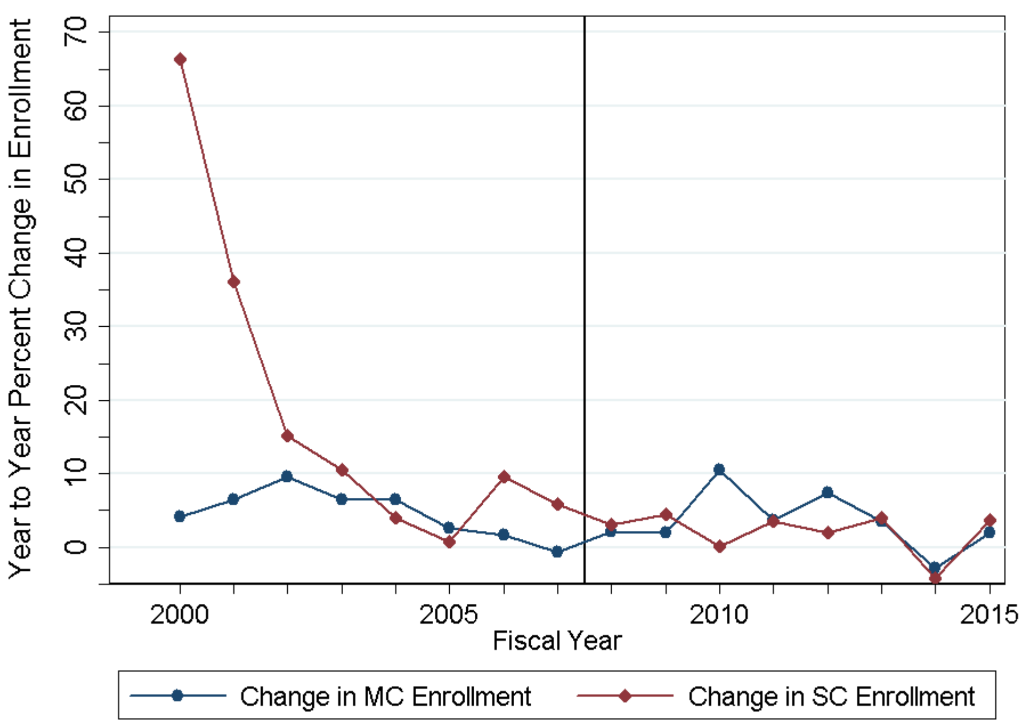


Figure 3.4: Enrollment vs. Unemployment by Year

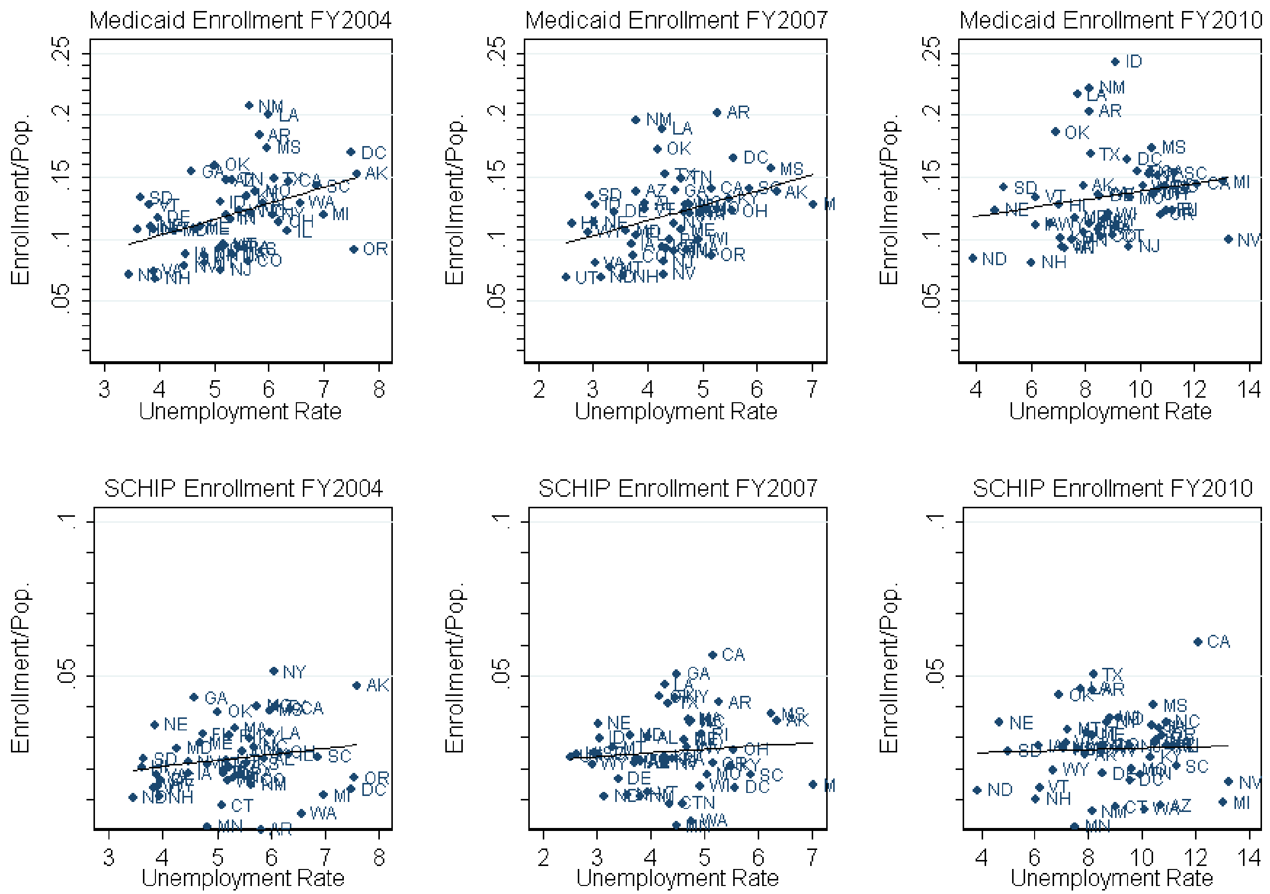
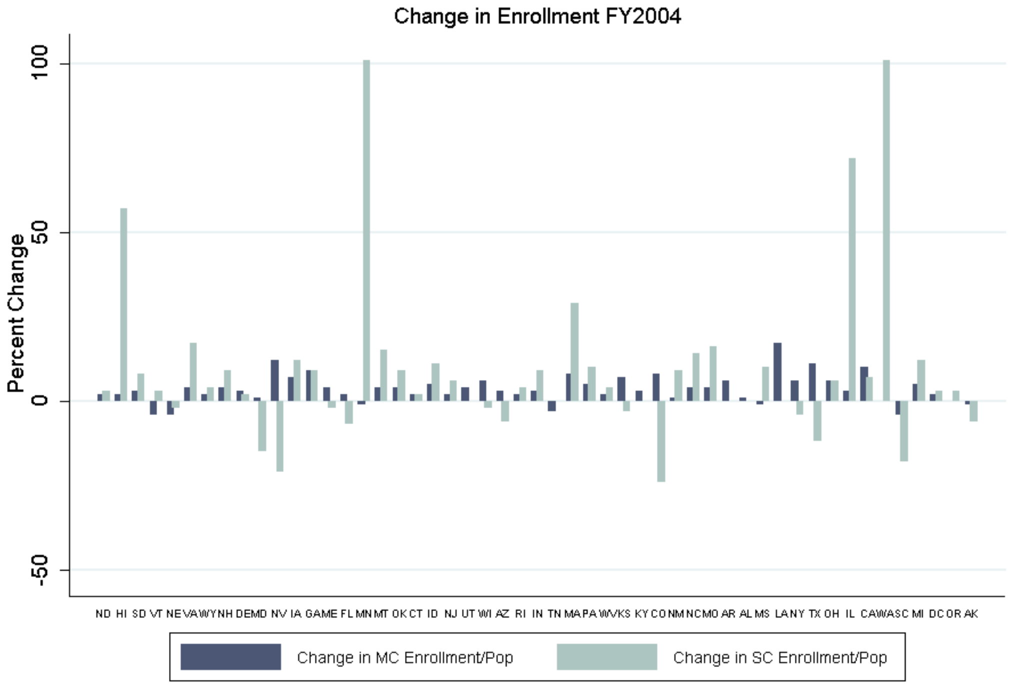


Figure 3.5: Change in Enrollment



Note: states sorted by unemployment rate. Percent change is capped at 100% for scale.

