The Impact of Participation in SNAP on Labor Force Decisions

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Abstract

Labor supply theory predicts that social welfare programs will induce counterproductive behaviors through work disincentives among low-paid workers. In response to concerns about welfare dependency, past policy reforms linked work requirements to the SNAP. As a result, for those subject to a work requirement the labor supply effect of SNAP participation is theoretically ambiguous. This paper examines the impact of SNAP enrollment on labor supply. To account for the potential endogeneity of SNAP, we use quasi-experimental variation in the purchasing power of SNAP benefit amounts as an instrument. For a household of the same composition, SNAP benefit levels are fixed across states, but local food prices vary widely, leading to substantial variation in the real value of SNAP benefits. Our IV results suggest that SNAP participation increases the likelihood of employment and full time work among low income households. Consistent with the work incentives provided by SNAP, we find that children in SNAP households are more likely to receive non-parental care than children in non-participating SNAP-eligible households. Potential mechanisms for work incentive effects of SNAP are work requirements and the ability to pay for job-related expenses such as childcare.

1. Introduction

The Supplemental Nutrition Assistance Program (SNAP, formerly known as the Food Stamp Program) is the largest public assistance program in the United States. While fewer than 10 million low-income individuals participated in the program in the early 1970's, by 2016, more than 44 million individuals were enrolled in SNAP at a total cost of approximately $70 billion (USDA, 2016). As SNAP caseloads have expanded, there has been a notable decrease in labor supply, in terms of both labor force participation of low-income heads of households (March CPS data). The concurrent expansion of SNAP caseloads and the decline in the labor supply of low-income households raises the question of whether the expansion of SNAP has contributed to the decline in labor supply. Given the increasing number of SNAP participants, any work disincentives caused by SNAP could result in large welfare losses.

Standard economic theory suggests that social welfare programs will reduce labor supply. Benefits in income support programs feature a guaranteed income benefit that is reduced with family income at the legislated benefit reduction rate. The guarantee produces an income effect and the benefit reduction rate reduces the net wage leading to an income and substitution effect. For example, a low-income worker may stop working after enrollment in a welfare program. Likewise, low-paid worker may have little incentive to work more hours or seek higher wages, because the extra earnings from doing so may be partially offset by a benefit reduction.

A large number of studies examine the impact of transfer programs on labor supply (Danziger, Haveman, and Plotnick (1981); Hoynes (1997); Moffitt (1992); Moffitt (2002)). Researchers find that Aid to Families with Dependent Children (AFDC) reduced labor supply while the Earned Income Tax Credit (EITC) increased labor supply among program participants

(Hausman (1981); Moffitt (1983)). Using the EITC program expansions in the 1990s, several studies note that single mothers increased their labor supply especially at the extensive margin (Eissa and Hoynes (2006); Meyer (2002)). Additionally, Kaestner et. al (2017) examine the expansion of Medicaid under the Affordable Care Act and find little effect on labor supply, with most estimates suggesting the expansion modestly increased labor supply.

Although SNAP benefits have the structure of a traditional income support program, the reduction rate in SNAP is substantially lower than that experienced by other safety net programs (Hoynes, 2015).[1] SNAP recipients are allotted a benefit amount equal to the difference between the federally defined maximum allotment for a given family size and the amount that the family is deemed to be able to afford to pay for food on its own according to the benefits formula (essentially 30 percent of cash income, minus some deductions). For example, in 2015, a two-member household receives maximum SNAP benefit of $357 per month, and a four-member household could receive at most $649 per month. Based on SNAP benefit calculation formula, SNAP households are financially better off if they are able to secure employment or increase their earnings.

Although labor supply theory suggests that the SNAP program may generate work disincentives for some SNAP participants, SNAP rules make labor supply decisions more complex. Work has been an increasing focus of policy reforms in the United States, culminating with a number of major policy changes in the 1990s intended to increase employment and by welfare recipients. In particular, the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA) imposed work requirements on Able Bodied Adults

[1] The benefit reduction rate in the AFDC (Aid to Families with Dependent Children) program was 100% by 1967. It was reduced to 67% in 1967, then increased again to 100% in 1981. After federal welfare reform in 1996, and the conversion to TANF, there is substantial variation across states in the program's benefit reduction rate.

