Low-Income Household Livelihood Strategies: Food Stamp Access and Private Aid Usage

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Sarah E. Barrows

Major Professor: Paul Lewin, Ph.D.
Committee Members: Daniel Hickman, Ph.D.; Liang Lu, Ph.D.
Department Administrator: Christopher McIntosh, Ph.D.

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Authorization to Submit Thesis

This thesis of Sarah E. Barrows, submitted for the degree of Master of Science with a Major in Applied Economics and titled " Low-Income Household Livelihood Strategies: Food Stamp Access and Private Aid Usage," has been reviewed in final form. Permission, as indicated by the signatures and dates below, is now granted to submit final copies to the College of Graduate Studies for approval.

Major Professor: ____________________________________ Date: __________
Paul Lewin, Ph.D.

Committee Members: ____________________________________ Date: __________
Daniel Hickman, Ph.D.

____________________________________ Date: __________
Liang Lu, Ph.D.

Department Administrator: ____________________________________ Date: __________
Christopher McIntosh, Ph.D.

Abstract

Does access to food stamps influence how low-income households use financial help from family and friends? Changes to the Supplemental Nutrition Assistance Program (SNAP) could affect not only low-income households but the informal financial networks of those households, leading to larger effects than anticipated. Using the Panel Study of Income Dynamics from 1999-2007, I exploit a change in SNAP categorical eligibility in 2000 in order to create a difference-in-difference model. I find that SNAP usage increases significantly due to this change in eligibility but that private aid usage does not. Two explanations seem likely: (1) the relationship between the two types of aid is weak, especially as private aid amount increases, (2) some households lack robust private aid networks. Low-income SNAP households that seem to have less private aid available to them are generally married, less educated, urban, and/or Black.

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I would like to thank my advisor, Dr. Paul Lewin, for his tireless dedication to helping me become a better researcher; Dr Jimmy Lu for always being willing to discuss the various ideas I bring to him; Dr. Daniel Hickman for going out of his way to tailor his classes to me and my research interests; the GPSA travel fund committee for making my presentation in Washington D.C. possible; the National Institute of Food and Agriculture, US Department of Agriculture HATCH grant which funded this research; and Anna Brown and her team at Emsi who were wonderful coworkers and who helped me learn about many practical applications of economic research.

Dedication

To my family for sacrificing as much as I did so that I could finish this.

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1: Introduction

1.1: Overview

Low-income households often must use a variety of livelihood strategies to make ends meet, working extra jobs, receiving welfare, or asking for help from others to survive. Despite the higher usage of government welfare by lower income households, little is understood about how changes to welfare access affect these households' other livelihood strategies. This thesis addresses one element of this question by looking at access to the Supplemental Nutrition Assistance Program (SNAP), formerly known as food stamps, and usage of financial help from private sources. Specifically, I want to know if access to SNAP affects low-income households' usage of private aid from family, friends, and others.

This question is especially relevant because SNAP eligibility requirements are once again being debated, but the effect of these changes on households' informal aid networks is not well understood. The debated changes would raise the age cap for work requirements making it much harder for states to waive work requirements. It has been argued that many people would likely lose SNAP benefits due to this change, as 2.8 million people on SNAP do not currently follow the work requirements (USDA, 2018). This is not the first time such policies have been debated, which only highlights the continuing importance of understanding how access to food stamps affects other income sources. This is especially true since these other income sources sometimes involve other households, which could lead to cascading effects.

Private transfers are already an important component of families' and individuals' economic resources (Edin & Lein, 1997; Gottlieb, Pilkauskas, & Garfinkel, 2014; Kalil & Ryan, 2010). In addition to monetary help, private aid from family and friends takes on a wide variety of forms, from childcare, to shared living arrangements, to in-kind assistance.

Estimates of the extent of private financial transfers vary quite a bit depending on the study. Those receiving private aid range from 5.3 percent (Gale and Scholz, 1991) to 28 percent (Gottlieb, Pilkauskas, and Garfinkel, 2018) of the full population. The size of the transfer also varies widely, from $400 a year on average for the full population (Schoeni, 1997) to $6,500-$7,500 a year for women (Haider and McGarry, 2005). Gale and Scholz (1994) find that in 1986, about $63 billion was given in intergenerational transfers in the U.S., not including college payments or bequests. Additionally, the share of private transfers in total income has increased over time (Haider and McGarry, 2005). Considering that some private aid goes unreported, these large numbers suggest that private aid is an important component of households' livelihood strategies.

If government benefits are taken away, households may increase private aid usage; thus, help from family and friends could be seen as a substitute for government aid. Previous studies have investigated the possibility that public aid and private aid may have an inverse relationship. One of the first of these studies was from Lampman and Smeeding (1983), concluding that private aid is slowly being replaced by public aid, since private aid decreased over the 30-year time span they investigated, while public aid increased. Their paper, and others, led to several studies examining the hypothesis that public aid 'crowds out'[1] private aid that was already there, which could make the benefits of public aid appear more significant than they are. These papers were motivated by the concern that public aid may be redundant or inefficient if it is crowding out private aid.

Mixed results are found in these studies. For the U.S., some find positive relationships between private aid value and public aid value, meaning that crowding out is not present (Cox and Jakubson, 1995; Cox, 1987; Cox and Rank, 1992). However, some show negative relationships, which means that some substitution is happening (Altonji, Hayashi, and Kotlikoff, 1997; McGarry and Schoeni, 1995; Rosenzweig and Wolpin, 1994; Schoeni, 1996).

International studies fare similarly. Some find evidence of public aid displacing private aid in locations where public aid is not well established, such as Cox, Hansen and Jimenez (2004) in the Philippines, Jensen (2003) in South Africa, and Kaufmann and Lindauer (1986) in El Salvador. However, other studies find a positive relationship between the two types of aid, meaning that displacement is not happening, such as Lucas and Stark, (1985) in Botswana, and Cox, Eser, and Jimenez (1998) in urban households in Peru.

Of these studies, domestic and international, only Jensen's uses a quasi-experimental method to examine the relationship of the two types of aid, exploiting expansions of South Africa's Old Age Pension system. The other studies' general method is to regress public aid value on

[1] These studies define 'crowding out' as displacement of extant private aid by public aid.

private aid value, sometimes instrumenting for government aid to address endogeneity in the variable. While these studies differ in their datasets, welfare types (AFDC, SSI, etc.), and subpopulations of interest, they have one similarity – they generally find very small effects. They mostly show that a dollar increase in public aid income results in an increase or decrease in private aid amount of only a few cents.

The studies mentioned previously and this ‘crowding-out’ framework do not address several important concerns. For example, they do not adequately explore the possibility of private aid and public aid being used together. Though they mention this as a possibility, and account for it in an ‘exchange’ framework where private aid is not altruistic, but given in return for something. However, this does not address the very real possibility that some households may need to use all aid available, which may show the two types of aid going together while still being given altruistically. For example, by program design, SNAP benefits are intentionally below total food costs for an average family, meaning that other income is required. This additional income may need to come from private aid for some households.

Furthermore, previous literature does not explore households’ access to private aid. Their focus is to account properly for aid effects so that public benefits are not overstated when looking on a national level. Many low-income households do not have access to significant private aid to be ‘crowded out,’ and these households and their livelihood strategies are not discussed meaningfully in previous literature.

Other studies have looked more specifically at SNAP usage versus food bank usage, as food banks could be considered part of private aid. Their general conclusions are that food banks are much smaller and therefore cannot fully cover the needs that SNAP does (Guo, 2009; Molnar, Duffy, Claxton, and Bailey, 2001; Tiehen, 2002). Some studies also find that their usage is positively correlated, especially if one looks over a larger time frame (Bhattarai, Duffy, and Raymond, 2005; Mosley and Tiehen, 2004). These more specific results suggest that the two types of aid are not as likely to be substitutes as one might initially suspect.

My thesis’s unique contribution is using a quasi-experimental method to examine private versus public aid usage in the U.S. It is also unique in specifically studying how SNAP relates to a general definition of private aid. As SNAP has some of the highest participation rates of any income-based welfare programs in the U.S., it is a significant part of the U.S. welfare system, addressing basic dietary needs of low-income households. Inadequate nutrition is a major underlying reason for low-income individuals' hospitalizations (Nelson, Brown, and Lurie, 1998), which suggests that any relationship of SNAP and private aid would be crucial to understand in order to help low-income households thrive.