Figure 3.6: Change in Enrollment

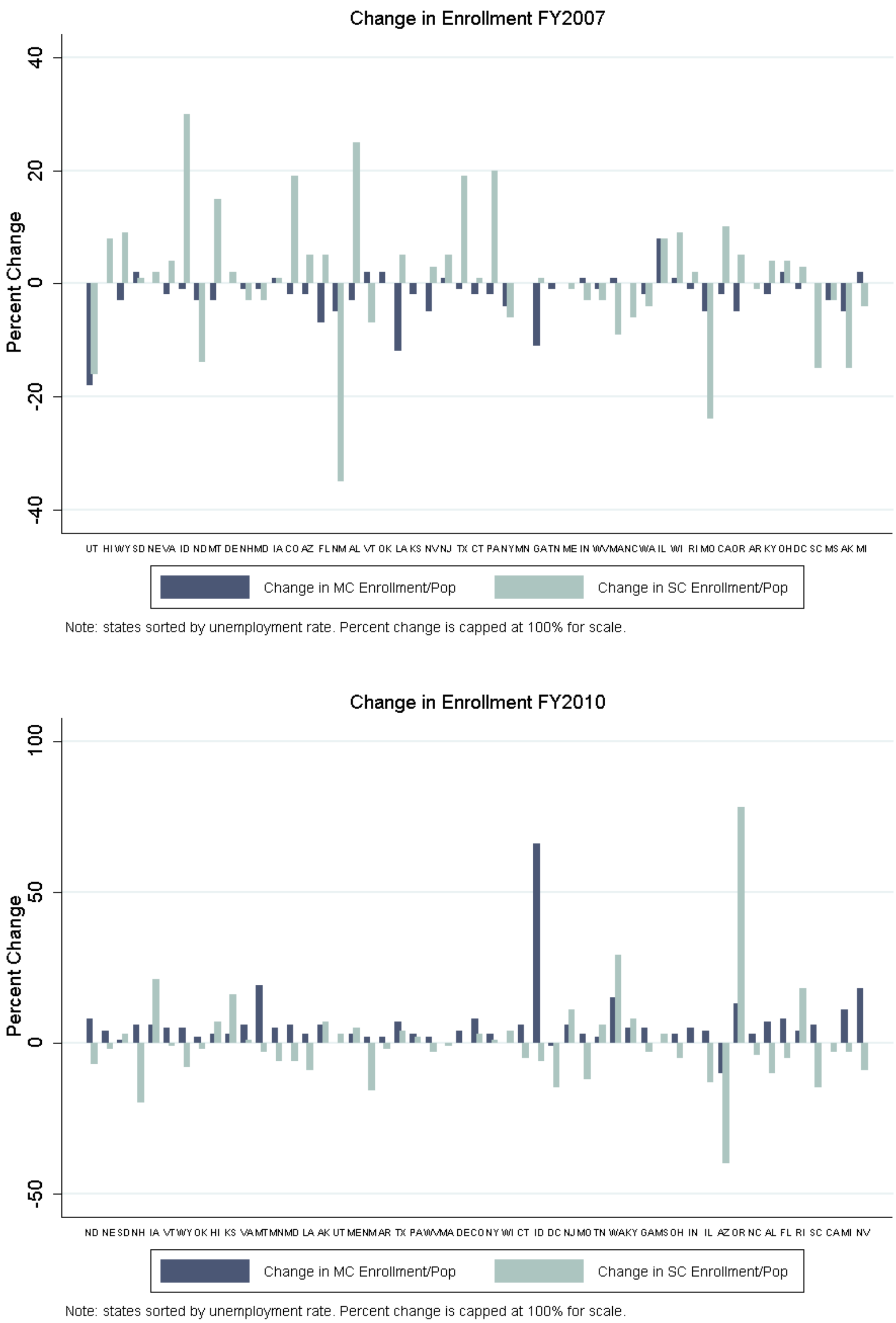


Figure 3.7: Change in Enrollment vs. Change in Unemployment

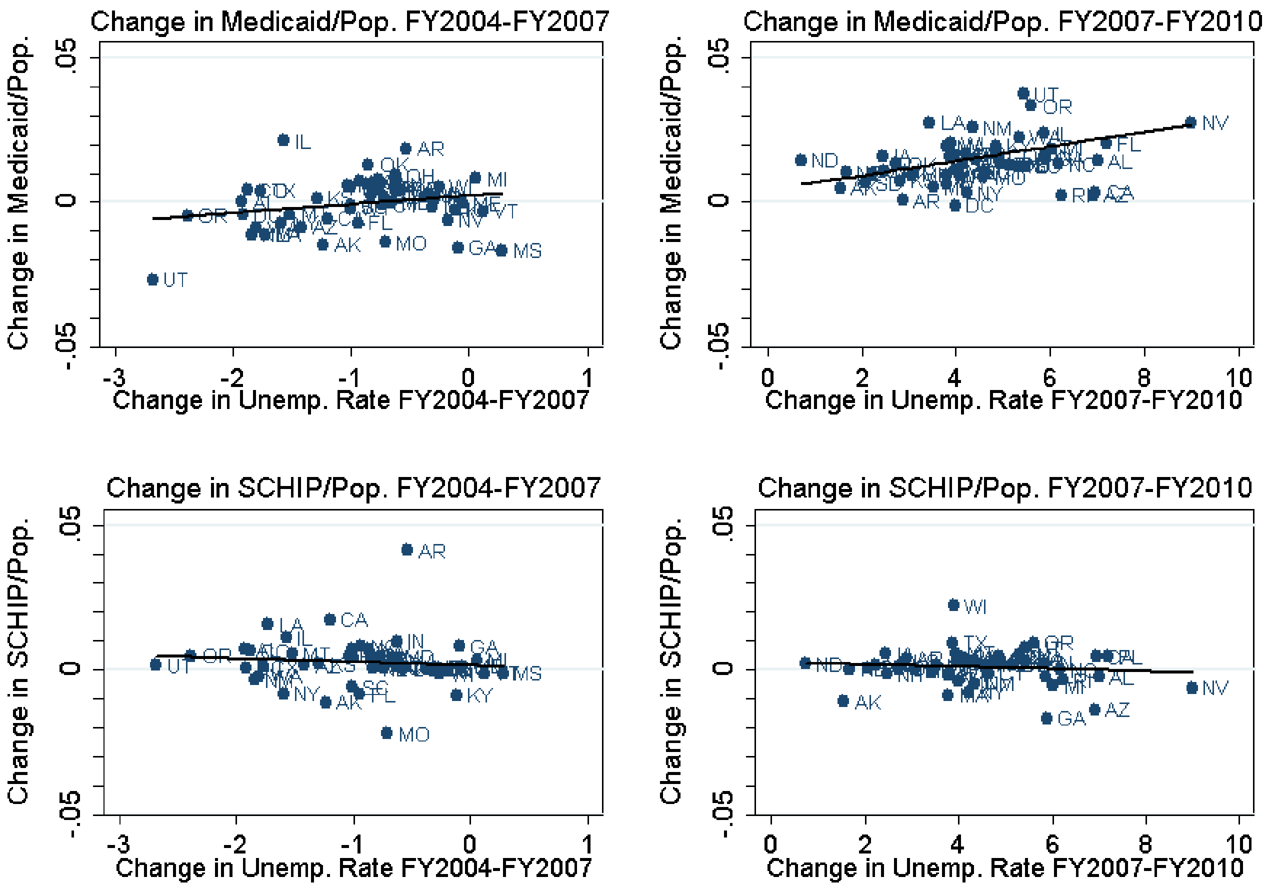


Figure 3.8: CPS Beneficiaries by Year

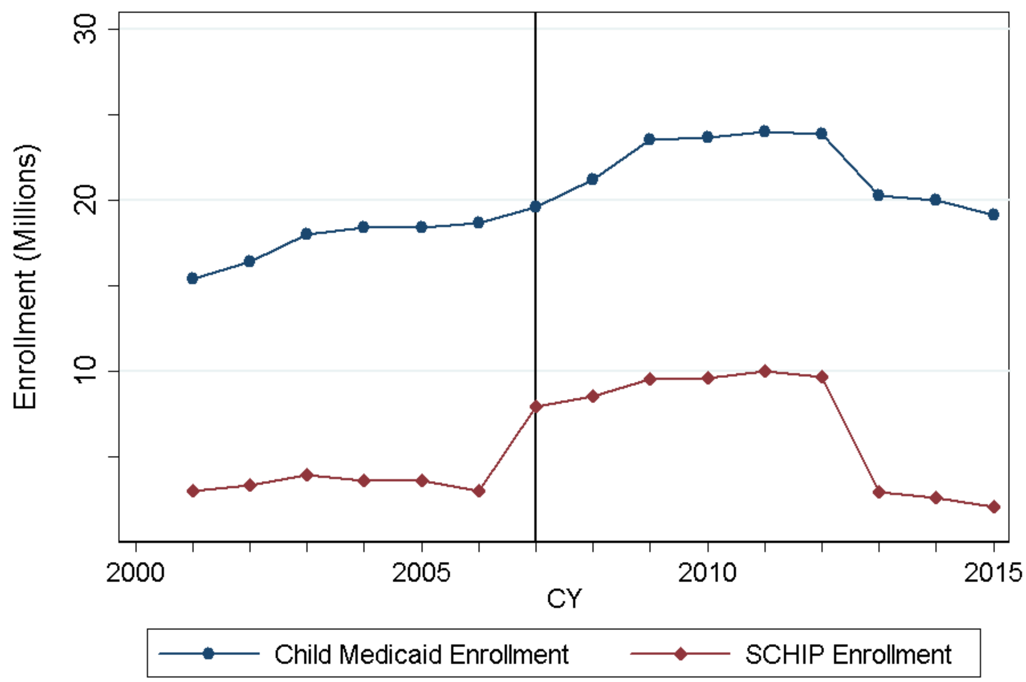


Figure 3.9: CPS Switchers by Year

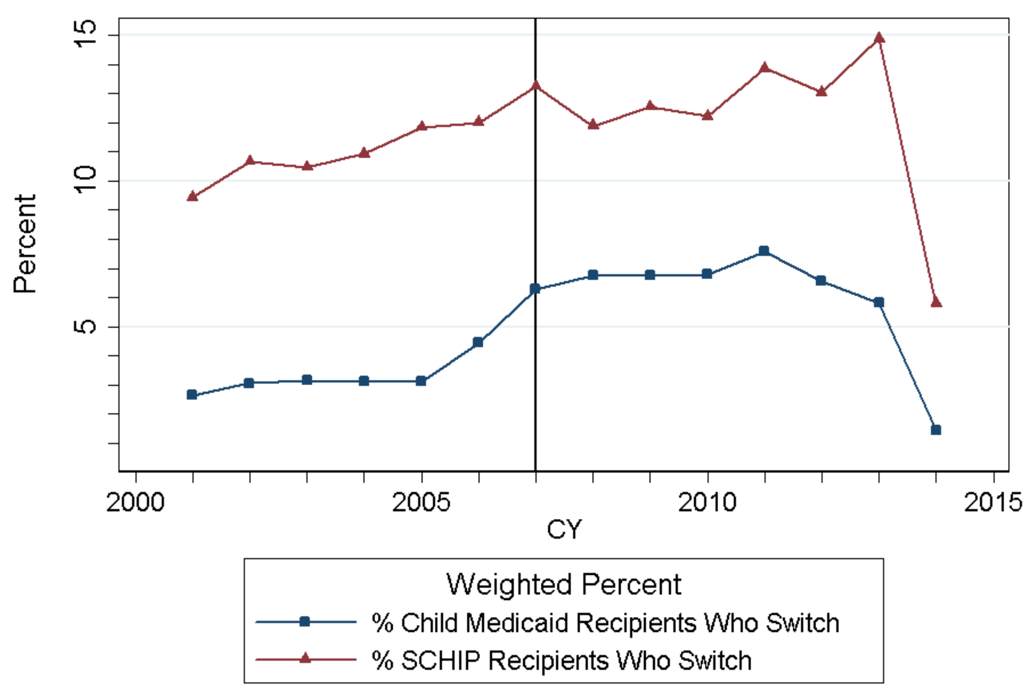


Table 3.1: State Medicaid and SCHIP Income Eligibility Standards

	Children				Pregnant Women	
	Medicaid Ages 0-1	Medicaid Ages 1-5	Medicaid Ages6-18	Separate SCHIP	Medicaid	SCHIP
Alabama	141%	141%	141%	312%	141%	*N/A*
Alaska	203%	203%	203%	*N/A*	200%	*N/A*
Arizona	147%	141%	133%	200%	156%	*N/A*
Arkansas	142%	142%	142%	211%	209%	*N/A*
California	261%	261%	261%	317%	208%	*N/A*
Colorado	142%	142%	142%	260%	195%	260%
Conn.	196%	196%	196%	318%	258%	*N/A*
Delaware	212%	142%	133%	212%	212%	*N/A*
D.C.	319%	319%	319%	*N/A*	319%	*N/A*
Florida	206%	140%	133%	210%	191%	*N/A*
Georgia	205%	149%	133%	247%	220%	*N/A*
Hawaii	308%	308%	308%	*N/A*	191%	*N/A*
Idaho	142%	142%	133%	185%	133%	*N/A*
Illinois	142%	142%	142%	313%	208%	*N/A*
Indiana	208%	158%	158%	250%	208%	*N/A*
Iowa	375%	167%	167%	302%	375%	*N/A*
Kansas	166%	149%	133%	238%	166%	*N/A*
Kentucky	195%	159%	159%	213%	195%	*N/A*
Louisiana	212%	212%	212%	250%	133%	*N/A*
Maine	191%	157%	157%	208%	209%	*N/A*
Maryland	317%	317%	317%	*N/A*	259%	*N/A*
Mass.	200%	150%	150%	300%	200%	*N/A*
Michigan	212%	212%	212%	*N/A*	195%	*N/A*
Minnesota	283%	275%	275%	*N/A*	278%	*N/A*
Mississippi	194%	143%	133%	209%	194%	*N/A*
Missouri	196%	150%	150%	300%	196%	300%
Montana	143%	143%	143%	261%	157%	*N/A*
Nebraska	213%	213%	213%	*N/A*	194%	*N/A*
Nevada	160%	160%	133%	200%	160%	*N/A*
New Hamp.	318%	318%	318%	*N/A*	196%	*N/A*
New Jersey	194%	142%	142%	350%	194%	200%
New Mex.	300%	300%	240%	*N/A*	250%	*N/A*
New York	218%	149%	149%	400%	218%	*N/A*
N. Carolina	210%	210%	133%	211%	196%	*N/A*
N. Dakota	147%	147%	133%	170%	147%	*N/A*
Ohio	206%	206%	206%	*N/A*	200%	*N/A*
Oklahoma	205%	205%	205%	*N/A*	133%	*N/A*
Oregon	185%	133%	133%	300%	185%	*N/A*
Penn.	215%	157%	133%	314%	215%	*N/A*
Rhode Isl.	261%	261%	261%	*N/A*	190%	253%
S. Carolina	208%	208%	208%	*N/A*	194%	*N/A*
S. Dakota	182%	182%	182%	204%	133%	*N/A*
Tennessee	195%	142%	133%	250%	195%	*N/A*
Texas	198%	144%	133%	201%	198%	*N/A*
Utah	139%	139%	133%	200%	139%	*N/A*
Vermont	312%	312%	312%	*N/A*	208%	*N/A*
Virginia	143%	143%	143%	200%	143%	200%
Washington	210%	210%	210%	312%	193%	*N/A*
W. Virginia	158%	141%	133%	300%	158%	*N/A*
Wisconsin	301%	186%	151%	301%	301%	*N/A*
Wyoming	154%	154%	133%	200%	154%	*N/A*

As of June 1, 2016. Source: https://www.medicaid.gov/medicaid/program-information/medicaid-and-chip-eligibility-levels/index.html

Table 3.2: Insurance Transition Matrix

	Medicaid_t	SCHIP_t	Uninsurance_t	Private_t	Other_t
Medicaid_{t-1}	0.66	0.14	0.08	0.11	0.01
SCHIP_{t-1}	0.34	0.43	0.09	0.14	0.01
Uninsurance_{t-1}	0.19	0.10	0.45	0.26	0.01
Private_{t-1}	0.03	0.02	0.03	0.92	0.01
Other_{t-1}	0.12	0.05	0.04	0.30	0.50

Note: columns will not sum to one since not all individuals are present in the data for two years.

Table 3.3: Summary Statistics by Insurance Type

	Medicaid (1)	SCHIP (2)	Uninsured (3)	Other (4)
Age	8.10	8.31	9.74	9.38
Black	0.24	0.22	0.15	0.10
Other Race	0.09	0.10	0.10	0.09
Hisp	0.35	0.33	0.43	0.18
Female	0.49	0.49	0.48	0.49
Wic	0.01	0.01	0.01	0.00
Good Health	0.04	0.03	0.02	0.01
Fam Married Flag	0.76	0.83	0.82	0.89
Fam HS Flag	0.85	0.88	0.85	0.84
Fam Col Flag	0.67	0.73	0.69	0.90
# <18 in Fam	2.48	2.38	2.17	2.12
<130 Pov	0.54	0.50	0.44	0.07
<200 Pov	0.69	0.72	0.63	0.17
Unemp	6.66	7.08	6.29	6.23
FMAP	58.11	57.77	58.30	57.28
Pop (Mil.)	14.33	13.79	15.36	12.93
St. Min. Wg.	6.71	6.80	6.35	6.49
Gov. Dem.	0.45	0.46	0.39	0.47
Cont. Enrolled	0.22	0.24		
Recieved MC & SC	0.15	0.35		
NSLP/Pop.	0.10	0.10	0.10	0.10
NSBP/Pop.	0.04	0.04	0.04	0.03
Obs.	248,633	70,007	74,134	552,725

Note: Individual weights used.

Table 3.4: Impact of Unemployment on ln(Beneficiaries/Pop.): FY1999-FY2015

	MC (1)	SC (2)	MC (3)	SC (4)	MC (5)	SC (6)
Unemp	0.063***	0.101***	0.008	−0.079**	−0.002	−0.076**
	(0.008)	(0.033)	(0.010)	(0.032)	(0.008)	(0.032)
FMAP					0.006	0.006
					(0.005)	(0.011)
Gov. Dem.					0.021	0.098
					(0.014)	(0.099)
$\%\Delta\frac{Emp.}{Pop.}$					−0.211	−0.369
					(0.373)	(2.688)
NSLP/Pop.					2.852	−5.108
					(2.438)	(9.349)
NSBP/Pop.					0.604	−11.044
					(3.165)	(8.435)
State FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
Obs.	914	857	914	857	896	840

Note: standard errors clustered at the state level. * p <0.10, ** p <0.05, *** p <0.01. MC represents the natural log of child Medicaid enrollment per person, SC represents the natural log of SCHIP enrollment per person.

Table 3.5: Impact of Unemployment on Enrollment

	MC (1)	SC (2)
Unemp	0.004**	0.002
	(0.002)	(0.003)
Age	−0.007***	−0.002***
	(0.000)	(0.000)
Black	0.230***	0.048***
	(0.009)	(0.004)
Other Race	0.084***	0.022***
	(0.015)	(0.004)
Hispanic	0.186***	0.058***
	(0.012)	(0.006)
Married	−0.169***	−0.036***
	(0.007)	(0.006)
High School	0.080***	0.022***
	(0.004)	(0.002)
College	−0.184***	−0.037***
	(0.006)	(0.003)
# <18 in Fam	0.044***	0.008***
	(0.002)	(0.001)
FMAP	0.003***	0.001
	(0.001)	(0.001)
Pop.	0.000	−0.000
	(0.000)	(0.000)
Min Wage	0.011**	0.002
	(0.004)	(0.005)
Dem. Gov.	0.000	−0.002
	(0.004)	(0.004)
NSLP/Pop.	−0.261	−1.303*
	(0.604)	(0.699)
NSBP/Pop.	−0.633	0.370
	(0.716)	(0.794)
Obs.	867,850	867,850

Note: standard errors clustered at the state level. * p <0.10, ** p <0.05, *** p <0.01. All models include state and year fixed effects. MC represents the probability a child is enrolled in Medicaid, SC represent the probability a child is enrolled in SCHIP.

Table 3.6: Transitions Among Insurance States

	MC (1)	SC (2)	Unins. (3)	MC (4)	SC (5)	Unins. (6)
$\text{SCHIP}_{ij(t-1)}$	0.484***	0.278***	0.027**			
	(0.026)	(0.035)	(0.012)			
$\text{Medicaid}_{ij(t-1)}$				0.598***	0.074***	0.015**
				(0.016)	(0.025)	(0.007)
Unemp	0.006**	−0.000	0.003*	0.001	−0.005**	0.004**
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
$\text{SCHIP}_{ij(t-1)} \times$ Unemp	−0.001	0.014***	−0.004**			
	(0.003)	(0.005)	(0.002)			
$\text{Medicaid}_{ij(t-1)} \times$ Unemp				0.002	0.018***	−0.004***
				(0.002)	(0.005)	(0.001)
Obs.	150,612	150,612	150,612	155,846	155,846	155,846

Note: standard errors clustered at the state level. Controls include FMAP, race, sex, age, education, ethnicity, marital status, state population, state min. wage, free school lunch recipients per person, free school breakfast recipients per person, governor party affiliation, and state and year fixed effects. * p <0.10, ** p <0.05, *** p <0.01. MC represents the probability a child is enrolled in Medicaid, SC represent the probability a child is enrolled in SCHIP.

Table 3.7: Impact of State Expenditure on Enrollment

	MC (1)	SC (2)
-ln(Exp/Pop)	−0.028	−0.058**
	(0.026)	(0.022)
Unemp	0.005**	0.003
	(0.002)	(0.003)
Age	−0.007***	−0.002***
	(0.000)	(0.000)
Black	0.230***	0.050***
	(0.009)	(0.004)
Other Race	0.086***	0.023***
	(0.016)	(0.004)
Hispanic	0.186***	0.061***
	(0.012)	(0.006)
Married	−0.176***	−0.036***
	(0.007)	(0.006)
High School	0.081***	0.024***
	(0.004)	(0.003)
College	−0.173***	−0.039***
	(0.006)	(0.004)
# <18 in Fam	0.044***	0.008***
	(0.002)	(0.001)
FMAP	0.002***	0.001
	(0.001)	(0.001)
Pop.	0.000	−0.000**
	(0.000)	(0.000)
Min Wage	0.012***	0.002
	(0.004)	(0.005)
Dem. Gov.	0.001	−0.002
	(0.004)	(0.004)
NSLP/Pop.	−0.121	−1.191
	(0.621)	(0.757)
NSBP/Pop.	−0.832	0.203
	(0.778)	(1.035)
Obs.	829,869	829,869

Note: standard errors clustered at the state level. * p <0.10, ** p <0.05, *** p <0.01. All models include state and year fixed effects. MC represents the probability a child is enrolled in Medicaid, SC represent the probability a child is enrolled in SCHIP.

Table 3.8: Transitions Among Insurance States

	MC (1)	SC (2)	Unins. (3)	MC (4)	SC (5)	Unins. (6)
$\text{SCHIP}_{ij(t-1)}$	0.349***	0.093	0.061			
	(0.074)	(0.085)	(0.036)			
$\text{Medicaid}_{ij(t-1)}$				0.483***	−0.187***	0.044**
				(0.053)	(0.069)	(0.021)
-ln(Exp/Pop)	−0.027	−0.038**	0.013	−0.021	−0.008	0.008
	(0.029)	(0.017)	(0.017)	(0.023)	(0.020)	(0.018)
$\text{SCHIP}_{ij(t-1)}\times$ -ln(Exp/Pop)	−0.064*	−0.135***	0.029			
	(0.035)	(0.042)	(0.018)			
$\text{Medicaid}_{ij(t-1)}\times$ -ln(Exp/Pop)				−0.065**	−0.189***	0.028**
				(0.026)	(0.037)	(0.010)
Unemp	0.007**	0.002	0.002	0.002	0.000	0.002
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Obs.	150,522	150,522	150,522	155,756	155,756	155,756

Note: standard errors clustered at the state level. Controls include FMAP, race, sex, age, education, ethnicity, marital status, state population, state min. wage, free school lunch recipients per person, free school breakfast recipients per person, governor party affiliation, and state and year fixed effects. * p <0.10, ** p <0.05, *** p <0.01. MC represents the probability a child is enrolled in Medicaid, SC represent the probability a child is enrolled in SCHIP.

Table 3.9: Effect of Unemployment Rate on Probability of Switching

	(1)	(2)	(3)
Medicaid_{ijt-1}	0.149***		0.056***
	(0.032)		(0.018)
SCHIP_{ijt-1}		0.664***	0.618***
		(0.021)	(0.022)
Unemp	−0.007***	0.002	−0.002
	(0.002)	(0.001)	(0.001)
$\text{Medicaid}_{ijt-1}\times$ Unemp	0.027***		0.013***
	(0.006)		(0.004)
$\text{SCHIP}_{ijt-1}\times$ Unemp		0.009***	−0.000
		(0.003)	(0.004)
Obs.	155,846	150,612	150,612

Note: standard errors clustered at the state level. Controls include FMAP, race, sex, age, education, ethnicity, marital status, state population, state min. wage, free school lunch recipients per person, free school breakfast recipients per person, governor party affiliation, and state and year fixed effects. * p <0.10, ** p <0.05, *** p <0.01.

Table 3.10: Effect of State Expenditure on Probability of Switching

	(1)	(2)	(3)
Medicaid_{ijt-1}	-0.206^{**}		-0.120^{**}
	(0.085)		(0.050)
SCHIP_{ijt-1}		0.542^{***}	0.651^{***}
		(0.078)	(0.093)
-ln(Exp/Pop)	0.034^{*}	-0.008	0.013
	(0.020)	(0.012)	(0.012)
$\text{Medicaid}_{ijt-1}\times$ -ln(Exp/Pop)	-0.266^{***}		-0.131^{***}
	(0.045)		(0.028)
$\text{SCHIP}_{ijt-1}\times$ -ln(Exp/Pop)		-0.089^{**}	0.019
		(0.039)	(0.047)
Obs.	155,756	150,522	150,522

Note: standard errors clustered at the state level. Controls include FMAP, race, sex, age, education, ethnicity, marital status, state population, state min. wage, free school lunch recipients per person, free school breakfast recipients per person, governor party affiliation, and state and year fixed effects. * p <0.10, ** p <0.05, *** p <0.01.

