Fiscal Structure and Program Response Over the Business Cycle

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Abstract

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 and 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 8% 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 0.5 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 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.

I. 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). President Donald Trump's proposed budget for 2018 includes 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 the funding 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).

This 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 in 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 these business cycle indicators. The first type of response is relatively straightforward. If economic conditions worsen, individuals might demand more of a benefit, and states may face pressure to decrease expenditure. 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 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 state-level panel data for fiscal years 1999 to 2015 to examine effect of business cycles on program Medicaid and SCHIP enrollment. I find that block grant funding limits the responsiveness of programs to increased demand for benefits. A one percentage point increase in the unemployment rate leads to a 8% decrease in the number of beneficiaries per

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

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 Current Population Survey 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.

II. 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, Medicaid is being strongly considered for reformulation, making its use as a test case increasingly salient.

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 around 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

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

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.

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

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 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 it's 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 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

[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. $EFMAP = FMAP + .3(1 - FMAP)$

[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-millio pdf

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. Another prominent feature of SCHIP is the role of premiums. 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.[7]

The program parameters are similar between Medicaid and SCHIP, with income limits and fiscal federalism playing a large role. Table A1 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 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. These income limits aren't stringently enforced. Individuals select which program they will participate in, with income validation coming later for some families.

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

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

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 makes 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. Contrarily, 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.[8] 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 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, as noted previously, requiring premiums. While waiting periods have become increasingly uncommon, 37 states imposed

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

waiting periods for SCHIP benefits in 2013.[9] 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, this makes it more difficult for states to directly impact the number of Medicaid recipients.

The second difference in the way the programs could respond stems from 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 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

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

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.

III. Model

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.

$$\max_{t,E_m,E_s} U((1-t)y, \alpha(E_m+E_s)) \tag{2}$$

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

$$G_s + tY = (1-FMAP)E_m + E_s \tag{3}$$

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. The Lagrangian for the maximization problem is

$$\mathcal{L} = U((1-t)y, \alpha(E_m+E_s)) + \lambda[G_s + tY - (1-FMAP)E_m - E_s] \tag{4}$$

The first order conditions for E_m and E_s are $\alpha U_{E_m} = \lambda(1-FMAP)$ and $\alpha U_{E_s} = \lambda$. Combining these two first order conditions, and substituting the formula for the FMAP from (1) gives the following.

$$U_{E_m} = [\frac{(\text{State Per Capita Income})^2}{(\text{National Per Capita Income})^2} \times 0.45]U_{E_s} \tag{5}$$

This condition describes the equilibrium of program benefits. Suppose the state receives a negative economic shock, such that $[\frac{(\text{State Per Capita Income})^2}{(\text{National Per Capita Income})^2} \times 0.45]$ decreases. To equate the left hand side with the right hand side, the state must adjust expenditure on either Medicaid or SCHIP. The state can do this by adjusting the number of beneficiaries or the level of benefits in either program. With diminishing marginal utility, U_{E_m} decreases or U_{E_s} increases, implying the number enrolled in or benefits for Medicaid increase, the number enrolled in or benefits for SCHIP decrease, or both. This condition implies that there is increased pressure to reduce expenditure in SCHIP and increase expenditure in Medicaid, and potential incentive for cross-program substitution.

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'm limited in the number of factors I'm 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

$$ln\Big(\frac{\text{Medicaid}_{jt}}{\text{Population}_{jt}}\Big) = \beta_1 \text{Unemp}_{jt} + X\beta_2 + \mu_{1j} + \mu_{1t} + \eta_{jt} \tag{6}$$

$$ln\Big(\frac{\text{SCHIP}_{jt}}{\text{Population}_{jt}}\Big) = \delta_1 \text{Unemp}_{jt} + X\delta_2 + \mu_{2j} + \mu_{2t} + \varepsilon_{jt} \tag{7}$$

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. 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 (5) suggests that $\beta_1 >= 0$ in equation (6) while $\delta_1 <= 0$ in equation (7), 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 (5) 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 individuals 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.

$$\begin{aligned}\text{Medicaid}_{ijt} = {} & \kappa_1 \text{SCHIP}_{ij(t-1)} + \phi_1 \text{Econ Ind}_{jt} \\ & + \rho_1 \text{SCHIP}_{ij(t-1)} \times \text{Econ Ind}_{jt} + X\xi_1 + \mu_{3j} + \mu_{3t} + \nu_{1ijt}\end{aligned} \tag{8}$$

$$\begin{aligned}\text{SCHIP}_{ijt} = {} & \kappa_2 \text{SCHIP}_{ij(t-1)} + \phi_2 \text{Econ Ind}_{jt} \\ & + \rho_2 \text{SCHIP}_{ij(t-1)} \times \text{Econ Ind}_{jt} + X\xi_2 + \mu_{4j} + \mu_{4t} + \nu_{2ijt}\end{aligned} \tag{9}$$

$$\begin{aligned}\text{Uninsurance}_{ijt} = {} & \kappa_3 \text{SCHIP}_{ij(t-1)} + \phi_3 \text{Econ Ind}_{jt} \\ & + \rho_3 \text{SCHIP}_{ij(t-1)} \times \text{Econ Ind}_{jt} + X\xi_3 + \mu_{5j} + \mu_{5t} + \nu_{3ijt}\end{aligned} \tag{10}$$

$$\begin{aligned}\text{Medicaid}_{ijt} = {} & \omega_1 \text{Medicaid}_{ij(t-1)} + \psi_1 \text{Econ Ind}_{jt} \\ & + \gamma_1 \text{Medicaid}_{ij(t-1)} \times \text{Econ Ind}_{jt} + X\zeta_1 + \mu_{6j} + \mu_{6t} + e_{1ijt}\end{aligned} \tag{11}$$

$$\begin{aligned}\text{SCHIP}_{ijt} = {} & \omega_2 \text{Medicaid}_{ij(t-1)} + \psi_2 \text{Econ Ind}_{jt} \\ & + \gamma_2 \text{Medicaid}_{ij(t-1)} \times \text{Econ Ind}_{jt} + X\zeta_2 + \mu_{7j} + \mu_{7t} + e_{2ijt}\end{aligned} \tag{12}$$

$$\begin{aligned}\text{Uninsurance}_{ijt} = {} & \omega_3 \text{Medicaid}_{ij(t-1)} + \psi_3 \text{Econ Ind}_{jt} \\ & + \gamma_3 \text{Medicaid}_{ij(t-1)} \times \text{Econ Ind}_{jt} + X\zeta_3 + \mu_{8j} + \mu_{8t} + e_{3ijt}\end{aligned} \tag{13}$$

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,[10] 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 a given insurance scheme due to a negative economic

[10]In equations (6) and (7), enrollment is essentially price×quantity, and state expenditure is essentially price, using expenditure would result in endogeneity issues.