To address this important question of the effect of SNAP access on private aid usage, I use data from the Panel Survey of Income Dynamics (PSID) to construct a dataset from 1999 to 2007. The PSID is advantageous in that it provides a comprehensive dataset of the income sources, expenditures, and welfare usage of thousands of Americans in annual waves from 1968 to 1996, then biennial waves from 1997 forward.

I then exploit a policy change that occurred in SNAP in November 2000 that created a new type of eligibility: broad-based categorical eligibility (BBCE). This policy suddenly made many households eligible for SNAP by allowing Americans who receive certain non-cash governmental benefits to qualify for SNAP. These non-cash benefits were determined by looser income and asset tests, effectively raising the income ceiling for SNAP participation.

I use a natural experiment created by the differing times of state policy adoption to create a difference-in-difference model. I find that the states with this new policy significantly change SNAP usage after the policy change, increasing SNAP use by 3.5 percentage points. However, I find that private aid usage is not statistically different with increased access to SNAP.

As other income sources did not change significantly during this time, it is likely that private aid usage did not change because of two things: a weak relationship between the two types of aid at higher income levels, and a lack of access to private aid for some lower-income households.

This suggests that SNAP policy changes would likely have a bigger effect on low-income households with weak private aid networks. Thus, policymakers should be aware that some households may not have other adequate aid networks for their needs were they to lose access to SNAP.

1.2: The Supplemental Nutrition Assistance Program

SNAP is one of the most widely used welfare programs provided in the U.S. The only welfare program with higher average participation rates is Medicaid, with an average monthly participation rate of 15.3 percent, in comparison to SNAP's 13.4 percent average participation rate (U.S. Census Bureau, 2015). To illustrate the magnitude of SNAP, in 2018 alone, the U.S. government provided over $60 billion in food assistance to over 40 million people through SNAP, an amount that has declined slightly over the past eight years (USDA, 2018).

SNAP is an in-kind assistance program, and is means-tested, meaning that recipients must have income and assets below a certain threshold to qualify[2]. This threshold depends on the size of the family. For example, in 2019 a one-person household must make less than $1,316 net pay a month to receive SNAP, while a three-person household must make less than $2,252 net pay a month. Benefits are provided through an EBT card, which only allows the purchase of certain goods through qualified retailers.

In addition to income and asset tests, households may qualify for SNAP through categorical eligibility, in which all household members qualify to receive either Temporary Assistance for Needy Families (TANF), Supplemental Security Income (SSI), or general assistance through some state programs.

However, in November 2000, the USDA allowed for a wider definition of categorical eligibility called broad-based categorical eligibility (BBCE) in which families only need to receive an in-kind or non-cash benefit that is at least 50-percent funded by TANF or state Maintenance of Effort (MOE) funds in order to qualify for SNAP. This benefit could be something as simple as a brochure or even an 800-number, both options suggested in a clarifying USDA memo in 2009 (USDA, 2009).

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[2] Since 1996, SNAP has also had work requirements for certain demographics. Able-bodied adults aged 18-49 without dependents (ABAWDs) must work at least 80 hours a month; otherwise they will be restricted to only three months of SNAP benefits in three years. However, states have some leeway in implementing these requirements; they can currently obtain waivers to these restrictions depending on state unemployment rates.

This technical loophole is still subject to income and asset tests, but most states apply only a gross income eligibility limit of 130 to 200 percent of federal poverty levels (FPL) to determine eligibility instead of the stricter limits used for traditional eligibility (Laird and Tripp, 2014). Thus, more households are eligible through BBCE than through traditional eligibility. Mathematica Policy Research estimates that about 3.4 percent of SNAP households who are eligible through BBCE would not be eligible through traditional eligibility (Laird and Trippe, 2014).

2: Theoretical Model

Drawing on the work of Keane and Moffit (1998), Hagstrom (1996), and Kang, Huffman, and Jensen (2004), I develop a household utility maximization model to describe joint labor-aid decisions. Since I am examining low-income households, I assume that labor hours cannot increase adequately to cover all consumption needs for most households. Thus, aid is needed, either from private sources such as family and friends, or from the government through programs such as SNAP.

Also, I must account for why many households who could participate in government aid without increasing work hours do not do so. Similarly, many who could likely draw on private aid also do not choose to do so. There are obviously other factors that affect aid choice, and which likely also affect labor supply, such as tastes and access.

Therefore, I assume that households attempt to maximize their utility, as defined by the function,

$$U = U(Y, H, \delta, \rho) \tag{1}$$

where Y is household income, H is hours worked by household head, δ represents a household's taste for government aid, and ρ is a household's taste for private aid. This is subject to income, as defined by

$$Y = Y(H, P_g, P_p, N) \tag{2}$$

where P_g is an indicator equal to 1 if the household receives government aid, P_p is an indicator equal to 1 if the household receives private aid, and N is non-labor income. More specifically,

$$Y = N + WH + P_g\left[B_g(H, R, S, N) - C_g\right] + P_p[B_p(A) - C_p]$$

where $B_g(H,R,S,N)$ and $B_p(A)$ are the benefits received from government aid and private aid, respectively. The size of government benefits is directly tied to household size, income, and asset level. This means that B_g is a function of labor hours H, asset level R, household size S, and non-labor income amount N. Private aid amount is tied to the access a household has to resources available from social connections, A. This private aid access is related to many difficult-to-measure components, such as one's trustworthiness, appeal to others, etc.

However, the amount of private aid available is capped at the amount of unallocated resources one's social connections have. Many households' access to private aid is difficult to change, as it is often linked to socio-demographic characteristics of the household and of the household's social connections.

The cost of participating in SNAP is C_g, and for private aid it is C_p. Household SNAP costs include disutility from such things as the burden of undergoing bureaucratic processes to get assistance and the stigma associated with government aid. These costs can explain why some eligible households do not choose to apply, and they are determined partially by the household's perceptions and preferences.

Similarly, costs for using private aid include the social costs of asking friends and relatives or others for assistance and the associated stigma or effect on a relationship. They also include reciprocity costs where some repayment is expected, whether monetary or otherwise. If the perceived costs of using either kind of aid are higher than the predicted benefit, that type of aid will not be chosen, and P_g or P_p will be zero.

The household simultaneously chooses the triplet (H,P_g,P_p) to maximize Equation (1) subject to Equation (2). In my study, I do not estimate this triplet, but rather look at the relationship between P_g and P_p since labor hours often cannot increase adequately for low-income households to meet their consumption needs entirely through labor. Thus, the substitution or multiple usages of the two aid types can be seen by estimating average participation rates, P_g and P_p, for my sample. Benefit size and access are also discussed though not formally tested.

3: Empirical Model

An ideal test of the hypothesis that SNAP access affects private aid usage would be to randomly assign SNAP eligibility to households in a heterogeneous sample. We could then see how private aid usage is affected. However, since this is not possible in the real world, I simulate it with a quasi-experimental difference-in-difference (DID) model. DID models have been used widely in policy economics, starting with Ashenfelter's seminal work in 1978 about training programs, and continuing to many recent examples, as described in Imbens and Wooldridge (2009).

In my DID model, I compare the change in outcomes before and after the new BBCE policy, exploiting the difference in state timing of policy adoption. The treatment states are those who have implemented the new policy, and control states are those who have not yet adopted it. This time-varying DID model is also known as a staggered adoption design or an event study design. An early example of time-varying DID is found in a paper by Athey and Stern (2000) in which counties adopt 911 technology at different times. Since then, this model has been used in many DID papers. In fact, Goodman-Bacon (2018) finds that half of the 93 DID papers he surveyed from 2014-2015 publications use time variation.

For this time-varying DID method to work, however, we assume that intervention is as good as random (Bertrand, Duflo, and Mullainathan, 2004). We also cannot have any anticipatory effects that would suggest dissimilar trends before states become treated (Angrist and Pishke, 2014). I show how my data fulfill these assumptions in Appendix A.

The regression model for time-varying DID is fairly straightforward. The regression is

$$Y_{ist} = \beta_0 + \beta_{DD} \cdot D_{ist} + \xi \cdot X_{it} + \eta_s + \varepsilon_{ist} \tag{4}$$

where Y_{ist} is either SNAP usage or private aid usage for an individual i in state s at time t. As a dependent variable, SNAP usage is not exclusive of private aid usage, nor is private aid usage exclusive of SNAP usage.