Table 3.11: Determinants of Entry

	Medicaid_{ijt} (1)	SCHIP_{ijt} (2)	Unins_{ijt} (3)	Priv._{ijt} (4)
Medicaid_{ijt-1}		0.073***	0.109***	0.227***
		(0.019)	(0.014)	(0.011)
SCHIP_{ijt-1}	0.380***		0.124***	0.223***
	(0.035)		(0.019)	(0.017)
Unins._{ijt-1}	0.179***	0.034**		0.381***
	(0.016)	(0.015)		(0.017)
Priv._{ijt-1}	0.058***	0.026***	0.050***	
	(0.005)	(0.005)	(0.009)	
Unemp.	0.001	−0.003**	0.003**	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$\text{Medicaid}_{ijt-1}\times$ Unemp.		0.012***	−0.003**	−0.004**
		(0.004)	(0.001)	(0.002)
$\text{SCHIP}_{ijt-1}\times$ Unemp.	−0.008*		−0.004*	−0.008***
	(0.005)		(0.002)	(0.002)
$\text{Unins.}_{ijt-1}\times$ Unemp.	0.004*	0.013***		−0.009***
	(0.002)	(0.003)		(0.002)
$\text{Priv}_{ijt-1}\times$ Unemp.	0.002***	0.002***	0.000	
	(0.001)	(0.001)	(0.001)	
Obs.	159,180	159,180	159,180	159,180

Note: standard errors clustered at the state level. Controls include FMAP, race, sex, age, education, ethnicity, marital status, state population, state min. wage, free school lunch recipients per person, free school breakfast recipients per person, governor party affiliation, and state and year fixed effects. * p <0.10, ** p <0.05, *** p <0.01.

Chapter 4: The Minimum Wage and Program Interaction

4.1 Introduction

Questioning the role and effectiveness of the minimum wage is not a new topic, with studies on the impacts of the minimum wage going back at least 100 years. Grounding the idea in basic economic theory is relatively simple; a binding price floor on labor should both increase the quantity supplied of labor and decrease the quantity demanded. In the real world, this suggests we should see more workers looking for jobs, but having a more difficult time finding them. Moreover, theory tells us that, depending on the marginal rate of technical substitution, we may see employers shifting away from low-wage labor towards capital in an attempt to lower costs.

While theory suggests detrimental effects from the minimum wage, recent policy has been moving the needle forward on minimum wage increases. From 1997 to 2007, the nominal federal minimum wage was $5.15 per hour. The Fair Minimum Wage Act of 2007 raised the minimum wage by over 40% between 2007 and 2009, with a current nominal minimum wage of $7.25 per hour. Many large increases at the state and local level have been enacted recently as well. Los Angeles recently increased its minimum wage to $15 per hour, with the rest of California to follow suit in the coming years.[1] Seattle also recently passed an ordinance to increase the minimum wage to $15 per hour.[2]

If theory suggests negative employment consequences, why then has the minimum wage seen a resurgence as a policy prescription to address income inequality and poverty? While the basic theory is clean and neat, the empirical research surrounding

[1] http://www.nbclosangeles.com/news/local/California-Minimum-Wage-374470051.html
[2] http://www.seattle.gov/laborstandards/minimum-wage

the observed effects of the minimum wage can get muddy. In a broad overview, Neumark et al. (2007) show that the estimates of the effect of the minimum wage on employment can vary significantly, but that overall, a majority of the work covered suggests that economic theory holds true, finding a decrease in the overall level of employment for low wage workers. Recent studies by Dube et al. (2016) find that the minimum wage reduces both hiring and turnover rates for affected workers, with little overall change in the stock of labor, while Jardim et al. (2017) find substantial negative effects from the large minimum wage increases in Seattle, both in terms of employment and overall earnings.

While the discussion surrounding the minimum wage often revolves around the employment effects of the minimum wage, at its heart the minimum wage is an anti-poverty policy tool. Gramlich et al. (1976) note that the minimum wage is "basically an attempt to alter the distribution of family income." This concept has driven a wide literature on the effect of the minimum wage on poverty and inequality (Dube, 2017; MaCurdy, 2015; Sabia and Nielsen, 2015; Sabia et al., 2012; Neumark et al., 2005; Neumark and Wascher, 2002). However, Gramlich et al. (1976) also note that the minimum wage has broad interactions in the wider economy, and that these interactions are understudied in the minimum wage literature, specifically, the interaction of minimum wage policy with the transfer system. And though these shortcomings were noted in 1976, more than 40 years later, we are still relatively uninformed about how minimum wages and public assistance programs interact.

Recent literature has made an attempt to study the broader implications of the minimum wage for the social safety net and poverty, however, the question remains about the overall efficacy of the minimum wage as one of many potential policy tools available. This paper is an attempt to address this shortcoming, and to understand the direct and indirect consequences of minimum wage policy on poverty and the safety net. Using data from the 1995-2016 Annual Social and Economic Supplement of the Current Population Survey (CPS ASEC or March CPS), I examine the effect of the minimum wage on welfare, food, and tax benefits, as well as the effect of the minimum wage on poverty. I limit my analysis to working age, citizen, heads of households less than 300% of the federal poverty line to capture the effect on primary wage earners, utilizing variation in state and federal minimum wages as well as variation in the self-reported dollar value of benefits received. I find that the minimum wage reduces the self-reported dollar value of safety net benefits received, with a 1% increase in the minimum wage reducing the dollar value of total reported benefits by approximately 0.24%. If I disaggregate these results, I find a 1% increase in the minimum wage reduces the self-reported dollar value of food stamp or Supplemental Nutrition Assistance Program (SNAP) benefits by 0.03%, the dollar value of Aid to Families with Dependent Children (AFDC) or Temporary Assistance to Needy Families (TANF) (depending on year of observation) benefits by 0.27%, Supplemental Security Income (SSI) benefits by 0.42%, and Earned Income Tax Credit Benefits by 0.43%. I then use these results to estimate the total effect of a change in the minimum wage on the income to poverty ratio, finding an own effect of a 1% increase in the minimum wage reduces the ratio by 0.55 percentage points. However, if I consider the joint impact of the minimum wage on the income to poverty ratio *and* benefits, I find that this effect attenuates by about 30% to 0.39 percentage points.

These results suggest that the minimum wage may be a blunt instrument when fighting poverty. While I find positive overall effects of the minimum wage on poverty, these effects are small and diminished by the mechanical relationship between means-tested programs and wages. This, coupled with the broad literature that typically finds negative employment effects of the minimum wage suggests that, if the goal of the minimum wage is to reduce poverty, there may be more efficient avenues for doing so. Studies such as those by Neumark and Wascher (2001), Tiehen et al. (2015), and Schmidt et al. (2015) suggest that portions of the safety net are making large strides in addressing the needs of America's poor. This paper provides evidence that suggests a more targeted, safety net based approach to poverty could be more effective than broad measures such as the minimum wage.

4.2 Background and Motivation

While the basic theory surrounding the effects of the minimum wage on employment are relatively straightforward, the theoretical predictions of the effect of the minimum wage on poverty are ambiguous. For low-income families, there are potentially offsetting effects from gains in wage income, employment losses, and losses in transfer income (be it in-kind or cash). Workers who see increased earnings from minimum wage increases could potentially be made better off. However, the loss in transfer income may reduce the benefit from increased wages. Workers who lose their jobs due to a minimum wage increase will experience higher rates of poverty. Here, these losses could be mitigated or aggravated by changes in transfer income. If transfer program assistance is provided with a work stipulation, these losses in wage income could be compounded by losses in transfer income. However, if no work requirement is present, the losses in wage income may be offset by increases in transfer income.

The following simple model describes the joint effect of the minimum wage and transfer program benefits on poverty. The first equation very generally models benefits, letting

$$\text{Benefit}_{ijt} = G_{ijt} - \tau_{jt}(w_{ijt}H_{ijt}(w_{ijt}) - D_{ijt}) \tag{4.1}$$

where G is the maximum benefit for family i in state j at time t, $w_{ijt}H_{ijt}(w_{ijt})$ is work income (where hours are a function of wages), D_{ijt} is deductions, and τ_{jt} is a potentially complex marginal tax rate. Let us slightly complicate the benefit formula by including work requirements, such that

$$\text{Benefit}_{ijt} = P(H_{ijt}(w_{ijt}) > k)[G_{ijt} - \tau_{jt}(w_{ijt}H_{ijt}(w_{ijt}) - D_{ijt})] \tag{4.2}$$

where k is some arbitrary work requirement threshold. Thus, if we wish to find the marginal effect of a change in wages, we have

$$\begin{aligned} \frac{\partial \text{Benefit}_{ijt}}{\partial w_{ijt}} =& P(H_{ijt}(w_{ijt}) > k)[-\tau_{jt}H_{ijt}(w_{ijt}) - \tau_{jt}w_{ijt}\frac{\partial H_{ijt}(w_{ijt})}{\partial w_{ijt}}] \\ &+ \frac{\partial P(H_{ijt}(w_{ijt}) > k)}{\partial w_{ijt}}[G_{ijt} - \tau_{jt}(w_{ijt}H_{ijt}(w_{ijt}) - D_{ijt})] \end{aligned} \tag{4.3}$$

Here, if we are completely general, the ambiguity of the direction of the response of hours to wages makes the general sign of equation (4.3) ambiguous. For simplicity, I will assume equation (4.3) refers to minimum wage workers, and that, as is widely found in the literature, the probability of employment decreases in response to an increase in the minimum wage (see Neumark et al. (2007) for an overview). I will also assume an upward sloping labor supply curve, with hours increasing as wage increases. This implies that $\frac{\partial H_{ijt}(w_{ijt})}{\partial w_{ijt}} > 0$. While a significant literature exists on the extensive margin of labor supply, the literature on the intensive margin is somewhat thinner. Couch and Wittenburg (2001) and Zavodny (2000) study the effect of the minimum wage on hours of work for teenagers, finding either negative or null effects. This, coupled with the literature on the extensive margin of labor supply, implies $\frac{\partial P(H_{ijt}(w_{ijt})>k)}{\partial w_{ijt}} < 0$. Since we know that public assistance benefits are non-negative, the second term in (4.3) is unambiguously non-negative. Furthermore, assuming an upward sloping labor supply curve implies the first term is unambiguously negative as well, suggesting that any empirical estimates of the effect of the minimum wage on means-tested benefits should be negative ($\frac{\partial \text{Benefit}_{ijt}}{\partial w_{ijt}} < 0$).

In this paper I will consider benefits from food stamps/SNAP, AFDC/TANF, SSI, and the EITC. The Food Stamp Program, now known as SNAP, is an in-kind food assistance program that provides food purchasing assistance to low-income families. The 2008 farm bill renamed the Food Stamp Program as the Supplemental Nutrition Assistance Program. Since this occurs in the middle of the time frame I study, I will use both names interchangeably. The role of SNAP has grown substantially in recent years, becoming one of the largest public assistance programs in the US (5th by expenditure, 3rd by recipients).

Aid to Families with Dependent Children (AFDC) was a cash assistance welfare program, and was reformulated into Temporary Assistance for Needy Families (TANF) by the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA). PRWORA gave states more flexibility in designing their welfare programs, and also changed the fiscal structure of welfare from a federal matching grant to a block grant. Subsequently, the real value of funding, as well as caseloads, have decreased in recent years. Since the reformulation took place in the middle of the time period I study, I will also use AFDC and TANF interchangeably.

Supplemental Security Income (SSI) is a means-tested program that provides cash assistance to low-income individuals who are either aged 65 or older, blind, or disabled (children included), often referred to simply as disability (although not the only disability program in the US). Spending on SSI has grown from $27 billion in 1995 to nearly $55 billion in 2016, an increase of 104%, making it one of the fastest growing, means-tested programs in the US.

Finally, the Earned Income Tax Credit (EITC) is a refundable tax credit for low-income individuals, providing a sliding subsidy depending on earned income. Key to the EITC is that it is only available for working tax filers. Spending on the EITC has grown from just over $30 billion in 1995 to nearly $60 billion in 2015, an increase of nearly 100%. Some states also have a state level EITC, providing a state level boost to federal assistance. Together, these programs make up a large portion of the social safety net.

Next, consider the following equation of the effect of the minimum wage on the income to poverty ratio, a measure which compares family incomes to poverty thresholds defined by the US Census Bureau[3] and which vary based on year and family size

$$\frac{\text{Income}}{\text{Poverty}}_{ijt} = \kappa_0 + \kappa_1 \text{Minimum Wage}_{jt} + \kappa_2 \text{Benefits}_{ijt} + \kappa_3 X_{ijt} + \varepsilon_{ijt} \tag{4.4}$$

where Min. Wage_{jt} is the minimum wage in state j at time t, Benefits_{ijt} is the value of safety net benefits, and X is some vector of individual and state level controls. If we are interested in the marginal effect of the minimum wage on poverty, we would have

$$\frac{\partial \text{Inc./Pov.}_{ijt}}{\partial \text{Min. Wage}_{jt}} = \kappa_1 + \kappa_2 \frac{\partial \text{Benefits}_{ijt}}{\partial \text{Min. Wage}_{jt}} \tag{4.5}$$

From equation (4.3) we know that $\frac{\partial \text{Benefits}_{ijt}}{\partial \text{Min. Wage}_{jt}} < 0$. This means that regardless of the own effect of the minimum wage on poverty (of which there is no consensus), the total effect, taking into account the change in program benefits, should be less than the own effect.

Much of the literature surrounding the minimum wage focuses on the employment effects of minimum wages. Gramlich et al. (1976) provide much of the foundation for minimum wage analysis, and Neumark et al. (2007) provide an in-depth overview of much of the minimum wage literature from 1990s and 2000s. Generally, there is no consensus on the effect of the minimum wage on employment, however, as Neumark et al. (2007) note, most studies find negative employment elasticities (Neumark, 2017; Aaronson et al., 2017; Jardim et al., 2017; Neumark, 2016; Meer and West, 2015;

[3]https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html

Sabia et al., 2012). However, a seminal study by Card and Krueger (1994) compares employment at fast-food restaurants along the borders of New Jersey (where the minimum wage had risen) and Pennsylvania, and finds no decline in employment. More recent studies from Dube et al. (2016) and Giuliano (2013) also fail to find negative associated employment effects of the minimum wage.

While the employment effects of the minimum wage are crucial to understand, as noted by Gramlich et al. (1976), the goal of the minimum wage is often seen as reducing poverty and inequality. The literature on the effect of the minimum wage on poverty and inequality generally fails to find consensus. MaCurdy (2015) simulates the consequences of a minimum wage increase using the first three waves of the 1996 SIPP panel, and finds a small redistributional effect from the minimum wage, however, he notes that increases in the minimum wage result in higher prices as well. He finds that 3 in 4 low-income families are actually net losers from changes in the minimum wage. MaCurdy (2015) notes, however, that the increased earnings due to increases in the minimum wage of the poorest families are only slightly higher than the increased earnings of the wealthiest families, with families in the top fifth and bottom fifth of the income distribution almost equally likely to have a low wage worker. Often this is associated with teenagers in higher income households earning the minimum wage. However, Dube (2017) finds that increased minimum wages reduce the poverty rate, with strong earnings gains in the lowest portions of the income distribution. Bárány (2016) finds that the minimum wage can affect the optimal choice of education across the income distribution and change the skill distribution of the workforce, thus impacting inequality through more than just the earnings of young people.

Figure 4.1 further examines the relationship between minimum wages and poverty, depicting the income to poverty ratio for minimum wage earners over time.[4] Here,

[4] Author's calculations from the CPS ASEC. A minimum wage earner is someone whose yearly earnings to yearly hours ratio falls below the effective minimum wage for that state.

during the time period examined by MaCurdy, I show that minimum wage earners were gaining in terms of the income to poverty ratio. In the mid to late 1990s, the average income to poverty ratio for minimum wage earners was below 200% FPL, with the upward trend in the income to poverty ratio beginning prior to the federal increases of 1997, and the downward trend in the ratio beginning slightly before the Great Recession. However, the decline in the ratio was relatively mild during the Great Recession, suggesting the minimum wage hikes of 2007-2009 may have mitigated downward macroeconomic pressure.

Many other authors have also examined the effect of the minimum wage on poverty. Neumark and Wascher (2002) and Neumark et al. (2005) both examine how the minimum wage influences low-income families, generally finding that the minimum wage increases movement both into and out of poverty. This reflects both the income boost the minimum wage provides to low-income families, as well as the disemployment effects of increased minimum wages. Lee and Saez (2012) suggest that this redistribution among low-income families may be desirable if the minimum wage is properly targeted, with employment effects concentrated among those with low work attachment. Neumark et al. (2004) also find an overall negative effect of the minimum wage on inequality, with an overall decrease in earned income for low wage workers. However, not all studies find negative effects on incomes from the minimum wage. Dube et al. (2010) finds consistently positive effects of the minimum wage on earnings, even when limiting analysis to contiguous border county-pairs, attributing many of the negative effects found in other studies to insufficient geographic and temporal trend controls. Autor et al. (2016) also find that increases in the minimum wage reduced inequality, again citing inadequate measurement of trends, along with the time window of previous analyses.

