
Public Assistance Usage and Higher Education

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ABSTRACT

This research demonstrates the negative relationship between postsecondary completion and public assistance use in Utah. This research uses data from two public assistance programs, Supplemental Nutrition Assistance Program (SNAP), and Temporary Assistance for Needy Families (TANF) between 2009 and 2019, combined with postsecondary enrollment and graduation information from the Utah System of Higher Education, along with wage, employment, and industry information from the Utah Department of Workforce Services. This study uses an inverse probability weighted staggered adoption difference-in-differences method to estimate the effect of postsecondary program completion on public assistance use. This study finds that those who complete a postsecondary program are expected to use fewer months of assistance after completion compared to before completion. The cohort average treatment effects are larger for those who graduated earlier in the observation time frame; after completion of a postsecondary program those who completed during the first year of assistance used half as many months per observation period than those who graduated in the last two years of observation. This study also demonstrates the differences in employment at the beginning and end of public assistance use between those who complete a postsecondary program and those who do not. Taken together it is reasonable to attribute the reduction in use to postsecondary education.

KEYWORDS

Welfare, Foodstamps, Utah, postsecondary education

1 | INTRODUCTION

1.1 | Background/Intro

The State of Utah, in conjunction with the Federal Government, administers two important public assistance programs. These are Supplementary Nutrition Assistance Program (SNAP) colloquially known as “food stamps,” and Temporary Assistance for Needy Families (TANF) colloquially known as “welfare.” Both of these programs are intended to help families in need become “self-sufficient” (HHS; USDA) and are purportedly designed to that end. With the established relationship between postsecondary education and earnings (discussed below), it stands to reason that the completion of a postsecondary program should complement the goals of these programs for public assistance users. This research finds that the completion of a postsecondary program in Utah leads to decreased use of SNAP and decreased TANF use.

To demonstrate the effects of the completion of a postsecondary program on public assistance use this study uses data from the Utah Department of Workforce Services along with the Utah System of Higher Education between the years 2009 and 2019 to create a treatment group, those who receive public assistance and complete a public postsecondary program, and a control group, those who receive public assistance but do not complete a public postsecondary program. The analysis is limited to those who complete a technical certificate, an Associate’s degree, or a Bachelor’s degree. The outcome measure is the number of months of use during each standardized half-year observation period. This study will use a novel method of identification, a staggered adoption difference-in-differences technique (Sun & Abraham, 2021). This will compare the outcomes of the program completers before and after program completion and present a treatment effect on the treated. Additionally, this study will describe the dynamics of use along with the employment dynamics of public assistance users.

The main measure for qualification for public assistance programs is income. Previous research from the Utah Data Research Center (UDRC) has shown that postsecondary program completion is associated with higher wages in Utah (Scott, 2019). Generally, more education is associated with higher wages (Heckman et al., 2018). The exact mechanism through which education is associated with income is not testable in this research but two plausible pathways exist. The first is through additional human capital. These are the increased skills and knowledge embodied in a person as they become more educated. This leads to higher productivity and given a favorable labor market structure this

leads to higher wages, see for example Becker (2009). A second plausible pathway is through the ability of education to signal productivity. If employers are unable to ascertain how productive a potential employee is educational attainment will group workers of the same productivity by how much education they complete (Arcidiacono et al., 2010). As those who use public assistance tend to be close to poverty before use there may be negative productivity signals that are canceled out with the completion of education.

Importantly, the population of interest’s earnings is sensitive to changes in education. Turner (2016) shows that completion of community college is associated with higher wages for welfare recipients in Colorado, a neighboring state of Utah. Martinez (2020) shows that in Utah a postsecondary education is associated with higher wages for those who experience intergenerational poverty, a subset of the population in this research. Beyond higher wages, postsecondary education is associated with a lower likelihood of time spent unemployed, and higher workforce attachment (Martinez, 2020). This shows that the population of interest for this study is sensitive to changes in educational attainment.

The current incarnation of SNAP and TANF stems from the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA), often referred to as “welfare reform.” This law had large effects on TANF and led to minor changes to SNAP. TANF moved from a federally funded program to joint federal and state administration and funding with federal block grants to states. In Utah, TANF is subject to a 36-month lifetime benefit limit. In Utah, there is no benefit limit for SANP use. The new system also prioritizes recipients finding employment and staying employed. This change was a response to critics of the old system who said it created work disincentives (Chan & Moffitt, 2018). This law is relevant to the findings of this work and will be discussed later in this section.

1.2 | Program Requirements

Eligibility for TANF and SNAP is mainly determined by income. The Standard Needs Budget (SNB) is used as the income limit for TANF, with the gross income cutoff being 185% of the SNB. In 2013, for a family of two, the SNB was \$456 a month. For SNAP eligibility the gross income cutoff was 1.3 times the Federal poverty level. The Federal poverty level varies based on family size; for a two-person household, the 2013 poverty level was \$15,510, and for an eight-person household it is \$39,630. The poverty level increased each year of this study.

The income that is counted for eligibility is not only the income of the recipient but the income of



adults living in the household. If a single parent was receiving SNAP benefits and had two children, one a teenager old enough to work and the other not, provided the teenager is under 18 and in school, the family income would only be the parent's income. In the case of a two-parent household with two young children, the income of both parents is counted as the household income.

Average wages for several of the common industries of employment (further discussed in section 3.1) increased during the ten-year time frame, shown in Table 1. During the period of this study, the poverty limit increased though the standard needs budget did not. Average wages increased faster than the poverty level in each industry as evidenced by the fewer hours needed to earn an income above that which qualifies for SNAP. For those working in administrative and support services, there was a 16.3% and 15.7% decrease in the number of hours needed to work during this period for two-person and four-person households. Those who worked retail with a two-person household needed to work 7% fewer houses to earn an income above the gross cutoff for SNAP and 6.6% fewer hours for a four-person household. Those employed in the fast food industry needed to work more than full time for all family sizes and periods, though there were reductions of 17.9% and 17.4% in the number of hours needed to earn more than the gross income cutoff.

There are additional eligibility requirements beyond income limits. Eligibility for TANF includes job training, education, and job search requirements, and limits on the total value of assets that belong to the family. SNAP recipients have the same non-income requirements and those who are employed

must work at least 20 hours a week. If there is a voluntary reduction of hours or the benefit recipient quits, they can lose benefits (Department of Workforce Services, 2021). Those who are not employed must submit proof of attempts to find work and have various education and training requirements (Department of Workforce Services, 2021).

In 2017 the average family size in Utah was 3.19 people per household (Kem C. Gardner Policy Institute, 2018). This falls in between the two household sizes reported in Table 1. For many industries, less than full-time employment but more hours than the mandated minimum can lead to enough income to phase out of the program. During the time spent in school, there is a tradeoff between the current hours that a benefit recipient can work and the future returns realized through higher wages. This happens due to the time that must be spent in the classroom; for a full-time degree seeker, this is between 12 and 15 hours a week (24 to 45 hours per week for full-time degree seekers). Beyond time spent in the classroom, there are additional hours that must be dedicated to studying and additional required work. Combined with the care work that most recipients have, this tradeoff may be the difference between continued qualification for benefits and not, while this is not an obstacle for those who are not in a postsecondary program.

1.3 | Literature Review

There are relatively few studies that directly test for a relationship between the completion of a postsecondary program and public assistance use.

Table 1: Average Wage and Hours of Work Need to Earn Above Program Income Cutoff. Based on working 52 weeks a year.

SNAP						
	Wage		2 Person		4 Person	
Industry	2009	2019	2009	2019	2009	2019
Admin and Support	\$15.22	\$21.10	24	20	36	31
Food Services	\$7.25	\$10.25	50	41	76	63
Retail	\$10.12	\$12.65	36	33	54	51
TANF						
Admin and Support	\$15.22	\$21.10	13	9	19	13
Food Services	\$7.25	\$10.25	27	19	39	28
Retail	\$10.12	\$12.65	19	15	28	22



The majority of studies surveyed here focus on the relationship between college attendance and completion and the use of cash-based assistance (Barrett, 2000; London, 2005, 2006). One study is from Canada (Barrett, 2000), while this study has different institutional settings, the results are still informative. All but one of the studies reviewed use national data (Barrett, 2000; London, 2005, 2006).

Barrett (2000) uses data from the Canada Assistance Plan, which provided financial assistance to needy individuals and families. This is administrative data between the years 1986 to 1993. This study uses the self-reported level of education at the onset of assistance use to measure postsecondary completion. Barrett (2000) uses a survival technique with the data organized by assistance spell. Women with postsecondary education are more likely to exit assistance sooner than those with only a high school education. Additionally, those who were in school were more likely to have longer spells of use (Barrett, 2000).

