‘Work-fare’ and Child Care: A Synthetic Instrumental Variables Analysis of Child Care Subsidies, Welfare Program Participation, and Labor Market Outcomes of Low-Income Parents

by

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Abstract

Inability to access quality and affordable child care represents a barrier to employment for many parents, but for low-income parents of young children, it can also be a barrier to compliance with the work requirements affiliated with most forms of public assistance in the United States. Though prior research remains unclear on whether welfare work requirements effectively increase economic self-sufficiency or functionally disqualify especially vulnerable individuals, subsidies for child care have been widely viewed as a way to enable parents to engage in employment and qualifying "Welfare-to-work" program activities. In this paper, I investigate the impacts of these subsidies on parental labor supply decisions and welfare program participation. I also attempt to examine the ways in which accessible childcare alters the screening effects of welfare work requirements, and whether the presence of accessible childcare reduces the disincentives to work inherent to receipt of welfare benefits. Using the Supplemental Nutrition Access Program as my program of interest, I leverage the 2014 reauthorization of the Child Care Development Block Grant and accompanying nationwide changes to eligibility requirements and recertification periods. Via a simulated instrumental variables method, I estimate near-zero effects of altering subsidy program generosity on employment or income and small but significant positive effects upon SNAP uptake among families predicted to be SNAP-eligible by household income amount.

Introduction

Child care expenses are a burden for many working families in the United States. As such, high costs of care may induce parents to exit the labor market in order to provide at-home care or to place their children in lower-quality child care arrangements (Kuziemko et al. 2018). These tradeoffs are intensified for low-income parents of young children and the inability to afford sufficient child care can be a barrier to compliance with the employment and hours requirements for receiving public assistance, post-1996 adoption of the "Personal Responsibility and Work Opportunity Reconciliation Act" (PRWORA). This runs counter to one of the central motivations behind such "welfare-to-work" reforms: to promote employment, self-sufficiency, and a "culture of work", quelling systemic welfare "dependence". Subsidization of child care may play a significant role in the ability and willingness of poor parents to seek employment or increase hours of labor, potentially increasing their ability to access welfare services or earn at levels which exceed their need for public assistance. I hope to contribute to the body of literature exploring whether child care subsidies end up supporting recipient efforts to leave welfare, or otherwise bolster the earnings and maintenance of stable employment for poor parents. While some of the results of my simulated IV approach do not align with expectations formed based on economic intuition and previous patterns in the child care subsidies literature, I attribute these to issues of instrumentation rather than a refutation of those previously-observed patterns. My results do indicate a statistically significant increase in uptake of SNAP benefits among the SNAP-eligible that is associated with an increase in the generosity of CCDF eligibility standards. Though I am unable to illustrate the causal mechanism, I highlight this finding as a point of interest for future research. I also discuss some of the practical and methodological challenges to studying child care subsidy programs with respect to these outcomes.

Nearly all social welfare programs in the United States are means-tested. Unlike social insurance programs, which base benefits on eligibility criteria such as age, disability or employment status, and military service history, social welfare programs use income limits and asset tests to restrict aid to only people with legitimate material need. Means tests are designed to investigate welfare applicants' needs and resources and to compel applicants to exhaust (within certain limits) what other economic means they may have, prior to the calculation and provision of aid benefits. Included in consideration of resources is the ability to work and thus compliance with a set of work rules has been a facet of means-tested aid eligibility since 1996, when Clinton-era welfare reforms ended the treatment of welfare as an entitlement program.

The incentive structure created by work requirements functions in two primary ways: First, requirements make welfare receipt less-attractive by attaching more onerous conditions. These conditions cause individuals with better outside options to substitute away from reliance on public assistance, effectively leaving the most needy to be targeted with aid where it has the greatest utility. Second, work requirements function as a deterrent mechanism, incentivizing "poverty-reducing investments" (Besley and Coate, 1992) in the form of human capital development — namely, productive job skills. Proponents of work requirements contest that unconditional public assistance causes individuals to develop patterns that increase the likelihood that they will have to draw on such support in future. Reminiscent of the "teach a man to fish" idiom, in this view, work requirements are a correction of latent social inefficiency.

However, these incentive theories of work requirements tacitly assume that qualifying employment opportunities are generally available to the individuals receiving welfare and that those recipients are choosing to draw on public assistance rather than work (Hahn, et al. 2017). Many adeptly raise the point that by removing people from welfare rolls for noncompliance, work requirements can functionally "screen out" otherwise-eligible potential beneficiaries who face other underlying obstacles to employment. This implies systematic exclusion of certain subsets of the population from public assistance. While children, seniors, pregnant women, and adults with physical or mental disability status are exempt from work requirements under all welfare programs, individuals with unverified disabilities, the previously-incarcerated, and those with dependent care of other family members remain subject, despite the numerous barriers to sufficient and steady employment for those groups. Indeed, analysis of SIPP panel data from 1993 to 2008 reveals that poor families with children were more likely than their counterpart poor households without children to experience a period of zero earned income (CLASP, 2014).

Child care subsidies were established largely with intent to mitigate the tradeoffs between employment and paying for nonparental care for dependent children. The federal child care subsidy program known as the Child Care Development Fund (CCDF) is one of the primary sources of federal funding dedicated to providing assistance with child care to low-income families who are working or participating in education and training (Cohen, 2012). The 2014 reauthorization of the Child Care Development Fund increased accessibility of child care subsidy access differentially across states, through several statutory changes that make it easier to qualify for and stay on CCDF than it was prior to 2014. In Section 1, I provide a brief overview of salient research on means tested public programs and child care and history of

CCDF subsidy programs.

While quality and affordable child care arrangements may be a necessary precondition to employment for some parents and employment itself a precondition to receipt of government assistance necessary to leverage a family out of poverty, increased accessibility of child care subsidies may not translate directly into uptake of subsidies, increases in other welfare program participation/compliance, or changes in employment status/income. As such, I leverage the relaxation of rules governing CCDF subsidy eligibility to investigate the relationship between child care accessibility, labor market outcomes, and SNAP program participation. In Section 1, I provide an overview of related research on means tested public programs and child care subsidies, and a brief history of CCDF subsidy programs. In Section 2, I explain the methodological underpinnings of my analysis and in Section 3, I discuss my data sources. In sections 4 and 5, I give my empirical specifications and present the results of my estimates. In section 6, I highlight areas for improvement and conclude.