Many of these analyses fail to fully account for the interaction between program benefits and changes in the minimum wage. As shown in equation (4.3) this effect is likely negative, and could potentially be important for an analysis of the relationship between the minimum wage and poverty. Moffitt et al. (1998) examine the interplay between wage inequality and social safety net benefits from 1969 to 1992. They find that there is a positive correlation between wage rates at the bottom end of the income distribution and the demand for welfare benefits. Using a state-level panel of wages and the demand for AFDC benefits, the authors find a positive correlation between low-income wages and the demand for AFDC benefits. What is especially interesting with their analysis is the lack of work requirements under AFDC. This could mute or negate the relationship shown in equation (4.3).

Some other studies have begun examining the role of program benefits as they relate to changes in the minimum wage. Dube (2017) examines the effect of the minimum wage on traditional poverty measures which exclude benefits from their calculations, as well as an expanded income definition which includes SNAP and EITC benefits. Dube finds generally significant poverty rate elasticities of between -0.22 and -0.55 for the minimum wage, similar to results presented in this paper. However, he also finds that including other program benefits in the definition of income reduces the magnitude of the results by approximately 28%. While Dube does account for benefits in his definition of income in some specifications, he does not explicitly model the relationship between the minimum wage and program benefits.

Clemens (2016) examines how changes in the minimum wage affect program receipt by comparing states that are bound by federal minimum wage increases to states that are unbound, finding income losses associated with minimum wage increases, and no changes in the value of safety net benefits. Using difference in differences methodologies, Sabia and Nielsen (2015) examine how minimum wages may impact various aspects of poverty from 1996-2007. They find relatively few statistically significant effects, and generally conclude that there is little evidence that the minimum wage reduced poverty or receipt of public benefits. While the authors do not conduct any explicit distributional analyses, they do look among varying populations that may be more or less sensitive to changes in the minimum wage, and find small redistributional effects among low-skilled individuals. Sabia and Nguyen (2017) also find little effect of minimum wage increases on reducing program benefits, examining SNAP/food stamps, housing assistance receipt, AFDC/TANF, and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC). However, many of these studies do not account for differential effects on programs based on employment status nor the fact that program benefits are targeted at low-income families.

Another group of studies focuses specifically on program take up and the minimum wage. Reich and West (2015) examine the response of SNAP to changes in the minimum wage, and using the CPS ASEC, find a 10% increase in the minimum wage would reduce SNAP enrollment by roughly 2-3%, and reduce SNAP expenditure by roughly 2%. The authors use state level heterogeneity in SNAP policies and minimum wages over time, and estimate linear probability models to capture the effects. Contrarily, Page et al. (2005) find that increasing the minimum wage actually increases welfare caseloads. Page et al. look at state level variation in caseloads, and tentatively attribute this increase to changes in employment probabilities associated with minimum wage increases. Two studies by Neumark and Wascher examine how the minimum wage interacts with the EITC. Neumark and Wascher (2001) use the minimum wage as a baseline to compare how the EITC affects poor and low-income families, finding that the EITC is more effective at raising families above the poverty threshold than the minimum wage. Neumark and Wascher (2011) extend this study by explicitly examining the interactions between the EITC and the minimum wage, remarking that arguments can be made for the minimum wage enhancing the effectiveness of the EITC. Merging state-level policy data with the CPS Annual Demographic Files, the authors use a few reduced form specifications to find that the interaction between the EITC and the minimum wage can produce a boost in employment and earnings for single women with children, but actually reduce employment and earnings for low-skill and childless minority individuals. Thus, it seems there is no clear impact of the minimum wage on program benefits, with results for take up and wage/employment effects that differ across program and family structure.

The studies mentioned above outline a few gaps that this paper attempts to fill. The first is examining how the minimum wage affects safety net benefits. As noted by Schmidt et al. (2015), program benefits are targeted at low-income individuals, and failing to account for this targeting could bias results towards zero. Much of the previous research on the minimum wage and the safety net either focuses on a single program or fails to account for this targeting. The second gap this paper attempts to fill is understanding the joint effect of minimum wages and program benefits on poverty. By separating these effects, rather than simply combining program benefits into a broad measure of income, I am able to examine the magnitudes of the joint effect both as a whole and program by program. Finally, this paper contributes to the ongoing literature regarding minimum wages and poverty, suggesting a broader approach may be helpful when thinking about antipoverty policy.

4.3 Model

I begin by examining the effect of the minimum wage on the value of program benefits. However, many individuals report no program benefits, creating censoring from below at zero. Thus, I estimate a Tobit model of the form

$$\text{Benefit}_{ijt} = \begin{cases} \text{Benefit}^*_{ijt} & \text{if Benefit}^*_{ijt} > 0 \\ 0 & \text{if Benefit}^*_{ijt} \leq 0 \end{cases} \tag{4.6}$$

with

$$\text{Benefit}^*_{ijt} = \beta_0 + \beta_1 ln(\text{Min. Wage}_{jt}) + \beta_2 X_{ijt} + \delta_j + \delta_t + t\delta_d + \varepsilon_{ijt} \tag{4.7}$$

where Benefit_{ijt} represents the dollar value of self-reported program benefits received for person i in state j at time t, and Benefit^*_{ijt} is the latent value of benefits observed only if $\text{Benefit}^*_{ijt} > 0$. Equation (4.6) shows that I do not observe anyone with negative benefits, which conceptually could be viewed as an individual willing to pay to stay out of the safety net in order to avoid any associated costs, such as stigma, transaction, or information costs. Thus, failing to account for this censoring could potentially bias my results.

In this paper, I will consider benefits from four of the largest means-tested programs in this time period—food stamps (or SNAP), AFDC/TANF, the EITC, and SSI, both individually and as the summed value of total benefits. $ln(\text{Min. Wage}_{jt})$ is the natural log of the higher of state or federal minimum wages, and X_{ijt} is a vector of state and individual level controls including sex, a quartic in age, race, ethnicity, marital status, education, family size, governor party affiliation, the unemployment rate, the 25th percentile of income, the log of the 50/10 income ratio, the employment to population ratio, and per capita income. With the addition of governor party affiliation, which is included to capture any systematic difference in benefit generosity based on state political climate, and the 25th percentile of income, the log of the 50/10 income ratio, and the employment to population ratio, which are included to more thoroughly capture changes in the macroeconomic circumstances of those at the lower end of the income distribution, these are the same controls used by Dube (2017) in his analysis of the minimum wage. I also include the canonical state and year fixed effects (δ_j and δ_t), as well as Census division by year fixed effects ($t\delta_d$) to capture minimum wage trends by region, as recommended by Dube (2017). Per Schmidt et al. (2015), I will limit the analysis to citizen family heads between the ages of 16 and 64 who are less than 300% of the federal poverty line. The Tobit model assumes the normality of the standard errors, ε_{ijt}, thus, I will also estimate (4.7) via a linear probability model (LPM). While the LPM does not require the strong assumptions of the Tobit model, it also does not account for the censoring of benefits. Thus, I consider the LPM a check on the Tobit specification.

The parameter of interest in equation (4.6) is β_1, the effect of the minimum wage on the value of means-tested program benefits. This is the empirical analog of equation (4.2), and from equation (4.3), we know β_1 should be negative if work requirements are in place and if labor supply slopes upward. For the benefits I examine, TANF[5] and the EITC are the two with the strongest ties to work, thus, I expect the strongest results for these two benefits. Since SNAP and SSI do not have uniform work requirements, the negativity of β_1 relies on the assumption of upward sloping labor supply. If individuals cannot find work, or wish to reduce hours in a response to an increase in the minimum wage, I may not find $\beta_1 < 0$.

I then use the results from equation equation (4.6) to estimate the empirical analog to equation (4.4)

$$\frac{\text{Inc.}}{\text{Pov.}}_{ijt} = \gamma_0 + \gamma_1 ln(\text{Min. Wage}_{jt}) + \gamma_2 \text{Benefit}_{ijt} + \gamma_3 X_{ijt} + \delta_j + \delta_t + t\delta_d + \eta_{ijt} \quad (4.8)$$

where Benefit_{ijt} is either the total value of benefits or a vector of self-reported benefits for SNAP, AFDC/TANF, SSI, and the EITC, and all other variables are defined as before. From equation (4.5) we know that the total marginal effect from a change in the minimum wage will be $\frac{\partial \text{Inc./Pov.}_{ijt}}{\partial ln(\text{Min. Wage}_{jt})} = \gamma_1 + \gamma_2 \times \beta_1$, here letting β_1 be either the marginal effect for total benefits or the vector of marginal wage effects for all benefits.

I may be hindered in estimating γ_2 due to the endogeneity of benefits. Mechanically, receiving cash or near cash benefits should increase the income to poverty ratio, unless the disemployment effects from SNAP or SSI outweigh any positive effect. Thus, I expect γ_2 to be positive. However, individuals who participate in the safety

[5]Means-tested cash welfare changes from AFDC to TANF in the third year of my sample.

net may be systematically different than those who do not. Furthermore, there is also mechanical endogeneity due to benefits being means-tested. Schmidt et al. (2015) note this endogeneity, and use a simulated eligibility instrumental variables approach where exogenously generated simulated benefits are used to capture the effect of own benefits. Here, I will present another approach to account for this endogeneity.

First, I will implement a control function approach. In order to identify (4.7) off of more than the functional form assumptions of the Tobit model, I will include the maximum benefit guarantees for food stamps/SNAP, AFDC/TANF, SSI, and the EITC, which will vary across family size, state (for all except SNAP) and year. With this approach, I assume that these program parameters only affect the income to poverty ratio through benefit levels, and not any other means. Thus, (4.7) will take the form

$$\text{Benefit}^*_{ijt} = \beta_0 + \beta_1 ln(\text{Min. Wage}_{jt}) + \beta_2 X_{ijt} + \beta_3 Z_{ijt} + \delta_j + \delta_t + t\delta_d + \varepsilon_{ijt} \tag{4.9}$$

where the maximum benefit guarantees are captured by the vector Z_{ijt}. I then utilize the method outlined in Vella (1998) to compute the generalized Tobit residuals, with

$$\hat{\varepsilon_{ijt}} = [1 - \mathbb{1}(\text{Benefit}_{ijt} > 0)] \times \frac{-\phi(X'\hat{\beta})}{1 - \Phi(X'\hat{\beta})} + \mathbb{1}(\text{Benefit}_{ijt} > 0) \times (\text{Benefit}_{ijt} - X'\hat{\beta}) \tag{4.10}$$

where $X'\hat{\beta}$ represents the estimated value of benefits from equation (4.9), and $\phi()$ and $\Phi()$ represent the normal distribution and cumulative normal distribution, respectively. I then re-estimate equation (4.8) including the residuals estimated by

(4.10)

$$\frac{\text{Inc.}}{\text{Pov.}}_{ijt} = \alpha_0 + \alpha_1 ln(\text{Min. Wage}_{jt}) + \alpha_2 \text{Benefit}_{ijt} + \alpha_3 X_{ijt} + \alpha_4 \hat{\varepsilon_{ijt}} + \delta_j + \delta_t + t\delta_d + \nu_{ijt} \tag{4.11}$$

Here, the goal is for $\hat{\varepsilon_{ijt}}$ to capture the endogeneity of benefits, allowing α_2 to capture the effect of program benefits on the income to poverty ratio, with the implied total marginal effect of the natural log of the minimum wage on the income to poverty ratio for low-income individuals being $\alpha_1 + \alpha_2 \times \beta_1$. I utilize this method for both the Tobit model and LPM, where the control function approach for the LPM is equivalent to a traditional instrumental variables approach with the maximum benefit guarantees used as the exogenous instruments. When using the LPM, I will also consider a fixed effects approach. While individual fixed effects would account for any time invariant heterogeneity, the nature of the data I use makes this approach unattractive for a few reasons which will be discussed in the next section.

4.4 Data

Individual characteristics, including information about the 50/10 income ratio, the 25th percentile of income, participation in public assistance programs, and the value of public assistance benefits come from the 1995-2016 waves of the Annual Social and Economic Supplement of the Current Population Survey (CPS ASEC or March CPS). The ASEC collects information on the receipt of many programs, of which I utilize information on the value of benefits from public assistance or welfare (AFDC/TANF)), the value of food stamp or SNAP Benefits, and SSI benefits. Over the time period considered in this paper, these programs are three of the largest programs in terms of means-tested program expenditure. The ASEC provides information on age, sex, race, marital status, educational attainment, family size, and family structure.

The sample design of the ASEC also allows for some individuals to be tracked over time. Madrian and Lefgren (2000) document the panel structure of the ASEC. Households are divided into 8 representative rotation groups, where they are interviewed for 4 consecutive months, followed by an 8 month break, and then interviewed again for 4 consecutive months. Since the ASEC is fielded every March, it is possible to match households interviewed in their first four months in sample in the subsequent year. Following the recommended Census procedure, I first match individuals on the basis of month in sample (months 1-4 for year 1, months 5-8 for year 2), sex, household identifier, household number, and line number of the individual in the household. I then check for consistency in race, age, and state of residence. If the race or state of residence changes, or the age attributed to the record changes by more than two years (as a result of the staggered timing of the initial and final interviews) I consider those records unique individuals. This procedure is also used in Hardy et al. (2017), Burns and Ziliak (2017), Ziliak and Gundersen (2016), and others. This results in approximately one-half of individuals being observed in multiple years. Observing individuals across time provides both benefits and drawbacks. Being able to account for latent, time invariant heterogeneity allows me to somewhat address the selection issue with families and public assistance programs. However, since the matching procedure requires individuals to remain in the same residence, and since I am only able to construct two year panels, any identifying variation in the minimum wage must come from within state changes. Since these changes are relatively infrequent, I may have difficulty identifying any effects from minimum wage changes in any fixed effect type model. I also remove individuals with imputed values of earnings, hours, and program benefits.

One of the fastest growing means-tested public assistance programs in this time period is the EITC. While the ASEC does include self-reported measures of tax credit receipt, I use NBER's *TAXSIM* program to estimate the value of the EITC. This provides a few benefits over using self-reported measures. The first is that any error in recall for the specific value of the credit is avoided, and the second being consistency in the measurement of the EITC across time. However, estimating EITC transfers using *TAXSIM* does assume that take-up is universal for eligibles. Moreover, some items used to compute tax burden are not available in the ASEC, such as mortgage interest paid and child care expenses. I collect monthly, seasonally adjusted unemployment data, as well as employment and population data, from the Bureau of Labor Statistics Local Area Unemployment Statistics collapsed to the interview frame of the ASEC (March to March). I use data on the minimum wage, maximum benefit guarantees, and the party affiliation of the state's governor from the University of Kentucky Center for Poverty Research National Welfare Database. The minimum wage is calculated as the greater of the state and federal minimum wages. I use governor party affiliation to adjust for any program characteristics that might be associated with state level political climate, ensuring I am not simply capturing the effect of overall state level generosity over and above a state fixed effect.

Table 4.1 presents weighted[6] summary statistics for the heads of families. Here, I follow Schmidt et al. (2015) and limit the scope of my analysis to heads of families who are citizens, and whose family income places them at less than 300% of the federal poverty line. This is to more closely identify the population that is likely to receive benefits. I also break out the summary statistics by whether the prevailing minimum wage in the state is the federal minimum wage (covered), or some higher, state minimum wage (uncovered). Here, over the entire time period, we see that take-up rates, even among relatively poor families, are low for both SSI and AFDC/TANF. SNAP take up rates are significantly higher, at 21-22% of families.

Uncovered states are much more likely to have a Democrat as governor, and

[6] I adjust the CPS survey weights via inverse probability weighting based on whether the individual was removed from the sample due to having imputed values of income or hours. Also, per Census recommendation, I drop individuals who did not participate in the redesigned ASEC in 2014.

to have more liberal social policies, with higher levels of total benefits, as well as higher SNAP, AFDC/TANF, and SSI benefits, and more likely to have a state EITC program. They have a higher threshold for the 25th percentile of income, and a lower 50/10 income ratio, suggesting the poorest individuals in these states have relatively higher incomes compared with covered states. These states are also more likely to have a higher proportion of White residents compared to other racial categories, more Hispanic residents, have higher levels of eduction, and higher unemployment rates.

Many of the differences between the two groups can be explained by geopolitical differences in the U.S. As noted by Dube (2017), minimum wage policy is highly regionally concentrated, with states in the Northeast, Midwest, and on the West Coast more likely to have higher minimum wages. Figures 4.2-4.4 show changes in the value of the real minimum wage across states from 1995-2015. Early in my sample period, the prevailing minimum wage in most states was the federal minimum wage. By 2005, the geopolitical patterns displayed in minimum wage policy are present. These patterns hold true in 2015 as well. Even though many more states were providing higher minimum wages than the federal minimum wage, those states in the Northeast, Midwest, and on the West Coast were systematically higher. Thus, following Dube (2017), I include Census division by year trends to capture the systematic difference between regions over time.

Figure 4.5 shows the variation in the number of changes in the minimum wage over the course of my sample. We see that some states had minimum wages that were never higher than the federal minimum wage,[7] with some states having slightly more changes in the state minimum wage than federal changes (5). However, this does not necessarily mean these states were providing consistently higher minimum wages, rather, they may have just been easing the transition between federal in-

[7]Alabama, Georgia, Indiana, Kansas, Kentucky, Louisiana, Mississippi, North Dakota, Oklahoma, South Carolina, Tennessee, Texas, Utah, Virginia, and Wyoming

creases. Among those states with the highest number of minimum wage changes are Connecticut, Vermont, Oregon, and Washington. These are also states that, geopolitically, reside in areas with systematically higher minimum wages. Thus, figure 4.5 shows that there is significant variation in the minimum wage across states and over time in this sample period, providing the variation I will need to identify the impact of the minimum wage.