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 (5), along with results from Marton and Wildasin (2007b) and Schmidt and Sevak (2004), provide predictions about the directions of ρ_1, ρ_2, γ_1 and γ_2. A negative economic shock should reduce enrollment in the block grant funded program (SCHIP) and increase enrollment in the matching grant funded program (Medicaid). Thus ρ_1 and γ_1 should be less than zero, and ρ_2 and γ_2 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.

$$\begin{aligned}\Delta P_{ijt} = {} & \pi_1 \text{Medicaid}_{ij(t-1)} + \pi_2 \text{SCHIP}_{ij(t-1)} + \pi_3 \text{Econ Ind}_{jt} \\ & + \pi_4 \text{Medicaid}_{ij(t-1)} \times \text{Econ Ind}_{jt} + \pi_5 \text{SCHIP}_{ij(t-1)} \times \text{Econ Ind}_{jt} \\ & + X\pi_6 + \mu_{9j} + \mu_{9t} + \omega_{ijt}\end{aligned} \tag{14}$$

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 andπ_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.

IV. 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 A3 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 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 affect of overall state level generosity over and above a fixed effect.

These state level, administrative data provide the most reliable estimates of enrollment. Figure 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 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 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 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.

Figure 5 examines 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 figure 5 does 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 5 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 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 1 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 1 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 7 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 answered "yes" were skipped over the SCHIP question. 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)[11]. 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 2 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

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

(2) of table 2 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 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 2 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 8 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.

V. 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. The standard errors for all models are robust to heteroscedasticity and clustered at the state level given the focus on state level macroeconomic conditions and program policy, and all models include state and year fixed effects.

Administrative Data

I begin by using administrative data to estimate equations (6) and (7), with results presented in table 3. 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 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 7% 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 effect estimate for Medicaid in column (2) is 0.009 (se=0.011), 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, and the percent change in employment per person in columns (5) and (6) do little to change these estimates.

These results are consistent with the implications from equation (5). 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, we can determine 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 A4 in the appendix demonstrates the sensitivity of these estimates to the inclusion of varying combination of fixed effects. Year fixed effects seem to negate all counter-cyclical properties of SCHIP, while leaving Medicaid strongly counter-cyclical.

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, 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. All models cluster standard errors at the state level.

Table 4 estimates the analog of equations (6) and (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 0.001 (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 4 the individual analog to the results in table 3, showing higher levels of responsiveness for the matching grant program.

To examine the economic impact of fiscal structure, it is useful to contextualize the estimates. In 2010, 44.5% of all children received Medicaid. If we consider changes in the probability of individual enrollment representative of changes in the overall percentage of children enrolled, a one percentage point increase in the unemployment rate results in an approximately 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 (5). 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 5. Using the unemployment rate measures the increased demand for public health insurance benefits from economic downturns. Table 5 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=0.004) for Medicaid, and 0.015 (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 1.5 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), as well as the implications from equation (5), 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 46 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 27 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 70% 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. The provision of benefits is tied to the state budget constraint, which is the foundation for much of my analysis. To measure the effect of state finances, I re-estimate equations (6), (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 6 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 -0.027 (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 -0.053 (0.022), while the coefficient on the unemployment rate is 0.002 (0.003). Interpreting the coefficients for -ln(Exp/Pop) is somewhat less intuitive than those for the unemployment rate. An unrevised interpretation of the coefficient means enrollment in SCHIP decreases by 5 percentage points for a 100% decrease in expenditure per person. However, a 100% decrease in expenditure is not only unlikely, but completely off the support of the data. Thus, for future discussions of economic significance, I will interpret the coefficients as a 10% decrease in expenditure per person, which is not only more reasonable in terms of the support of the data, but provides comparable interpretations with a 1 percentage point decrease in the unemployment rate.[12] 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 4 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.

[12]The average unemployment rate over this time frame was approximately 6%. Thus, a one percentage point decrease in the unemployment rate is a 17% decrease in the unemployment rate.

Table 7 examines cross-program substitution as a result of changing state expenditure. Similar to the results in 5, 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 is 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 1.5 percentage points, and decreases the probability a child enrolls in Medicaid by 0.8 percentage points, but increases the probability a child is uninsured by 0.4 percentage points (statistically significant at the 10% level). While this still does not provide evidence of cross program substitution, it does suggest the loss of benefits for block grant funded 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 0.7 percentage points, decreases the probability they enroll in SCHIP by 1.7 percentage points, and increases the probability they are uninsured by 0.3 percentage points. The coefficient on the unemployment rate suggests, for Medicaid, these decreases from state expenditure might be offset by increases in the probability of enrollment from increases in the unemployment rate.

To address the misclassification bias from the survey skip pattern of the CPS, I present adjusted estimates for tables 4, 6, 5, and 7 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 8 and 9 estimate the switching regressions from equation (14). These switching regressions are looking only at children who transition between (or remain enrolled in) Medicaid and SCHIP for two years. Table 8 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 9 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 21 percentage points for children previously enrolled in Medicaid, and further decreases by 2.2 percentage points for a 10% decreases 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.

VI. 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 8% 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 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 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 0.5 percentage point decrease in the probability an individual is enrolled in a block grant program. Clemens and Ippolito (2017) simulate the budgetary shortfall as a result of converting Medicaid to a block grant. They find the shortfall averages 4 percent of own-source revenue under an a cyclical block grant. This would result in a 0.2 percentage point decrease in the probability a child is enrolled in Medicaid over the time period. In 2011 34 million children were enrolled in Medicaid, out of a total of 73.9 million children, or approximately 46% of children. Thus, this 0.2 percentage point decrease results in the loss of healthcare for 160,000 children. Moreover, regardless of metric of economic conditions, I find that block grant funded programs are inherently more volatile than matching grant funded programs, with significantly higher levels of churn than matching grant funded programs.