1. Literature Review

CCDF:

Prior to 1996, there were 3 welfare programs and 1 non-welfare program dedicated to providing child care assistance; after the enactment of 1996 PRWORA, these programs were merged into 1: the Child Care Development Fund. The CCDF has 1 set of program rules, 1 target population, and 1 lead agency per state. Funding for CCDF primarily comes from discretionary funding in the form of block grants authorized by the Child Care and Development Block Grant (CCDBG Act) of 1990 (Urban, 2019) and allocated according to a statutory formula. A long-term qualitative study by the Urban Institute of recipient families has documented perceptions of the role of child care subsidies in making it possible for low-income parents to seek/maintain employment and engage in welfare-to-work program activities (Snyder, et al. 2006). In the words of one interviewee, “If it wasn’t for [the subsidy], we would have to bring our kids to school, or we would have to stay home and get nowhere”(ibid).

In 2014, the CCDBG was reauthorized with several significant policy alterations. Though states have flexibility in administering the subsidy program, the Child Care Development Fund sets certain standards for eligibility criteria at the federal level which must be addressed by the states and met by families to receive services. The federal standards are functionally guidelines for program rules which are binding in one direction; for example, one standard stipulates that family income be “at or below 85 percent of the state median income (SMI)”, giving lead agencies the flexibility to set maximum income for eligibility, provided it does not exceed 85 percent of SMI (CCTAN, 2021). Lead agencies are also then given leeway in their options to deduct or exclude some types of income when determining eligibility, so some states may be more or less generous in their exclusions. Similar such “wiggle room” for state rule-setting was built into nearly every federal guideline for the CCDF.

The resulting heterogeneity in stringency means that the 2014 reauthorization policy changes altered the accessibility of child care subsidies differentially across states. The 2014 statutory changes included additional restrictions to what may be included in asset tests, solidified eligibility during job searches, extended grace periods for reporting changes in employment/income, higher income eligibility thresholds, extensions of redetermination period length, and reductions to monthly copayment amounts. Together, these changes make it easier both to qualify for and to stay on CCDF subsidies than it was prior to 2014, but the implementation of these rule changes was not simultaneous nationwide — states were given a multi-year span in which to come into compliance. In many cases, states also went beyond requirements. Note that future uses of ”leniency” and ”generosity” are interchangeable unless specified otherwise and that both terms are used to refer to these rule changes that allow a greater portion of individuals to be considered eligible for child care subsidies.

Research on child care subsidies indicates that low-income families receiving subsidies are more likely to remain employed for longer periods than those that do not (Boushey 2002). Loprest (2003) finds that welfare leavers with access to child care subsidies are less likely to return to welfare within three months than those without subsidies, which could suggest that parents are increasing their labor supply to a point of “earning out” of welfare eligibility as a result of receiving child care assistance.

In an adjacent policy niche, Pepin (2019) leverages variation in Child and Dependent Care Credit benefit amount generosity over time and across states to estimate the effects of what is functionally a child care subsidy on family outcomes, finding a 10 percent increase in Care Credit is associated with a subsequent 4 percent increase in annual earnings from increased parental employment. In keeping with these findings, I expect to see a positive relationship of similar magnitudes between CCDF generosity and parents' employment and annual income from labor.

There are multiple venues by which the income eligibility cap can functionally be lifted: by changing the types of income that may be counted and persons in a household whose incomes may be included in the amount used to determine eligibility. We can also expect decreasing marginal utility of subsidies as income increases, so in raising maximum eligible household income past a certain (undetermined) point, we might expect to see decreasing levels of impact on usual hours worked. Additionally, families may respond to subsidy receipt in multiple ways. If not already consuming child care at their preferred quantity, they can use subsidies to increase the hours of care, then using that time free of care-giving labor to work more more hours or pursue a better, higher-paying job. Alternately, they could hold the amount of care purchased constant, now using subsidies to decrease the cost of purchasing that care, leaving the family with additional disposable income.

Work Requirements:

In order to theorize about the impacts of child care subsidy access on SNAP participation, it's necessary to understand the latent incentive structure created by work requirements, which both SNAP and CCDF programs have. Much recent research has endeavored to understand the causal impact of work requirements in means-tested programs on program participation and work. Central to the discussion is the inherent trade-off between the provision of safety net benefits and reduction of employment incentives (Besley and Coate, 1992). Welfare-related work disincentives are documented in the empirical literature and a number of analyses find that attempts to counteract such disincentives via work requirements increase both employment and rate of welfare program exit, but decrease total income due to many leaving the program without employment or being removed for inability to comply (Card and Hyslop 2005, Chan and Moffitt 2018, among others). By examining the historical periods in which work requirements have been suspended and reimplemented, we can observe a trend of greater welfare participation when work requirements are inactive or made less binding. For instance, Ganong and Liebman (2018) find that work requirement waivers can explain 10 percent of increases in SNAP participation during and after the Great Recession. As such, I hypothesize a positive effect of increased leniency in CCDF eligibility standards on the proportion of SNAP-eligible parents actually participating in SNAP.

Naturally, I expect to see a greater increase in the proportion using SNAP among those with SNAP-eligible levels of income than among the entire restricted sample, but I make no predictions about whether the SNAP-eligible portion of my sample holds constant over time or what relation that has to the proportion eligible for CCDF subsidies. If expanding access of to child care subsidies does indeed leverage families at the upper end of SNAP eligibility income-wise into "earning out", I might expect for loosening the child care subsidy eligibility requirements to actually generate reduction in SNAP participation among the whole sample.