Figures 4.6 and 4.7 show how the distribution of the minimum wage has changed across states over time. Figure 4.6 shows that the bottom two quintiles of states in terms of the value of the minimum wage have been exactly equal during this period, with the third lowest quintile differing only slightly. Prior to the federal minimum wage increases in the mid 2000s, the real value of the minimum wage in these 30 states decreased sharply. After the federally mandated increases, the real value has eroded, such that for the bottom 20 states, the real value of the minimum wage is only approximately 25 cents higher in 2016 than it was in 2000. States at the second highest quintile have seen moderate growth in the real minimum wage over this time frame, with states in the upper quintile seeing moderate growth prior to the Great Recession of the late 2000s, and much faster growth after the Great Recession.

Figure 4.7 shows that the distribution of minimum wages was much more concentrated in the early years of my sample, but has become much more dispersed over time. In 1995, for any given quintile of the minimum wage, the difference between that quintile and the one above or below it was approximately 25 cents. At the extreme, the average of the top quintile of the minimum wage was approximately $7.00, the average of the bottom quintile was $5.50, for a difference of $1.50 in 1995. In 2016, the dispersion is not only greater, but more varied across quintiles, with some being more tightly clustered than others. At the extremes, the difference in the top and bottom quintiles was approximately $2.60. These figures show that, even among low wage earners, inequality in earnings has increased.

4.5 Results

Here, I first present graphical analysis depicting the relationship between the minimum wage and program benefits. I then present first stage results of the effect of the minimum wage on program benefits using the Tobit, followed by second stage results for the joint effect of the minimum wage and benefits on the income to poverty ratio. Finally, I present results from linear probability models as an additional check on the Tobit specification. All models include the controls mentioned above, as well as state, year, and division by year fixed effects. All models are weighted by adjusted CPS person weights, and all standard errors are clustered at the state level.

4.5.1 Main Specification: Tobit

First, I examine how the value of benefits change as the minimum wage changes. Figure 4.8 depicts changes in the average yearly value of SNAP or food stamp, AFDC/TANF, SSI, and EITC benefits on the left axis, and the average real value of the minimum wage on the right axis. In the early years of my sample, food stamps and AFDC were the largest means-tested transfer programs by the value of benefits. Following the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA), which reformulated AFDC into TANF, the value of cash-welfare benefits began a substantial decline, from which it never recovered. Important to note is that PRWORA also implemented work requirements for cash-welfare benefits, which could play a potentially large role in TANF's responsiveness to minimum wage shocks. While the value of food stamp benefits declined in the late 1990s, the level of benefits ultimately became the largest of the means-tested programs I consider, at approximately $1,100 yearly. This trend in the increase of SNAP is also noted by Ziliak (2015).

Barring the EITC expansions associated with the Jobs and Growth Tax Relief

Reconciliation Act of 2003,[8] the real value of the EITC has remained relatively constant over the course of my sample, at about \$200 per year. The real value of SSI benefits has been slowly increasing in this time frame, from approximately \$150 in 1995 to \$250 in 2015. This shows how safety net policy has been changing the landscape of benefits, diminishing the role of some facets of the safety net and highlighting the role of others.

I contrast this with changes in the minimum wage. The average real value of the minimum wage was roughly \$6.00 per hour in 1995, and approximately \$7.50 in 2015. The minimum wage expansions of the late 2000s began a sharp increase in the real value of the minimum wage, which has somewhat eroded in subsequent years. Figure 4.8 does not depict any striking relationship between the minimum wage and benefits. While the increase in the minimum wage in the late 2000s roughly tracked the increase in SNAP and SSI benefits, the downturn in benefit levels in the early 2010s saw, if anything, a slight increase in the real value of the minimum wage.

Figure 4.9 shows the percent of recipients of benefits and those earning the minimum wage living under 100%, 200%, and 300% of the federal poverty line. AFDC/TANF recipients are by far the most likely to live under 100% of the federal poverty line, with nearly 80% of recipients falling below this threshold. Moreover, nearly all recipients of AFDC/TANF fall below 300% FPL, suggesting almost all recipients experience a substantial degree of poverty. While food stamp or SNAP recipients are much less likely to fall below 100% FPL than are cash-welfare recipients, they are nearly as likely to fall below 300% FPL. This suggests that the depth of poverty might not be as extreme for SNAP recipients. SSI and EITC beneficiaries experience a substantial degree of poverty (approximately 90% of recipients fall below 300% FPL), however, not at the same level as those receiving other benefits. Minimum wage earners seem

[8] An additional \$4,300 was made available to taxpayers with two or more qualifying children. For more information, see Kalinka (2003) and Crandall-Hollick (2018).

the most insulated from poverty, with only 35% falling below 100% FPL, and 70% falling below 300% FPL. As noted by MaCurdy (2015), many minimum wage earners lie in the upper tail of the income distribution, representing earnings by young people. While the figures here focus on family heads, many young heads of families may also receive additional support from other family members.

Table 4.2 uses the insights from figure 4.9, as well as Schmidt et al. (2015), to estimate equation (4.9) for citizen heads of families between the ages of 16 and 64 who are also less than 300% FPL. Here, I show the marginal effects of the Tobit model, at means, for the effect of the natural log of the minimum wage on total benefits, as well as on the individual programs as well. I find a 1% increase in the minimum wage reduces total benefits by \$2.93, and reduces the value of self-reported program benefits received by \$0.20 for food stamps/SNAP, \$0.47 for AFDC/TANF, \$0.98 for SSI, and \$1.08 for the EITC.[9] These results validate the predictions in equation (4.3), showing that increasing the minimum wage for low-income workers reduces the value of received benefits. This implies that using the minimum wage as an anti-poverty tool could be a double-edged sword, increasing wages at the expense of safety net benefits. Using the means reported in table 4.1, I find minimum wage elasticities for total reported benefits to be -0.24. For individual programs, I find minimum wage elasticities of -0.03 for SNAP, -0.27 for AFDC/TANF, -0.42 for SSI, and -0.43 for the EITC.

Tables A.11-A.15 in the appendix perform the McDonald-Moffitt decomposition per McDonald and Moffitt (1980), which decomposes the total marginal effect into the marginal effect at the intensive margin of benefits vs. the extensive margin of benefits. Here we can see that the marginal effect at the extensive margin is

[9] Benefits are reported at a yearly level. If the average minimum wage is \$7.75 an hour, then a 1% increase in the minimum wage results in a \$161.20 increase in total yearly wages for a full-time, minimum wage earner. Thus, this \$161.20 increase in total wages results in a \$2.93 decrease in benefits.

much larger than the marginal effect at the intensive margin. This suggests that work requirements may play a large roll in the response of benefits to changes in the minimum wage. As discussed previously, many studies find that increases in the minimum wage decrease overall levels of employment, especially for low income workers. If benefits are provided with a work requirement, this loss of employment could decrease overall program participation, producing the relatively large, negative marginal effects at the extensive margin.

Next, I estimate equation (4.11) to determine the effects of the minimum wage and program benefits on the income to poverty ratio. I present these results in table 4.3. Column (1) sums the dollar value of self-reported benefits for food stamps/SNAP, AFDC/TANF, SSI, and the EITC into total benefits, while column (2) breaks out the value of benefits for individual programs. I then calculate the total marginal effect ($\alpha_1 + \alpha_2 \times \beta_1$), which takes into account the changes in benefits due to changes in the minimum wage, and include it at the bottom of the table. In column (1), I find a positive, significant effect of the minimum wage on the income to poverty ratio, with a 1% increase in the minimum wage increasing the income to poverty ratio by 0.55 percentage points. In column (2), this result becomes negative and statistically insignificant.

However, I do find a strong relationship between program benefits and the income to poverty ratio for individuals less than 300% FPL, with a $1 increase in total benefits reducing the income to poverty ratio by about 0.05 percentage points. Once again, using the means presented in table 4.1, this suggests a 1% increase in the dollar value of self-reported benefits increases the income to poverty ratio by 0.64 percentage points, slightly higher than the effect for the minimum wage. Column (2) suggests that SSI and the EITC have significantly positive relationships with the income to poverty ratio, while SNAP has a statistically significant negative relationship and AFDC/TANF has no relationship. These negative results could be due to the differing nature of the programs, but are more likely related to the identifying power of the control function approach for the given programs.

I find the range of elasticities for the minimum wage on the income to poverty ratio to be between -0.06 to 0.55, similar to the -0.22 to -0.55 poverty rate elasticity range found by Dube (2017). The total marginal effects in table 4.3 show how the joint effect of the minimum wage and program benefits influence the income to poverty ratio. Here, the relationship discussed in equation (4.11) becomes quite clear; even if the minimum wage improves poverty, the negative effects of the minimum wage on benefits reduce its effectiveness as an antipoverty tool. Column (1) shows that the small positive effect of the minimum wage decreases by about 30% when accounting for benefit decline, from 0.55 percentage points to 0.39 percentage points. Column (2) shows the small negative effect of the minimum wage on poverty becomes more negative by approximately 20%.

The main finding of this paper is that the minimum wage, in essence, works against itself as an antipoverty policy tool. Tables 4.2 and 4.3 show that the minimum wage works against many of the largest components of the social safety net, reducing benefits while trying to lift wages. The results in table 4.3 suggest only modest improvements to poverty from the minimum wage, and even these small gains are significantly offset by losses in benefit income for low-income families. These losses in benefit income suggest that the minimum wage may be less effective than other studies, which do not account for transfer income, find.

4.5.2 Alternative Specifications: Linear Probability Models

I now examine the linear probability analogs of the earlier Tobit findings. These results have the benefit of relaxing the functional form assumptions of the Tobit models, however, they do not account for the censoring of benefits at zero. Table 4.4 shows the corresponding estimates to table 4.2 for linear probability models. Each entry in table 4.4 represents $\hat{\beta}_1$ from equation (4.9), with the dependent variable listed in the leftmost column. Using the LPM allows me to estimate equation (4.8) for both the level and natural log of benefits. Using the natural log requires that I drop all zero entries, which could potentially bias my results upwards. I also estimate equation (4.9) using individual fixed effects, presented in column (2). As previously noted, the short windows and lack of variation could make identification difficult in the fixed effects models.

Column (1) of table 4.4 gives a negative point estimate for all values of the level of benefits, and most of the point estimates for the natural log of benefits, suggesting the results derived in equation (4.3) hold, and that increasing the minimum wage reduces the overall value of benefits. Interpreting the coefficients for the levels of benefits, I find a 1% increase in the minimum wage decreases the dollar value of self-reported total benefits by \$5.95, SNAP or food stamp benefits by \$0.95, the value of AFDC/TANF benefits by \$2.44, the value of SSI benefits by \$0.65, and the value of EITC benefits by \$2.43, with the elasticity of benefits with respect to the minimum wage being -0.49 for total benefits, -0.16 for SNAP, -1.41 for AFDC/TANF, -0.28 for SSI, and -0.98 for the EITC. While I obtain negative point estimates for all benefits examined, only total benefits, AFDC/TANF and EITC benefits are statistically significant. This suggests that the negative relationship between the minimum wage and benefits is strongest when strong work requirements are present, once again confirming the intuition presented in equation (4.3).

Table 4.5 presents the corresponding linear probability second stage estimates, using the residuals from the models in table 4.4 to capture the endogeneity of program benefits. This methodology is equivalent to an instrumental variables approach. Columns (1), (2), and (4) present models that do not account for the endogeneity of benefits. In column (1), I include no benefits in the regression equation, and find the minimum wage reduces the income to poverty ratio by 0.89 percentage points. In column (2), I include total benefits but do not account for the endogeneity of benefits. Here, the coefficient on both the minimum wage and total benefits are negative and statistically significant. The negative coefficient on total benefits suggests the bias is large enough to flip the sign on total benefits, implying receiving additional funds from the safety net actually reduces the income to poverty ratio. Column (3) accounts for this bias, and shows a negative and statistically insignificant coefficient for the natural log of the minimum wage, and a positive and weakly significant coefficient for total benefits. This suggests that the minimum wage has little effect on poverty, but that this weak, negative effect is deepened through the reduction in benefits, with the total marginal effect suggesting a 1% increase in the minimum wage actually *decreases* the income to poverty ratio by 0.92 percentage points. Columns (3) and (4) break out the individual programs, telling a similar story to that of total benefits. However, here we see the strongest relationship between the safety net and the income to poverty ratio in the coefficient on SNAP, suggesting an additional dollar of SNAP benefits increases the income to poverty ratio by 0.024 percentage points.

These results compliment the earlier Tobit models, suggesting the results above are not driven purely through functional form assumptions. In the appendix, I include both fixed effects results using the short, two year panels in the ASEC, as well as results using the natural log of benefits, which drops those with zero dollars in benefits. These results show that the fixed effects approach is insufficient to deal with the endogeneity of program benefits, and that those with zero dollars in benefits contribute to the overall estimation procedure.

4.6 Conclusion

As noted by Gramlich et al. (1976) the minimum wage is “basically an attempt to alter the distribution of income,” thereby attempting to reduce poverty and promote the well-being of low-income individuals. However, the social safety net is also designed to serve this function by providing cash or in-kind assistance to low-income families. While different safety net programs may differ in their administration or specific goals, ultimately, they are tools designed to reduce poverty and improve the well-being of low-income families. A large literature has developed attempting to understand the minimum wage's role in reducing poverty and inequality, and has generally failed to find consensus in the last 40 years.

In this paper, I examine the minimum wage through the lens of the traditional safety net, not only accounting for the effect of the minimum wage on poverty, but also analyzing how it changes the traditional social safety net. I find that the minimum wage has a small, positive effect on the income to poverty ratio, but also reduces the value of program benefits. This joint effect attenuates the own effect of the minimum wage by approximately 30%, suggesting that even those studies finding a positive effect of the minimum wage on poverty and inequality may be overstating their case if they do not adequately account for changes in the safety net.

This analysis could provide invaluable insight for policy makers looking for tools to move the needle on poverty. Many studies find the minimum wage to be a blunt instrument, doing more harm than good with respect to poverty. Regardless, many large increases in the minimum wage have been enacted, especially at local levels (Jardim et al., 2017). These large local increases also fall outside the ranges typically analyzed, potentially producing effects larger than previously estimated. Thus, it is important for both policy makers and researchers to take a broad view of the minimum wage as they study its effects in the economy.

This paper suggests that the minimum wage may be an imprecise tool to address poverty. Compounding the negative employment effects and the increase in price levels found in previous studies, the results here suggest the minimum wage could have larger negative consequences outside of those previously identified. If the minimum wage works against the traditional safety net in fighting poverty, policy makers may want to reassess whether the minimum wage is the most effective tool for the job. Moving forward, these results provide a basis for discussing broad tools to address poverty, rather than considering the effect of the minimum wage alone.