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`)

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VII. Tables and Figures

Figure 1: Public Healthcare Funding

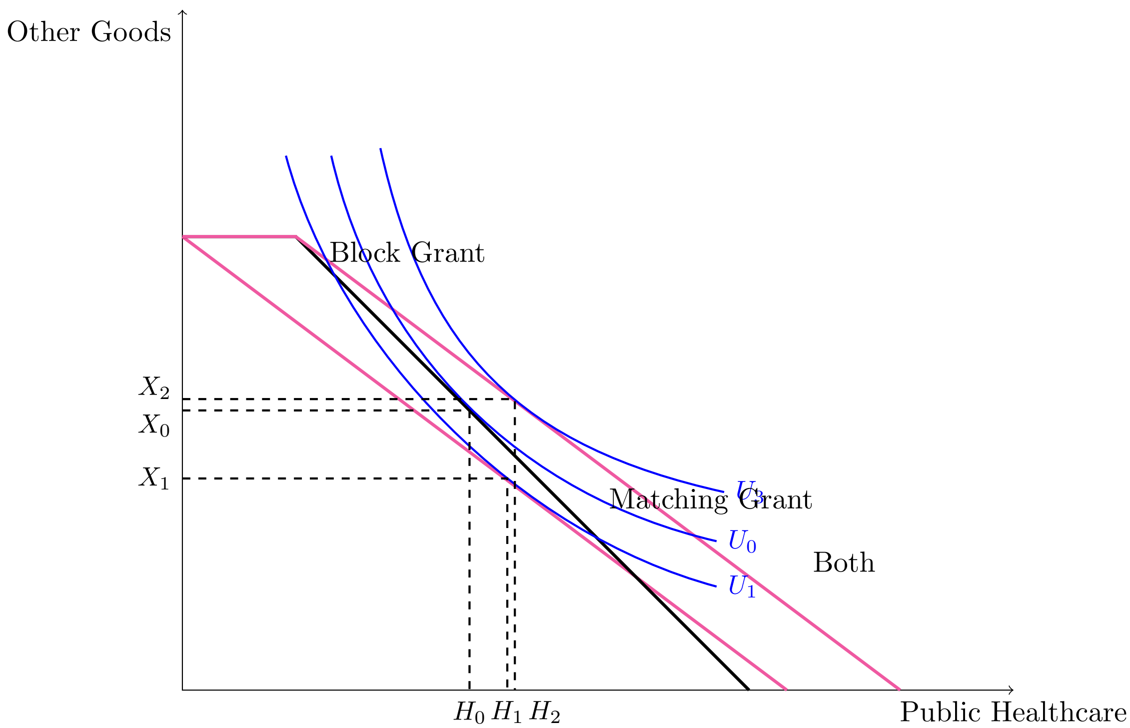


Figure 2: Administrative Enrollment by Year

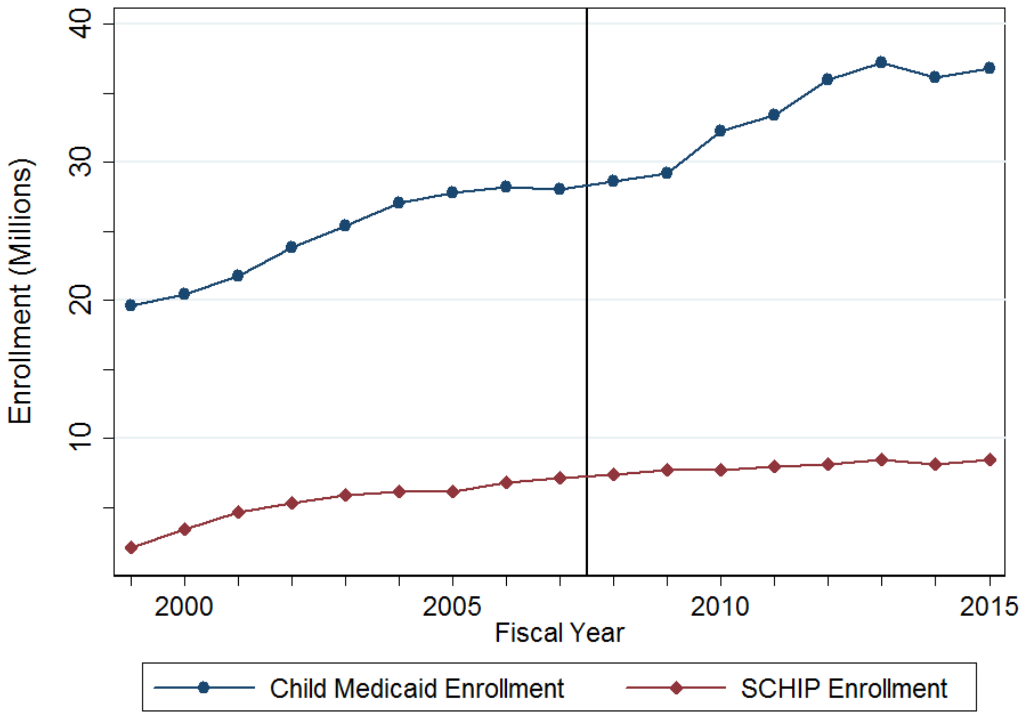