2. Methodology

The scope of my analysis is nationwide, from 2009-2019. I leverage the increases in eligibility by moving from initial rule positions to full compliance with 2014 federal standards to assess the impacts of child care subsidies on (my set of dependent variables). Being that actual child care subsidy use reflects personal decisions which may be correlated with unobservable characteristics about the households in question, I adopt an instrumental variables approach. The natural choice to instrument for subsidy take-up would seemingly be imputed subsidy eligibility, given that eligibility is strongly correlated with actual use of the subsidies.

$$Y_i = \alpha + \gamma U_i + \beta X_i + \epsilon_i$$
$$\rightarrow Y_i = \alpha + \gamma E_i + \beta X_i + \epsilon_i$$

Hoynes (2008) describes the following “naïve cross-section estimator approach” where U is an indicator variable for subsidy use. Substitution with E (an indicator for imputed subsidy eligibility) removes the issue of unobservables like attitude toward subsidies correlating with outcomes. In my case, I cannot directly observe take-up of the subsidies or perfectly impute eligibility for individual households, because neither subsidy use nor many of the requisite pieces of information for credibly determining CCDF subsidy eligibility are recorded in large non-administrative national datasets.

Furthermore, imputed eligibility for own state of residence presents additional endogeneity issues for my outcomes of interest, as things like household income and employment status are themselves factors involved in determining eligibility. The paper most similar to mine that I’ve located on this topic (Enchautegui, et al, 2016) uses a difference-in-difference approach with the treatment group being women simulated to be eligible and the comparison group being women whose simulated eligibility is ”unlikely”. While I much prefer the identification that difference-in-difference strategies provide, in this case I am uncomfortable with the assumption of those groups as sufficiently comparable. My goal is to abstract from characteristics of the household or family that may be correlated with both eligibility and my dependent variables, and to achieve identification using only legislative variation in the accessibility of child care subsidies.

As noted in each of the Currie and Gruber's Medicaid expansion papers (QJE 1996, JPE 1996), one way to achieve this kind of identification would be to instrument for imputed individual household eligibility with the percentage of households in the same state+year and income range of interest who are eligible, calculated from the ACS. This would excise the specific household characteristic sources of variation in eligibility, but still capture differences in child care subsidy eligibility rules across states and years.

An issue with this approach is that these proportion estimates fail to control for state-specific year-specific attributes that may be correlated with both eligibility and with propensity to actually use child care subsidies. These could be characteristics associated with the population of a state in a given state and year, like average number of children per family, poverty status, within-state economic conditions, or attitudes toward work. Omission of these characteristics could bias estimates of the effect of subsidy access. For these reasons, I follow Currie and Gruber and adopt a "simulated instrument" strategy.

My simulated instrument is constructed to vary only with a state's changes in rules for initial eligibility determination and eliminate reflection of its population makeup or economic characteristics. My methods for building the instrument are as follows: First, I pull nationally-representative random samples of size 10% from my income-restricted ACS samples for each year. I remove the states of residence and then run each sample through my coding of subsidy eligibility rules for every state in that year, calculating the percentage of households in each annual sample that would be eligible for subsidies. I do not attempt to impute a predicted subsidy copayment amount.

I then treat that percentage measure as a functional parameterization of differences in rule stringency in each state/year. Because this measure is calculated using a nationally-normalized population, it allows me to make comparisons in policy generosity between states using a uniform scale of reference. The remaining potential problem is that of omitted variables with changes that are correlated with changes in state child care subsidy policy and also with changes in subsidy need. In my regression equations I attempt to mitigate effects of those unobserved changes by including state and year fixed effects, as well as a demographic vector capturing race, sex, age, and marital status. I interact state*age and year*age, but omit state-year interactions, as these would absorb much of the rule variation I'm trying to observe.

The paper most similar to mine that I've located on this topic (Enchautegui, et al, 2016) uses a difference-in-difference approach with the treatment group being women simulated to be eligible and the comparison group being women whose simulated eligibility is "unlikely". While I much prefer the identification that difference-in-difference strategies provide, in this case I am uncomfortable with the assumption of those groups as sufficiently comparable.

3. Data

I use annual data from years 2009-2019 of the American Community Survey (ACS), an ongoing national survey conducted every month of every year by the United States Census Bureau, since 2005. Disseminated to approximately 3.5 million addresses, the ACS functions like a supplement to the decennial census and contains information on topics not asked about on the census, including such as education, employment, internet access, and transportation.

My primary unit of analysis is the individual, but eligibility determinations are made at the level of the household, so I utilize ACS categorization of respondents by relation to a designated "head of household" to attribute household eligibility status to individuals within the household. I restrict my sample to households with dependent children and total household incomes within 170% of the maximum allowable household income for SNAP eligibility. I perform this restriction because I am only interested in the impacts of child care subsidy policy changes on the population to whom those changes are relevant, i.e. the population in closest proximity to the range of eligible income amounts. With more time, I would have liked to experiment with using various income cutoffs to define my analytic sample. In Enchautegui, et al (2016) which also uses an eligibility imputation to analyze the CCDF-eligible population, they run specifications over samples demarcated at 85%, 70% and 50% percent of state median income. These lower cutoffs may more accurately capture families who are actually eligible and reflect that those who are most likely to be served are the families most in need.

Table 1: Average Values/Proportions of Dependent Variables

	Years 2009-2019	
	Mean	Std. deviation
Total Household Income	51,921	27,572
Usual Hours Worked Per Week	29.634	19.342
Personal income from wages	22,743	27,276
Employment Status		
Employment	0.700	0.458
Unemployment	0.068	0.253
Out of labor force	0.231	0.422
SNAP participation	0.272	0.445
School attendance	0.080	0.272

My total number of households across all 10 years is 1,812,810, with 3,323,602 total individual respondent records. Note that this is not a longitudinal dataset, so I am unable to follow the same household across multiple years. My annual random samples are 10% of the sample for that year.