The dummy variable D_{ist}, is 1 if the household lives in a state that has BBCE at time *t*. Goodman-Bacon (2018) describes how β_{DD} is a variance-weighted average of all possible two-by-two DID estimators that compare timing groups to each other. [3] In this way, β_{DD} is an *average* of average treatment effects on the treated (ATT).

The rest of the model is quite simple. The parameter X_{it} is a vector of covariates describing household characteristics. The parameter η_s represents state fixed effects.

It is important to note that this DID model uses a binary regressor in a traditional OLS framework which can lead to heteroscedasticity and issues with standard errors. While the problem of a binary dependent variable is typically addressed by using a nonlinear model such as logistic regression or probit regression, these techniques have several issues when applied to DID models and are rarely used in that context (Norton and Ai, 2003; Puhani 2012, Karaca-Mandic et al. 2012).[4]

Another limitation of this empirical model is that the policy change was in a positive direction – increasing SNAP access – while most policy concerns are in a negative direction – loss of SNAP benefits. This may be of greater concern when analyzing income sources that are automatic or recurring, such as other government aid or even wages. In these cases, households are more likely to simply increase their incomes with the addition of SNAP benefits. However, private aid is typically not an automatic income source, requiring a household to ask for financial help if needed. If the private aid is not really needed, then it may be less likely to be sought and acquired. Thus, even a positive SNAP policy change may still cause an effect on private aid usage, if there is a relationship between the two types of aid.

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[3] In my regressions I name this dummy 'Treat_post.'

[4] The main issue with nonlinear models is the interaction term of D_{ist}. Ai and Norton (2003) point out that interaction terms in nonlinear models do not represent the marginal effect of the interaction term, and therefore the DID estimator is no longer merely the coefficient of the interaction term. Puhani (2012) shows that the average treatment effect on the treated (ATT) in a nonlinear DID model is a difference in cross differences – namely, the cross difference of the observed outcome minus the cross difference of the potential non-treatment outcome. However, with varying implementation times, the post-policy non-treatment outcome is not defined, since the control group consists of only pre-policy states. Thus, a nonlinear DID cannot be calculated using Puhani's method when using differences in timing to construct treatment and control groups.

4: Data

4.1: Sample Description

I use data from the Panel Survey of Income Dynamics (PSID) because of its extensive information on income sources, expenditures, and assets, in addition to its detailed demographic information. I use panel waves from 1999 to 2007 in order to gain a sense of the trends of aid usage over time. I do not consider pre-1998 data, as SNAP eligibility rules changed significantly in 1996 due to welfare reform, becoming fully implemented by July 1997. I also restrict my observation period to exclude effects from the Great Recession, which began in 2007 and stretched beyond 2009.

I also limit my dataset to only household heads, for several key reasons. First, economic well-being is measured at the household level in the United States. Ideally, therefore, one should track households over time. However, it is difficult to arrive at a satisfactory definition of a “longitudinal household” since household composition changes considerably even over short periods (see Duncan and Hill, 1985 for a detailed discussion). The household head serves as a good proxy for the household since the bulk of household income is earned by householders. Only considering the household head also makes other analyses more simple, for example, modeling labor supply effects. Another reason for choosing the householder as the unit of analysis is that the PSID provides the most comprehensive information for these household head. Though some demographic information about other household members may be lost, my key variables of interest still involve the entire household: SNAP usage is determined on a household basis, and private aid is considered as any financial aid given from non-governmental sources to either the household head or the head’s spouse.

I further restrict my sample to household heads between the ages of 18-64 so that I can consider only non-elderly households who could more feasibly work as a component of their livelihood strategy. This is so that labor changes, if any, could be evident. I also exclude U.S. citizens who are residents of other countries, since SNAP is generally not available to them. I also did not include students, because they are usually not eligible for SNAP except under very rare circumstances. I did not consider residents of Alaska and Hawaii, merely because my sample sizes were very small for these states and their SNAP income eligibility thresholds were quite different from the contiguous states'. I use the PSID's weights to account for the PSID's sample clusters, strata, and longitudinal population weights for all estimations.

Variable definitions, means, and standard errors for my sample are given in Table 4.1. I use the sample weights given in the PSID to construct these sample means.

Table 4.1: *Variable means and balance tests for treatment and control groups, N=30,255*

Variable	Definition	Mean	Std. Dev.	Min	Max
Age	Age of HH head	42.46	11.07	18	64
Male	Whether HH head is male or not	0.73	0.42	0	1
Married	HH head is married or permanently cohabiting	0.54	0.47	0	1
Disabled	HH head is permanently disabled	0.04	0.19	0	1
Healthy	HH head has good or excellent health, self-reported	0.87	0.32	0	1
White	HH head is White	0.76	0.40	0	1
Black	HH head is Black	0.15	0.34	0	1
Less than HS	HH head completed fewer than 12 years education	0.15	0.34	0	1
HS grad	HH head completed 12 years education	0.29	0.43	0	1
Some college	HH head attended at least one year of college but did not obtain a college degree	0.24	0.41	0	1
College degree	HH head has a college degree	0.32	0.44	0	1
Avg work hours	Avg weekly hours worked by HH head	37.17	16.92	0	112
Child under 5	HH has a child under age 5	0.16	0.35	0	1
Child 5-18	HH has a child age 5 to 18	0.36	0.46	0	1
Num in HH	Number of people in HH	2.56	1.39	1	13
Metro	HH is located in a metropolitan area, as measured by the Beale index	0.66	0.45	0	1
Income	HH total income in thousands, adjusted to 2017 dollars	90.49	127.20	-1,293.5	6,948.3
Northeast	Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont	0.18	0.36	0	1

Variable	Definition	Mean	Std. Dev.	Min	Max
Northcentral	Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, Wisconsin	0.27	0.42	0	1
South	Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, Washington DC, West Virginia	0.33	0.45	0	1
West	Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, Wyoming.	0.22	0.39	0	1
SNAP	HH is on SNAP benefits	0.07	0.24	0	1
SNAP value	Value of SNAP benefits, if using, in 2017 dollars	480.94	923.10	11.87	9,320.96
Private aid	HH received financial help from family/friends	0.14	0.33	0	1
Private aid value	Value of private aid from family and friends, if using, in 2017 dollars	4,499.28	10,823.95	1	160,319
Treat_post	HH lives in one of the treatment states after policy implemented	0.17	0.36	0	1

4.2: Treatment and Control Groups

My treatment and control groups are defined by timing of state implementation of the new SNAP policy. States were given leeway in when they implemented BBCE, if they implemented it at all. Only nine states were early implementers of BBCE, adopting it within the first two years of the policy change. They remained the only states with BBCE until 2004 when Washington and Wisconsin also adopted it. By 2007, thirteen states had adopted BBCE: Arizona, Delaware, Maine, Maryland, Massachussetts, Michigan, Minnesota, North Dakota, Oregon, South Carolina, Texas, Washington, and Wisconsin. Figure 4.1 shows the staggered timing of BBCE adoption by these thirteen states. As of 2019, all but ten states offer BBCE.