London (2006) tests for the effect of postsecondary graduation for TANF recipients. This study uses the 1979 National Longitudinal Survey of Youth (NLSY) restricted to women. This is a 20-year panel that can address how the completion of either a two or four-year college degree relates to employment, return to welfare, and family poverty both one and five years after the first spell on TANF. Using an Instrumental Variables technique graduation from a college program is associated with lower poverty and higher employment one and five years after TANF use and lower TANF use five years after initial TANF use (London, 2006).

Johnston (2020) focuses on SNAP recipients in Utah. This study uses UDRC data to determine SNAP use by those who earned a degree or certificate. The sample is anyone who received SNAP benefits in 2013 and degree or certificate awardees in 2013. All analysis starts from 2014. This study finds that the attainment of a degree or a certificate is associated with fewer months of SNAP use after the initial year of observation (Johnston, 2020).

In related work, the NLSY is used to test the relationship between attending college and the number of months of public assistance use (London, 2005). Attending college while on TANF is associated with 9 additional months of TANF use. The relationship between those who graduate college while not receiving TANF benefits becomes strongly negative; this subgroup is expected to use 29 fewer months of TANF benefits. Finally, those who enter TANF while enrolled in college are more likely to graduate than those who enroll in college after starting TANF (London, 2005).

This work has three main contributions to the recent

literature: this research uses a broader definition of postsecondary completion by accounting for both degrees and technical certificates. This research uses both SNAP and TANF as public assistance programs of interest. Finally, this research uses administrative data from Utah to look at the population over several years rather than just a sample.

2 | METHODS

2.1 | Data

The two public assistance programs, TANF and SNAP, come from the State of Utah Department of Workforce Services Management Information Systems (MIS). MIS compiled all SNAP and TANF users from 2008 to 2020 in separate data sets. These two data sets were added to UDRC's databases for de-identification and matched through UDRC's person-matching algorithm. To avoid counting users who may have used public assistance before data were available, stopped use, and then started using again when the data were available only those users whose first month of use was between January 2009 and December 2015 were included in this study. Missing the first spell of use would reduce the number of months eligible for TANF and potentially bias the results. This cut-off, 12 months after the first available user, is the 77th percentile of the maximum number of months between months of use for SNAP users, and the 87th percentile for TANF users so it is reasonable to use without losing too many observations or including too many individuals who are on a second welfare spell.

Each data set is organized by the individual, by each month, and by year of use. Additionally, each data set contains information on household size, veteran status, gender, race, birthdate, highest level of education upon first applying for aid, and Zip Code of residence. This list was filtered to those who were between 18 and 60 years old on the first month of use, whose first month on public assistance was between January 2009 and December 2014, and those who had less than a Bachelor's degree as prior education. The final month of observations was December 2019, so results are consistent due to Federal and state governments waiving benefit limits and other eligibility requirements during the 2020 coronavirus pandemic recession.

Each data set only contains the month and year during which an individual used the public assistance program. To create the first outcome probability of use of the public assistance program of interest on any month after the initial month of use 60 months were added to the initial month in R (R Core Development Team, 2019). These were

merged by month and year that each individual used public assistance and the outcome variable was marked as “1” for using public assistance. The months that the individual did not use public assistance were marked “0” as not using public assistance. These data sets were merged by quarter and year to wage and industry data from DWS Unemployment Insurance pay-ins. This data contains quarterly income and industry of employment as North American Industry Classification System (NAICS) code. For individuals who had multiple industries of employment in one quarter, the industry from which the individual earned the most income was counted as the primary industry. All industries were aggregated at the three-digit subsector.

The variable of interest is the completion of a postsecondary program. This data comes from the Utah System of Higher Education (USHE) and is limited to public technical colleges or universities in Utah. The treatment is the completion of a technical certificate, Associate’s degree, or Bachelor’s degree, during the observation time frame. Those who completed a graduate degree during the time frame were dropped from the analysis. If an individual completed a degree or certificate during the five years, they are marked as a completer for the month they complete their program and each month thereafter and are part of the treatment group. This measure can take the values of “1,” for those who completed a postsecondary program, or “0” for those who did not complete a postsecondary program during the period. Due to differences in the scope and length of the technical programs compared to degree programs each treated group was separated from the other. This was to allow for potential differences in treatment effect. Operationally, those who earned a technical certificate were compared to those who did not complete a postsecondary program but were not compared to those who earned a degree. Those who earned a degree were compared to those who did not complete a postsecondary program but not those who earned a technical certificate. Two separate analyses were done, one for degree completers and one for certificate completers. For those who completed multiple programs, only the last completed program was counted as the treatment.

Additional individual characteristics provided by MIS were gender, race, birthdate, veteran status, and the highest level of education in the first month of public assistance use. Gender was reported as male or female. The race category does not cover ethnicity and has values: American Indian or Alaska Native, Asian, Black or African American, Multi-race, Native Hawaiian or Pacific Islander, Other,

Unspecified/Undeclared, white, and missing. Those with missing values were converted to Unspecified/Undeclared. Without ethnicity, it was not possible to know if an individual was Hispanic or Middle Eastern, or North African. The possible values of veteran status are: Under 30% disabled, greater than 30% disabled, regular, reserve or National Guard, and spouse. Individuals that did not have a veteran status were marked as non-veteran. Birthdate was used to calculate the age at the start of each month for each individual with the month containing an individual’s birthdate marked as older of the two possible ages. Highest education takes values: 1-15, GED, HS Diploma, Certificate of Attendance or Completion, Associate, Bachelor, Postsecondary Degree or Certificate, Grad Study or Degree, and None or Unknown. Those with education values from 1-11 were marked as “less than high school;” those with “12,” “GED,” and “HS Diploma” were grouped as “High School;” those with reported values of “13-15” were assigned “some college.” These are self-reported education levels. Those with “Grad Study or Degree” were dropped.

The data were standardized to a relative time frame where the first month of use was set as the first observation month with each subsequent month being observation months two through 60. The data was aggregated into six-month observation periods. This was done to address two issues, the first was to ensure that each observation period had enough completers to estimate the effect of graduation. The second addressed computer memory limitations, to estimate the effect of completion R had to allocate a vector of greater than 17 GB, which was greater than the physical RAM on the computer used for analysis. After aggregation, each individual had 10 observation periods.

2.2 | Empirical Strategy

The main outcome is the number of months spent on public assistance for each standardized half-year observation period. The variable of interest is the completion of a postsecondary program. In a regression technique, it is common to control for additional variables beyond the independent variable of interest. This was not possible in this analysis due to the already noted physical limitations of the hardware used. To compensate for this a two-stage process was used to quantify the relationship between postsecondary program completion and public assistance. First, a propensity score technique, explained in section 2.2.1, was used to create inverse probability weights (IPW) for each individual. This technique is a way to control for confounding variables before a regression technique. The propensity score is used to create IPWs which put higher weight on observations in



the control group, those who did not complete a postsecondary program, that are most similar to the treatment group, those who did complete a postsecondary program, while putting less weight on the observations from the control group that are least similar to the treated group. The propensity measures the probability that any individual is treated, this is then transformed into a weight to weight each observation in the second stage regression. This is to control for confounding variables that cannot enter into the difference-in-differences approach due to the previously mentioned limitations of hardware available for analysis. The second stage is a staggered adoption difference-in-differences (DID) approach, explained in section 2.2.2. Since not every individual who was treated was treated in either the same standardized observation period or the same calendar month and year this leads to a “staggered adoption” of treatment. The DID approach allows for the relationship to not only be quantified but can point to the changes in public assistance use being caused by the completion of a postsecondary program.

2.2.1 | Propensity Score and Weighting

The first stage of the analysis is to create inverse probability weights (IPW) for use in the staggered adoption difference-in-differences technique. The weighting technique ensures that members of the control group who are most similar to members of the treatment group are compared to members of the treated group. Normally, in regressions, control variables are included in the model to control confounding variables so the relationship between the variable of interest and outcome is not biased. In the context of propensity score matching, rather than explicitly using control variables in the regression of the treatment on the outcome, the IPW is used to put more weight on the observations of members of the control group who are “most similar” to the treated group (Huntington-Klein, 2021). In the context of the propensity score, the most similar refers to those of the control who were most likely to be treated but were not. This is determined through a regression.