Figure 3: Percent Change in Enrollment by Year

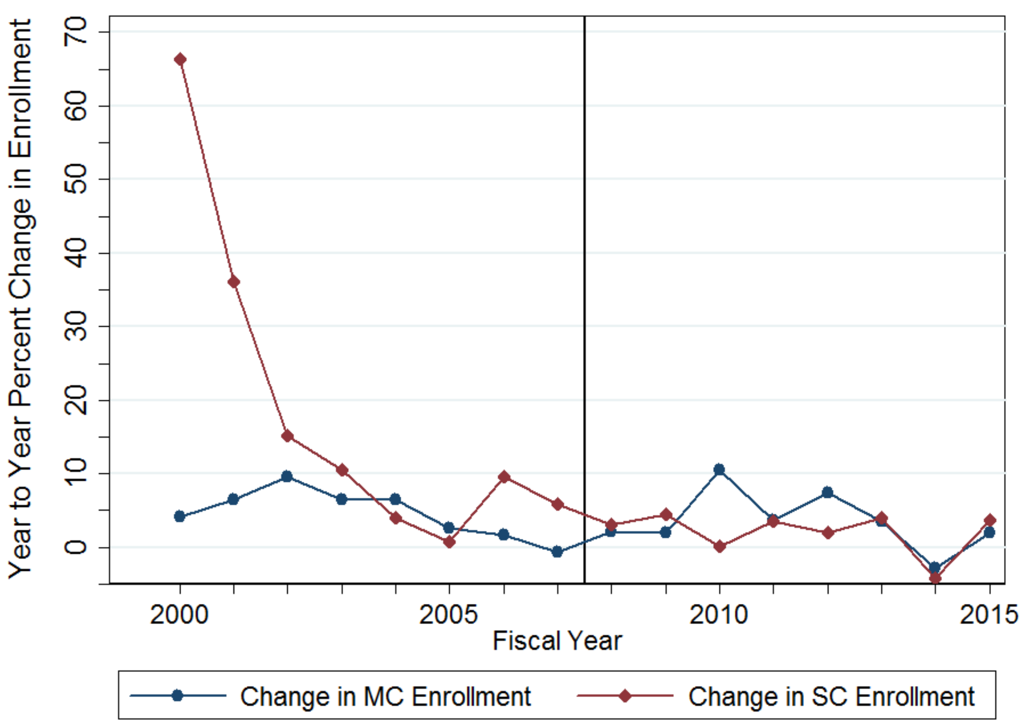


Figure 4: Enrollment vs. Unemployment by Year

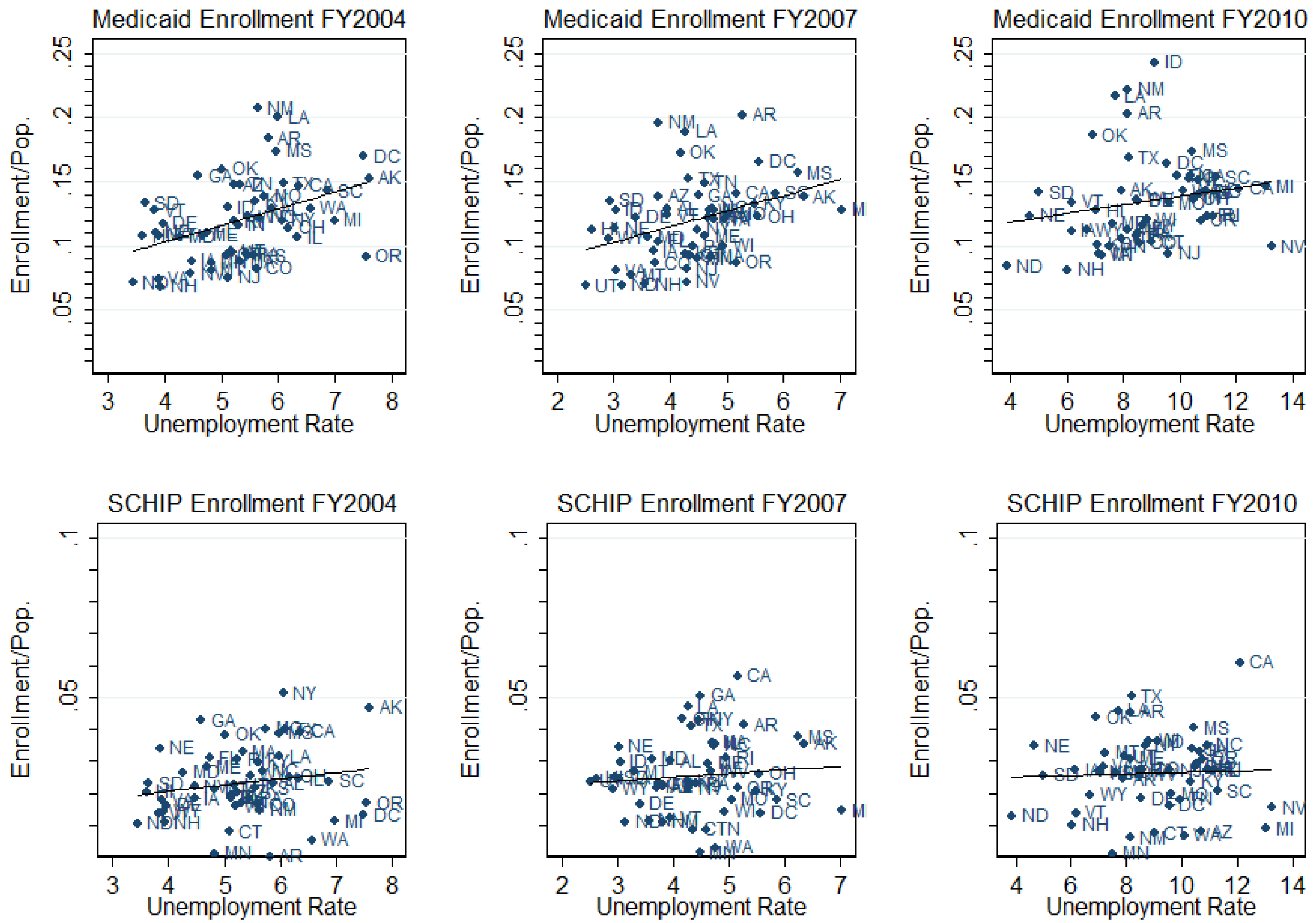
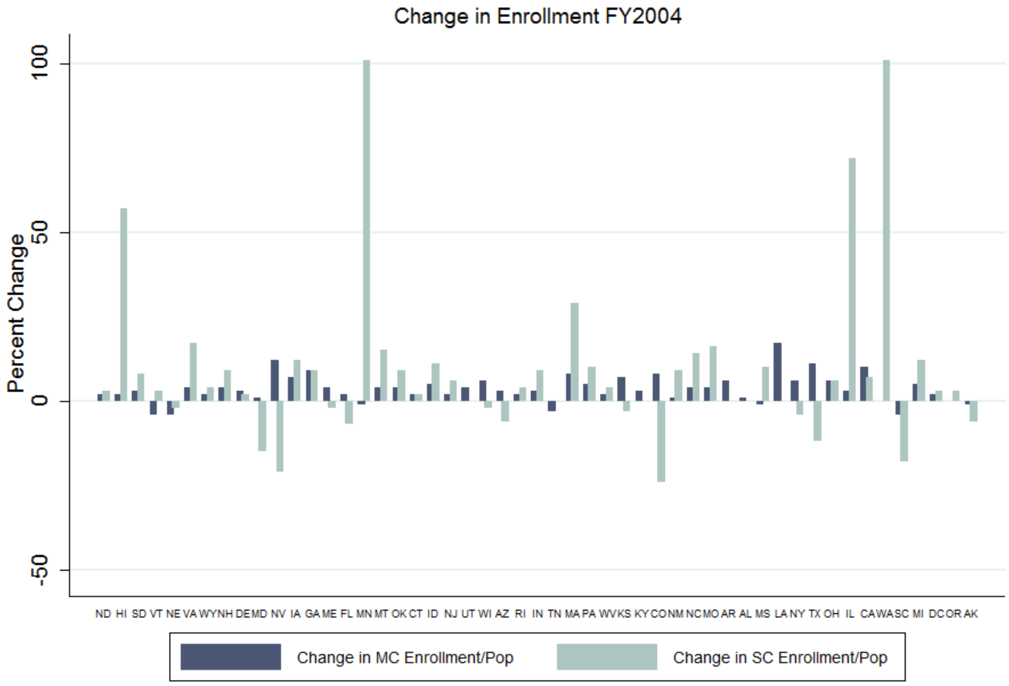
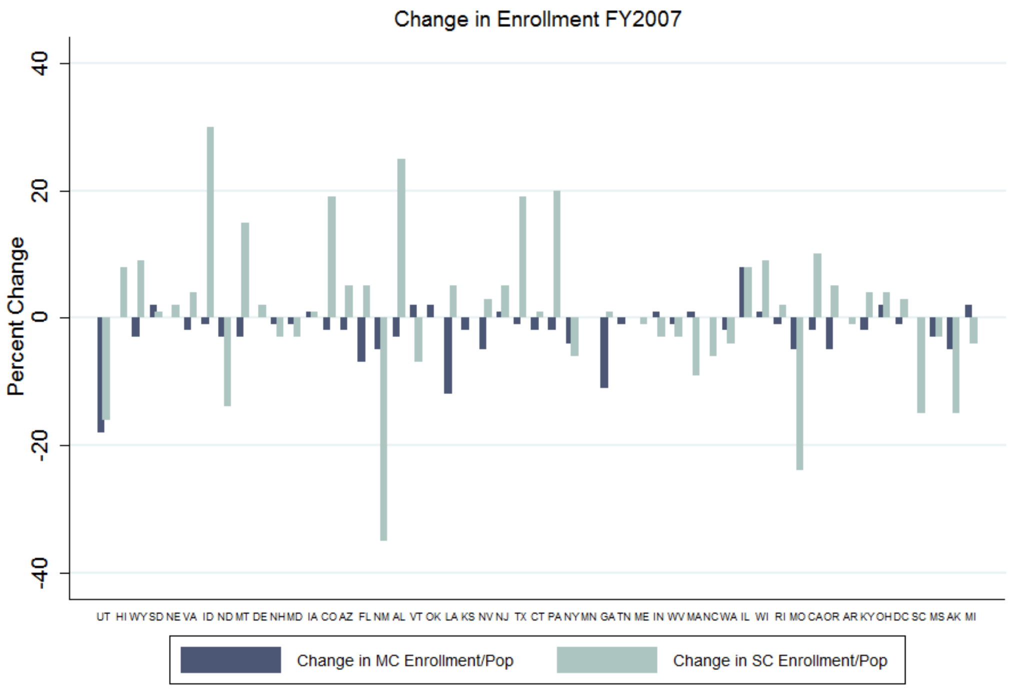