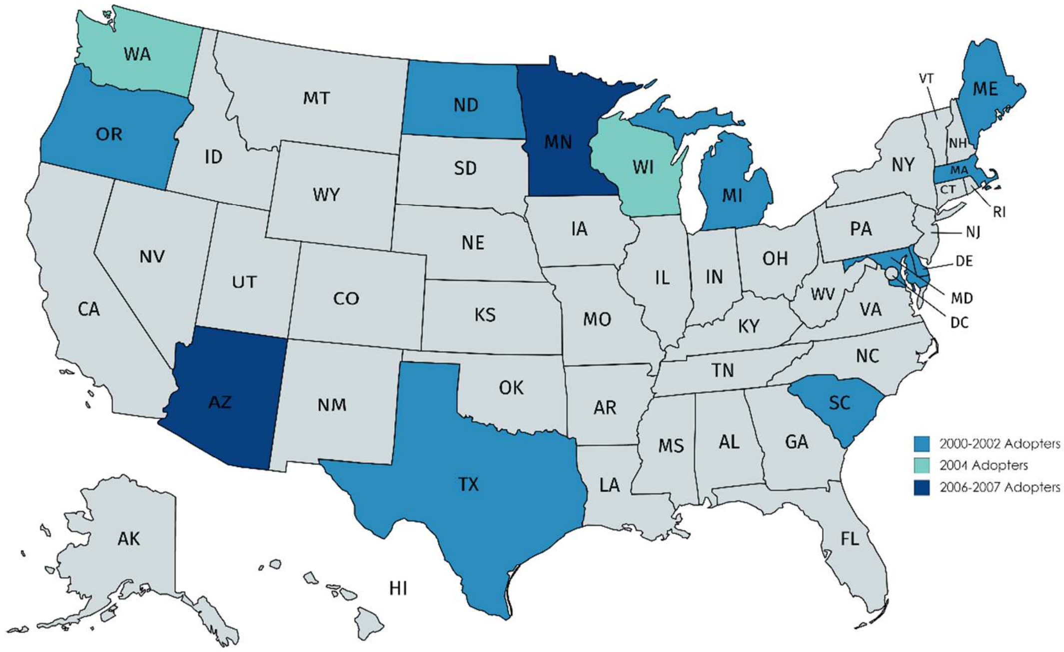

Figure 4.1: State Adoption of BBCE from 2000-2007

In my study, I create a treatment group defined by a dummy representing whether the state has BBCE at a given time period. Thus, my control group consists only of pre-policy states, or states who never implemented the policy. As a group, it shrinks over time as the treatment group grows. In order to see if my groups are balanced, I test to see if any covariates change significantly with the policy implementation. I run my DID model with each covariate as my dependent variable, leaving out other covariates and state fixed effects. None of these regressions yields significant changes in the covariates when the policy changes. Thus, it appears that my covariates are stable across group and time despite the way the treatment and control groups change in size over time.

To further test for violations of the parallel trends assumption, I use a method that derives from tests developed by Angrist and Pischke (2014). My test searches for anticipatory effects in SNAP or private aid usage trends that would violate the parallel trends assumption[5]. I find none, which suggests that DID is justified.

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[5] A more formal description of this test and the results are found in Appendix A.

4.3: SNAP and Private Aid Users

To gain a better understanding of the characteristics that are associated with households who use SNAP and/or use private aid, I create a table of means by each group. Table 4.2 shows these means for the two non-exclusive groups: SNAP users and private aid users. There is some overlap in these groups, but it is only three percent of the sample, as shown later in Table 4.3.

Table 4.2: *Composition of households by SNAP and private aid usage, nonexclusive categories*

	SNAP Users *N= 3,844*				Private Aid Users *N=5,002*			
Variable	Mean	Std. Dev	Min	Max	Mean	Std. Dev.	Min	Max
Age	38.32	13.54	18	64	35.42	11.89	18	64
Male	0.41	0.59	0	1	0.57	0.51	0	1
Married	0.28	0.54	0	1	0.33	0.48	0	1
Disabled	0.20	0.48	0	1	0.07	0.26	0	1
Healthy	0.66	0.56	0	1	0.83	0.39	0	1
White	0.48	0.60	0	1	0.74	0.45	0	1
Black	0.40	0.59	0	1	0.20	0.41	0	1
Less than HS	0.42	0.59	0	1	0.16	0.38	0	1
HS grad	0.33	0.56	0	1	0.26	0.45	0	1
Some college	0.20	0.48	0	1	0.28	0.47	0	1
College degree	0.05	0.27	0	1	0.29	0.47	0	1
Avg work hours	19.58	22.35	0	105	31.15	19.36	0	109
Child under 5	0.33	0.56	0	1	0.20	0.41	0	1
Child 5-18	0.56	0.59	0	1	0.30	0.47	0	1
Num in HH	3.13	2.14	1	10	2.23	1.45	1	11
Metro	0.63	0.58	0	1	0.67	0.48	0	1
Income	24.84	25.47	-132.2	305.7	53.17	62.13	-32.8	1643.5
Northeast	0.13	0.40	0	1	0.16	0.38	0	1
Northcentral	0.27	0.53	0	1	0.26	0.45	0	1
South	0.40	0.59	0	1	0.36	0.49	0	1
West	0.20	0.48	0	1	0.22	0.43	0	1
SNAP	1.00	0.00	1	1	0.15	0.37	0	1
Private aid	0.29	0.54	0	1	1.00	0.00	1	1
Treat_post	0.20	0.48	0	1	0.17	0.39	0	1

We see that household heads who use SNAP are slightly older, have children, and are more often disabled in comparison to those that use private aid. SNAP usage decreases with increasing education, while the reverse is true for private aid. White households tend to use private aid more often than SNAP, and Black households seem to do the reverse.

SNAP users tend to have lower incomes than those who use private aid, which is an unsurprising result, given that SNAP eligibility is tied to income. We would also suspect that lower income households would use both types of aid at greater rates since their needs are greater. This is true, as shown in Table 4.3. However, we also see that households rarely use both SNAP and private aid together, no matter their income level.[6]

Table 4.3: *Aid usage at varying income quintiles, both treatment and control states*

Aid type	Entire Sample	Low Income	Middle Class	High Income
		<200% FPL	*≥200% FPL <500% FPL*	*≥500% FPL*
SNAP only	7%	18%	2%	0%
Private aid only	11%	17%	13%	7%
Both	3%	8%	1%	0%
Neither	79%	57%	84%	93%
Avg income	$90,493	$20,518	$60,462	$164,688
Avg SNAP value	$481	$496	$418	$429
Avg Private aid value	$4,499	$1,882	$4,131	$10,801

Note: Due to rounding, non-zero values appear to be zero.

Table 4.3 also shows that higher income households use larger average values of private aid than lower income households. The increase in private aid value suggests that wealthier households have more private aid available to them, possibly using them for much different purposes than low-income households.

[6] No definition is considered standard for identifying low-income, middle class, and high-income households. For the purposes of my thesis, low income is defined as incomes below 200% of federal poverty levels. Middle class is defined as incomes of 200-500% of federal poverty levels. High income is defined as incomes above 500% of federal poverty levels.

5: Results and Discussion

Regression results for my DID models for each dependent variable (SNAP usage and private aid usage) are found in Table 5.1 with standard errors reported in parentheses. Initial models differ in their inclusion of state fixed effects and covariates. Additionally, using a method from Bertrand, Duflo, and Mullainathan (2004), I adjust for serial correlation, a known issue with longitudinal DID models. Results are found in columns 4 and 9 in Table 5.1, showing nominal changes to standard errors. Detailed explanations of the serial correlation adjustments and full results are found in Appendix B.

Similar to Hoynes and Schanzenbach (2012), I use the PSID data as a repeated cross section and run pooled OLS on the dataset for all my models. However, when I include household random effects, the results are qualitatively similar, as shown in columns 5 and 10. Because of software limitations (Stata), I am unable to fully account for PSID survey structure in my random effects model. It is difficult to say if more information is gained by including household random effects or lost by removing the survey structure of the panel.

Across my models, I find that SNAP usage significantly increased due to the policy change, as was expected. I use the most detailed models in columns 3 and 4 for my SNAP results as these models appeared the most explanatory. I find that SNAP access increased the probability of SNAP participation by 3.5 percentage points. This percentage increase can be thought of as the average of all possible average treatment effects on the treated (ATT).

Table 5.1: *DID Regression Results*

	SNAP Models					Private Aid Models				
	(1)	(2)	(3)	(4)±	(5)†	(6)	(7)	(8)	(9)±	(10)†
Treat_post	0.017	0.034***	0.035***	0.035***	0.020**	-0.000	0.013	0.015	0.015	0.012
	(0.010)	(0.009)	(0.008)	(0.008)	(0.006)	(0.008)	(0.008)	(0.008)	(0.009)	(0.006)
State FE		x	x	x			x	x	x	
Covariates			x	x	x			x	x	x
HH random effects					x					x
# of Obs	32,749	32,749	32,552	32,552	33,140	32,775	32,775	32,577	32,577	33,165
R sq	0.001	0.019	0.210	0.210		0.000	0.007	0.108	0.108	
DF	63	63	63	1192		63	63	63	1193	
<u>Covariates:</u>										
Age			-0.002***	-0.002***	-0.002***			-0.007***	-0.007***	-0.008***
			(0.000)	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)
Male			-0.059***	-0.059***	-0.101***			-0.049***	-0.049***	-0.050***
			(0.009)	(0.008)	(0.009)			(0.011)	(0.010)	(0.010)
Avg work hrs			-0.002***	-0.002***	-0.002***			-0.002***	-0.002***	-0.002***
			(0.000)	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)
Disabled			0.030***	0.030***	0.027***			-0.007	-0.007*	-0.011***
			(0.004)	(0.004)	(0.003)			(0.004)	(0.003)	(0.002)
Healthy			0.138***	0.138***	0.101***			0.020	0.020	0.003
			(0.024)	(0.023)	(0.015)			(0.015)	(0.020)	(0.013)
White			-0.042***	-0.042***	-0.038***			-0.048***	-0.048***	-0.050***
			(0.009)	(0.008)	(0.006)			(0.010)	(0.008)	(0.006)
Black			0.078***	0.078***	0.085***			0.013	0.013	0.030***
			(0.011)	(0.011)	(0.009)			(0.012)	(0.011)	(0.007)
Married			-0.046***	-0.046***	-0.018**			-0.023*	-0.023**	-0.031***
			(0.007)	(0.007)	(0.007)			(0.010)	(0.009)	(0.009)