Equation 1¹ models the propensity for treatment for both those who completed a degree and those who completed a technical certificate. Those who

¹ An additional model included the weighted average of distance to nearest university and the square of the weighted average to the nearest postsecondary institution based on zip code of residence. The resulting IPWs were nearly identical to those that did not include distance but excluded individuals. To keep as many observations as possible these propensity scores and IPWs were not used in the analysis.

completed one type of postsecondary program were not included in the estimation of the other; when estimating the propensity for treatment for those who completed a technical certificate those who earned a degree were dropped and vice-versa. The control group will have two propensity scores, one for earning a technical certificate and one for earning a college degree. Those who completed a postsecondary program will have a single propensity score for their treatment. Equation 1 was estimated using probit regression.

$$\text{Probit}(y_i) = \beta_0 + \beta_1 \text{Gender}_i + \beta_2 \text{Race}_i + \beta_3 \text{Age}_i + \beta_4 \text{Age}_i^2 + \beta_5 \text{HouseHoldSize}_i + \beta_6 \text{HoursQ}_{t-1,i} + \beta_7 \text{HoursQ}_{t-2,i} + \beta_8 \text{HoursQ}_{t-3,i} + \beta_9 \text{HoursQ}_{t-4,i} + \delta_1 \text{Month}_i + \delta_2 \text{Year}_i + \varepsilon_i \quad (1)$$

Equation 1 is used for both types of postsecondary graduates, those who earned a degree and those who earned a certificate. The outcome, y_i , is a binary variable that takes the value 1 if the individual completed the postsecondary program and 0 if they did not. *Gender* is a categorical variable with females as the reference category. The variable *Race* is a categorical variable with white as the reference category. *Age* and *Age*² capture the relationship between age and graduation from a postsecondary program, the square term allowing for diminishing returns to age. The imputed number of hours worked for each of the 4 quarters before including the first month of use is $\text{HoursQ}_{t-n,i}$, the calculation is shown in Appendix A. *Month* is a categorical variable controlling for the first calendar month with January as the reference group; this is to address potential seasonal trends. *Year* controls for the first calendar year of use and controls for effects of changes to economic conditions over time which may affect both the choice to enroll in and stay in a postsecondary program. The variable ε_i is the individual error term.

The IPW is used to make the treatment and control groups as similar as possible (Huntington-Klein, 2021). To create the IPW first the propensity for each unit was recovered from Equation 1, the propensity score is simply the probability a given unit was treated. The propensity score ranges from zero to one and is therefore transformed with the IPW otherwise the only units that could receive full weight would be those with a treatment propensity of 1. For those who were treated the IPW is calculated as $1/PS$, where PS is the propensity score. The IPW for those who did not complete a postsecondary program is $1/(1-PS)$. These weights were used to weight each individual in the second

stage regression.

2.2.2 | DIFFERENCE-IN-DIFFERENCES

The difference-in-differences approach estimates the average treatment effect on the treated. Adopting the potential outcomes terminology, the outcome of interest is Y (Cunningham, 2021). If an individual is treated the outcome is Y^1 , and if an individual is not treated than the outcome is Y^0 . While there is the potential for any individual to be treated or not treated only one of those outcomes occurs and is observed. This is represented as:

$$Y_i = D_i Y_i^1 + (1 - D_i) Y_i^0 \quad (2)$$

Equation 2 is the observed outcome, where D_i is the treatment indicator, taking a value of 1 if the individual was treated and 0 otherwise. The observed outcome will be Y_i^1 for an individual that was treated and Y_i^0 for one who was not treated. If it were possible to observe the same individual's outcome from both states, treated and not treated, the treatment effect is:

$$\delta_i = Y_i^1 - Y_i^0 \quad (3)$$

Equation 3 is the treatment effect for an individual, the mean of all individual treatment effects would be the average treatment effect. This is not possible to observe as an individual can only be treated or not treated but not both. Difference-in-differences allows a way to calculate an Average Treatment Effect on the Treated (ATT) through the use of observing outcomes before, pre, and after treatment, post, for groups that were not treated, $D_i = 0$ (U), and groups that were treated, $D_i = 1$ (T). The estimated ATT is:

$$\hat{\delta}_{T,U} = (\bar{Y}_T^{\text{post}(T)} - \bar{Y}_T^{\text{pre}(T)}) - (\bar{Y}_U^{\text{post}(T)} - \bar{Y}_U^{\text{pre}(T)}) \quad (4)$$

In Equation 4 all \bar{Y} s are the average outcomes. The subscripts represent the treated, T, and the untreated, U. The superscripts represent the time period relative to a common treatment time. Equation 4 is the difference between the differences in average outcomes between the treated and the untreated in the pre and post-treatment periods. Given parallel pretreatment trends of outcomes, this gives the average treatment effect on the treated (ATT).

This simple setup assumes that all individuals are treated at the same time and that the observations can neatly be divided into two time periods that are

the same for all individuals, pre and post-treatment, and two groups treatment and control. The ATT is then estimated with a regression with two groups by two time periods (2x2). Given the staggered treatment of this study dividing the data into many pre and post-treatment groups and creating many 2x2 pairs, the estimation method can lead to bias (Goodman-Bacon, 2021). To address this potential identification issue due to the staggered nature of graduation the second stage will follow Sun and Abraham (2021). This also allows for the recovery of both the ATT, cohort-specific ATT (CATT), and dynamic treatment effects.

In the staggered adoption DID method treatment cohort, E , is the standardized observation period, t , that an individual graduated and can take values 1-10, those who were not treated were assigned a cohort of ∞ . The time period centered around the treatment period, l , takes values -8 through 9 for those who were treated, and -100 for those who were not treated. The CATT is estimated using:

$$Y_{i,t} = \alpha_i + \lambda_t + \sum_{e \neq \infty} \sum_{l \neq -1} \delta_{e,l} (\mathbf{1}\{E_i = e\} \cdot \mathbf{1}\{t - E_i = l\}) + \epsilon_i \quad (5)$$

Equation 5 controls for individual and time-specific trends with fixed effects α for each individual, and λ for each time period. The double sum is the interaction between time period relative to treatment and treatment cohort with $\mathbf{1}\{E_i = e\}$ is an indicator that takes a value 1 when individual i 's treatment cohort is equal to the specific cohort and 0 for others, $\mathbf{1}\{t - E_i = l\}$ is an indicator that takes the value of 1 when the difference between the individual i 's treatment cohort and the relative time period are l periods apart. The error term is ϵ_i . The control group is those who did not complete a postsecondary program. The control is not included in the double interaction term but enters through λ_t , the time fixed effects. As previously noted the assistance programs are designed to transition users off of use quickly so each period there should be exit regardless of treatment status, this is captured in time period fixed effects and provides the counter-factual trend for those who are treated. The CATT is $\hat{\delta}_{e,l}$ multiplied by a weight for each cohort, discussed in depth in Sun and Abraham (2021), gives the ATT.

2.3 | SOFTWARE

The analysis for this project was done with R (R Core Development Team, 2019) and in RStudio (RStudio Team, 2020). Additionally, the Tidyverse suite of packages was used (Wickham et al., 2019) along with Lubridate (Grolemund & Wickham, 2011)



and extrafont (Chang, 2022). The Difference-in-Differences analysis was completed using the fixest package (Berge, 2018).

3 | RESULTS

3.1 | DESCRIPTIVE STATISTICS

Between January 2009 and December 2015 321,304 Utahns used SNAP, and 19,384 Utahns used TANF. Table 2 shows the demographic composition of SNAP and TANF users. The majority of SNAP users and TANF users, 54.3% and 61.6% were white. The second largest group for both SNAP and TANF users, 37.8% and 27.2% respectively, did not have race specified. Black Utahns were 2.1% of SNAP users and 4.4% of TANF users. American Indian or Alaska Native users were 3% and 3.3% of SNAP and TANF users respectively, Native Hawaiian or Pacific Islander users were 3% of SNAP users and 3.3% of TANF users. Finally, Asian users were 1.4% of SNAP users and 2.1% of TANF users; people who identify as any other race or multi-racial each were less than 0.5% of each program’s users. Compared to state-level demographics, white users, 77.8% of Utahns, are under-represented in both programs while Black Utahns, 1.5%, are over-represented along with American Indian or Alaska Native, 1.6% (U.S. Census Bureau, 2020). The vast majority of public assistance users did not graduate from a postsecondary program. The gender difference in use between TANF and SNAP is large, 85.5% of TANF users were women while 53.8% of SNAP users were

Table 2: Demographic makeup of public assistance users.