Figure 5

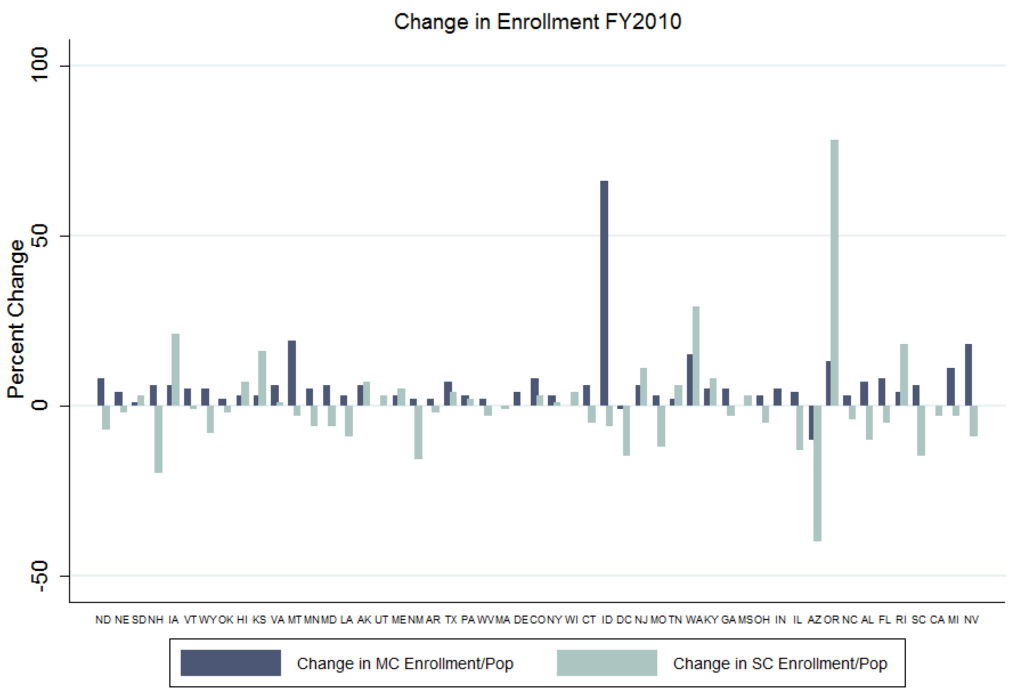


Note: states sorted by unemployment rate. Percent change is capped at 100% for scale.

Figure 5 (Cont.)