	SNAP Models					Private Aid Models				
	(1)	(2)	(3)	(4)±	(5)†	(6)	(7)	(8)	(9)±	(10)†
Metro			-0.010	-0.010	-0.016**			-0.002	-0.002	-0.008
			(0.006)	(0.006)	(0.006)			(0.006)	(0.007)	(0.006)
HS grad			-0.069***	-0.069***	-0.084***			-0.003	-0.003	-0.024*
			(0.008)	(0.008)	(0.008)			(0.010)	(0.010)	(0.010)
Some college			-0.082***	-0.082***	-0.107***			0.029**	0.029**	0.014
			(0.009)	(0.009)	(0.008)			(0.010)	(0.011)	(0.011)
College degree			-0.095***	-0.095***	-0.132***			0.032**	0.032**	0.011
			(0.009)	(0.008)	(0.008)			(0.009)	(0.010)	(0.011)
Child under 5			0.048***	0.048***	0.059***			0.003	0.003	0.010
			(0.009)	(0.011)	(0.007)			(0.012)	(0.011)	(0.009)
Child 5-18			0.012*	0.012	0.017**			-0.005	-0.005	-0.011
			(0.005)	(0.007)	(0.005)			(0.009)	(0.008)	(0.008)
Income			-0.000**	-0.000*	-0.000***			-0.000***	-0.000***	-0.000***
			(0.000)	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)
Northcentral			-0.064*	-0.064	0.010			-0.136	-0.136	-0.008
			(0.031)	(0.036)	(0.010)			(0.075)	(0.107)	(0.009)
South			-0.029	-0.029	-0.010			-0.159*	-0.159	0.000
			(0.042)	(0.037)	(0.009)			(0.073)	(0.110)	(0.009)
West			-0.063	-0.063	0.000			-0.089	-0.089	0.010
			(0.033)	(0.036)	(0.011)			(0.074)	(0.107)	(0.014)

***p<0.001, ** p<0.01, * p<0.05. OLS. Standard errors given in parentheses. Standard errors for all regressions were calculated using Taylor linearization. Columns 1-3 and 6-8 standard errors account for the PSID's sample clusters, stratum, and longitudinal population weights.
±Columns 4 and 9 cluster standard errors by state to account for serial correlation caused by state treatment timing.
†Columns 5 and 10 include household random effects. Standard errors are now clustered by PSID strata only, no longer including population weights or clusters, because of limitations with the software used (Stata).

Looking at columns 6-10, I see that private aid usage did not significantly change. In fact, for all private aid regressions, estimates are insignificant. Thus, it appears that the policy change did not affect private aid usage.

Using USDA data on SNAP usage[7] and U.S. Census Bureau data on U.S. households[8] I calculate that from 2000 to 2007, SNAP participation rates increased by 4 percentage points for households in the treatment states, which is very similar to the 3.5 percentage point increase found in columns 3 and 4 in Table 5.1. This 3.5 percentage point increase translates to 1.3 million new households on SNAP in the treatment states during that timeframe. This is a large group, using approximately $3.6 billion in additional SNAP benefits annually in the treatment states. The fact that private aid still did not change with such a large influx of SNAP dollars suggests that the two types of aid do not have a strong relationship.

Since low-income households may have the largest effects for SNAP uptake, I re-run my DID model in columns 3 and 8 with only low-income households (those with incomes below 200% of FPL). I find that SNAP usage increased by 9.5 percentage points for this restricted group due to the policy change. However, private aid usage still did not change significantly[9]. Thus, even for low-income households who were more significantly impacted by the SNAP policy, it appears that private aid is not acting as a substitute for SNAP benefits.

If the policy change significantly impacted SNAP usage, especially for low-income households, why might private aid usage have remained the same? One possibility is that other income sources may have been changing at the same time. In particular, reduced usage of other government aid or reduced work hours could both affect income, which could be

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[7] Source: USDA SNAP Data Tables. National and/or State Level Monthly and/or Annual Data. FY69 through FY18. Accessed June 2019 at https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap

[8]Source: U.S. Census Bureau, Population Division, Annual Estimates of the Resident Population: April 1, 2010 to July 1, 2018

[9] Appendix C shows full results for these regressions.

muting the effects. To investigate this, I run separate DID models with these two other income sources, and with income itself, as the dependent variable, compiling my results in Table 5.2.

Table 5.2: *Significance of other income sources' DID estimators*

Dependent variable=	Income (Thousands)	Other Government Aid Usage†	Avg Weekly Working Hours
Treat_post	1.295	0.014	-1.027*
	(4.937)	(0.010)	(0.396)
Covariates	x	x	x
State FE	x	x	x
Number of Obs	32,577	32,577	32,577
R sq	0.152	0.099	0.249
Age	1.288***	-0.001***	-0.163***
	(0.087)	(0.000)	(0.021)
Male	11.317*	-0.018*	3.220***
	(4.383)	(0.008)	(0.611)
Avg work hrs	0.803***	-0.003***	
	(0.072)	(0.000)	
Num in HH	3.273*	0.020***	0.392*
	(1.240)	(0.005)	(0.177)
Disabled	-1.121	0.056***	-27.197***
	(3.200)	(0.015)	(0.910)
Healthy	15.253***	-0.022	4.936***
	(2.332)	(0.012)	(0.588)
Black	-16.428***	0.061***	-3.239***
	(2.723)	(0.012)	(0.444)
Married	39.063***	-0.024**	3.827***
	(5.128)	(0.009)	(0.550)
Metro	17.185***	-0.023**	0.311
	(2.807)	(0.008)	(0.491)
HS grad	16.937***	-0.052***	3.195***
	(3.599)	(0.013)	(0.593)
Some college	30.741***	-0.070***	2.848***
	(3.182)	(0.014)	(0.562)
College degree	64.400***	-0.094***	3.933***
	(4.096)	(0.015)	(0.574)
Child under 5	-3.849	0.035***	-1.520**
	(3.769)	(0.010)	(0.510)
Child 5-18	5.180*	0.029**	0.998*
	(2.574)	(0.009)	(0.414)
Northcentral	32.279	-0.036	16.469*

Dependent variable=	Income (Thousands)	Other Government Aid Usage†	Avg Weekly Working Hours
	(23.255)	(0.113)	(7.684)
South	26.868	-0.128	15.515*
	(22.986)	(0.115)	(7.674)
West	26.564	-0.086	15.712*
	(22.514)	(0.117)	(7.728)

***p<0.001, ** p<0.01, * p<0.05. OLS. Standard errors given in parentheses. Standard errors for all regressions were calculated using Taylor linearization, accounting for the PSID's sample clusters, stratum, and longitudinal population weights. If the dependent variable was previously a covariate, it was removed as a covariate for that regression.
† Government aid usage is a binary variable that equals one for any household that used either TANF, unemployment insurance, housing assistance, or 'other' welfare. This 'other' welfare category is a catch-all variable included by the PSID and does not specify type, though it theoretically should include all other government welfare.

I find in Table 5.2 that income, other government aid usage, and work hours did not change significantly for states that had BBCE. Though income may have changed by about $1,300 for BBCE states, the standard errors are so large that this result is still statistically zero. Similarly, other government aid usage increased by 1.4 percentage points, theoretically, for BBCE states, but the standard errors are so large that this is also insignificant. Average weekly working hours reduced by one hour a week. While this is statistically significant, it is a relatively small change in a practical sense. Thus, it seems that any change in SNAP usage was not mitigated by other income factors, which would give us more cause to suspect a change in private aid to be present.