	TANF	SNAP
White	62%	54%
Unspecified	27%	38%
Black or African American	4%	2%
Native Hawaiian or Pacific Islander	1%	1%
American Indian or Alaska Native	3%	3%
Asian	2%	1%
Other	0%	0%
Multi-race	0%	0%
Female	85%	54%
Male	16%	46%
Graduate/Treated	3%	4%
Observations	19,384	321,304

women. For SNAP users 96.1% did not graduate from a postsecondary program and 96.9% of TANF recipients did not graduate from a postsecondary program, shown in Table 2. During the observation window 12,530, 3.9%, SNAP users and 601, 3.1%, TANF users completed a postsecondary program. While these are a small relative percent of overall public assistance users there are enough observations to use the chosen methods.

There are differences in demographics between those who completed a postsecondary program and those who did not. Table 3 shows the demographics of those who were treated and those who were not. Compared to the control group the treated group is whiter, with 12 percent more for TANF users and only 0.9 percent more for SNAP users. Those who were treated were younger in the first month of use compared to the control group. TANF users

Table 3: Demographic differences between treatment and controls groups. Groups with a dash were repressed for privacy..

	TANF		SNAP	
	Control	Treated	Control	Treated
Average Age	31	29.80	32.9	28.5
Average Household Size	2.9	2.90	2.9	3.3
White	61%	69%	54%	55%
Unspecified	27%	23%	38%	40%
Black or African American	5%	3%	2%	2%
American Indian or Alaska Native	3%	4%	3%	2%
Asian	2%	-	1%	1%
Native Hawaiian or Pacific Islander	1%	-	1%	-
Multi-race	-	-	-	-
Other	-	-	-	-
Average Months of Use	9.7	10.7	33.1	29.7



who completed a postsecondary program were roughly 1.2 years younger than the control group. For TANF users there is no difference between the average household size between the control and the treatment group. For SNAP users the average household is 13.8 percent (.4 people) larger for the treatment group than for the control group. Overall TANF recipients use about a third of the number of months of assistance as SNAP users, under one year of use compared to around two and three-quarter years of use. The treated group of TANF users used an average of 10.7 months of assistance during the 60-month observation window. The control group of TANF users had one fewer month of use on average, 9.7 months of use. The opposite relationship exists for SNAP users. The treated group of SNAP recipients used 3.4 fewer months of assistance on average than the control group, 29.7 compared to 33.1. Overall TANF users used fewer months of assistance than SNAP users.

By the end of the five-year observation window, the majority of public assistance users were no longer receiving assistance regardless of postsecondary completion status. Figure 1 shows the percentage of public assistance users who are still receiving benefits by observation month. As noted earlier, those who did not complete a program in the five-year observation period are the control group and

were used as the comparison group for both those who completed a degree and those who completed a certificate. The top row of Figure 1 shows patterns of use over time for SNAP users while the bottom row is TANF recipients. The left column compares certificate earners with the control group and the right column compares degree earners with the control group, the vertical dashed line is the average graduation month. For SNAP users there is a steady decrease in use for the first roughly half year then a slight increase as some people who previously stopped receiving benefits start again. This pattern repeats for roughly the first 21 months of use. For SNAP recipients the average use per observation period is similar between the treatment and control groups for degree earners, while there is a noticeable divergence after the average completion period between the control group and the certificate earners. TANF degree earners tend to use more months per observation period than the control group until the average graduation period with a slight divergence between the control and treated by the end of the observation window, the same pattern holds for those TANF recipients who complete a certificate. Overall there is evidence for parallel pre-treatment trends between those who complete a postsecondary program and those who do not.

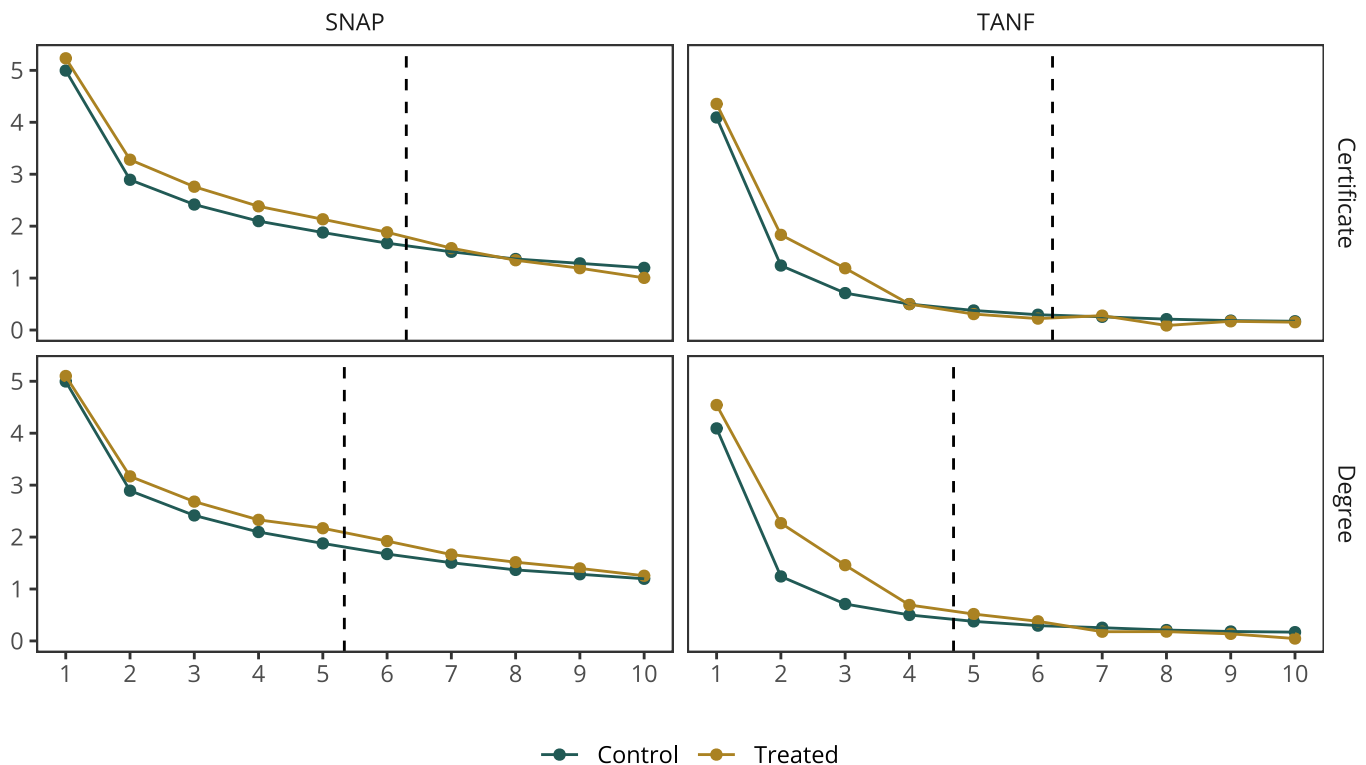


Figure 1: Average months of public assistance use by public assistance program type and postsecondary program type.



During the first month of public assistance use, only those who go on to complete a postsecondary program and used SNAP were more likely to be employed than unemployed. There are differences in the top five industries of employment between those who go on to complete a postsecondary program and those who do not complete a postsecondary program. The main industries of employment at the start of assistance use are shown in Figure 2, with the columns showing completion status and the rows showing public assistance programs. Admin and Support Services is a main industry of employment for all groups, as is Food Services. Retail is an important industry for those who do not complete a postsecondary program, while Educational Services is a main industry of employment for those who go on to complete a postsecondary program. Educational Services as a main industry of employment for completers point to the possibility that there is already a premium placed on education among those who go on to complete a postsecondary program. Additionally, this is not an artifact of public assistance users who are already enrolled in a postsecondary program having work-study aid counted as employment as work-study is not considered employment and does not pay into unemployment insurance.

After using a public assistance program, those who completed any postsecondary program are more likely to be employed than those who did not complete a postsecondary program. Figure 3 is organized the same as Figure 2 and demonstrates the main industries of employment after public assistance use. Admin and support services remain a key industry of employment for all four groups, and food services are no longer one of the main industries for TANF users who complete a postsecondary program but remain a main industry of employment for those who do not. Healthcare becomes a main employer for postsecondary completers from TANF, an industry that tends to have higher than average wages (U.S. Bureau of Labor Statistics, 2022). Though the majority of those who were employed were not employed in any of these industries. This demonstrates that for many, postsecondary program completion is a key to access to both employment and industries that tend to pay better.