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



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

Figure 6: Change in Enrollment vs. Change in Unemployment

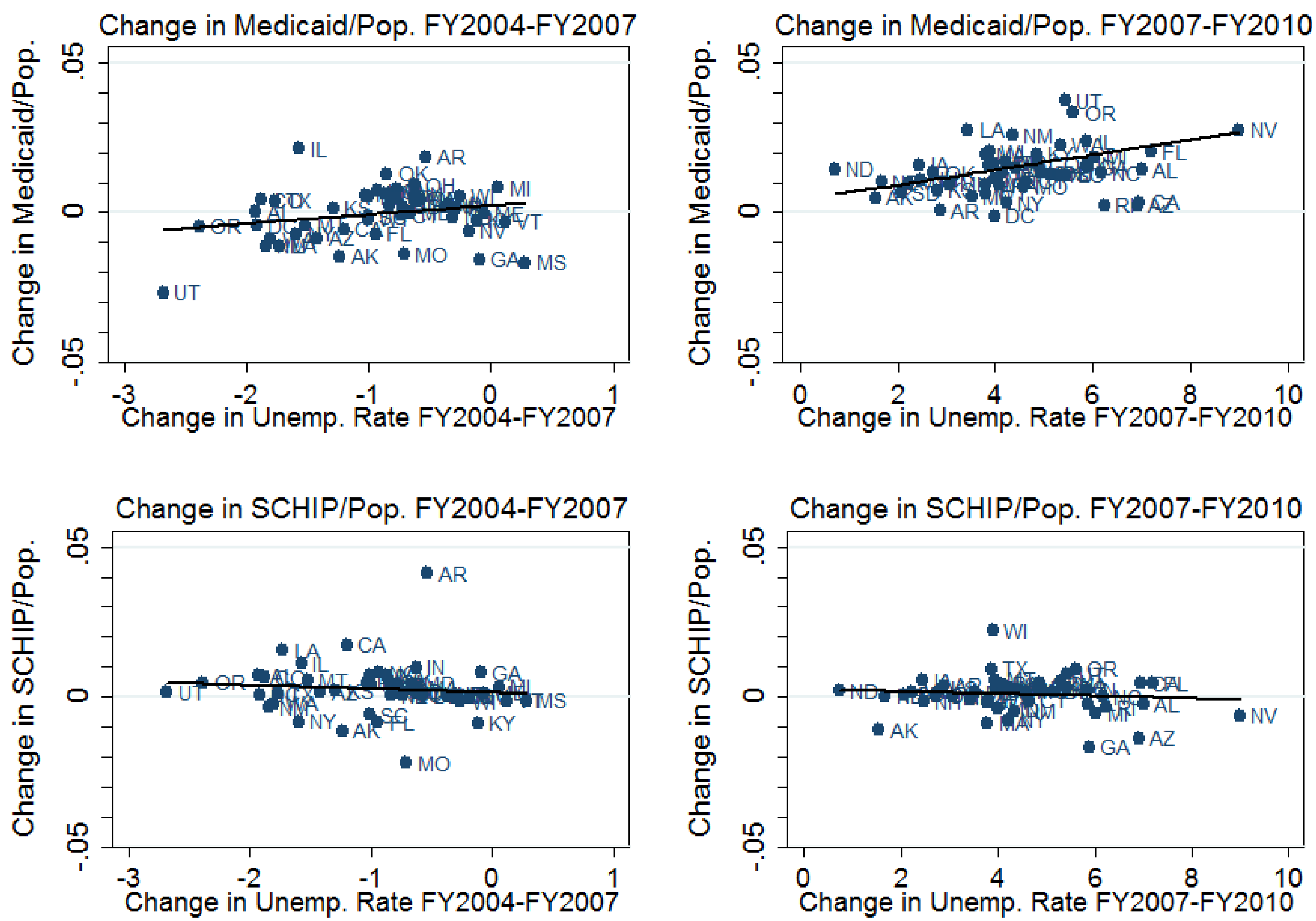


Figure 7: CPS Beneficiaries by Year

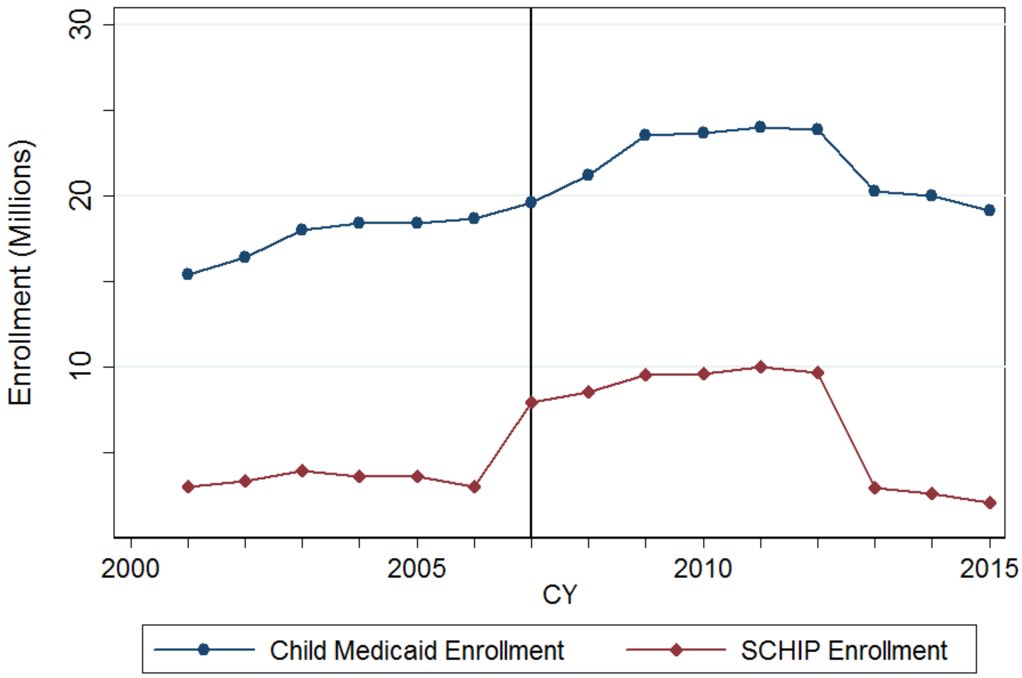


Figure 8: CPS Switchers by Year

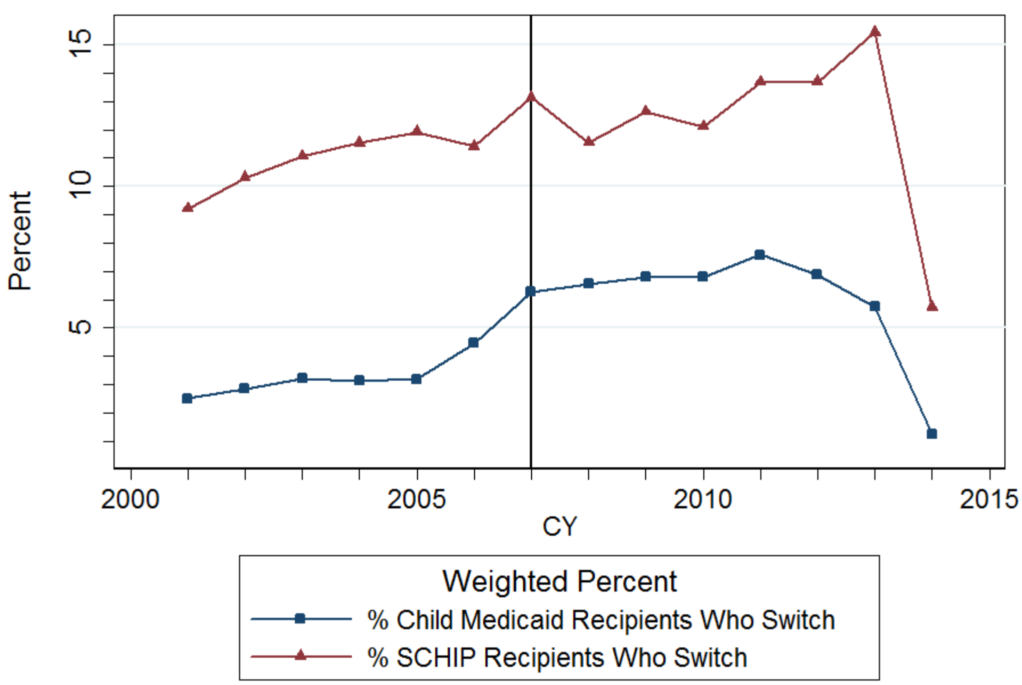


Table 1: Insurance Transition Matrix

	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 2: 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		
Obs.	248,633	70,007	74,134	552,725

Note: Individual weights used.