Thus, it does not appear that the lack of change in private aid usage is due to other income sources changing. It may be that the two types of aid act in very different ways. Unlike SNAP, private aid is sometimes used for things like paying off loans, buying cars or houses, or starting businesses[10], all of which are very different than subsistence expenses. Because of

[10] Though not a rigorous study, a 2016 survey from iLoan shows that individuals borrow money from family and friends for a variety of reasons; education, car repair, starting businesses, medical/legal fees, basic necessities, and renovating homes were all top reasons listed for borrowing (iLoan, 2016). Another informal survey from Finder.com shows that people use money from family and friends to pay utilities and bills, rent, and medical emergency costs (Chow, 2017).

this potential difference in how benefits are obtained and used, there may be a weak relationship between the two types of aid, especially at different income levels.

Therefore, I use quantile regression to see if larger values of private aid have a different relationship to SNAP benefits than smaller values of private aid. Quantile regression allows me to explore the relationship between aid values at different points in the conditional distribution of private aid value. Also, quantile regression is more robust to outliers than OLS and is semi-parametric so residuals do not need to have a parametric distribution (Cameron and Trivedi, 2010).

For my quantile regression, I regress the log of SNAP benefit size on the log of private aid value at the 20^{th}, 40^{th}, 60^{th}, 80^{th}, and 95^{th} percentiles of the private aid value distribution. I only include households who use both types of aid, which allows me to find if the amount of private aid used changes the way SNAP benefit value affects private aid value on a dollar-for-dollar level. Results are given in Table 5.3 with standard errors in parentheses. OLS regression is presented for comparison.

Table 5.3: *Quantile regression of logged private aid value*

	OLS Entire Sample	20th percentile	40th percentile	60th percentile	80th percentile	95th percentile
log SNAP value	0.204***	0.402	0.053	0.034	0.030	0.027
	(0.040)	(0.217)	(0.032)	(0.017)	(0.029)	(0.026)
Avg private aid value	$4,499	$111	$345	$689	$1,619	$5,260
# Obs	1,198	1,198	1,198	1,198	1,198	1,198
R sq/Psuedo R sq	0.060	0.044	0.036	0.048	0.064	0.058
Covariates:						
Age	-0.001	-0.004	-0.005	-0.001	0.005	0.002
	(0.011)	(0.011)	(0.008)	(0.005)	(0.009)	(0.013)
Male	0.369	0.251	0.046	-0.105	-0.097	-0.387
	(0.343)	(0.272)	(0.220)	(0.145)	(0.247)	(0.243)
Avg work hrs	-0.002	0.005	0.002	-0.006	-0.009**	-0.011
	(0.007)	(0.006)	(0.003)	(0.002)	(0.003)	(0.007)
Num in HH	0.056	-0.065	0.004	0.001	0.005	-0.010
	(0.078)	(0.086)	(0.053)	(0.039)	(0.043)	(0.111)
Disabled	-0.764*	-0.614	-0.379	-0.230	-0.284	-0.015
	(0.325)	(0.443)	(0.250)	(0.236)	(0.225)	(0.341)
Healthy	-0.192	-0.246	-0.487***	-0.183	-0.139	-0.164
	(0.234)	(0.278)	(0.112)	(0.122)	(0.125)	(0.178)
Black	-0.590**	-0.332	-0.665***	-0.495***	-0.480**	-0.283
	(0.224)	(0.258)	(0.137)	(0.145)	(0.169)	(0.193)
Married	-0.137	-0.092	-0.064	0.154	0.023	0.103
	(0.393)	(0.298)	(0.334)	(0.288)	(0.363)	(0.295)
Metro	0.102	-0.160	0.033	0.103	-0.080	0.006
	(0.214)	(0.239)	(0.130)	(0.112)	(0.158)	(0.176)
HS grad	0.052	0.117	0.139	0.112	0.169	0.107
	(0.224)	(0.192)	(0.136)	(0.156)	(0.192)	(0.193)
Some college	0.625*	0.679**	0.677***	0.395***	0.499**	0.254
	(0.250)	(0.222)	(0.131)	(0.117)	(0.189)	(0.209)
College degree	0.508	0.784*	0.629**	0.485**	0.644**	0.024
	(0.403)	(0.217)	(0.242)	(0.187)	(0.239)	(0.423)
Child under 5	0.162	0.392	0.330	0.193	0.186	0.353
	(0.348)	(0.353)	(0.324)	(0.151)	(0.173)	(0.410)
Child 5-18	0.211	0.497	0.547	0.235	0.100	0.064
	(0.317)	(0.293)	(0.285)	(0.144)	(0.166)	(0.298)
Income	0.016**	0.012*	0.009**	0.022***	0.025***	0.029***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)	(0.006)
Northcentral	0.089	-0.017	0.145	-0.018	-0.108	-0.059
	(0.383)	(0.274)	(0.187)	(0.185)	(0.259)	(0.275)
South	0.088	-0.192	0.065	-0.006	-0.289	-0.148
	(0.371)	(0.297)	(0.179)	(0.216)	(0.311)	(0.266)
West	0.166	0.247	0.026	0.083	-0.028	-0.219
	(0.424)	(0.443)	(0.279)	(0.265)	(0.483)	(0.374)

***p<0.001, ** p<0.01, * p<0.05. Quantile regression standard errors calculated by bootstrapping. OLS standard errors calculated by Taylor linearization.

Only OLS gives significant results for SNAP value, showing that increasing SNAP value by one percent actually increases private aid value by 20 percent. It seems that households who use private aid along with their SNAP benefits do not reduce private aid amounts when SNAP benefit is increased. For quantile regression, the coefficient on SNAP value at the 20^{th} and 40^{th} percentiles is significant at the 90 percent level. At the 20^{th} and 40^{th} percentiles, a one percent increase in SNAP benefit is associated with a 40 percent increase and 5 percent increase, respectively. However, none of the other quantiles show significance for SNAP value. Additionally, Wald tests of the quantile regression coefficients also show that the coefficients on the log of SNAP value are statistically the same even between the 20^{th} and the 95^{th} percentile of private aid value. This is a bit surprising, especially because the coefficient for the 20^{th} percentile seems much larger than the other percentiles.

Still, despite the lack of statistical significance, we see that as private aid value increases, the relationship between the two types of aid seems smaller. Perhaps this is because private aid value is larger so that any relative changes are less pronounced. However, it may also be true that those using lower values of private aid tend to use the two types of aid in more synergistic ways.

It is also worth noting that other covariates seem to influence private aid amount in significant ways. I find that Black households have 38-40% lower values of private aid than non-Black households. This trend is true at all levels of private aid value. I also find that having a college degree or even some college tends to increase the amount of private aid value at all levels of private aid value, though this relationship is most pronounced at lower private aid values. I observe that higher incomes are associated with slightly higher private aid amounts, with a $1,000 increase in income corresponding to a 1-2.9% increase in private aid amount. Thus, private aid amount seems to increase with income and education level but decrease for Black households. It may be that wealthier, more educated, and non-Black households have more access to private aid and are therefore using larger amounts of it.

The OLS results for the whole sample show that the relationship between SNAP value and private aid value is significant and positive, which warrants a more thorough discussion into what raises SNAP benefit value and private aid value. SNAP benefit increases are driven by increasing household size and decreasing income, which would suggest that increasing SNAP benefit sizes is associated with greater household need. It would make sense, then, that the amount of private aid also tends to increase as SNAP benefit increases when households use both types of aid.

It would follow that household needs may be driving this positive relationship between aid values for the overall sample. One way to investigate this is to look at how private aid usage and SNAP usage change by income level, to see if income level itself changes the relationship between aid types. The relationship may be stronger at lower income levels where both types of aid are used more frequently.

Therefore, I divide the sample into subpopulations based on income level and run logistic regressions of SNAP usage on private aid usage. Table 5.4 shows the odds ratios from these regressions for three exclusive subpopulations: low-income, middle class, and high-income households, with income level defined in italics. Regressions include covariates and state fixed effects.