I chose the ACS because of the large sample size and the fact that it records SNAP participation. Unfortunately, SNAP participation is a self-reported category in the ACS and not directly input via administrative linkages and thus there may be latent issues of underreporting or misreporting program participation (Meyer, Mok and Sullivan, 2009). The Survey of Income and Program Participation(SIPP) does directly record program participation and also has a supplementary longitudinal portion that would be useful in analyzing alterations in labor market behaviors within the household as a result of changing subsidy eligibility rule changes.

My outcomes of interest are adapted from the following ACS variables: Total household income (HHINCOME), employment status (EMPSTAT), SNAP benefit receipt (FOODSTMP), personal income from labor (INCWAGE), usual hours worked per week (UHRWORK) and school enrollment status (SCHOOL). I use the IPUMS variable CPI99 (the CPI-U multiplier) to adjust for inflation, converting all dollar values to constant 1999 dollars, and then use the 1.535 scaling factor to put all in 2019 dollars. I recode SCHOOL to produce a binary indicator for school enrollment. I include school enrollment in addition to the aforementioned outcomes because I wanted to attempt to differentiate from decreases in employment or hours-worked due to substituting away from labor versus decreases due to human capital investment via return to school.

My coding of eligibility determination hinges upon use of the Child Care Development Fund policy database, maintained by the Urban Institute, to track rule changes to individual parameters over the 2014-2016 period and create a simulation of each state's CCDF policy. The CCDF database marks start and stop dates for every individual rule within an individual state. I use these to create separate sets of "active" rules in every state in a given year. Unfortunately, these codings are quite incomplete relative to the actual rule sets, as I have only coded the rules that corresponded to an observable characteristic to which I had access via the ACS. This calls into question the accuracy of my eligibility simulation. I expand upon this in the limitations and discussion section of my paper. Notably, I did not code for changes in copayment policies, length of redetermination periods, the standards required for a child care facility to be authorized for subsidy payout, or CCDF state program funding amounts. The rules I was able to code for include the following:

- Income eligibility thresholds
- Employment requirements
- Minimum required hours worked per month
- Length of job search permissible
- Qualifying non-work activities (school attendance, job search, temporary disability)
- Whether parents in school must also work / how much they must work
- Definition of the family unit and whose incomes are considered for eligibility determinations
- Maximum age at which a child is considered eligible for subsidies
- Asset tests

4. Empirical Specification

The basic IV model I estimate is the following:

$$Y_{ist} = \alpha + \gamma SIMELIG_{ist} + \beta X_i + \delta_s + \eta_t + \epsilon_i$$

where Y_{ist} denotes the outcome of interest - household income, hours worked per week, employment status, wage income, SNAP participation, or school attendance. SIMELIG is my simulated instrument, equivalent to the fraction of a national sample eligible in a given state s at time t. X_i represents a demographic vector for age, race, sex, marital status, and age of youngest child. δ and η denote state and year fixed effects, respectively, and ϵ is the random error term. I include interaction terms for age*year and age*state.

5. Results

First, for comparison against the IV results, I estimate linear probability models for my categorical and non-categorical outcomes of interest using OLS and my imputation of individual eligibility. Results are shown in Table 2. For categorical variables, coefficients may be multiplied by 100 and understood as percentage point effects on the likelihood of an outcome, while the coefficients for continuous numeric variables may be understood in the same units as the variable itself – the predicted marginal effect (in dollars or hours) of being eligible for subsidies, relative to the non-eligible in my sample.

As shown below, eligibility for child care subsidies in one's own state of residence is associated with working roughly 20 more hours a week than non-eligible counterparts, having an annual gross wage income of approximately $14,000 more, and a total household income of about $6,300 more. Additionally, eligible individuals are 50% more likely to be employed, relative to ineligible individuals. Relative to the eligible population, a non-eligible individual is 5% more likely to be unemployed and 45% more likely to be out of the labor market altogether. The table also shows that the CCDF eligible population is approximately 5.5% less likely to be receiving SNAP benefits and 5.3% more likely to be actively enrolled in school.

Table 2: OLS/LPM Estimates

	Coefficient	Standard error
Total Household Income	6,304.061***	32.923
Usual Hours Worked Per Week	19.739***	0.020
Personal income from wages	13,926.96***	32.220
Employment Status:		
Employed	0.504***	0.001
Unemployed	-0.050***	0.001
Out of labor force	-0.453***	0.001
SNAP participation	-0.055***	0.001
School attendance	0.053***	0.001

* denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level

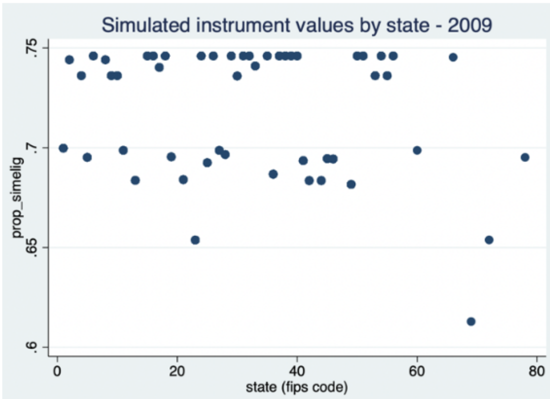
These are merely correlative findings and it is unclear whether there is any direction of causality. For instance, the eligible population may be eligible for subsidies in part because they hold a job, are students, or work a greater number of hours per week, but it is also possible that, at lease in some cases, it is the eligibility (and presumed uptake) of the child care subsidy that makes it possible for some parents to increase their hours worked or (re-)enroll in school. The higher total household income and higher wage income seemingly follow from the higher percentage of employment among the eligible population and their greater amounts of time worked, but given that there are maximum income restrictions to subsidy eligibility and my encoding of the provisions to help temporarily-unemployed or the unemployed-yet-participating-in-approved-activities people was designed to catch those individuals and mark them too as eligible, I am inclined to interpret the distinctly higher patterns of income and employment among the eligible as a suggestion of the positive relationship between subsidy access and the ability to reenter the labor force or secure higher-paying employment.