Without Dependents (ABAWDs) receiving SNAP benefits.[2] The legislation also requires provisions that encourage work for all participants in the SNAP. As a result of the PRWORA legislation, all non-exempt household members participating in the SNAP (with or without dependents) must meet general work requirements in order to remain eligible for SNAP.[3] These work requirements include registering for work, not voluntarily quitting a job or reducing work effort below 30 hours a week, taking a job if offered, and participating in employment and training programs assigned by the state. Failure to comply with these requirements can result in disqualification from the program. While SNAP's general work requirements do not restrict the enrollment of unemployed individuals, working participants are prevented from quitting their job if they are to maintain their eligibility. As a result, the labor supply effect of SNAP is theoretically ambiguous. On one hand, the work disincentives are created by tying SNAP benefit receipt to income levels, but on the other hand, SNAP's work requirements could create work incentives. Ultimately, the effect of participation in SNAP on work incentives is an empirical question

Although there is a large literature on the work incentive effects of AFDC and the EITC, relatively little is known about the work incentive effects of the SNAP and all of the existing literature use data prior to the PRWORA legislation imposing work requirements and other disqualifications related to employment and job training. Fraker and Moffitt (1988) use structural models and kinked budget constraints to estimate labor supply and participation in two welfare programs, AFDC and SNAP, for female headed households. They find that SNAP participation reduces hours of work by 1 hour per week. Keane and Moffitt (1998) using a similar specification

[2] ABAWDs are defined as those who are between 18 and 50 years of age, not responsible for a child or incapacitated household member, and medically fit for employment. See the official FNS website for more details: https://www.fns.usda.gov/snap/able-bodied-adults-without-dependents-abawds

[3] Work requirements apply to those who are mentally and physically fit and over the age of 15 and under the age of 60. See the official FNS website for more details: https://www.fns.usda.gov/snap/eligibility

to simultaneously model AFDC, SNAP, Medicaid and housing benefits, and find find larger elasticities than Fraker and Moffitt (1988). Hagstrom (1996) estimates the impact of the SNAP on labor supply among married couples, and find small negative impacts of changes in the benefit amount on labor supply. Hoynes and Schanzenbach (2012) exploit variation in county level the initial program rollout to control for the selection to the program, and find that participation in SNAP reduces employment and hours worked, among families headed by single woman.

Early research on the effects of enrollment in the SNAP on labor supply concludes that SNAP participation discourages work. However, there is no research on how the program, in its current form, affects work incentives. As Beatty and Tuttle (2015) note, SNAP has evolved considerably since its rollout. Notable changes in work requirements, eligibility, and program administration may have altered the characteristics of the population served by SNAP, and the work incentives faced by enrollees. Moreover, the role of women in the labor force has changed substantially over this period, which could also result in changes to the previous impact on labor supply decisions. Rosenbaum (2013) argues that the SNAP participation does not generate work disincentives among recipients. However, the study is largely descriptive and thus makes it difficult to conclude on the causal impact of the SNAP.

New research is therefore needed to understand the causal relationship between participation in SNAP and the labor supply over the past two decades. This paper helps to fill that gap. In order to identify the causal effect of SNAP participation on labor supply decisions, one needs to find a natural experiment that creates exogenous variation in SNAP participation without directly affecting employment. SNAP benefits and eligibility rules are legislated at the federal level and do not vary across states, leaving few opportunities for quasi-experimental analysis. Our research approaches this question from a new angle, using variation across markets

in the real value of maximum benefit allotment for a household of the same composition as the instrument for SNAP participation. Annual cost of living adjustments are made to SNAP benefit levels to account for national inflation in the cost of food. However, regional variation in food prices are not part of adjustment formula. Because real food prices vary results in geographic variation in the purchasing power of SNAP benefits.[4] We use USDA' Quarterly Food At Home Price Database (QFAHPD) to measure regional food prices, and assign them to the restricted access Medical Expenditure Panel Survey (MEPS). Our estimates suggest that changes in SNAP enrollment in fact increase overall labor supply, and therefore that the expansion in SNAP enrollment actually helps to slightly boost labor force participation and hours worked. Potential mechanisms for work incentive effects of SNAP are work requirements and the ability to pay for job-related expenses such as child care.

2. Empirical Approach

In order to estimate the impact of SNAP participation on employment decisions, we use the following estimating equation:

$$Y_{imt} = f(\alpha + \beta D_{imt} + X_{imt}\varphi + \varepsilon_{imt}), \quad (1)$$

where Y_{imt} is the labor market outcome of interest for individual i who resides in market group m in year t, and D_{imt} is the measure of SNAP participation. X_{imt} is a vector of covariates including individual and family-level demographic and socioeconomic variables, self-reported health status and a measure of disability.

[4] Studying data from the Quarterly Food at Home Price Database (QFAHPD), we find that regional food prices vary from 70 to 90 percent of the national average at the low end to 120 to 140 percent at the high end.