Figure 4.1: The Minimum Wage and Poverty

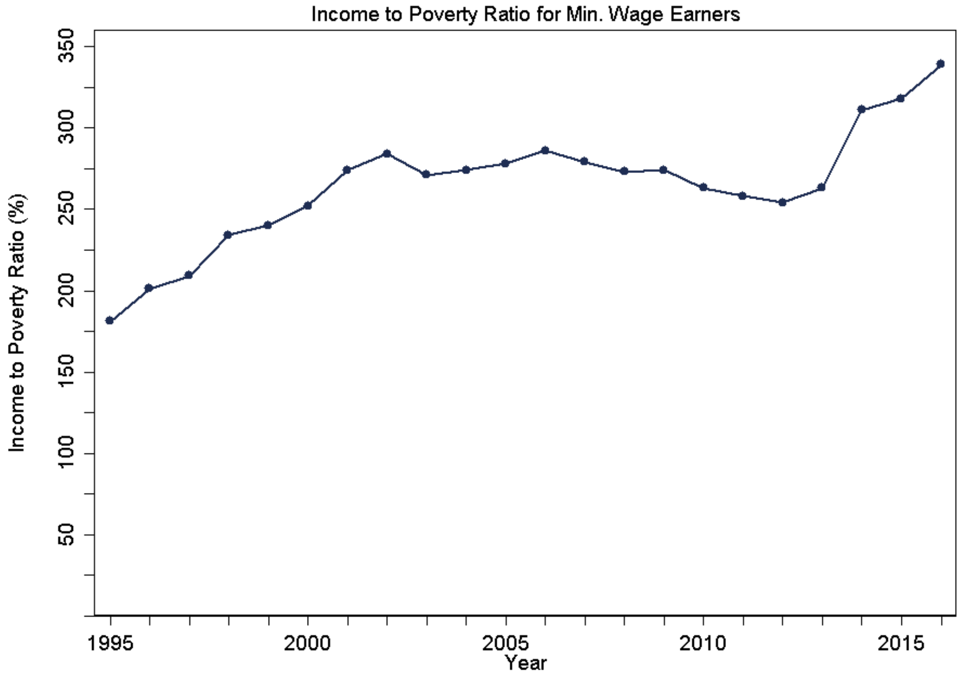


Figure 4.2: Real Minimum Wage: 1995

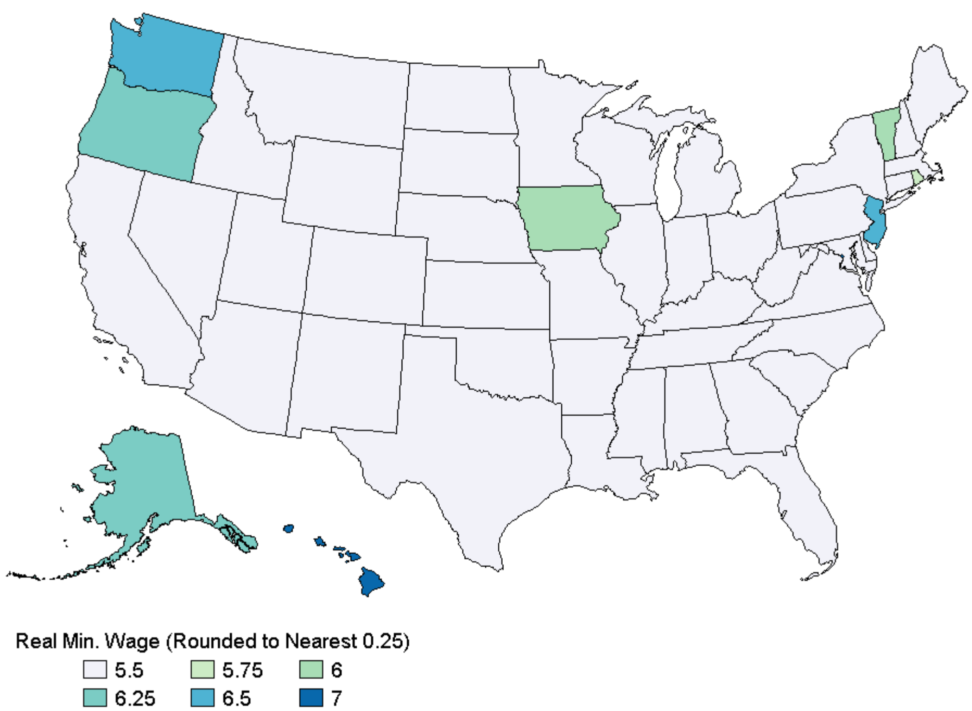


Figure 4.3: Real Minimum Wage: 2005

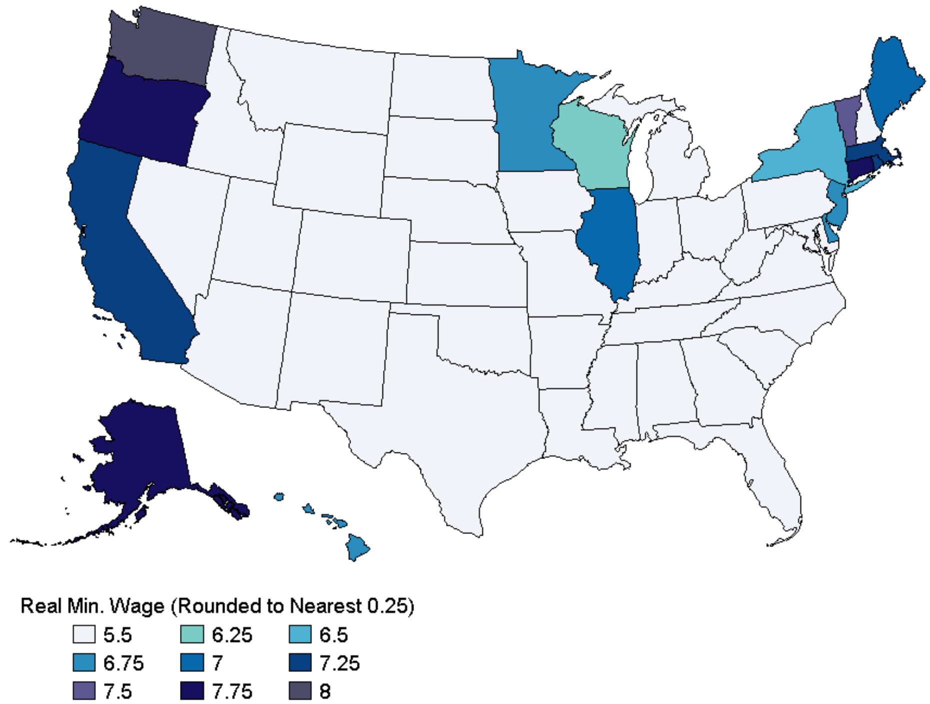


Figure 4.4: Real Minimum Wage: 2015

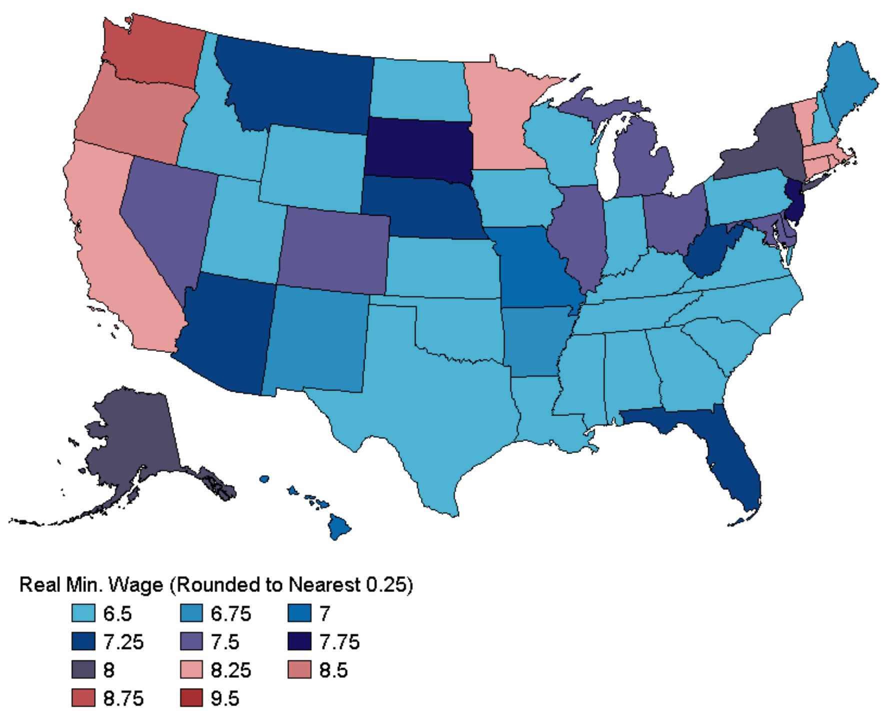


Figure 4.5: Number of Changes in the Minimum Wage

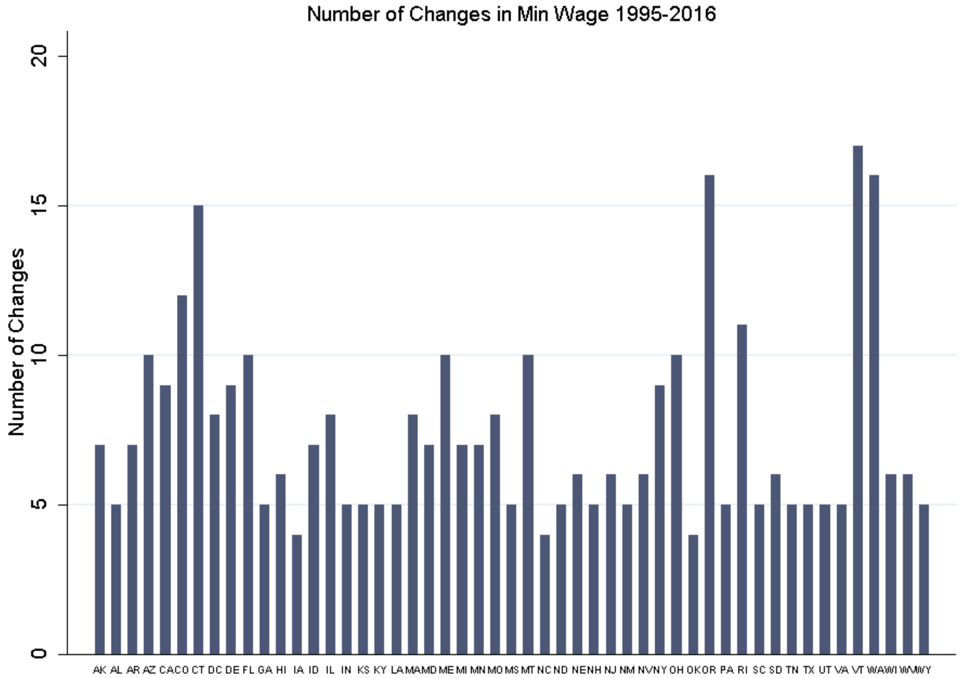


Figure 4.6: Average of Minimum Wage by Quintile of State

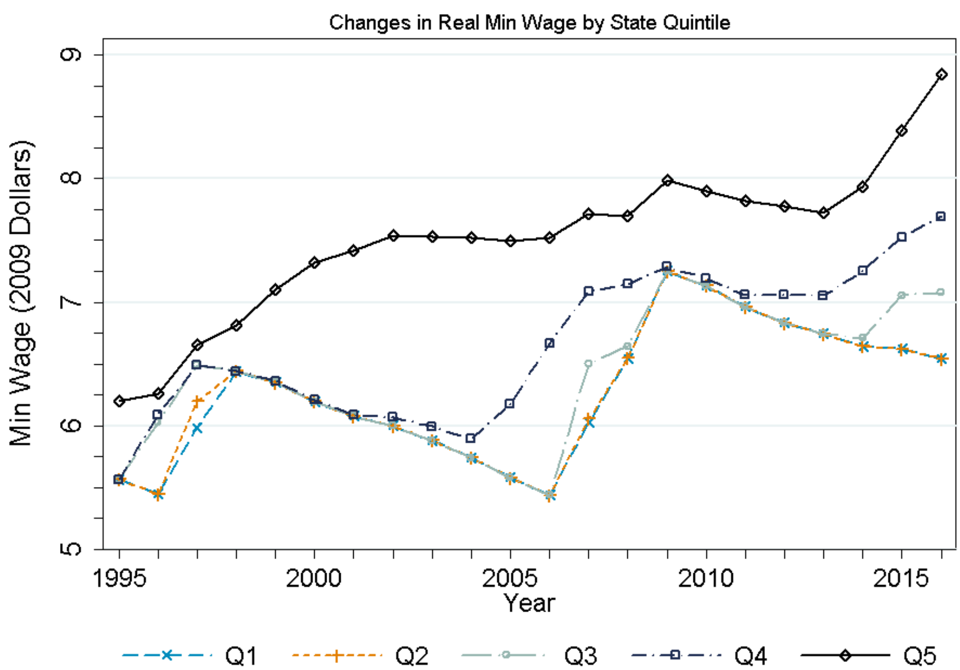


Figure 4.7: Average of Quintile of Minimum Wage

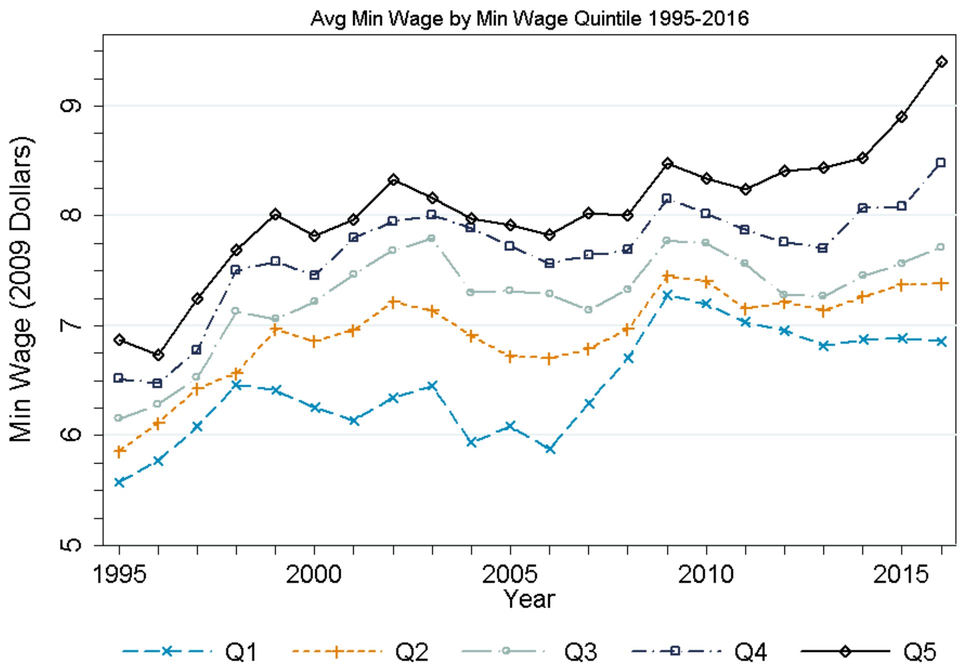


Figure 4.8: Safety Net Benefits Over Time

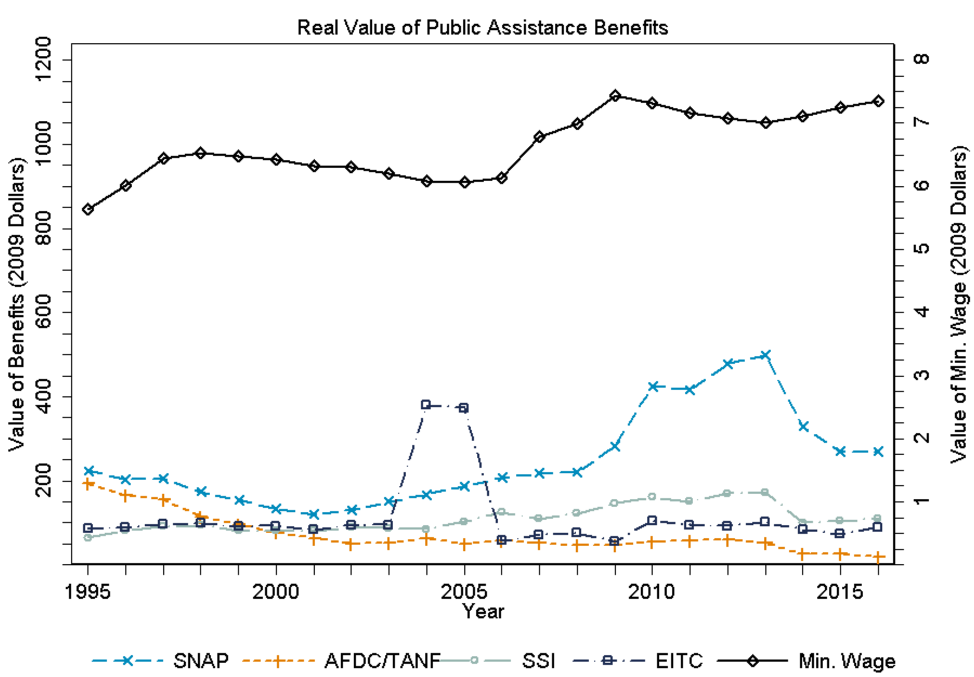


Figure 4.9: Benefits and Poverty

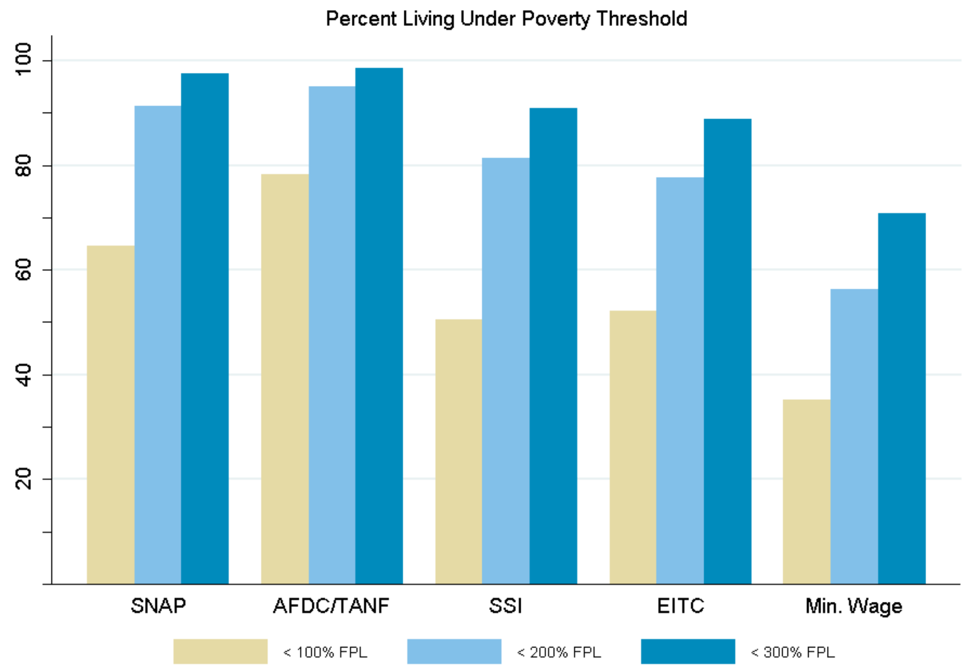


Table 4.1: Summary Statistics by Covered Status

	All Ind.	Uncovered	Covered
Total Benefits	1213.42	1353.95	1160.18
SNAP	0.21	0.22	0.21
SNAP Ben.	600.03	663.00	576.17
AFDC/TANF	0.05	0.06	0.05
AFDC/TANF Ben.	172.66	232.46	150.01
SSI	0.04	0.04	0.04
SSI Ben.	231.43	268.03	217.57
Tot. EITC	248.10	228.29	255.49
Min Wage	6.59	7.39	6.28
White	0.75	0.80	0.74
Female	0.56	0.59	0.55
Age	38.87	39.37	38.68
Black	0.21	0.15	0.23
Other Race	0.04	0.05	0.03
Hisp.	0.10	0.15	0.09
Married	0.52	0.50	0.53
High School	0.40	0.37	0.41
Some College	0.32	0.36	0.31
College	0.12	0.14	0.11
Num. Child	1.49	1.48	1.50
Dem. Gov.	0.41	0.62	0.33
State EITC	0.04	0.06	0.03
Unemp.	6.00	6.72	5.73
Per Cap. Inc.	0.05	0.06	0.05
ln(50/10)	1.70	1.65	1.72
25th pctile	15131.73	16355.88	14667.97
Emp./Pop.	0.47	0.47	0.47
Obs.	249,200	74,311	174,889

Note: adjusted survey weights used.