The descriptive evidence points to similar patterns of use before postsecondary program completion as shown in Figure 1. For SNAP recipients the level of use is also similar between the treatment and the control group, for TANF users the control group's use per period before completion is slightly higher. Figure 1 also shows evidence of divergence in



Figure 2: Main Industries of employment during the first quarter of public assistance use.

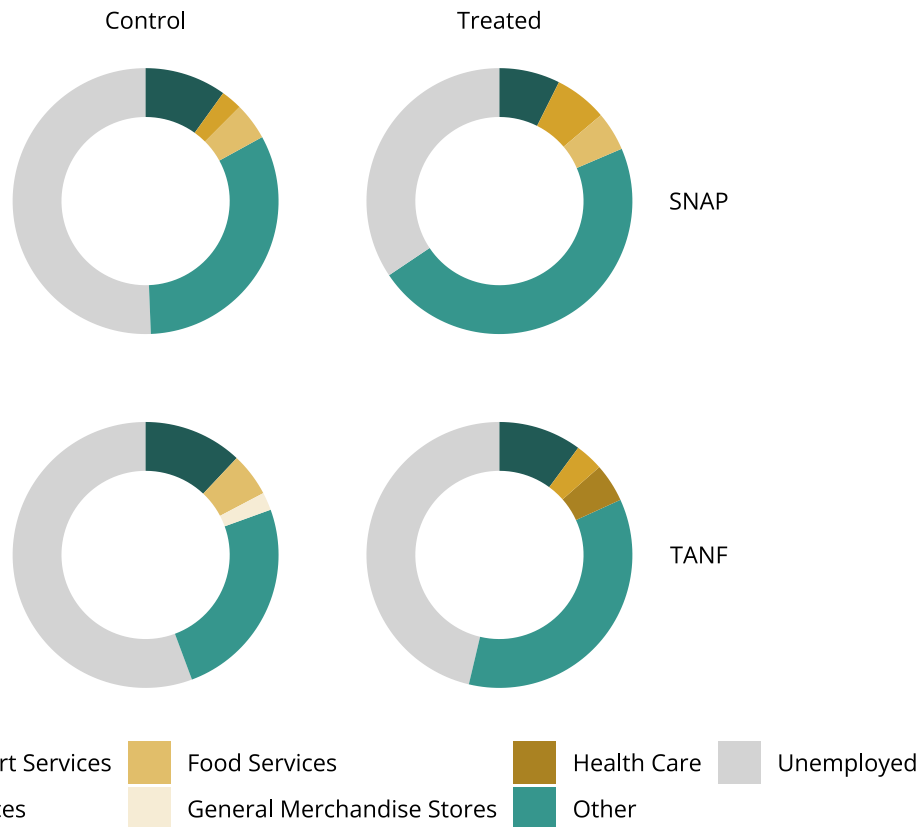


Figure 3: Main Industries of employment during the quarter containing the month of public assistance use.

average use between the treated and the control after the average treatment period. These similar patterns show evidence of parallel trends between the treated and the control group. After public assistance use, those who complete a program are more likely to be employed than those who did not complete a program. Furthermore, those who did receive a postsecondary education are employed in different industries than those who did not complete a postsecondary program. This presents evidence of both an effect of completion of a postsecondary program and the mechanism through which it works, employment.

3.2 | REGRESSIONS RESULTS

Completion of a postsecondary program decreases the expected number of months of post-graduation use for SNAP and TANF users regardless of the type of credential obtained. The ATTs are shown in Figure 4. The completion of a degree leads to 1.7 fewer expected months of SNAP use every six months after graduation compared to before graduation for the graduates. The completion of a certificate leads to 1.1 fewer expected months of SNAP use every half year after program completion. The effect is smaller for TANF users, with certificate completers expected to use 1.01 fewer months per half-year period and degree completers expected to use

0.6 fewer months after completion than before completion. The results for both SNAP and TANF users are robust to various placebo tests, the results are shown in Appendix B, lending more evidence to the casual nature of graduation on public assistance use.

The treatment effect by cohort demonstrates the longer-run payoff to postsecondary program completion. The CATTs are shown in Figure 5. The earliest graduating cohorts tend to have the largest treatment effect, while the latest treated cohorts tend to have an effect that is no different from zero. For the group treated in the last period, this is expected as there are no post-treatment observation periods. For those who completed programs during the second observation window, between months 7 and 12 of assistance use the CATT is larger than the ATT. For SNAP users it is 0.8 and 1.4 additional fewer expected months for degree and certificate earners. For TANF users those who earn a degree are expected to use 0.4 months fewer than the ATT those who earn a certificate are expected to use roughly the same as the ATT. The more recent CATTs trend towards zero. By the fifth or sixth cohort, there is no treatment effect.

Average Treatment Effect on the Treated

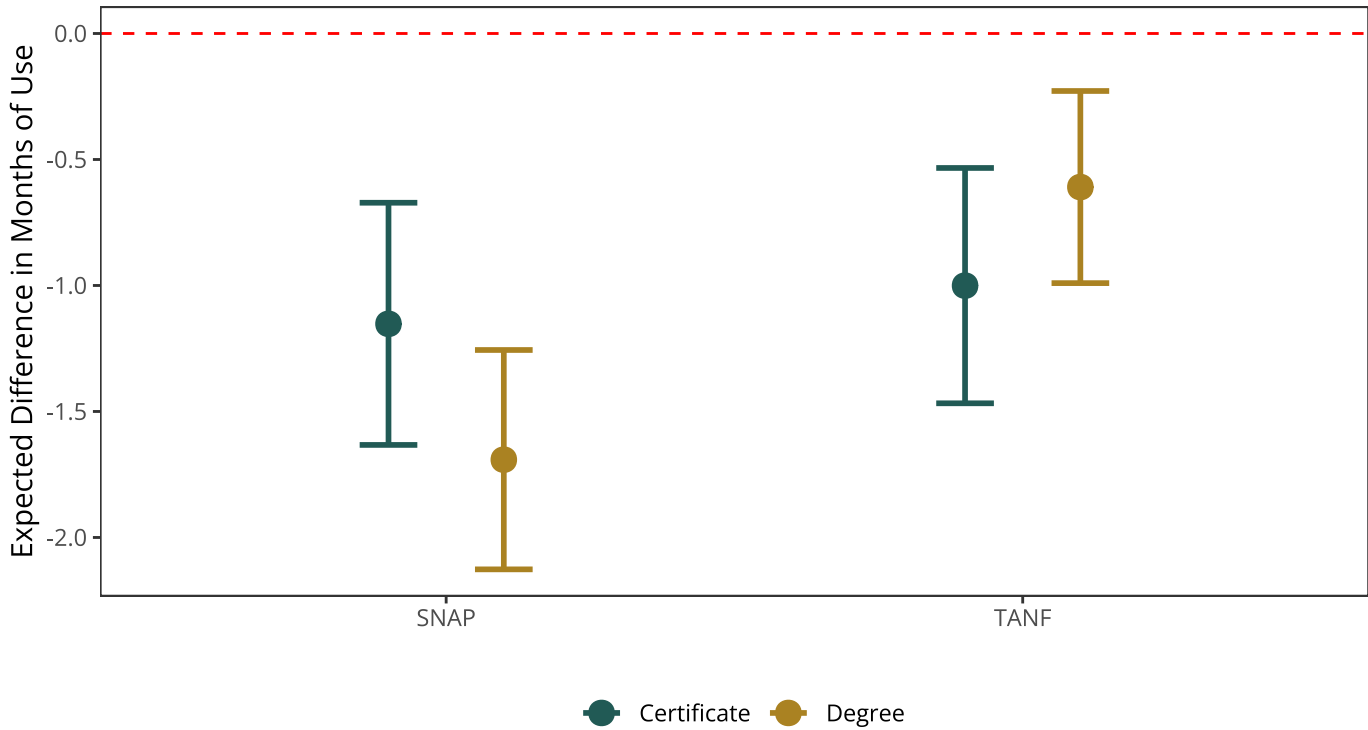


Figure 4: Average Treatment Effect on the Treated. This figure shows the expected difference of months of use before and after post-secondary program completion after controlling for general use trends.

4 | DISCUSSION

These results show a negative relationship between postsecondary completion and public assistance use, completing a postsecondary program is associated with decreased public assistance use after graduation. Beyond establishing a negative relationship between completion and use the method used shows that the timing of the decrease in SNAP and TANF use is due to program completion. The method combined with an analysis of type and level of employment after use provides strong qualitative and quantitative evidence that the completion of a postsecondary program decreases SNAP and TANF use.