We estimate both a discrete measure of participation in SNAP and a continuous measure of SNAP benefit level. The discrete variable equals zero if individuals are non-participants in SNAP and equals one if individuals are participants. The continuous measure is the natural logarithm of SNAP benefits levels, which we set equal to zero for those who are not enrolled in SNAP. These distinct specifications allow us to distinguish between the average effect of SNAP participation and the marginal effect of an additional dollar of benefit on employment decisions.

In both specifications, we must account for the endogeneity of the SNAP variable to get consistent estimates of our outcomes of interest (Meyerhoefer and Yang 2011). Endogeneity of the discrete measure of SNAP participation caused by adverse selection of individuals with lower SES or health status into SNAP. Along with concerns regarding selection into the program, our estimates for the continuous treatment specification suffer from simultaneity bias. This is because benefits are reduced, when labor market earnings increase. We identify the causal effect of SNAP using instrument variables to account for both self-selection into SNAP and simultaneity bias.

2.1. Identification

Our identification strategy relies on quasi-experimental variation in the purchasing power of the maximum expected SNAP benefit.[5] Though SNAP benefits are implicitly adjusted for cost of living through allowed deductions, there is some evidence indicates these adjustments are not sufficient to equalize real benefits, particularly in high cost areas (Hoynes, Bronchetti and Christensen, 2017). As a result, households living in areas of the country with food prices that are higher than the national average supplement SNAP with cash to a greater extent for their food

[5] SNAP benefit level received by a household is endogenous to member's employment decisions, so we use the maximum expected SNAP benefit instead.

purchases.[6] By implication, variation in the purchasing power of SNAP benefits will affect individuals' enrollment decision.

We use the ratio of the maximum allotment of SNAP benefits based on household composition to the regional food price as an instrument for SNAP participation. Direct use of the regional food price in a non-linear model would largely eliminate our ability to account for unobservable shocks and differential trends in food prices across market regions. To ensure appropriate statistical inference, we partial out market-by-year characteristics, and use the residual price to construct our instrument. Letting m denotes food market groups, F_{mt} denotes the market's food price in year t, we estimate:

$$F_{mt} = X_{imt}\varphi_0 + \delta_t + \lambda_m + e_{mt} \quad (2)$$

across food market groups and time. λ_m and δ_t are market area and year fixed effects. We add residuals from this regression to the intercept to calculate the purchasing power of households' maximum allotment across market groups.[7] Variation in the instrument is due to differences in the cost-of-living across regions, and in household composition. Additionally, in 2009, the American Recovery and Reinvestment Act (ARRA) increased per household benefits by an average of $80 per household, which creates another source of variation in the instrument.

2.2. Econometric Models

Continuous measure of SNAP: We estimate the following conditional (recursive) mixed process model that includes a censored regression (Tobit) for our endogenous variable, the logarithm of SNAP benefits (we observe the amount of benefit only if individuals are SNAP

[6] Studying data from the Quarterly Food at Home Price Database (QFAHPD), we find that regional food prices vary from 70 to 90 percent of the national average at the low end to 120 to 140 percent at the high end.
[7] In general, there will be a small residual. To avoid precision loss, we add the constant term to the residual to construct our instrument.

participants), and a second equation for employment status among SNAP-eligible individuals using a latent variable approach as follows:

$$B^*_{imt} = \alpha_0 + \gamma Z_{imt} + X_{imt}\varphi_0 + S_{mt}\rho_0 + \delta_t + \lambda_m + \varepsilon_{imt}, \quad (3)$$

$$B_{imt} = \begin{cases} B^*_{imt}, & if\ B^*_{imt} > 0 \\ 0, & if\ B^*_{imt} \leq 0 \end{cases} \quad (4)$$

$$E^*_{imt} = \alpha_1 + \beta B_{imt} + X_{imt}\varphi_1 + S_{mt}\rho_1 + \delta_t + \lambda_m + \zeta_{imt}, \quad (5)$$

$$\Pr(E_{imt} = 1) = \Pr(E^*_{imt} > 0) = \Phi(\alpha_1 + \beta B_{imt} + X_{imt}\varphi_1 + S_{mt}\rho_1 + \delta_t + \lambda_m), \quad (6)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, and E_{imt} is the employment status. B^*_{imt}, and E^*_{imt} are the latent variables determining the log of SNAP benefits and employment. Z_{imt} is the real value of maximum allotment.