Table 3: Impact of Unemployment on ln(Beneficiaries/Pop.): FY1999-FY2015

	MC (1)	SC (2)	MC (3)	SC (4)	MC (5)	SC (6)
Unemp	0.065***	0.101***	0.009	-0.079^{**}	0.003	-0.082^{**}
	(0.009)	(0.033)	(0.011)	(0.032)	(0.009)	(0.036)
FMAP					0.007	0.002
					(0.005)	(0.010)
Gov. Dem.					0.020	0.105
					(0.013)	(0.101)
$\%\Delta\frac{Emp.}{Pop.}$					-0.033	-0.353
					(0.346)	(2.700)
State FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
Obs.	863	857	863	857	846	840

Note: standard errors clustered at the state level. * p <0.10, ** p <0.05, *** p <0.01.

Table 4: Impact of Unemployment on Enrollment

	MC (1)	SC (2)
Unemp	0.004**	0.001
	(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***	0.000
	(0.001)	(0.001)
Pop.	−0.000	−0.000**
	(0.000)	(0.000)
Min Wage	0.010**	0.001
	(0.004)	(0.005)
Dem. Gov.	0.001	−0.003
	(0.004)	(0.004)
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.

Table 5: Transitions Among Insurance States

	MC (1)	SC (2)	Unins. (3)	MC (4)	SC (5)	Unins. (6)
$\text{SCHIP}_{ij(t-1)}$	0.456***	0.266***	0.038***			
	(0.030)	(0.035)	(0.012)			
$\text{Medicaid}_{ij(t-1)}$				0.588***	0.069***	0.015*
				(0.015)	(0.025)	(0.008)
Unemp	0.007***	−0.001	0.001	0.002	−0.006***	0.002
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
$\text{SCHIP}_{ij(t-1)} \times$ Unemp	0.002	0.015***	−0.005***			
	(0.004)	(0.005)	(0.002)			
$\text{Medicaid}_{ij(t-1)} \times$ Unemp				0.003	0.019***	−0.004***
				(0.002)	(0.005)	(0.001)
Obs.	150,728	150,728	150,728	155,844	155,844	155,844

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

Table 6: Impact of State Expenditure on Enrollment

	MC (1)	SC (2)
-ln(Exp/Pop)	-0.027	-0.053^{**}
	(0.026)	(0.022)
Unemp	0.005^{**}	0.002
	(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^{**}	0.000
	(0.001)	(0.001)
Pop.	-0.000	-0.000^{***}
	(0.000)	(0.000)
Min Wage	0.011^{***}	0.001
	(0.004)	(0.005)
Dem. Gov.	0.001	-0.002
	(0.004)	(0.004)
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.

Table 7: Transitions Among Insurance States

	MC (1)	SC (2)	Unins. (3)	MC (4)	SC (5)	Unins. (6)
$\text{SCHIP}_{ij(t-1)}$	0.320***	0.058	0.082*			
	(0.081)	(0.083)	(0.043)			
$\text{Medicaid}_{ij(t-1)}$				0.478***	−0.203***	0.051**
				(0.055)	(0.070)	(0.023)
-ln(Exp/Pop)	−0.020	−0.034*	0.001	−0.028	−0.008	−0.001
	(0.031)	(0.018)	(0.017)	(0.020)	(0.022)	(0.018)
$\text{SCHIP}_{ij(t-1)}\times$ -ln(Exp/Pop)	−0.075*	−0.153***	0.038*			
	(0.038)	(0.041)	(0.021)			
$\text{Medicaid}_{ij(t-1)}\times$ -ln(Exp/Pop)				−0.066**	−0.198***	0.031**
				(0.027)	(0.037)	(0.012)
Unemp	0.008***	0.001	0.001	0.004**	−0.001	0.001
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Obs.	150,648	150,648	150,648	155,764	155,764	155,764

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

Table 8: Effect of Unemployment Rate on Probability of Switching

	(1)	(2)	(3)
Medicaid_{ijt-1}	0.145***		0.051***
	(0.031)		(0.017)
SCHIP_{ijt-1}		0.645***	0.604***
		(0.025)	(0.026)
Unemp	−0.007***	0.002	−0.002*
	(0.002)	(0.001)	(0.001)
$\text{Medicaid}_{ijt-1}\times$ Unemp	0.028***		0.014***
	(0.006)		(0.003)
$\text{SCHIP}_{ijt-1}\times$ Unemp		0.011***	0.001
		(0.003)	(0.004)
Obs.	155,844	150,728	150,728

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

Table 9: Effect of State Expenditure on Probability of Switching

	(1)	(2)	(3)
Medicaid$_{ijt-1}$	-0.212^{**}		-0.136^{***}
	(0.083)		(0.048)
SCHIP$_{ijt-1}$		0.518^{***}	0.638^{***}
		(0.092)	(0.111)
-ln(Exp/Pop)	0.033	0.000	0.019^{*}
	(0.021)	(0.011)	(0.011)
Medicaid$_{ijt-1}\times$ -ln(Exp/Pop)	-0.269^{***}		-0.139^{***}
	(0.044)		(0.026)
SCHIP$_{ijt-1}\times$ -ln(Exp/Pop)		-0.098^{**}	0.016
		(0.046)	(0.056)
Obs.	155,764	150,648	150,648

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

Table 10: Determinants of Entry

	Medicaid$_{ijt}$ (1)	SCHIP$_{ijt}$ (2)	Unins$_{ijt}$ (3)	Priv.$_{ijt}$ (4)
Medicaid$_{ijt-1}$		0.072***	0.102***	0.188***
		(0.022)	(0.013)	(0.011)
SCHIP$_{ijt-1}$	0.386***		0.118***	0.211***
	(0.038)		(0.019)	(0.015)
Unins.$_{ijt-1}$	0.169***	0.045***		0.313***
	(0.016)	(0.013)		(0.019)
Priv.$_{ijt-1}$	0.049***	0.023***	0.044***	
	(0.004)	(0.004)	(0.007)	
Unemp.	0.004**	−0.004***	0.003**	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Medicaid$_{ijt-1}$× Unemp.		0.013***	−0.003*	−0.007***
		(0.004)	(0.001)	(0.001)
SCHIP$_{ijt-1}$× Unemp.	−0.009*		−0.003	−0.008***
	(0.005)		(0.002)	(0.002)
Unins.$_{ijt-1}$× Unemp.	0.003	0.010***		−0.005*
	(0.003)	(0.002)		(0.003)
Priv$_{ijt-1}$× Unemp.	0.001***	0.001**	0.000	
	(0.001)	(0.001)	(0.001)	
Obs.	136,606	136,606	136,606	136,606