Much previous research has shown higher levels of overall public assistance use for those who earn a college degree while using public assistance. This is not necessarily inconsistent with the results presented in this work due to the different methods. Often the increased use is early on or in the initial spell of use, with lower use after program completion. This research presents differences between pre and post-completion of a postsecondary program and does not directly compare assistance use with those who did not complete a postsecondary program, the CATTs show that the further from treatment the greater the

effect on public assistance use which does fit with the narrative of less use long-term.

College enrollment has previously been linked with higher overall cash-based assistance use, London (2005) shows those who graduate from a college program are expected to use 25.7 additional months of cash-based assistance than those who did not attend college. Much of this occurred during the initial use London (2005) finds that those who graduate college have a 38% lower chance to reuse TANF. London (2006) shows that graduation from college reduces the chance of additional welfare spells five years after the initial welfare spell by 5.7 percentage points. These additional findings are consistent with the dynamic treatment effects, the further an individual was from treatment the fewer expected months of TANF use. London (2005, 2006) did not test SNAP use but results presented here for SNAP users are consistent with the evidence of long-term benefits to postsecondary program completion.

Johnston (2020), finds that in Utah completion of a postsecondary program is associated with fewer months of SNAP use. This measured use after the first year of use and compared those who completed a postsecondary program with those who did not. These findings fit with the findings in this research showing the effects of completion

Cohort Average Treatment Effect on the Treated

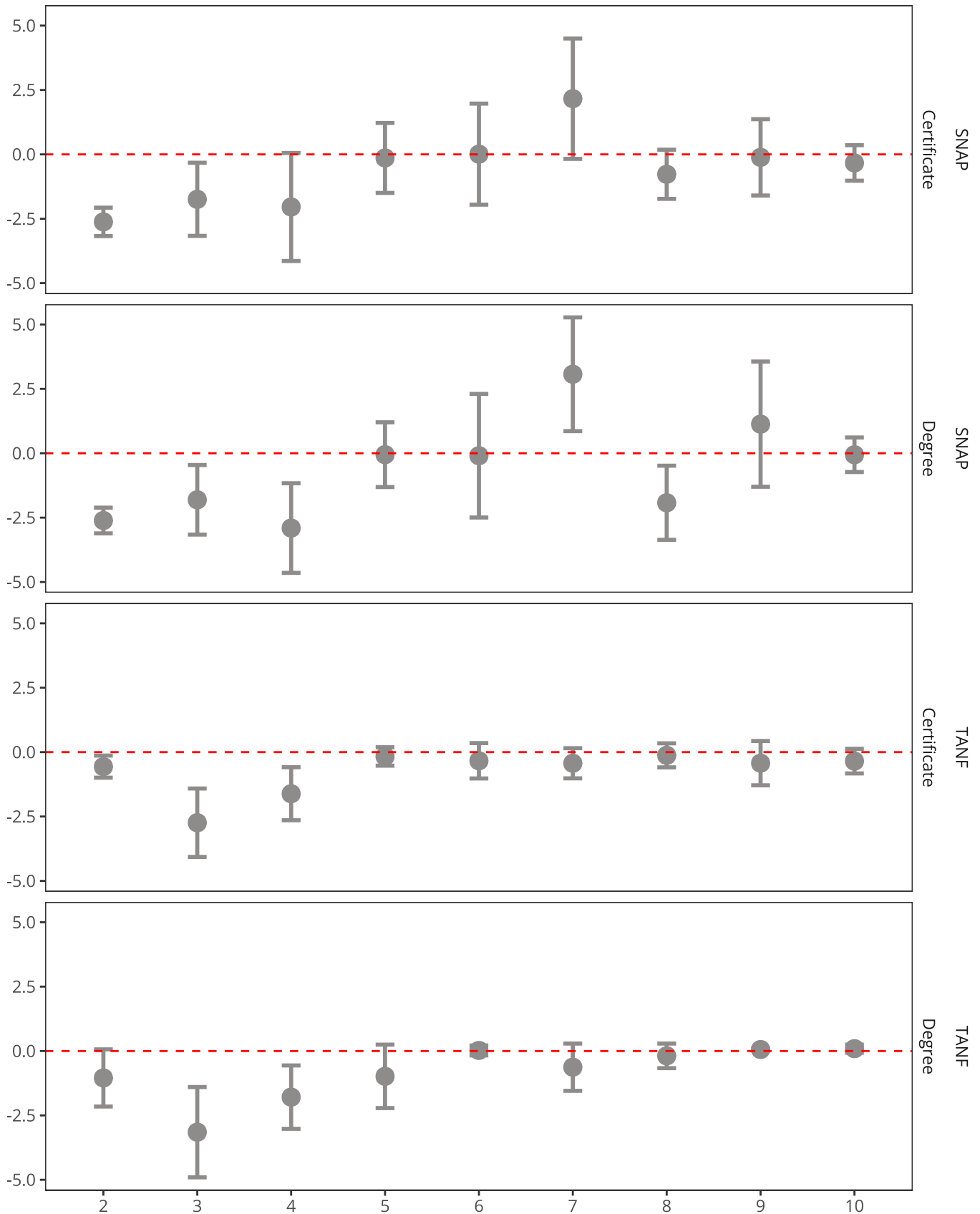


Figure 5: Cohort Average Treatment Effects. This figure shows the expected difference of months of use before and after post-secondary program completion for each cohort after controlling for general use trends. The cohort is the standardized observation period a treated individual completed a postsecondary program.



increasing over time.

These results are hard to compare to Barrett (2000) who finds that women with postsecondary education have the highest exit rate from public assistance. Barrett (2000) uses the level of education upon public assistance entrance as the measure. Barrett (2000) includes a variable for school enrollment and finds that current enrollment decreases the exit rate, again consistent with this research. Overall these exit discrepancies partially represent differences in methodology and measurement.

TANF users who attended college were more likely to be employed both one and five years after the initial spell of use (London, 2006). Additionally, London (2006) shows that attending and completing college leads to reduced family poverty both one and five years after the initial welfare spell. These results are similar to descriptive findings in this study, that TANF and SNAP postsecondary program completers are more likely to be employed immediately following the initial spell on assistance. Additionally, this research demonstrates there are changes to the main industries of employment for public assistance users into industries with above-average wages (U.S. Bureau of Labor Statistics, 2022). Taken together, this research fits with previous research that points to enhanced long-term employment and poverty outcomes for those who complete a postsecondary program.

The results of this research complement and extend previous research by showing the effects of the completion of a postsecondary program on SNAP and TANF use. Previous research has shown that in the long-term completers are more likely to be employed and less likely to be in poverty (London, 2005), and have shorter or fewer spells of use (London, 2006). This research shows that those who complete a public postsecondary program use fewer months than before graduation after controlling for overall use trends. This effect is larger for those who graduated earliest.

4.1 | Limitations and Future Research

This research suffers from several limitations, some of which can be addressed in future work, some of which cannot. The limitations that can be addressed with future research stem from model design, observation length, and variable limitations. The limitations that cannot be addressed in future work are unobservable confounding variables. Additionally, the method used in this research is traditionally used with a natural experiment such as changes in state-level laws for example see Card and Krueger (1993). In this research, the treated group self-selected into treatment rather than through a

quasi-random assignment. Taken as a whole, these limitations make this research a starting point rather than an ending point for studying the relationship between public assistance use and postsecondary program completion.

This study was not able to account for an important characteristic of public assistance users. The SNAP and TANF data did not contain information on the marital status of the benefit recipient. The presence of a spouse can bring in additional income, which makes spells of use not fully determined by the person who received the benefit. These control variables are important for several outcomes (Barrett, 2000; London, 2005, 2006) and in determining who attends college (London, 2005, 2006). Without the ability to control for these, the results of work may be biased. Future research should address both the marital status and the number of dependents of benefit recipients.

Given the time frame of this data, any long-term changes in wealth, income, or poverty for completers have not been observed. The CATTs show the treatment effect increasing the further from postsecondary program completion users were. Given a longer observation window it would allow a description of if this pattern levels off or continues as shown in this research.

This research was not able to address the potential endogenous nature of the choice to attend a postsecondary program. This was due to insufficient data to instrument the choice to attend a postsecondary program. In this case, those who complete a postsecondary program may have certain unobservable characteristics that not only would make it easier to complete a postsecondary program but also find employment, stay employed, and be employed in a higher-paying job. All of these would determine the number of months of use and could be incorrectly attributed to the change in education. This leads the estimated treatment effect to be an upper bound of the effect of postsecondary program completion. Future research should address the endogenous nature of the choice to attend and complete a postsecondary program. This can be done using an instrumental variables technique, provided additional information is available such as aptitude and availability of postsecondary programs.