One concern is that local food prices might have a direct effect on employment decision, invalidating our identification. We test this possibility by estimating first difference regression of purchasing power of SNAP benefit and employment among continuously participating adults, and find the effect is not statistically different from zero.[8] To further address this concern, we include state-level regional price parities calculated by the Bureau of Economic Analysis to control for the differences in price levels across states. We also include CPI for the four census regions obtained from the Bureau of Labor Statistics to control for changes in price over time.

Another concerns is that food prices could be correlated with other unobservable regional characteristics that affect SNAP participation. To address this concern, we include control variables in our models for a number of state characteristics. The vector S_{mt} includes state-level housing cost, state-level per-capita income, poverty rate, and educational attainment (percentage

[8] The supplementary appendix contains the result of this test.

of bachelor's degree for persons 25 years of age and older). Per capita income, poverty rate, and educational attainment were obtained from the U.S. Census Bureau and the housing cost measure was obtained from the Freddie Mac.[9] The main coefficient of interest, β represents the causal effect of a 1% change in SNAP benefits on employment.

Discrete measure of SNAP: To identify the causal effect of SNAP participation on employment, we estimate a recursive bivariate probit model. The first equation in the model predicts SNAP participation and the second equation, which is a function of SNAP participation, predicts employment status as follows:

$$\Pr(SNAP_{imt} = 1) = \Phi(\alpha_0 + \gamma Z_{imt} + X_{imt}\varphi_0 + S_{mt}\rho_0 + \delta_t + \lambda_m), \quad (7)$$

$$\Pr(E_{imt} = 1) = \Phi(\alpha_1 + \beta SNAP_{imt} + X_{imt}\varphi_1 + S_{mt}\rho_1 + \delta_t + \lambda_m). \quad (8)$$

We modify both the model indicated in equations (3)-(6), and the model indicated in equations (7)-(8) to investigate whether SNAP causes any transitions between full-time and part-time employment. First, we create three categories of weekly hours worked: less than 30 hours a week, between 30 and 40 hours a week, and at least 40 hours a week (full-time). In order to estimate the impact of the log of SNAP benefit levels on employment, we estimate a conditional mixed process model that use a tobit regression for the endogenous logged SNAP benefit amount and an ordered probit to predict full-time versus part-time work status among SNAP-eligible individuals. Likewise, we estimate a conditional mixed process estimator that includes a probit regression for SNAP participation status and an ordered probit to determine employment status (Roodman, 2017).

[9] The annual home price index is the average of the monthly home price indices, by state, published by Freddie Mac as the Freddie Mac Home Price Index (FMHPI), found at http://www.freddiemac.com/finance/ fmhpi/.

Effects of SNAP at the intensive margin: Our identification strategy allows to estimate the impact of changes in SNAP benefits among participant households. In contrast to models of SNAP participation, measurement error is of less concern. Previous research suggests mis-reports of SNAP participation are mostly "false negative" reports by households that do not report participation, but are in fact enrolled in SNAP (Bollinger and David 1997; Meyer, Mok, and Sullivan 2009). In the presence of substantial reporting error in participation, drawing definitive conclusions about the effects of SNAP can be challenging. (Kreider et al. 2012; Alamada, McCarthy, and Tchernis 2016). In order to examine the possibility that our results are confounded by measurement error, we also estimate our models on the sample of participant households, and compare the results to models that make use of the full sample of SNAP eligible individuals. We therefore modify the recursive mixed process model above to a 2SLS specification that includes a linear regression for the logarithm of SNAP benefits.

As an alternative, we estimate the direct effect of variation in the real value of SNAP benefits on employment among adults who report receiving SNAP. We estimate the effect of additional SNAP benefits on employment in the following reduced form model:

$$E_{imt} = \alpha_1 + \beta Z_{imt} + X_{imt}\varphi_1 + S_{mt}\rho_1 + \delta_t + \lambda_m + \varepsilon_{imt}. \quad (9)$$

3. Data

We use two main sources to document how participation in SNAP affect labor force decisions. The main source of variation in our instrument, regional food prices, comes from USDA' Quarterly Food At Home Price Database (QFAHPD). Our outcome variables come from the Medical Expenditure Panel Survey (MEPS), subset to individuals aged 18-64 years.