Table 5.4: *Odds Ratios after logistic regression by income group, y= private aid usage*

	Entire Sample	Low Income	Middle Class	High Income
		(<200% FPL)	*(≥ 200% FPL, <500% FPL)*	*(≥500% FPL)*
SNAP usage	0.338***	0.324**	0.507**	0.578
	(0.088)	(0.101)	(0.175)	(0.736)
Average income	$90,493	$20,518	$60,462	$164,688
Covariates	x	x	x	x
State FE	x	x	x	x
# Obs	32,552	8,802	13,875	9,833
Prob > F	0.011	0.000	0.000	0.000
<u>Covariates:</u>				
Age	-0.061***	-0.055***	-0.063***	-0.058***
	(0.003)	(0.005)	(0.004)	(0.007)
Male	-0.283***	0.014	-0.488***	-0.729***
	(0.081)	(0.147)	(0.115)	(0.174)
Avg work hrs	-0.016***	-0.017***	-0.010***	-0.007
	(0.002)	(0.003)	(0.003)	(0.004)
Num in HH	-0.076	-0.101	0.009	0.042

	Entire Sample	Low Income	Middle Class	High Income
		(<200% FPL)	*(≥ 200% FPL, <500% FPL)*	*(≥500% FPL)*
	(0.042)	(0.055)	(0.059)	(0.080)
Disabled	0.114	-0.016	0.066	0.606
	(0.101)	(0.119)	(0.182)	(0.491)
Healthy	-0.394***	-0.168	-0.530***	-0.657***
	(0.086)	(0.101)	(0.130)	(0.156)
Black	0.031	-0.119	0.087	-0.331
	(0.098)	(0.122)	(0.141)	(0.219)
Married	-0.186*	-0.484**	0.015	0.143
	(0.086)	(0.158)	(0.114)	(0.207)
Metro	0.058	0.025	0.184	0.088
	(0.061)	(0.114)	(0.094)	(0.165)
HS grad	0.080	0.147	0.198	-0.477
	(0.099)	(0.115)	(0.148)	(0.286)
Some college	0.422***	0.367**	0.661***	-0.118
	(0.097)	(0.134)	(0.137)	(0.299)
College degree	0.525***	0.594***	0.716***	0.159
	(0.084)	(0.135)	(0.125)	(0.270)
Child under 5	0.183	-0.112	0.227	0.242
	(0.123)	(0.139)	(0.160)	(0.273)
Child 5-18	0.098	-0.214	0.174	-0.086
	(0.104)	(0.139)	(0.144)	(0.226)
Income	-0.005***	0.000	-0.014***	-0.002**
	(0.001)	(0.005)	(0.003)	(0.001)
Northcentral	-0.964	1.519	-1.259*	-2.229
	(0.521)	(1.262)	(0.596)	(1.367)
South	-1.214*	1.906	-1.678**	-4.693**
	(0.507)	(1.339)	(0.602)	(1.458)
West	-0.547	0.956	-0.369	-1.205
	(0.507)	(1.388)	(0.524)	(1.504)

***p<0.001, ** p<0.01, * p<0.05. Logistic regressions. Standard errors calculated using Taylor linearization and group by PSID strata and cluster, and account for longitudinal population weights.

Results in Table 5.4 show that SNAP usage decreases the odds of private aid usage for the entire sample. Though there may be questions of reverse causality with these regressions, the results still show that the two types of aid do not tend to go together. Since the two types of aid are only used together by three percent of the sample, this is not surprising.

However, we see that the relationship is different at different income levels. Low-income households see the largest decrease in odds of using private aid when using SNAP with odds of 0.32. Middle class households see a slight decrease in the odds of using private aid with odds of 0.51. High-income households also see a decrease in the odds of using private aid, but this result is not statistically significant. Thus, high-income households do not seem to have a strong relationship between SNAP and private aid usage, possibly driven by lower access to SNAP at high income levels.

Low-income households seem to have a more pronounced relationship between SNAP and private aid. Since 79 percent of SNAP households in my dataset fit into the low-income category, we may be seeing that the increase of SNAP usage at lower incomes does not have a corresponding increase of private aid usage of the same magnitude.

There are two differing explanations for why SNAP usage seems to decrease the odds of private aid usage for these low-income households: (1) SNAP is actually substituting for private aid for these households, or (2) Some of these households still have the need for private aid but don’t have access to it.

SNAP values are on average much lower than private aid values, with the average SNAP benefit being only $481 while the average private aid value being $4,499. It seems unlikely that SNAP could adequately substitute for these larger private aid amounts. Additionally, for households who use both types of aid, increases in SNAP benefit size tend to be associated with increases in private aid value, as shown in Table 5.3.

It seems, then, that households who are using both types of aid do so in complementary ways, rather than in substitutionary ways. If many SNAP households in the lowest income quintile did not have access to private aid, then SNAP usage would appear to reduce private aid usage, even if the household would prefer to use both types of aid. If the households without private aid had certain systematic similarities, then any loss of access to SNAP would disproportionately affect these households if other income sources were not available.

This disparity in private aid network strength is especially possible because private aid most often comes from relatives in my sample.[11]

To explore this possibility, I examine private aid usage of low-income SNAP households by demographics in Table 5.5, looking at the percent who use private aid and the average amount of private aid that they use. Any large differences in usage rate or amount may point to differences in informal aid network strength by demographics.

Table 5.5: *Private aid usage rates and average amounts for low-income (<200% FPL) households using SNAP*

Variable	% using private aid	Avg private aid amount
Male	29%	$1,506
Female	31%	$1,649
Single	32%	$1,533
Married	24%	$1,821
Childless	30%	$1,264
Children in HH	30%	$1,754
White	33%	$1,862
Black	30%	$1,285
Less than HS	26%	$1,258
HS grad	31%	$1,454
Some college	33%	$2,274
College degree	55%	$1,962
Metro	27%	$1,656
Nonmetro	35%	$1,512
Parents rich	37%	$1,752
Parents not rich	28%	$1,539

[11] In my sample, private aid most often comes from relatives (79 percent of private aid households) versus nonrelatives (31 percent of private aid households), with some overlap as a few households obtain private aid from both types of sources.

Looking at Table 5.5, we see that males are slightly less likely to use private aid than females. This is similar to findings from Loxton (2019) which show that parents tend to give money more frequently to their daughters than to their sons partially because of expectations of future care from daughters. Though Loxton's findings are limited to private aid from parents, this trend may be part of what is driving this difference.

I also find that couples are less likely to use private aid than singles. Perhaps the social signal of being married causes others to perceive the household as less needy, making private aid less common. However, households with and without children use private aid at similar rates.

White households use private aid at slightly higher rates than Blacks, which would suggest more robust informal aid networks. Additionally, if we look at average private aid amounts for each race, we see that low-income White SNAP households' average private aid value is $1,862 while Blacks' is $1,285. It appears that Black households may have slightly less private aid available to them.

This corroborates other research that shows that Blacks generally have less money available through informal networks. According to a Pew Charitable Trust survey, Blacks have fewer liquid assets from which to lend to each other (Pew Charitable Trust, 2015). According to this survey, a typical White household has enough liquid financial assets to last a month, while Black households have enough for only five days. It is important to note that Black households are almost twice as likely to have incomes below 200% of FPL than non-Hispanic whites (U.S. Census Bureau, 2018). In my sample, Black households tend to use SNAP more than private aid while White households tend to do the opposite. This means that Black households would likely be disproportionately affected by lack of access to SNAP if private aid were their only alternative.

Table 5.5 also shows that, as education level increases so does usage level of private aid, from 26 percent using private aid for those with less than high school education to 55 percent for those with a college degree. The amount of private aid they use also tends to be larger at higher education levels. This suggests that those with higher education may have stronger informal networks to draw upon. They also may have different reasons for using private aid, such as paying off student loans, which may also increase their usage of private aid.

It appears that those in rural locations use private aid more frequently than metro households, but we do not see a difference in private aid amounts. This suggests that rural households may have stronger informal networks even if the dollar amount of private aid available to them is not any different.

We also see that household heads with wealthy parents use private aid at a higher rate than those without wealthy parents, though the amount of private aid is only slightly higher. This would suggest that these households have more money available to them, possibly because of their parents.

Thus, are several important differences in the demographics of aid usage, many of which might point to systematic disparities in private aid access. Households that might have less private aid available appear to be married, Black, less educated, and in urban areas. Changing government aid eligibility may disproportionately affect these households because of private aid availability.

6: Conclusions

My quasi-experimental method is unique in its approach to the important question: does access to public aid such as food stamps (SNAP) alter low-income households' usage of private aid from family and friends? This question has been asked by other researchers, most of whom are concerned about the possible 'crowding out' of private aid networks by public aid. I note, however, that this concern leaves out an important element: there are some households who do not have adequate private aid networks from which to get help in times of need. Current debates about SNAP eligibility requirements once again highlight the importance of understanding what happens to households when they do not have access to SNAP. Do some households fall through the cracks when aid is not available from either source?

My difference-in-difference estimates using PSID data from before and after a USDA policy change in 2000 suggest that, while SNAP usage changed significantly between states with broad-based categorical eligibility (BBCE) and those without, private aid usage was not significantly different. Though my DID model has some limitations, such as the usage of binary dependent variables in an OLS regression, still this should not cause bias in the results, even if they cannot be used for predictive purposes.