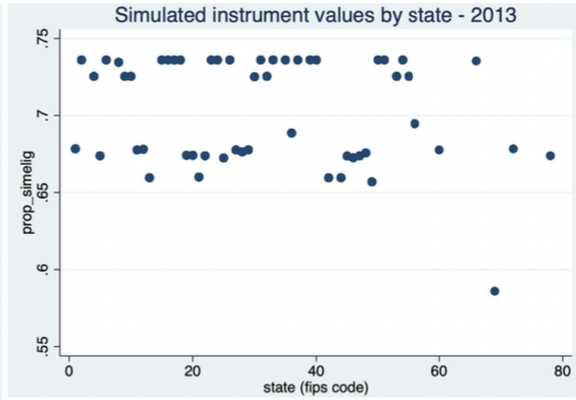
For my categorical variables of interest, I also estimate logit models to see how those differ from the linear probability model results. Those support the same patterns as above, but estimate percentage point effects of slightly different magnitudes, so I include those estimates in the appendix of this paper.

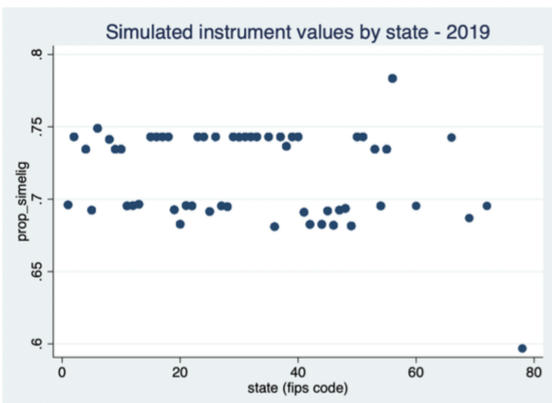
5.1 Instrumental Variable

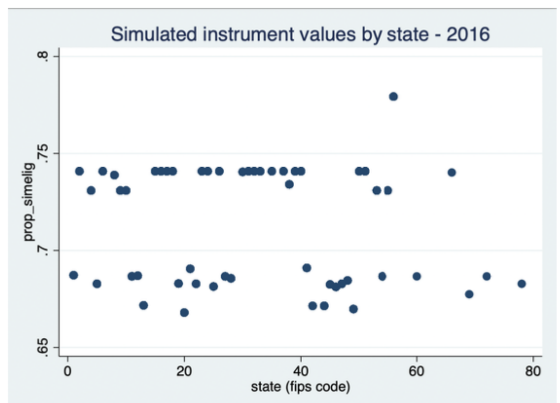
To visualize the spread of values that the simulated instrument takes, the following four tables show the proportion of the random sample simulated to be eligible in each state during a given year. I show years 2009, 2013, 2016 and 2019 to showcase the adjustment of policy generosity over time. We can observe clustering around 0.74 and 0.68 in later years, indicating that in most states, approximately 68-74% of the individuals in the random national sample were simulated to be eligible by 2019.

For simplicity of communication in the following paragraphs, I will refer to an increase in the proportion eligible among that random sample (my simulated instrument value) as an "increase in generosity" or an "increase in the eligibility rate". This of course requires the assumption that my simulated instrument accurately functions as a measure of rule leniency that is comparable across states and the assumption that there are no unobserved factors contemporaneously affecting the dependent vari-









able values for my population of interest. These assumptions are somewhat dubious but must be temporarily accepted for the sake of this analysis.

Recall that linear regression coefficients show the change in the dependent variable associated with a 1-unit increase in the independent variable and that my instrument takes a fractional value between 0 and 1 for all individuals, representing the percentage of a sample of people simulated to be eligible for subsidies in a given state. Thus, a 1-unit change in the instrument represents a move from 0% of the individuals in the random national sample being eligible under state s's rules to 100% being eligible. Naturally, this is far outside the magnitude of changes in state policy or magnitude of differences between states that we observe in the data. First, I will interpret the results in this form and then I will translate them into magnitudes more representative of the actual observed variation in rule stringency.

The results shown in Table 3 suggest that a 100% increase in the rate of eligibility is associated with a 0.6% decrease in employment among my sample of low-income parents, significant at the 1% level. We also see a highly-statistically-significant 0.4% increase in active unemployment and 0.2% increase in individuals having left the labor force altogether. Going from an eligibility rate of 0% to an eligibility rate of 100% is also associated with a roughly $300 decrease in the personal income from wages of individuals in the restricted sample, a 0.43-hour (26 minute) reduction in the number of hours worked per week, and a 0.3% increase in likelihood of school enrollment, both significant at the 1% level. The model also estimates an increase in individual household income of approximately $95 and a 1% increase in utilization of SNAP benefits but these coefficients lack statistical significance.

Table 3: IV Coefficients: Instrumenting Simulated Percentage for Individual Imputed Eligibility

Years 2009-2019

	Mean	Std. error
Total Household Income	95.271	91.934
Employment Status:		
Employment	-0.006***	0.002
Unemployment	0.004***	0.001
Not in labor force	0.002	0.001
SNAP Participation	0.001	0.001
Usual Hours Worked Per Week	-0.433***	0.063
Personal income from wages	-301.391***	91.960
School attendance	0.003***	0.001

* denotes significance at 10% level, ** 5% level, *** 1% level

Several things should catch our eye. First, the signs on these coefficients are largely opposite from what would be expected from such a change in policy. The values are also very small, relative to the magnitude of policy change that would result in going from 0% of people in the restricted sample being eligible to 100% being (theoretically) eligible. Additionally, several of these coefficients have quite high significance levels. Taken together, these pieces of information suggest that what we are observing may actually be precisely-estimated zeroes or near-zero effects. In other words, if the credibility of my simulated eligibility instrument is to be believed, this model exhibits strong evidence of a near-zero effect of increasing the generosity in eligibility determination for child care subsidies.