Table 4.2: Effect of ln(Minimum Wage) on the Value of Benefits: Tobit

	Total (1)	SNAP (2)	AFDC/TANF (3)	SSI (4)	EITC (5)
ln(Min. Wage)	-292.527^{***}	-20.393^{***}	-47.421^{***}	-98.188^{***}	-107.573^{***}
	(3.062)	(0.316)	(3.522)	(3.541)	(1.390)
Max SNAP	173.173^{***}	46.657^{***}	-8.199^{***}	8.248^{***}	81.102^{***}
	(2.161)	(1.023)	(0.598)	(0.370)	(1.158)
Max TANF	-106.969^{***}	-39.184^{***}	-1.702^{***}	-23.928^{***}	-27.213^{***}
	(1.163)	(0.798)	(0.121)	(0.873)	(0.351)
Max SSI	-0.040^{***}	-0.280^{***}	-0.034^{***}	-0.162^{***}	0.014^{***}
	(0.001)	(0.005)	(0.002)	(0.006)	(0.001)
Max EITC	0.104^{***}	0.014^{***}	0.003^{***}	-0.024^{***}	0.008^{***}
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Obs.	105,037	105,037	105,037	105,037	88,196

Note: standard errors clustered at the state level. Controls include sex, quartic in age, race, ethnicity, marital status, education, family size, governor party affiliation, unemployment rate, the log of the 50/10 income ratio, the 25th percentile of income, the employment to population ratio, and per capita income as well as state, year, and division by year fixed effects. * p <0.10, ** p <0.05, *** p <0.01.

Table 4.3: Effect of Minimum Wage and Benefits on Income to Poverty Threshold: Tobit

	(1)	(2)
ln(Min. Wage)	54.539**	−6.341
	(25.287)	(8.373)
Total Ben	0.053***	
	(0.002)	
SNAP		−0.009***
		(0.000)
AFDC/TANF		−0.000
		(0.001)
SSI		0.005***
		(0.000)
EITC		0.009***
		(0.001)
Total ME	39.129	−7.622
Obs.	270,286	85,371

Note: standard errors clustered at the state level. Controls include sex, quartic in age, race, ethnicity, marital status, education, family size, governor party affiliation, unemployment rate, the log of the 50/10 income ratio, the 25th percentile of income, the employment to population ratio, and per capita income as well as state, year, and division by year fixed effects. * p <0.10, ** p <0.05, *** p <0.01.

Table 4.4: Effect of ln(Minimum Wage) on the Value of Benefits

	(1)	(2)
Total	-594.504^{*}	480.327
	(299.892)	(315.489)
ln(Total)	-0.696^{*}	-0.010
	(0.348)	(0.438)
SNAP	-94.882	147.712
	(178.371)	(176.473)
ln(SNAP)	-0.092	0.160
	(0.347)	(0.301)
AFDC/TANF	-244.334^{**}	-214.117
	(103.700)	(182.217)
ln(AFDC/TANF)	-0.023	-0.837
	(0.414)	(0.823)
SSI	-64.884	537.705^{**}
	(114.073)	(252.361)
ln(SSI)	0.178	-2.122^{**}
	(0.449)	(0.869)
EITC	-243.127^{***}	13.911
	(71.354)	(128.966)
ln(EITC)	-0.630^{*}	-0.502
	(0.331)	(0.632)
FE	No	Yes

Note: standard errors clustered at the state level. Controls include sex, quartic in age, race, ethnicity, marital status, education, family size, governor party affiliation, unemployment rate, the log of the 50/10 income ratio, the 25th percentile of income, the employment to population ratio, and per capita income as well as state, year, and division by year fixed effects. * p <0.10, ** p <0.05, *** p <0.01.

Table 4.5: Effect of Minimum Wage and Benefits on Income to Poverty Threshold

	(1)	(2)	(3)	(4)	(5)
ln(Min. Wage)	−8.936	−13.114**	−4.822	−15.301*	63.914
	(6.264)	(6.258)	(6.424)	(8.942)	(56.557)
Total Ben		−0.007***	0.007*		
		(0.000)	(0.004)		
SNAP				−0.014***	0.024***
				(0.000)	(0.007)
AFDC/TANF				−0.002***	0.280
				(0.001)	(0.179)
SSI				−0.001***	−0.099
				(0.000)	(0.073)
EITC				−0.018***	0.037
				(0.001)	(0.078)
Total ME		−8.677	−9.19	−9.009	−9.310
Control Function	No	No	Yes	No	Yes
Obs.	105,037	105,037	105,037	88,196	88,196

Note: standard errors clustered at the state level. Controls include sex, quartic in age, race, ethnicity, marital status, education, family size, governor party affiliation, unemployment rate, the log of the 50/10 income ratio, the 25th percentile of income, the employment to population ratio, and per capita income as well as state, year, and division by year fixed effects. * p <0.10, ** p <0.05, *** p <0.01.

Appendix

Chapter 1 Appendix

Figure A.1

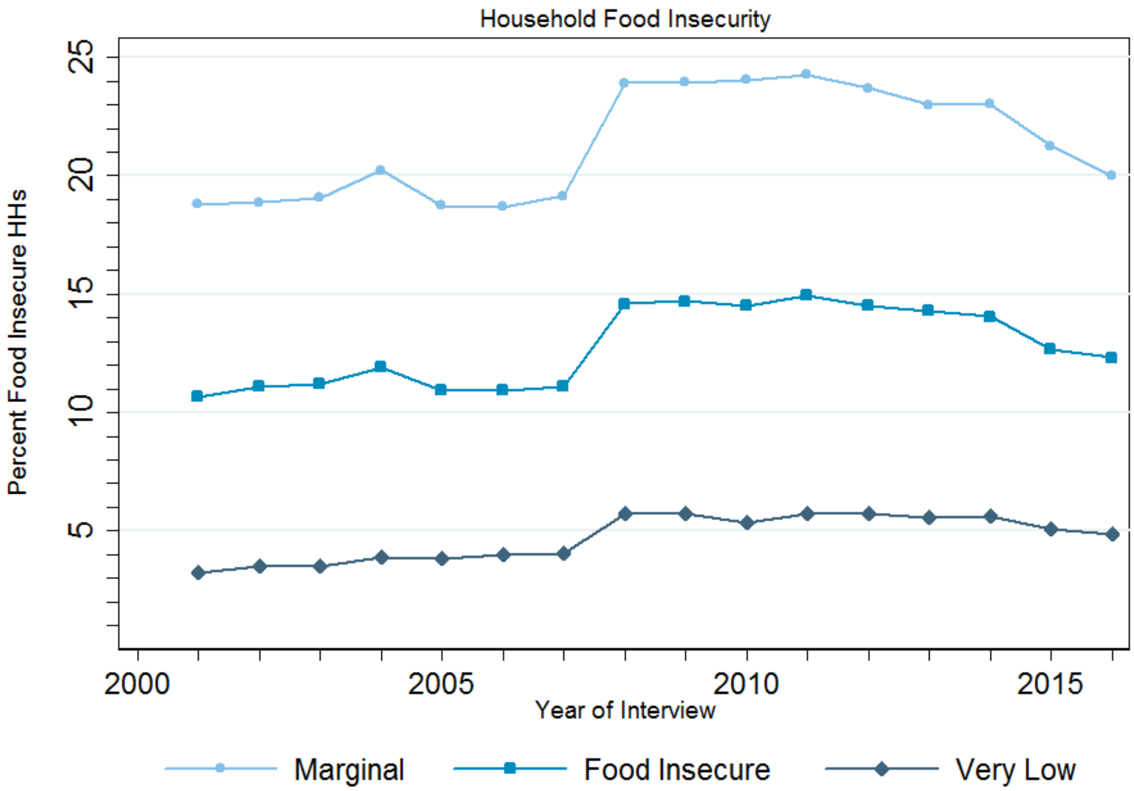


Table A.1: Ordered Probit Coefficients and Marginal Effects

	Coeffs. (1)	Marginal FS (2)	Low FS (3)	Very Low FS (4)
ACA	-0.221^{***}	-0.015^{***}	-0.038^{***}	-0.035^{***}
	(0.033)	(0.002)	(0.006)	(0.005)
SNAP	0.609^{***}	0.042^{***}	0.104^{***}	0.097^{***}
	(0.010)	(0.001)	(0.001)	(0.002)
ACA × SNAP	0.136^{***}	0.009^{***}	0.023^{***}	0.022^{***}
	(0.030)	(0.002)	(0.005)	(0.005)
Obs.	284,804	284,804	284,804	284,804

Note: standard errors clustered at the state level, * p <0.10, ** p <0.05, *** p <0.01. Ordering for probit is 0—fully food secure, 1—marginal food security, 2—low food security, 3—very low food security. Household survey weights used. Controls include gender, household size, number of children, marital status, age, age squared, disability status, race, education, urban/rural status, number of medicaid beneficiaries in the state, governor party affiliation, the 50/10 income ratio, the 25th percentile of income, and the unemployment rate

Table A.2: Triple Differece: LPM

	Food Insecure (1)	Marginal FI (2)	Very Low FI (3)
ACA	-0.064^{***}	-0.108^{***}	-0.024^{***}
	(0.008)	(0.011)	(0.005)
SNAP	0.219^{***}	0.241^{***}	0.117^{***}
	(0.003)	(0.003)	(0.003)
ACA × SNAP	0.039^{***}	0.066^{***}	0.013
	(0.010)	(0.011)	(0.008)
Obs.	284,804	284,804	284,804

Note: standard errors clustered at the state level, * p <0.10, ** p <0.05, *** p <0.01. Household survey weights used. Controls include gender, household size, number of children, marital status, age, age squared, disability status, race, education, urban/rural status, number of medicaid beneficiaries in the state, governor party affiliation, the 50/10 income ratio, the 25th percentile of income, and the unemployment rate

Table A.3: Alternative Measures of Food Hardship: LPM

	FI Gap (1)	FI Gap Squared (2)	Inc. Gap (3)
ACA	-0.018^{***}	-0.002	-1.535^{***}
	(0.006)	(0.004)	(0.375)
SNAP	0.111^{***}	0.088^{***}	8.823^{***}
	(0.004)	(0.003)	(0.269)
ACA × SNAP	-0.009	-0.032^{***}	0.697
	(0.006)	(0.005)	(0.701)
Obs.	194,565	194,565	264,521

Note: standard errors clustered at the state level, * p <0.10, ** p <0.05, *** p <0.01. Household survey weights used. Controls include gender, household size, number of children, marital status, age, age squared, disability status, race, education, urban/rural status, number of medicaid beneficiaries in the state, governor party affiliation, the 50/10 income ratio, the 25th percentile of income, and the unemployment rate

Table A.4: Real Average Weekly Food Expenditure 2011-2016: OLS

	OLS Avg. Weekly Spending
ACA	-1.468
	(1.031)
SNAP	-0.778
	(0.969)
ACA × SNAP	-0.737
	(1.533)
Obs.	96,522

Note: standard errors clustered at the state level, * p <0.10, ** p <0.05, *** p <0.01. Household survey weights used. Controls include gender, household size, number of children, marital status, age, age squared, disability status, race, education, urban/rural status, number of medicaid beneficiaries in the state, governor party affiliation, family income, the 50/10 income ration, the 25th percentile of income, and the unemployment rate.

Chapter 2 Appendix

Table A.5: Federal Medical Assistance Percentages, FY1999 & FY2015

State	FMAP 1999	FMAP 2015	EFMAP 1999	EFMAP 2015
Alabama	69.27	68.99	78.49	78.29
Alaska	59.80	50.00	71.86	65.00
Arizona	65.50	68.46	75.85	77.92
Arkansas	72.96	70.88	81.07	79.62
California	51.55	50.00	66.09	65.00
Colorado	50.59	51.01	65.42	65.71
Connecticut	50.00	50.00	65.00	65.00
Delaware	50.00	53.63	65.00	67.54
District of Columbia	70.00	70.00	79.00	79.00
Florida	55.82	59.72	69.07	71.80
Georgia	60.47	66.94	72.33	76.86
Hawaii	50.00	52.23	65.00	66.56
Idaho	69.85	71.75	78.89	80.23
Illinois	50.00	50.76	65.00	65.53
Indiana	61.01	66.52	72.71	76.56
Iowa	63.32	55.54	74.32	68.88
Kansas	60.05	56.63	72.03	69.64
Kentucky	70.53	69.94	79.37	78.96
Louisiana	70.37	62.05	79.26	73.44
Maine	66.40	61.88	76.48	73.32
Maryland	50.00	50.00	65.00	65.00
Massachusetts	50.00	50.00	65.00	65.00
Michigan	52.72	65.54	66.91	75.88
Minnesota	51.50	50.00	66.05	65.00
Mississippi	76.78	73.58	83.75	81.51
Missouri	60.24	63.45	72.17	74.42
Montana	71.73	65.90	80.21	76.13
Nebraska	61.46	53.27	73.02	67.29
Nevada	50.00	64.36	65.00	75.05
New Hampshire	50.00	50.00	65.00	65.00
New Jersey	50.00	50.00	65.00	65.00
New Mexico	72.98	69.65	81.09	78.76
New York	50.00	50.00	65.00	65.00
North Carolina	63.07	65.88	74.15	76.12
North Dakota	69.94	50.00	78.96	65.00
Ohio	58.26	62.64	70.78	73.85
Oklahoma	70.84	62.30	79.59	73.61
Oregon	60.55	64.06	72.38	74.84
Pennsylvania	53.77	51.82	67.64	66.27
Rhode Island	54.05	50.00	67.83	65.00
South Carolina	69.85	70.64	78.89	79.45
South Dakota	68.16	51.64	77.71	66.15
Tennessee	63.09	64.99	74.16	75.49
Texas	62.45	58.05	73.72	70.64
Utah	71.78	70.56	80.25	79.39
Vermont	61.97	54.01	73.38	67.81
Virginia	51.60	50.00	66.12	65.00
Washington	52.50	50.03	66.75	65.02
West Virginia	74.47	71.35	82.13	79.95
Wisconsin	58.85	58.27	71.20	70.79
Wyoming	64.08	50.00	74.86	65.00

Source: https://aspe.hhs.gov/federal-medical-assistance-percentages-or-federal-financial\
-participation-state-assistance-expenditures

Table A.6: Years With Missing Enrollment

State	Year	Child MC Enrollment	SCHIP Enrollment
Hawaii	1999	89,211	
Washington	1999	504,099	
Wyoming	1999	25,236	
Minnesota	2002	310,002	
Tennessee	2002	705,850	
Arkansas	2003	356,710	
Tennessee	2003	685,027	
Tennessee	2004	670,246	
Tennessee	2005	678,144	
Tennessee	2006	703,138	
Massachusetts	2009		143,044
Utah	2009		59,806
Wisconsin	2009		153,917
Maine	2011		35,986

Table A.7: Impact of Unemployment on ln(Beneficiaries/Pop.): FY1999-FY2015

	MC (1)	SC (2)	MC (3)	SC (4)	MC (5)	SC (6)
Unemp	0.030***	0.051**	0.034**	0.015	0.032***	0.072**
	(0.004)	(0.019)	(0.015)	(0.059)	(0.008)	(0.030)
FMAP	0.002	−0.014	0.003	0.016	0.001	0.006
	(0.006)	(0.013)	(0.003)	(0.025)	(0.003)	(0.023)
Gov. Dem.	0.042***	0.224*	0.014	0.013	0.014	0.062
	(0.015)	(0.116)	(0.027)	(0.100)	(0.027)	(0.111)
$\%\Delta\frac{Emp.}{Pop.}$	1.111***	0.627	−0.289	2.414	0.714	2.240
	(0.334)	(1.749)	(0.931)	(3.186)	(0.622)	(2.178)
NSLP/Pop.	−4.485**	−12.837	−0.649	−6.429	−1.290	−5.667
	(1.899)	(11.452)	(1.350)	(10.140)	(1.208)	(9.533)
NSBP/Pop.	15.696***	32.622***	12.630***	8.701	14.845***	15.372**
	(1.589)	(7.211)	(1.928)	(9.070)	(1.443)	(7.164)
State FE	Yes	Yes	No	No	No	No
Year FE	No	No	Yes	Yes	No	No
Obs.	896	840	896	840	896	840

Note: standard errors clustered at the state level. * p <0.10, ** p <0.05, *** p <0.01. MC represents the natural log of child Medicaid enrollment per person, SC represents the natural log of SCHIP enrollment per person.

Misclassification Bias

Receipt of public health insurance is systematically under-reported in the CPS ASEC. Figure 3.8 shows that weighted child enrollment falls below administrative reported enrollment for all years. Davern et al. (2009) have shown that reporting of overall Medicaid enrollment was 43% lower than administrative reporting, and that even after correcting for this under-reporting using matched MSIS/CPS data, the partially adjusted estimates still do not fully correct for under-reporting.