The overarching result I find across my models is that private aid usage and SNAP usage do not seem to have a strong relationship, even when only looking at low-income households for whom this relationship may be strongest. The two types of aid do not seem to be substituting for each other at any income level or private aid amount.

In cases where households use both types of aid, quantile regression of SNAP benefit amount on private aid amount shows that they have a weakly positive relationship, and that larger values of private aid may have slightly weaker effects from SNAP benefit size. However, no matter the private aid value, these types of aid do not seem to be used as substitutes.

Previous studies have hypothesized that a lack of significant relationship between these two types of aid is evidence that public aid has already crowded out private aid (Cox, Hansen, and Jimenez, 2004), calling it a 'fait accompli'. However, the relatively high usage of private aid (almost twice that of SNAP) suggest to me that my insignificant results don't mean that private aid is already crowded out, but rather that the two types of aid are not strong substitutes for each other. It seems possible that having SNAP benefits is not going to strongly affect a household's need for financial help with a sudden car repair, for example. Nor would financial help with paying student loans necessarily makes a household no longer need SNAP. In fact, the households whose needs are greatest may need both types of aid in these types of situations. Thus, since they are not acting as substitutes, it seems that private aid is not always a viable alternative for SNAP. This is relevant to policymakers who may suggest that informal networks take the place of SNAP.

Interestingly, my logistic regressions of SNAP usage on private aid usage at varying income levels show that using SNAP tends to decrease the odds of using private aid, though the relationship is strongest for low-income households. Since substitution does not appear to explain these decreased odds of using private aid, one reasonable explanation is that some low-income households on SNAP may lack access to private aid. This might also explain why private aid usage did not change significantly with the policy change that increased SNAP usage. It may be that many low-income households never had access to adequate private aid and therefore did not use it in either time period. Though not addressed in previous literature and difficult to study, it appears that access to private aid may be as important as access to public aid when looking at how the strength of the relationship between the two types of aid.

If private aid were less available to certain demographic groups, then these households would be systematically left behind if their only financial safety net were money from private aid networks. Policymakers should be aware of these disparities in private aid networks so that income equality is not exacerbated by loss of public financial safety nets.

My sample shows that private aid usage and amounts differ by demographics for low-income SNAP households. This means that certain groups may be disproportionately disadvantaged by a loss in SNAP benefits. Households who seem to use less private aid are married, Black, less educated, and live in urban areas. They also have parents who are not wealthy. These households may systematically have less access to private aid, which may make SNAP access more important to their well-being.

My study is limited by the lack of more granular information about private aid motivations in the PSID, as well as the limitations of the particular policy change used to investigate this relationship. However, my findings that private aid is not significantly affected by SNAP are similar to previous studies that find only nominal effects of public aid on private aid. Future work may benefit by including more detailed information about private aid usage and motivations. This would allow a more thorough understanding of private aid access, which seems to be as important as public aid access when understanding the relationship between the two.

This private aid availability should be of concern to researchers and policymakers when considering major changes to public aid benefits so that income inequality can be reduced and so that households who are without any safety net do not fall through the cracks.

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Appendix

Appendix A: Tests of Assumptions

Parallel Trends Assumption

One of the most important underlying assumptions of difference-in-difference regressions is that the two groups we are comparing are sufficiently similar before the treatment effect. This allows us to isolate the changes due to the treatment alone when comparing the differences in slopes after the treatment period.

In order to more formally test the parallel trends assumption, I follow the work of Angrist and Pishke (2014), Autor (2003), and Hoynes and Schanzenbach (2012) to construct a test for the violation of the parallel trends assumption. This test essentially allows us to see if there are any other effects causing unexpected trends in the outcome variables before the policy change occurs. While passing this test is necessary for the underlying assumption to hold, it is not sufficient. However, no test exists for testing both necessity and sufficiency since this relies on unobservable counterfactuals.

First, I define a variable measuring the distance between the current year, *t*, and the year the policy was implemented. This distance-from-treatment variable is only created for states which implement the policy. I then create a dummy variable, τ, for each value of distance-from-treatment variable.

I then use Angrist and Pishke's outcome equation with time fixed effects, and covariates included. I let k be the time at which the policy is implemented.

$$Y_{ist} = \beta_0 + \sum_{j=-m}^{q} \beta_j(\tau = k + j) + \ \xi \cdot X_{st} + \eta_t + \ \varepsilon_{ist} \qquad (4)$$

This allows for m 'leads' and q 'lags' around the policy implementation date. The β_j coefficient is for the jth lead or lag. For example, the β_{k+q} coefficient measures the time q periods after the policy occurred. Theoretically, if the parallel trend assumption holds, the 'leads' or the coefficients before the policy occurred, should be statistically equal to zero. In other words, there shouldn't be any anticipatory effects. I run the regression shown in Equation 4 and then test the hypothesis

$$H_0\colon\ \beta_j = 0 \qquad \forall j < 0$$

Not rejecting this hypothesis means that the parallel trends assumption has not been violated, which is a necessary condition.

The results of this test on both SNAP usage and private aid usage show that the coefficients on the pre-policy time dummy are not significantly different from zero. Thus, there are no anticipatory effects, meaning that the parallel trends assumption has not been violated.

Appendix B: Serial Correlation Adjustments

Another important issue to address is serial correlation. Serial correlation is also a known issue in longitudinal DID models ((Bertrand, Duflo, & Mullainathan, 2004). The longer the timeframe used, the worse this problem is. With positive correlation, this leads to an understatement of the standard errors. This can make results seem significant when they perhaps are not.

Bertrand, Duflo, and Mullainathan (2004) point out several methods to deal with this problem, some of which perform better than others. One method, which is viable when sample sizes were sufficiently large is an arbitrary variance-covariance matrix. This matrix allows for correlation patterns within states over time – so when individuals in a state become treated at the same time, this matrix should still be consistent. This method essentially clusters standard errors at the level of the unit that is observed over time – the state – rather than by strata or individual. This reduces problems with autocorrelation. Bertrand, Duflo, and Mullainathan (2004) use a generalized White-like formula given by

$$V = (X'X)^{-1}\left(\sum_{j=1}^{n_c} u'_j u_j\right)(X'X)^{-1}$$

where n_c is the total number of states, X is a matrix of independent variables and u_j is defined to be the summation of all elements in the state:

$$u_j = \sum_{t=1}^{T} e_{jt} x_{jt}$$

where e_{jt} is the residual at time t in that state and x_{jt} is a row vector of dependent variables. I find no change in the DID estimate with the arbitrary variance-covariance matrix method, as shown in Table 5.1.

Appendix C: Low-Income DID Regression Results

Table C1: Full DID Regression Results, Low-Income Households Only

	y=SNAP usage	y=private aid usage
Treat_post	0.095**	-0.011
	(0.035)	(0.024)
State FE	x	x
Covariates	x	x
# of Obs	8,816	8,832
R sq	0.230	0.137
DF	63	63
Covariates:		
Age	-0.003***	-0.010***
	(0.001)	(0.001)
Male	-0.105***	-0.001
	(0.022)	(0.027)
Avg work hrs	-0.003***	-0.003***
	(0.000)	(0.000)
Disabled	0.055***	-0.009
	(0.008)	(0.007)
Healthy	0.121***	-0.003
	(0.034)	(0.019)
White	-0.053**	-0.031
	(0.018)	(0.016)
Black	0.069***	-0.019
	(0.019)	(0.021)
Married	-0.013	-0.067**
	(0.023)	(0.025)
Metro	-0.020	0.002
	(0.017)	(0.019)
HS grad	-0.068***	0.009
	(0.017)	(0.017)
Some college	-0.046*	0.051*
	(0.022)	(0.023)
College degree	-0.131***	0.094***
	(0.027)	(0.023)
Child under 5	0.164***	-0.037
	(0.025)	(0.022)
Child 5-18	0.131***	-0.044*
	(0.020)	(0.020)
Income	-0.007***	-0.000
	(0.001)	(0.001)
Northcentral	-0.048	0.110
	(0.067)	(0.110)
South	-0.011	0.156
	(0.059)	(0.122)
West	-0.142*	0.034
	(0.055)	(0.132)

***p<0.001, ** p<0.01, * p<0.05. OLS. Standard errors given in parentheses. Standard errors for all regressions were calculated using Taylor linearization. Standard errors account for the PSID's sample clusters, stratum, and longitudinal population weights.