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

Table 11: Determinants of Entry

	Medicaid$_{ijt}$ (1)	SCHIP$_{ijt}$ (2)	Unins$_{ijt}$ (3)	Priv.$_{ijt}$ (4)
Medicaid$_{ijt-1}$		0.072***	0.102***	0.188***
		(0.022)	(0.013)	(0.011)
SCHIP$_{ijt-1}$	0.386***		0.118***	0.211***
	(0.038)		(0.019)	(0.015)
Unins.$_{ijt-1}$	0.169***	0.045***		0.313***
	(0.016)	(0.013)		(0.019)
Priv.$_{ijt-1}$	0.049***	0.023***	0.044***	
	(0.004)	(0.004)	(0.007)	
Unemp.	0.004**	−0.004***	0.003**	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Medicaid$_{ijt-1}\times$ Unemp.		0.013***	−0.003*	−0.007***
		(0.004)	(0.001)	(0.001)
SCHIP$_{ijt-1}\times$ Unemp.	−0.009*		−0.003	−0.008***
	(0.005)		(0.002)	(0.002)
Unins.$_{ijt-1}\times$ Unemp.	0.003	0.010***		−0.005*
	(0.003)	(0.002)		(0.003)
Priv$_{ijt-1}\times$ Unemp.	0.001***	0.001**	0.000	
	(0.001)	(0.001)	(0.001)	
Obs.	136,606	136,606	136,606	136,606

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

Appendix A.-Additional Figures and Robustness

Table A1: 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 A2: 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 A3: 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 A4: Impact of Unemployment on ln(Beneficiaries/Pop.): FY1999-FY2015

	MC (1)	SC (2)	MC (3)	SC (4)	MC (5)	SC (6)
Unemp	0.064***	0.118***	0.054***	0.054	0.068***	0.116***
	(0.006)	(0.022)	(0.018)	(0.062)	(0.010)	(0.035)
FMAP	−0.007	−0.032***	0.015***	0.016	0.014***	0.013
	(0.007)	(0.011)	(0.004)	(0.014)	(0.003)	(0.014)
Gov. Dem.	0.024	0.186	0.023	0.041	0.027	0.090
	(0.020)	(0.119)	(0.034)	(0.121)	(0.035)	(0.133)
$\%\Delta\frac{Emp.}{Pop.}$	2.995***	4.451***	−0.101	3.714	2.275**	4.656**
	(0.425)	(1.454)	(1.281)	(3.315)	(0.932)	(2.268)
State FE	Yes	Yes	No	No	No	No
Year FE	No	No	Yes	Yes	No	No
Obs.	846	840	846	840	846	840

Note: standard errors clustered at the state level. * p <0.10, ** p <0.05, *** p <0.01.

Misclassification Bias

Receipt of public health insurance is systematically under-reported in the CPS ASEC. Figure 7 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

$$\frac{\partial Pr(Ins_{pijt} = 1|x)}{\partial x} = (1 - \alpha_{0pjt} - \alpha_{1pjt})\beta \tag{A1}$$

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

$$\alpha_{0pjt} = \frac{\text{CPS Enrollment}_{pjt} - \text{Administrative Enrollment}_{pjt}}{\text{CPS Enrollment}_{pjt}} \tag{A2}$$

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

$$\alpha_{0pjt} = \frac{\text{Administrative Enrollment}_{pjt} - \text{CPS Enrollment}_{pjt}}{\text{Administrative Enrollment}_{pjt}} \tag{A3}$$

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 4 and 6 in table A5, analogous results from table 5 in table A6, and analogous results from table 7 in table A7. 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 A5: Enrollment Adjusted for Misclassification

	MC (1)	SC (2)	MC (3)	SC (4)
-ln(Exp/Pop)			−0.050	−0.064
			(0.036)	(0.052)
Unemp	0.007**	0.002	0.007***	0.003
	(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***	0.071***	0.285***	0.071***
	(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***	0.087***	0.226***	0.087***
	(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**	0.002	0.003**	0.002
	(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**	0.001	0.013**	0.000
	(0.005)	(0.010)	(0.005)	(0.010)
Dem. Gov.	0.006	−0.000	0.005	−0.001
	(0.006)	(0.007)	(0.006)	(0.007)
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.

Table A6: Transitions Adjusted for Misclassification

	MC (1)	SC (2)	MC (3)	SC (4)
$\text{SCHIP}_{ij(t-1)}$	0.592***	0.358***		
	(0.037)	(0.056)		
$\text{Medicaid}_{ij(t-1)}$			0.747***	0.096**
			(0.024)	(0.037)
Unemp	0.010***	−0.003	0.005**	−0.010**
	(0.003)	(0.004)	(0.002)	(0.004)
$\text{SCHIP}_{ij(t-1)} \times$ Unemp	−0.003	0.029***		
	(0.005)	(0.008)		
$\text{Medicaid}_{ij(t-1)} \times$ Unemp			−0.001	0.029***
			(0.003)	(0.006)
Obs.	150,624	150,624	155,786	155,786

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

Table A7: Transitions Adjusted for Misclassification

	MC (1)	SC (2)	MC (3)	MC (4)
$\text{SCHIP}_{ij(t-1)}$	0.496***	−0.036		
	(0.105)	(0.153)		
$\text{Medicaid}_{ij(t-1)}$			0.651***	−0.302***
			(0.099)	(0.111)
-ln(Exp/Pop)	−0.008	−0.009	−0.021	0.024
	(0.040)	(0.044)	(0.030)	(0.048)
$\text{SCHIP}_{ij(t-1)} \times$ -ln(Exp/Pop)	−0.036	−0.293***		
	(0.052)	(0.083)		
$\text{Medicaid}_{ij(t-1)} \times$ -ln(Exp/Pop)			−0.047	−0.298***
			(0.049)	(0.057)
Unemp	0.010***	−0.000	0.005**	−0.002
	(0.003)	(0.004)	(0.002)	(0.005)
Obs.	150,624	150,624	155,786	155,786

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