A related weakness of this research is how the completion of a postsecondary program affects public assistance use. While the timing of the decrease in use is attributed to program completion the mechanism is not directly testable. As noted a postsecondary education creates a trade-off between current and future earnings; a student must sacrifice some income-earning work hours to attend a postsecondary program. This leads to lower



immediate income. It is possible the extra hours available for income-earning work after graduation was enough to decrease use in and of itself. This would falsely attribute the decreased use to the completed education rather than the newly freed-up time. This is difficult to test without being able to directly measure hourly wage and or hours worked.

This study was unable to account for the private administration of assistance. Beyond SNAP and TANF, the Federal Government has encouraged states to partner with charities to administer additional aid (Hager, 2021). In Utah, the major private provider of assistance is The Church of Jesus Christ of Latter-day Saints (Hager, 2021); since this is a private provision, any recipient is not part of the data used in this study but may otherwise qualify for SNAP or TANF. Private providers of assistance set their own standards of who can qualify, so some individuals may not feel comfortable using a service run by a religious institution or might be excluded based on religious grounds. If this exclusion or inclusion is also related to postsecondary attainment, these results will be biased if it allows for an early exit from the public assistance rolls.

Finally, this study was not able to observe if an assistance user attended a private college or university in Utah. There is anecdotal evidence that a non-trivial number of students who attend BYU also use public assistance. These users show up in the rolls of use but might be wrongly assigned to the control cohort. If this is the case this group might have biased the results downward for the effect of completion of a postsecondary program.

5 | CONCLUSION

SNAP and TANF users who complete a postsecondary program use fewer months of assistance after graduation than before graduation after taking general long-term trends of use into account. This research quantifies the relationship between postsecondary program completion and public assistance use for those who complete a program. This research shows different dynamics in employment and industry from the start to the end of assistance use between those who complete a program and those who do not.

Data for SNAP and TANF users from January 2009 to December 2015 were combined with DWS wage data and USHE certificate and degree data. This study used a propensity score to create weights for each individual who used SNAP or TANF.

These weights were used in a staggered adoption difference-in-differences to estimate the average treatment effect on the treated. It showed that those who complete a degree use less public assistance after completion than before completion

even taking general trends of decreased use over time into account. Coupled with the changes to employment it is reasonable to attribute at least some of this decrease not only to the completion of the program but to the education itself.

Overall SNAP degree earners use 1.7 fewer months of assistance every half year after completion of their program than before completion, the earliest cohorts had 2.5 fewer expected months of use. The pattern is the same for SNAP users who earned a certificate though the magnitudes are different. For TANF certificate earners completion leads to an overall decrease of 1.1 fewer months of use after completion compared to before completion for those who completed, while the second cohort is expected to use 2 fewer months of assistance every six months. The long-term effects are larger than the short-term effects.

This study also included a descriptive analysis of public assistance users. While the majority of users are White, minority users make up a disproportionate amount of public assistance users when compared to state demographics. While most users of public assistance were likely to be unemployed at the beginning of their assistance use, by the end of their use SNAP and TANF users who completed a postsecondary program were more likely to be employed at the end of their spells of use. This does not hold for those who did not complete a program. Additionally, those who completed a program were likely to be employed in hospitals or health care services. These industries tend to have higher pay (U.S. Bureau of Labor Statistics, 2022) than the main industries of employment that those who do not complete a postsecondary program are employed in after assistance use.

These results add to the understanding of the relationship between postsecondary completion and public assistance use but do suffer from several main limitations. Overall the time frame of this study does not allow for a complete quantification of the long-term relationship between postsecondary completion and assistance use. Due to data availability, this study is also missing important variables including additional demographics, private postsecondary programs, and reason for no longer receiving public assistance these can potentially bias the results. Finally, this study is not able to establish the causal mechanism between postsecondary completion and decreased public assistance use. This study should be revisited when it is possible to extend the observation period and when additional information about the public assistance recipients is available.



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REFERENCES

- Arcidiacono, P., Bayer, P., & Hizmo, A. (2010). Beyond Signaling and Human Capital: Education and the Revelation of Ability. *American Economic Journal: Applied Economics*, 2(4), 76–104. <https://doi.org/10.1257/app.2.4.76>
- Barrett, G. F. (2000). The effect of educational attainment on welfare dependence: Evidence from Canada. *Journal of Public Economics*, 77(2), 209–232.
- Becker, G. (2009). *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago Press.
- Berge, L. (2018). Efficient estimation of maximum likelihood models with multiple fixed-effects: The R package FENmlm. *CREA Discussion Papers*, 13.
- Card, D., & Krueger, A. B. (1993). Minimum Wages and Employment: A Case Study of the Fast Food Industry in New Jersey and Pennsylvania (Working Paper No. 4509). National Bureau of Economic Research. <https://doi.org/10.3386/w4509>
- Chan, M. K., & Moffitt, R. (2018). Welfare reform and the labor market. *Annual Review of Economics*, 10, 347–381.
- Chang, W. (2022). *extrafont: Tools for Using Fonts* (R package version 0.18). <https://CRAN.R-project.org/package=extrafont>
- Congressional Budget Office. (2021, August 4). *The Distribution of Household Income, 2018*. <https://www.cbo.gov/publication/57404>
- Cunningham, S. (2021). *Causal Inference: The Mixtape*. Yale University Press.
- Department of Workforce Services. (2021, October 1). 342 SNAP Work Requirements. https://jobs.utah.gov/infosource/eligibilitymanual/300_Participation_Requirements/342_SNAP_Work_Requirements.htm
- Goodman-Bacon, A. (2021). Difference-in-Differences with Variation in Treatment Timing. *Journal of Econometrics*, 225(2), 254–277.
- Grolemund, G., & Wickham, H. (2011). Dates and Times Made Easy with lubridate. *Journal of Statistical Software*, 40(3), 1–25.
- Hager, E. (2021, December 3). How has Utah saved \$75 million on welfare? By providing next to none and taking credit for LDS welfare instead. *The Salt Lake Tribune*. <https://www.sltrib.com/news/2021/12/02/utah-makes-welfare-so/>
- Hansen, J. (2006). The effect of human capital and earnings supplements on income assistance dependence in Canada. *Social Research and Demonstration Corporation*.
- Heckman, J. J., Humphries, J. E., & Veramendi, G. (2018). Returns to Education: The Causal Effects of Education on Earnings, Health, and Smoking. *Journal of Political Economy*, 126(51), 50. <https://doi.org/10.1086/698760>
- HHS. (n.d.). Temporary Assistance for Needy Families (TANF). Retrieved January 5, 2022, from <https://www.acf.hhs.gov/ofa/programs/temporary-assistance-needy-families-tanf>
- Huntington-Klein, N. (2021). *The Effect: An Introduction to Research Design and Causality*. CRC Press.
- Johnston, B. (2020). *The Relationship between Educational Attainment and Reliance on Government Assistance among Utahns. An analysis of low-income Utahns participating in the Supplemental Nutrition Assistance Program (SNAP)*. University of Utah.
- Kem C. Gardner Policy Institute. (2018). *Utah at a Glance*. Kem C. Gardner Policy Institute. https://gardner.utah.edu/wp-content/uploads/UtahAtAGlance_20180207.pdf
- London, R. A. (2005). Welfare Recipients' College Attendance and Consequences for Time-Limited Aid*. *Social Science Quarterly*, 86(s1), 1104–1122. <https://doi.org/10.1111/j.0038-4941.2005.00338.x>
- London, R. A. (2006). The Role of Postsecondary Education in Welfare Recipients' Paths to Self-Sufficiency. *The Journal of Higher Education*, 77(3), 472–496. <https://doi.org/10.1080/00221546.2006.11778935>
- Martinez, K. (2020). Impacts of Intergenerational Poverty on Workforce Metrics. Utah Data Research Center.
- R Core Development Team. (2019). *R: A Language and Environment for Statistical Computing* (3.6.0). R Foundation for Statistical Computing. URL <https://www.R-project.org/>
- RStudio Team. (2020). *RStudio: Integrated Development Environment for R*. RStudio, PBC. <http://www.rstudio.com/>
- Scott, S. (2019). Education Appropriations' Return on Investment of Career and Technical Education Provided by the Utah System of Technical Colleges. Utah Data Research Center. <https://udrc.utah.gov/utechroi/report.pdf>
- Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2), 175–199. <https://doi.org/10.1016/j.jeconom.2020.09.006>
- Turner, L. J. (2016). The returns to higher education for marginal students: Evidence from Colorado Welfare recipients. *Economics of Education Review*, 51, 169–184. <http://dx.doi.org/10.1016/j.econedurev.2015.09.005>
- U.S. Bureau of Labor Statistics. (2022, January 7). *Employment and Earnings Table B-3a. Current Employment Statistics*. <https://www.bls.gov/web/empsit/cese3a.htm>
- U.S. Census Bureau. (2020). *U.S. Census Bureau QuickFacts: Utah*. <https://www.census.gov/quickfacts/fact/table/UT/POP010220>
- USDA. (n.d.). *Supplemental Nutrition Assistance Program (SNAP) | Food and Nutrition Service*. Retrieved January 5, 2022, from <https://www.fns.usda.gov/snap/supplemental-nutrition-assistance-program>
- Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., ... Yutani, H. (2019). Welcome to the Tidyverse. *Journal of Open Source Software*, 4(43), 1686. <https://doi.org/10.21105/joss.01686>