Meyer and Mittag (2017) show that misclassification can bias estimates, but that there is a tendency for misclassification to attenuate results. Misreports can come in two types, the first is a "false negative" where the respondent states they do not receive public health insurance when in fact they do, and the second is a "false positive" where the respondent states they receive public health insurance when in fact they do not. Adjusting for this misclassification bias is not straightforward, especially with regard to binary dependent variables. I follow an approach similar Hausman et al. (1998) and assume that misreporting is independent of model covariates for all individuals in a given state and year. This implies

$$\frac{\partial Pr(Ins_{pijt} = 1|x)}{\partial x} = (1 - \alpha_{0pjt} - \alpha_{1pjt})\beta \tag{A.1}$$

where $Pr(Ins_{pijt} = 1|x)$ is the conditional probability a child participates in program p. α_{0pjt} is the false positive reporting rate in state j at time t for program p and α_{1jt} is the false negative reporting rate in state j at time t for program p. To construct these false positive and false negative rates, I compare administrative enrollment records with the total weighted enrollment from the CPS in a given state year. If the weighted number of CPS recipients is greater than the administrative number, I construct the false positive rate as

$$\alpha_{0pjt} = \frac{\text{CPS Enrollment}_{pjt} - \text{Administrative Enrollment}_{pjt}}{\text{CPS Enrollment}_{pjt}} \tag{A.2}$$

If the weighted number of CPS recipients is less than the administrative number, I construct the false negative rate as

$$\alpha_{0pjt} = \frac{\text{Administrative Enrollment}_{pjt} - \text{CPS Enrollment}_{pjt}}{\text{Administrative Enrollment}_{pjt}} \tag{A.3}$$

In this specification, either the false positive rate or the false negative rate will be zero for a given state in a given year, depending on whether the weighted count of CPS enrollment is larger or smaller than administrative enrollment. If the CPS count is larger, the false negative rate will be zero. If the CPS count is smaller, the false positive rate will be zero. I then rescale all right hand side variables by this correction.

I present analogous results from tables 3.5 and 3.7 in table A.8, analogous results from table 3.6 in table A.9, and analogous results from table 3.8 in table A.10. Overall, the conclusion from Meyer and Mittag (2017) holds—the interpretation of the results remains the same, with SCHIP, the block grant program, responding more poorly to business cycles and being overall more variables. The results from adjusting for misclassification suggest that the results from the main specifications might be slightly attenuated, but that the signs of the coefficients are valid.

Table A.8: Enrollment Adjusted for Misclassification

	MC (1)	SC (2)	MC (3)	SC (4)
-ln(Exp/Pop)			−0.051	−0.069
			(0.037)	(0.049)
Unemp	0.007**	0.003	0.008***	0.004
	(0.003)	(0.005)	(0.003)	(0.005)
Age	−0.009***	−0.003***	−0.009***	−0.003***
	(0.001)	(0.000)	(0.001)	(0.000)
Black	0.285***	0.072***	0.285***	0.072***
	(0.012)	(0.006)	(0.012)	(0.006)
Other Race	0.104***	0.034***	0.104***	0.034***
	(0.019)	(0.007)	(0.019)	(0.007)
Hispanic	0.226***	0.088***	0.226***	0.088***
	(0.013)	(0.009)	(0.013)	(0.009)
Married	−0.213***	−0.050***	−0.213***	−0.050***
	(0.009)	(0.008)	(0.009)	(0.008)
High School	0.099***	0.037***	0.099***	0.037***
	(0.005)	(0.004)	(0.005)	(0.004)
College	−0.210***	−0.055***	−0.210***	−0.055***
	(0.009)	(0.006)	(0.009)	(0.006)
# <18 in Fam	0.054***	0.012***	0.054***	0.012***
	(0.003)	(0.001)	(0.003)	(0.001)
FMAP	0.003**	0.003	0.003***	0.003
	(0.001)	(0.002)	(0.001)	(0.002)
Pop.	−0.000	−0.000*	−0.000	−0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Min Wage	0.013**	0.003	0.013**	0.003
	(0.005)	(0.010)	(0.005)	(0.010)
Dem. Gov.	0.006	−0.001	0.005	−0.001
	(0.006)	(0.008)	(0.006)	(0.008)
NSLP/Pop.	−0.205	−2.033	−0.274	−2.084
	(0.823)	(2.008)	(0.821)	(2.008)
NSBP/Pop.	−0.302	0.046	−0.287	0.028
	(1.047)	(2.095)	(1.042)	(2.108)
Obs.	829,869	829,869	829,869	829,869

Note: standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models include state and year fixed effects. MC represents the probability a child is enrolled in Medicaid, SC represent the probability a child is enrolled in SCHIP.

Table A.9: Transitions Adjusted for Misclassification

	MC (1)	SC (2)	MC (3)	SC (4)
$\text{SCHIP}_{ij(t-1)}$	0.615***	0.386***		
	(0.037)	(0.052)		
$\text{Medicaid}_{ij(t-1)}$			0.759***	0.114***
			(0.024)	(0.035)
Unemp	0.009***	−0.001	0.004*	−0.007
	(0.003)	(0.004)	(0.002)	(0.004)
$\text{SCHIP}_{ij(t-1)} \times$ Unemp	−0.006	0.023***		
	(0.005)	(0.007)		
$\text{Medicaid}_{ij(t-1)} \times$ Unemp			−0.002	0.025***
			(0.003)	(0.006)
Obs.	150,522	150,522	155,756	155,756

Note: standard errors clustered at the state level. Controls include FMAP, race, sex, age, education, ethnicity, marital status, state population, state min. wage, free school lunch recipients per person, free school breakfast recipients per person, governor party affiliation, and state and year fixed effects. * p <0.10, ** p <0.05, *** p <0.01. MC represents the probability a child is enrolled in Medicaid, SC represent the probability a child is enrolled in SCHIP.

Table A.10: Transitions Adjusted for Misclassification

	MC (1)	SC (2)	MC (3)	MC (4)
$\text{SCHIP}_{ij(t-1)}$	0.472^{***}	-0.017		
	(0.123)	(0.148)		
$\text{Medicaid}_{ij(t-1)}$			0.642^{***}	-0.286^{***}
			(0.099)	(0.102)
-ln(Exp/Pop)	-0.038	-0.031	-0.034	0.016
	(0.039)	(0.042)	(0.031)	(0.046)
$\text{SCHIP}_{ij(t-1)}\times$ -ln(Exp/Pop)	-0.051	-0.279^{***}		
	(0.060)	(0.078)		
$\text{Medicaid}_{ij(t-1)}\times$ -ln(Exp/Pop)			-0.052	-0.286^{***}
			(0.049)	(0.053)
Unemp	0.009^{***}	0.002	0.004^{*}	0.000
	(0.003)	(0.004)	(0.002)	(0.005)
Obs.	150,522	150,522	155,756	155,756

Note: standard errors clustered at the state level. Controls include FMAP, race, sex, age, education, ethnicity, marital status, state population, state min. wage, free school lunch recipients per person, free school breakfast recipients per person, governor party affiliation, and state and year fixed effects. * p <0.10, ** p <0.05, *** p <0.01. MC represents the probability a child is enrolled in Medicaid, SC represent the probability a child is enrolled in SCHIP.

Chapter 3 Appendix

Table A.11: McDonald Moffitt Decomposition: Total

	MFX (1)	Int. Partial (2)	Ext. Partial (3)	Int. Margin (4)	Ext. Margin (5)
ln(Min Wage)	−292.527	−262.353	−0.071	−75.998	−216.529
Max SNAP	173.173	155.310	0.042	44.990	128.183
Max TANF	−106.969	−95.935	−0.026	−27.790	−79.179
Max SSI	−0.040	−0.036	−0.000	−0.010	−0.030
Max EITC	0.104	0.093	0.000	0.027	0.077

Controls include sex, quartic in age, race, ethnicity, marital status, education, family size, governor party affiliation, unemployment rate, the log of the 50/10 income ratio, the 25th percentile of income, the employment to population ratio, and per capita income as well as state, year, and division by year fixed effects. * p <0.10, ** p <0.05, *** p <0.01. MFX represents the total marginal effect, Int. Partial and Ext. Partial represent the partial effects at the intensive and extensive margins, and Int. Margin and Ext. Margin are the marginal effects at the intensive and extensive margins.

Table A.12: McDonald Moffitt Decomposition: SNAP

	MFX (1)	Int. Partial (2)	Ext. Partial (3)	Int. Margin (4)	Ext. Margin (5)
ln(Min Wage)	−20.393	−30.476	−0.008	−3.672	−16.721
Max SNAP	46.657	69.728	0.019	8.401	38.256
Max TANF	−39.184	−58.559	−0.016	−7.055	−32.128
Max SSI	−0.280	−0.418	−0.000	−0.050	−0.229
Max EITC	0.014	0.021	0.000	0.003	0.011

Controls include sex, quartic in age, race, ethnicity, marital status, education, family size, governor party affiliation, unemployment rate, the log of the 50/10 income ratio, the 25th percentile of income, the employment to population ratio, and per capita income as well as state, year, and division by year fixed effects. * p <0.10, ** p <0.05, *** p <0.01. MFX represents the total marginal effect, Int. Partial and Ext. Partial represent the partial effects at the intensive and extensive margins, and Int. Margin and Ext. Margin are the marginal effects at the intensive and extensive margins.

Table A.13: McDonald Moffitt Decomposition: AFDC/TANF

	MFX (1)	Int. Partial (2)	Ext. Partial (3)	Int. Margin (4)	Ext. Margin (5)
ln(Min Wage)	−47.421	−558.842	−0.022	−4.397	−43.024
Max SNAP	−8.199	−96.621	−0.004	−0.760	−7.439
Max TANF	−1.702	−20.060	−0.001	−0.158	−1.544
Max SSI	−0.034	−0.405	−0.000	−0.003	−0.031
Max EITC	0.003	0.030	0.000	0.000	0.002

Controls include sex, quartic in age, race, ethnicity, marital status, education, family size, governor party affiliation, unemployment rate, the log of the 50/10 income ratio, the 25th percentile of income, the employment to population ratio, and per capita income as well as state, year, and division by year fixed effects. * p <0.10, ** p <0.05, *** p <0.01. MFX represents the total marginal effect, Int. Partial and Ext. Partial represent the partial effects at the intensive and extensive margins, and Int. Margin and Ext. Margin are the marginal effects at the intensive and extensive margins.

Table A.14: McDonald Moffitt Decomposition: SSI

	MFX (1)	Int. Partial (2)	Ext. Partial (3)	Int. Margin (4)	Ext. Margin (5)
ln(Min Wage)	−98.188	−470.067	−0.016	−11.374	−86.813
Max SNAP	8.248	39.486	0.001	0.955	7.292
Max TANF	−23.928	−114.553	−0.004	−2.772	−21.156
Max SSI	−0.162	−0.774	−0.000	−0.019	−0.143
Max EITC	−0.024	−0.115	−0.000	−0.003	−0.021

Controls include sex, quartic in age, race, ethnicity, marital status, education, family size, governor party affiliation, unemployment rate, the log of the 50/10 income ratio, the 25th percentile of income, the employment to population ratio, and per capita income as well as state, year, and division by year fixed effects. * p <0.10, ** p <0.05, *** p <0.01. MFX represents the total marginal effect, Int. Partial and Ext. Partial represent the partial effects at the intensive and extensive margins, and Int. Margin and Ext. Margin are the marginal effects at the intensive and extensive margins.

Table A.15: McDonald Moffitt Decomposition: EITC

	MFX (1)	Int. Partial (2)	Ext. Partial (3)	Int. Margin (4)	Ext. Margin (5)
ln(Min Wage)	−107.573	−114.743	−0.084	−23.959	−83.614
Max SNAP	81.102	86.507	0.063	18.063	63.038
Max TANF	−27.213	−29.026	−0.021	−6.061	−21.152
Max SSI	0.014	0.015	0.000	0.003	0.011
Max EITC	0.008	0.009	0.000	0.002	0.006

Controls include sex, quartic in age, race, ethnicity, marital status, education, family size, governor party affiliation, unemployment rate, the log of the 50/10 income ratio, the 25th percentile of income, the employment to population ratio, and per capita income as well as state, year, and division by year fixed effects. * p <0.10, ** p <0.05, *** p <0.01. MFX represents the total marginal effect, Int. Partial and Ext. Partial represent the partial effects at the intensive and extensive margins, and Int. Margin and Ext. Margin are the marginal effects at the intensive and extensive margins.

Table A.16: Effect of Minimum Wage and Benefits on Income to Poverty Threshold

	(1)	(2)
ln(Min. Wage)	−1.162	12.511
	(11.568)	(14.688)
ln(Total Ben)	-3.189^{***}	16.941
	(0.429)	(13.629)
Total ME	−8.677	−9.19
Control Function	No	Yes
Obs.	34,469	34,469

Note: standard errors clustered at the state level. Controls include sex, quartic in age, race, ethnicity, marital status, education, family size, governor party affiliation, unemployment rate, the log of the 50/10 income ratio, the 25th percentile of income, the employment to population ratio, and per capita income as well as state, year, and division by year fixed effects. * p <0.10, ** p <0.05, *** p <0.01.

Table A.17: Effect of Minimum Wage and Benefits on Income to Poverty Threshold: Fixed Effects

	(1)	(2)	(3)	(4)	(5)
ln(Min. Wage)	9.626	9.852	28.990***	5.188	1.466
	(9.771)	(9.788)	(10.221)	(8.627)	(21.723)
Total Ben		−0.000**	−0.043***		
		(0.000)	(0.007)		
SNAP				−0.004***	0.019
				(0.001)	(0.030)
AFDC/TANF				0.003***	0.022
				(0.001)	(0.046)
SSI				0.001***	0.010
				(0.000)	(0.037)
EITC				−0.012***	−0.134***
				(0.001)	(0.033)
Total ME		−8.677	−9.19	−9.009	−9.310
Control Function	No	No	Yes	No	Yes
Obs.	105,037	105,037	105,037	88,196	88,196

Note: standard errors clustered at the state level. Controls include sex, quartic in age, race, ethnicity, marital status, education, family size, governor party affiliation, unemployment rate, the log of the 50/10 income ratio, the 25th percentile of income, the employment to population ratio, and per capita income as well as state, year, and division by year fixed effects. * p <0.10, ** p <0.05, *** p <0.01.

Table A.18: Effect of Minimum Wage and Benefits on Income to Poverty Threshold: Fixed Effects

	(1)	(2)
ln(Min. Wage)	5.390	5.008
	(19.846)	(19.988)
ln(Total Ben)	−0.462	−29.715*
	(0.514)	(14.835)
Total ME	−8.677	−9.19
Control Function	No	Yes
Obs.	34,469	34,469

Note: standard errors clustered at the state level. Controls include sex, quartic in age, race, ethnicity, marital status, education, family size, governor party affiliation, unemployment rate, the log of the 50/10 income ratio, the 25th percentile of income, the employment to population ratio, and per capita income as well as state, year, and division by year fixed effects. * p <0.10, ** p <0.05, *** p <0.01.

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Vita

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Education

M.S. in Economics	University of Kentucky	2014
M.S. in Economics	University of Wisconsin-Madison	2011
B.A. in Economics	University of Oklahoma Summa Cum Laude, Phi Beta Kappa	2010
B.A. in Letters	University of Oklahoma Special Distinction, Phi Beta Kappa	2010

Research

Moellman, Nicholas and Aparna Mitra (2013): "Indian Gaming in Oklahoma: Implications for Community Welfare," *Journal of Socio-Economics*, 45.

Professional Experience

Research Assistant

University of Kentucky Center for Poverty Research	2015 - 2017
U. Kentucky Center for Business and Economic Research	2014 - 2015
Professor Aaron Yelowitz	2014

Teaching Experience

Instructor of Record

University of Kentucky	ECO 391-009,010 Economic and Business Statistics (4 sections)	2017-2018
University of Kentucky	ECO 401-020 Intermediate Microeconomics	Summer 2017
University of Kentucky	Math Camp for incoming graduate students	Summer 2015
University of Kentucky	Math Camp for incoming graduate students	Summer 2014
University of Kentucky	ECO 201-022 Principles of Microeconomics	Summer 2014

Teaching Assistant

University of Kentucky	ECO 703 Graduate Econometrics	Spring 2015
U. Wisconsin-Madison	MATH 171 Calculus I	Fall 2011

Awards and Certificates

Excellence in Teaching Award	UK Dept. of Economics	2017-2018
Mark Berger Best Paper Award	Kentucky Economics Assoc.	Oct. 2017
Graduate Student Award Session	Southern Economics Assoc.	Nov. 2016
Gatton Fellowship	University of Kentucky	Fall 2015
Gatton Fellowship	University of Kentucky	Fall 2014
Max Steckler Fellowship	University of Kentucky	Fall 2013
McNair Scholars Fellowship	University of Kentucky	Fall 2013
Advanced Opportunity Fellowship	U. Wisconsin, Madison	Fall 2010

Conferences and Presentations

2017		
Southern Economics Association	Tampa, Florida	November
Kentucky Economics Association	Bowling Green, Kentucky	October
(Mark Berger Award for Best Paper)		
Centre College	Danville, Kentucky	September
2016		
Southern Economics Association	Washington, D.C.	November
Kentucky Economics Association	Lexington, Kentucky	October