From 2009-2019, the standard deviation in eligibility rates is 0.08658, meaning one standard deviation is an increase or decrease of approximately 8 percentage points. To put our coefficient estimates into these terms, a 1-standard-deviation increase in the eligibility rate (for instance, moving from 60% of the sample being eligible to 76% being eligible) is associated with a 0.09% decrease in employment among the sample population. Table 4 shows each of the associated effects of a 1-standard-deviation increase:

Table 4: Effects of a 1-Std. Deviation Increase in CCDF Subsidy Generosity

	Value of difference	Equivalent %, rounded
Total Household Income	8.25	–
Employment	-0.0005	-0.05%
Unemployment	0.0004	0.04%
Out of labor force	0.00015	0.015%
SNAP Participation	0.00016	0.016%
Usual hours worked per week	-0.0376	–
Personal income from wages	-26.095	–
School attendance	0.00024	0.024%

According to my model, a 1-standard-deviation increase in the generosity of subsidies is associated with an \$8.25 increase in annual total household income, a 0.05% decrease in employment, a 0.016% increase in SNAP participation, and a \$26 decrease in personal wage income. Presenting the estimates in this way emphasizes just how small the predicted effects are, relative to the theoretical rule changes necessary to go from 0% of the income-restricted sample population being eligible to 100% being eligible.

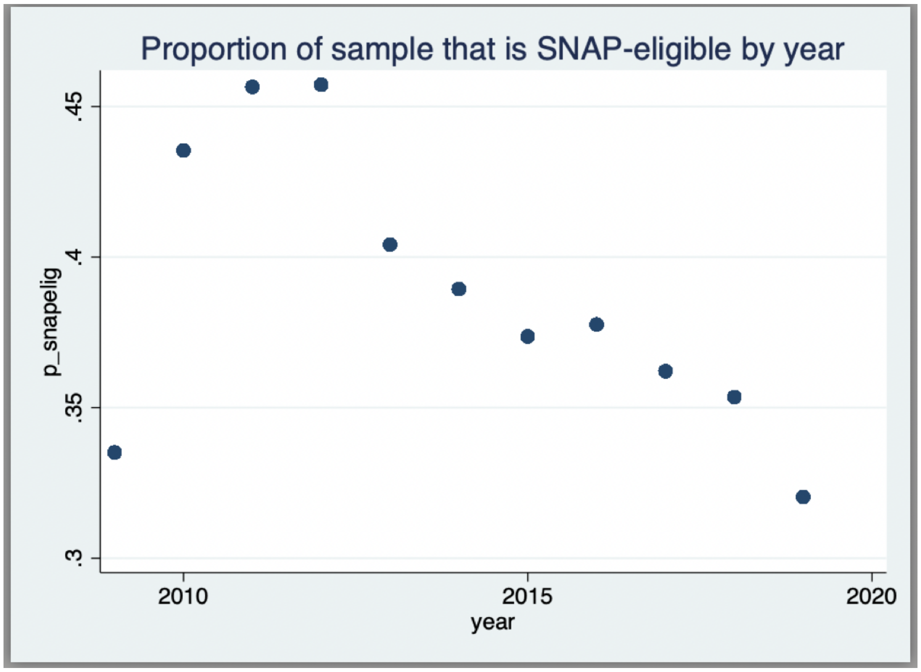
Another way to contextualize would be to look at the minimum and maximum simulated eligibility rates, calculate the percentage point difference between them, and scale the coefficients to that difference. Doing this shows the predicted impact of shifting the most stringent set of eligibility policies nationwide to most generous. Table 5 shows those scaled values. Interpretation is the same as above.

Table 5: Effects of Shifting the Generosity Level of the Least Generous State to that of the Most Generous State

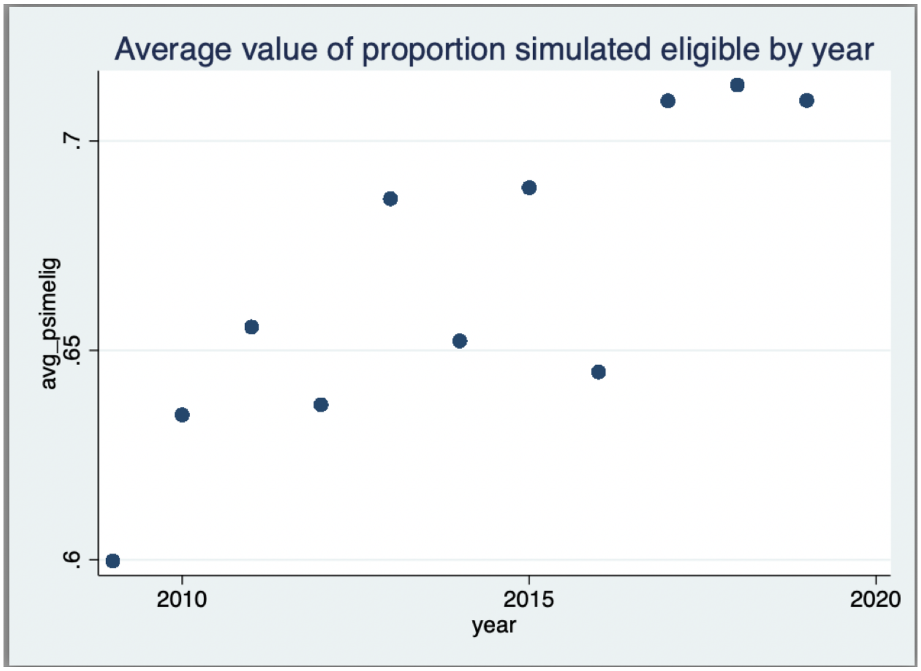
	Value of difference	Equivalent %, rounded
Total Household Income	47.63567	–
Employment	-0.0029	-0.29%
Unemployment	0.0021	0.21%
Out of labor force	0.0008	0.08%
SNAP Participation	0.0005	0.05%
Usual hours worked per week	-0.2169	–
Personal income from wages	-150.70	–
School attendance	0.0014	0.14%

5.2 SNAP participation among the SNAP-eligible

For this analysis, I condition my sample on having an income level at or below the maximum eligibility threshold for SNAP and examine what happens to the program partition rate among that portion of the population when child care subsidy programs become more generous with their eligibility determinations.