APPENDIX A | CALCULATION FOR HOURS OF WORK

The unemployment data only reports quarterly earnings. To move from quarterly earnings to average quarterly hours the wage earned by each employee is needed. This is not directly available but can be imputed. This process involved wage, industry, hours of work, income, and poverty data from the Current Population Survey (CPS). The industry that is available in the CPS does not directly link to NAICS which is how unemployment data is coded. To create a crosswalk the American Community Survey (ACS) was used. The ACS has both Census Industry from the CPS and NAICS. This was aggregated to the three-digit NAICS and the unemployment wage data was truncated to the three-digit NAICS.

Total income is $\text{hours} \times \text{wage}$, for the population of interest, non-labor income is not a factor and is not needed for consideration of total income (Congressional Budget Office, 2021). Income is known but both wage and hours are unknown, to address this Figure 1A shows the joint distribution of hours and wages for those who are below the income cutoff for SNAP and those who are above the income cutoff. There is a clear pattern, those who qualify for SNAP have a tight distribution around a very low wage, and the hours they work vary much more. This is shown by the concentric ovals around minimum wage. This is in stark contrast to those who work the same jobs but do not qualify for SNAP, this group works full-time, as evidenced by the tight band around 40 hours, and has a more variable wage. Given that those who qualify for SNAP have variable hours around a low wage using a measure of central tendency as a proxy for a wage would return an approximation for hours worked given reported income.

To impute quarterly hours worked CPS was filtered to only those who fell in the poverty threshold for qualifying for SNAP. The log of income and wage was taken and the median log wage for each year and industry was used to divide quarterly income for the SNAP and TANF users in this study and return quarterly hours worked. The median wage was used rather than the mean due to the mean being more sensitive to outliers.

Joint Density of Hours Worked and Hourly Wage

Top Three Industries of Employment for Utahns Who Received SNAP Benefits

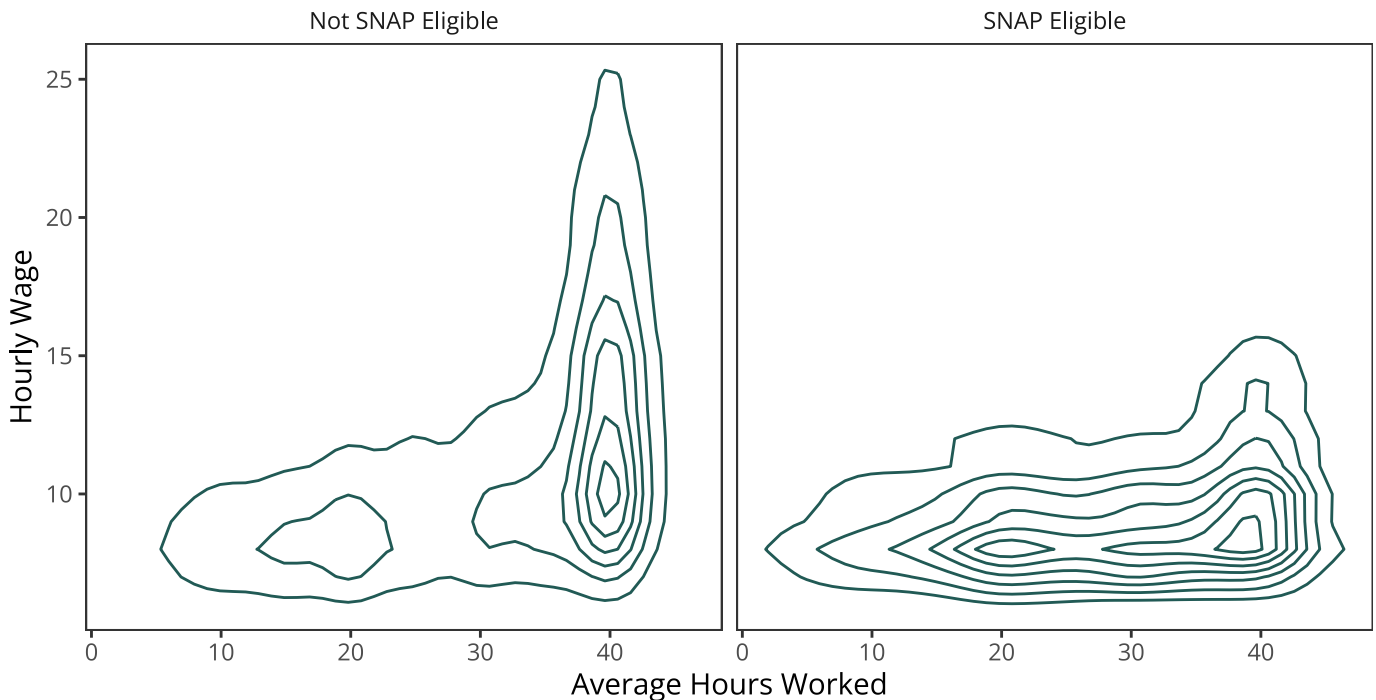


Figure A1: Joint distribution of wages and hours worked. Data from the CPS.

APPENDIX B | PLACEBO TESTS

This appendix presents the placebo tests for staggered adoption difference-in-differences. To test if the change in public assistance use can be attributed to the graduation from a postsecondary program a common test is to create a placebo treatment date before the actual treatment date. From Equation 5 each individual who graduated had a cohort E_i which was equal to t , the observation period in which they graduated. Each individual was assigned a first placebo cohort $E_i^{p,n}$ which took the value $t-n$, where $n = 1$ for the first placebo cohort, $n = 2$ for the second placebo, and so on. If an individual graduated in the fourth six-month observation period their true cohort was $E_i = 4$ and their first placebo cohort was $E_i^{p-1} = 3$. The staggered DID was rerun for each possible placebo, 1-8. If the placebo regressions returned similar results to the initial DID regression it would not have been possible to say the estimated effects were caused by the completion of a postsecondary program. In the context of SNAP graduates, the placebo ATTs and CATTs quickly reduced in magnitude, then switched signs and were statistically insignificant. This points to effects estimated with the true equation being the results of graduation. The placebo ATTs are reported in Table B1.

Table B1 :Placebo Tests for Average Treatment Effect on the Treated. Numbers in the parenthesis represent 95% confidence intervals. Stars represent significant: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Placebo	SNAP		TANF	
	Degree	Certificate	Degree	Certificate
1	-0.85* (-1.48, -0.21)	-0.5 (-1.05, 0.05)	-0.28* (-0.55, -0.01)	-0.66* (-0.88, -0.43)
2	-0.91* (-1.34, -0.47)	-0.71* (-1.13, -0.28)	-0.17 (-0.42, 0.07)	-0.35* (-0.59, -0.11)
3	-0.22 (-0.81, 0.37)	-0.14 (-0.65, 0.38)	-0.02 (-0.24, 0.2)	-0.15 (-0.44, 0.13)
4	-0.31 (-1.06, 0.43)	-0.25 (-0.89, 0.4)	0.04 (-0.22, 0.29)	0.01 (-0.31, 0.33)
5	-0.11 (-0.79, 0.57)	0.11 (-0.6, 0.81)	0.05 (-0.26, 0.37)	0.07 (-0.26, 0.39)
6	1* (0.27, 1.72)	0.39 (-0.34, 1.11)	-0.31 (-0.72, 0.11)	0.37* (0.01, 0.73)
7	0.69 (-0.32, 1.7)	0.11 (-0.71, 0.94)	-0.46 (-0.95, 0.03)	0.18 (-0.3, 0.65)
8		0.11 (-1.21, 1.44)	-0.3 (-0.81, 0.21)	0.46 (-0.25, 1.16)