In the above graph, we can clearly see that the proportion of the total annual sample that is SNAP-eligible by income is decreasing from the year 2012 onward. We also know that as the years increase, the average value of the simulated instrument - our generosity measure - is generally increasing, if in a somewhat oscillatory fashion. What's particularly salient is that within individual years, I find no evidence of positive or negative correlation pattern between having a high generosity measure and having a low proportion of state population with SNAP-eligible incomes. The evidential correlation tables are in the appendix to this paper. The lack of monotonic correlative relation here suggests that the more "generous" states are not simply the ones with the most or least affluent populations.



Running the same IV specification as given in Section 4 shows that a 0-100% increase in the generosity of CCDF eligibility standards is associated with a 23% increase in the uptake of SNAP benefits among the SNAP-eligible population, significant at the 1% level. Decomposing this along demographic characteristics, we see that the increases in SNAP uptake were greatest among married women and Black people, with magnitudes of 0.523 (52% increase) and 0.302 (a 30% increase), respectively.

Table 6: CCDF Subsidy generosity and SNAP participation among the SNAP-eligible

	Years 2009-2019		
	Coefficient	Std. error	Conf. Int
Full sample	0.237***	0.014	[0.209, 0.264]
Women	0.177***	0.012	[0.153, 0.201]
Black	0.302***	0.020	[0.263, 0.342]
Married:			
Women	0.523***	0.101	[0.326, 0.720]
Men	-1.286***	0.265	[-1.806, -0.766]

* denotes significance at 10% level, ** 5% level, *** 1% level

A couple things could be driving these observed effects: 1. The pool of individuals who are eligible for SNAP is decreasing in states that are simultaneously increasing generosity of child care subsidies, meaning that the neediest (lowest-income) and most-likely to be SNAP participants are constituting a larger portion of the shrinking total SNAP-eligible populations. 2. Among the SNAP-eligible population, parents that previously were not taking-up SNAP benefits now are, either due to a change in taste or a change in their ability to meet other requirements for SNAP participation. These need not be mutually exclusive.

In line with Theory 1, one possible explanation could be that people with incomes near the maximal boundary for SNAP eligibility are discontinuing their SNAP participation concurrently with (or potentially because of) an increase in the generosity of their state's child care subsidy policies. I hesitate to suggest an "earning out" effect because there is no evidence of increases in household or personal income as a result of increased generosity of subsidies. An alternate possible explanation could be that instead of increased access to child care subsidies enabling parents to work more or get better jobs that pay enough to bump them above the max income amount for SNAP eligibility, parents near the upper range of SNAP-eligible income could be substituting in CCDF subsidy uptake for SNAP upon becoming eligible for the subsidies. This would not be rational behavior for families who could simultaneously draw on both benefits, but is fathomable in instances where transfers are considered income for eligibility determination purposes and families may not claim both without having their income amount exceed the allowable amount for one or both.

Additionally (and in line with Theory 2), more individuals with incomes well below the maximum for SNAP eligibility may be enrolling in SNAP due to changes in taste or another non-accounted-for phenomenon. Increases in the eligibility rate for child care subsidies may be translating into increased ability to meet the work requirements for SNAP, allowing previous non-participants to sign up and/or those who otherwise may have been quickly removed from SNAP rolls to remain in the program. In future analyses, I intend to identify a subset of states that made the largest changes to relax their work requirements for CCDF subsidies and examine whether increases in employment and in SNAP participation among those states' SNAP income eligible population are correlative with work rule changes. In order to further determine credence of these explanations, I believe more analysis is necessary of the employment and income effects of increased subsidy generosity, decomposed along demographic lines. Running the same IV regressions as in 5.1 on only the

SNAP-eligible reveals that a 0%-100% increase in generosity is associated with a 2% decrease in employment, $82 increase in total household income, and, puzzlingly, a $390 decrease in personal income from wages. Regression outputs are included in the appendix. In addition to being of extremely small magnitude relative to that of a 0-100% proportion-eligible policy change, those results do not bolster either of the above explanations.

6. Limitations, Future Directions, and Conclusion

In this section, I discuss the credibility of my results and present a post-mortem on my research strategy. First, it is important to remember that this simulated instrument method lacks identification at the individual level. The simulated instrument takes the same fractional value for every resident of the same state in a given year, because theoretically the stringency level of eligibility determination rules is a "treatment" on every member of the potentially-eligible population, but this doesn't allow us to directly look at the outcomes of only those who are eligible or do actually use the child care subsidies. This failing of my method can potentially skew the entire estimation if there are significant differences in dependent variable values between people who are and are not eligible within a given state.

I had several hopes for this thesis that I unfortunately will not be able to realize within the time constraints of the semester, but hope to continue exploring in the future. First, I specifically had hoped to codify accessibility of subsidies in more ways than just initial eligibility determinations. As mentioned earlier in this paper, many of the rule changes concern things like lengths of grace periods, degree of immediacy required for the reporting of changes in wage/employment, amount of time between redeterminations of eligibility, copay amounts, the times during which child care can be subsidized, and which providers are acceptable. These parameters are all extremely important because they relate to the multiplicity of factors that influence whether or not a working parent finds child care, including the availability/proximity of sufficient-quality options, the price parents face for those options, and how they options fit the parent's scheduling and other needs (Compton and Pollak, 2014., Morrisey, 2017). Longer grace periods can provide sustained assistance to families who have "earned out" of eligibility and are transitioning off of subsidy reliance or maintain the eligibility of a family for subsidies while a parent experiences a prolonged joblessness spell. The length of recertification periods can also have some notable effects on program participation and the labor supply decisions of parents. Zhuan Pei (2017) discusses this in the context of Medicaid:

> Setting the recertification period involves the tradeoff between targeting accuracy of the program and the costs in certifying eligibility. A short recertification period allows the state to quickly disenroll families who are no longer the most needy, but certifying eligibility consumes resources. It demands government workers to check eligibility and requires the beneficiaries to collect and provide information. A long recertification period, on the other hand, provides what I call "dynamic opt-in" incentives for families to strategically adjust their income. More specifically, a dynamic neoclassical labor supply model predicts that families may be induced to temporarily lower their income in order to gain program eligibility. As a result, lengthening the recertification period may create a dip-and-rebound pattern in the average income process around eligibility

> checks, and the optimal recertification frequency depends on the extent of the dip and rebound (Pei, 2017).

One can imagine that the speedy disenrollment of families who just marginally exceed the maximum allowable monthly income limit may have destabilizing effects as the parents are saddled with the unsubsidized cost of child care, potentially inhibiting further upward mobility and creating a "welfare lock"-like effect.

The effects of this and other rule changes relating to ongoing eligibility redetermination are something that I would have loved to examine, but unfortunately neither my empirical approach nor my data are sufficient to credibly analyze changes in the rules pertaining to the already-eligible and their effects on program participation and the longer-term economic outcomes of participant families. I believe administrative data at the state level may be necessary in order to approach such questions. If I could access sufficiently detailed individual-level longitudinal data on a low-income population within a state, with actual program participation recorded in said data, I would attempt to improve my simulation for eligibility determination and continue to use imputed eligibility to instrument for uptake. I would drop the between-states comparison angle, avoiding the need for using the simulated fraction eligible of a random national sample as the instrument rather than the 0/1 indicator for imputed eligibility. Additionally, given my methodology and the concurrent changes of many rule parameters, I was also unable to isolate and attribute portions of effect to certain rule changes. This would have required a focus at the level of an individual state program.

It is important to note that as with any research focusing on a very low-income population and welfare program participation, many large national survey datasets have significant issues with underreporting of means-tested transfers and undercounting of people without stable housing. As much as 35% of true SNAP benefit recipients do not report themselves as such in the ACS (Meyer, et al. 2018). When underreporting varies nonrandomly with household characteristics, this can skew multivariate analyses. Linking survey and administrative data or restricted Census microdata can mitigate these issues.

Furthermore, the stringency of entry rules is hardly the only (or even best) measure of the accessibility of child care subsidies. One can imagine a program that is very easy to gain acceptance to, but has very strict and difficult-to-comply-with rules for maintaining one's eligibility, has high copay amounts, or is selective with the particular child care facilities it authorizes. It is not clear whether this scenario describes any particular states, as that would require text analysis of a large number of non-numerically-coded rules, but it illustrates hypothetically the ways in which the ease of use of a CCDF subsidy program is jointly determined and seemingly generous provisions in one area may be counteracted by harsh rules in another. With this in mind, I hope to try future analyses where I select a couple specific rules regarding determination of ongoing eligibility (creation of grace periods and extensions of the redetermination period) and make treatment indicators for pre/post rule change, treating those treatment variables as additional instruments in my regression.

As a final consideration, there are even extremely influential facets of the public assistance pipeline which are almost wholly unrecorded in analyzable data forms: case worker interactions are an important example. In a set of focus group interviews, Kathleen Snyder reports that parents who have used CCDF subsidies expressed frustration with what they perceived as limited information from case workers about the child care services they might be eligible for and/or had received (Snyder, 2006). Particularly, many recounted a belief that they were not proactively offered information about these subsidy programs. Subtleties like those in service provision can make huge differences - whether or not child care subsidies are jointly offered to people applying for other types of public assistance, how smooth and streamlined social services agencies make the process of applying, certifying eligibility, and finding a government-accepted care provider, and whether individual social workers actually make the effort to assist parents with getting their subsidies set up may shape subsidy use and the effects that child care subsidies are currently having on the lives of children and families in ways that we have yet to empirically understand.

In all, I believe my analysis shows nothing conclusive about the effects (or lack thereof) of loosening the stringency of CCDF child care subsidy eligibility rules, but that it provides some evidence of a relationship between child care subsidy accessibility and SNAP program participation, the mechanisms of which demand further investigation.

Appendix

Table 7: Logistic Regression Coefficients

	Log likelihood	Std. error
Unemployment*:	-1.828***	0.005
Not in labor force*:	-3.091***	0.004
SNAP Participation:	-0.313	0.003
In school:	0.873***	0.006

* denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level

(I apologize for not formatting these better; I was trying to focus on the content of the paper and ran out of time)

Table 8: Cross-correlation table 2009

Variables	p_snapelig_state	prop_simelig
p_snapelig_state	1.000	
prop_simelig	-0.214	1.000

Table 9: Cross-correlation table 2010

Variables	p_snapelig_state	prop_simelig
p_snapelig_state	1.000	
prop_simelig	-0.091	1.000

Table 10: Cross-correlation table 2011

Variables	p_snapelig_state	prop_simelig
p_snapelig_state	1.000	
prop_simelig	-0.111	1.000

Table 11: Cross-correlation table 2012

Variables	p_snapelig_state	prop_simelig
p_snapelig_state	1.000	
prop_simelig	-0.077	1.000

Table 12: Cross-correlation table 2013

Variables	p_snapelig_state	prop_simelig
p_snapelig_state	1.000	
prop_simelig	0.110	1.000

Table 13: Cross-correlation table 2014

Variables	p_snapelig_state	prop_simelig
p_snapelig_state	1.000	
prop_simelig	0.138	1.000

Table 14: Cross-correlation table 2015

Variables	p_snapelig_state	prop_simelig
p_snapelig_state	1.000	
prop_simelig	0.172	1.000

Table 15: Cross-correlation table 2016

Variables	p_snapelig_state	prop_simelig
p_snapelig_state	1.000	
prop_simelig	-0.026	1.000

Table 16: Cross-correlation table 2017

Variables	p_snapelig_state	prop_simelig
p_snapelig_state	1.000	
prop_simelig	0.055	1.000

Table 17: Cross-correlation table 2018

Variables	p_snapelig_state	prop_simelig
p_snapelig_state	1.000	
prop_simelig	0.061	1.000

Table 18: Cross-correlation table 2019

Variables	p_snapelig_state	prop_simelig
p_snapelig_state	1.000	
prop_simelig	0.050	1.000

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