The MEPS is a nationally representative household survey of the US civilian noninstitutionalized population. Each panel of respondents was interviewed in five rounds covering two calendar years. MEPS contains detailed information for each individual in the household on demographic characteristics, socioeconomic status, health status, as well as employment information. The MEPS contains several key variables that are useful for our analysis. MEPS respondents are asked whether anyone in the household received some amount of SNAP benefits in the past year, for how many months, and the monthly value of the benefit. We construct a group of eligible households. To be eligible for the SNAP, a household has to pass gross income, net income, and asset tests. The net income calculation requires subtracting certain deductions from a household's basic (or gross) monthly income. Since our data does not contain information on household assets and allowed deductions, we only simulate the gross income to determine households' eligibility status (we define the eligibility status based on the first-year observation of individuals). The Gross monthly income limits are set at 130 of the poverty level for the household size (USDA, 2016b).[10]

In order to calculate the real value of maximum SNAP benefit, we construct the regional price of Thrifty Food Plan (TFP). The TFP constructed by the USDA provides a representative healthful and minimal cost meal plan that shows how a nutritious diet may be achieved with limited resources. Maximum allotments are set at the monthly cost of the TFP for a four person family consisting of a couple between ages 20 and 50 and two school-age children, adjusted for family size. We use the Quarterly Food-at-Home Price Database (QFAHPD) available from 1999 to 2010 as the source of information about food prices. ERS researchers aggregated the food purchases from household food-at-home purchase data from Nielsen Homescan data to estimate

[10] Monthly income eligibility standards for 1996-2003 were obtained from USDA/FNS.

household-level quarterly prices for over 50 food groups. The household-level prices were then aggregated to estimate quarterly market-level prices. Quarterly prices for these goods are derived for 35 market groups: 26 metropolitan areas, and 9 based on households in nonmetropolitan (nonmetro) areas, though for 1999-2001 only 4 nonmetropolitan areas are captured.[11] We follow Gregory and Coleman-Jensen (2013) and create food basket price for each market and year during 1999-2010 in two steps. First, we map the QFAHPD food categories to the 29 TFP food group prices in the market basket using an expenditure-weighted average of the prices for the QFAHPD foods, the weights are a fraction of yearly national expenditures in the TFP category for the QFAHPD good (most TFP food items consist of multiple QFAHPD food groups). Once we have constructed the region-by-year price for 29 TFP food group, we calculate our basket (TFP) price using the amounts recommended for a family of four comprised of two adults and two children.

An example (borrowed from Gregory and Coleman-Jensen (2013)) is illustrative. The TFP food category "whole fruit" consists of two QFAHPD food groups: "fresh/frozen fruit" and "canned fruit." In Hartford (market group 1), in the first quarter of 2002, expenditures on fresh/frozen fruit were $35.7 million, and expenditures on canned fruit were $5.8 million. This yields expenditure weights for whole fruit (in Hartford in quarter 1 2002) of 0.86 and 0.13, respectively. Repeating for each market group, we then average these expenditure shares across all market groups to generate the national expenditure shares (for this item in this period). In 2002, these national expenditure weights are 0.84 and 0.16 for fresh fruit and canned fruit, respectively. Returning to Hartford, the first-quarter 2002 prices of fresh/frozen and canned fruit in the Hartford market group are $0.218 and $0.244 per 100 grams, respectively. Therefore, the

[11] For consistency, we use the 4 nonmetro areas throughout.

price for whole fruit in Hartford for the first quarter of 2002 is 0.84×$0.218+0.16×$0.244 = $0.222 per 100 grams.

We assign the market region-by-year TFP prices to households in the MESP based on the household's county of residence (which we map into the QFAHPD market area that includes the county) and the year of interview. We measure the purchasing power of SNAP benefit using the ratio of the maximum SNAP benefit to the TFP price faced by the household.[12,13]

We control for a full set of socio-demographic characteristics, and health status variables in our models. Our main control variables include (dichotomous indicators for age 30–39, 40–50, 51–64 with age 18–29 as the omitted category), gender, race and ethnicity (Hispanic, black, and other race with white as the omitted category), region (South, Midwest, and West with Northeast omitted), urban residence, education (high school diploma, any college, with less than a high school degree omitted), family size, number of children in the household under 5 or 18 in the household, whether the household has a disabled member, whether the household has an elderly member, and the log of income earned by other family members normalized by the square root of household size. In order to control for health status, we use self-reported mental and physical health (poor/fair health in all rounds, poor/fair health in some rounds, excellent health in some rounds, excellent health in all rounds, good/very good health in all rounds, and self-reported health is missing, with good/very good health in some rounds serving as the omitted category for both mental and physical health) and a measure of disability status. The latter is a binary variable that indicates whether the person had an IADL (Instrumental Activities of Daily

[12] Allotments are adjusted for food price inflation annually, each October, to reflect the cost of the TFP in the immediately previous June. We use weighted average of monthly amounts to obtain the allotment for each calendar year.
[13] We obtained maximum allotment amounts for 1999-2004 from USDA/FNS.

Living) or ADL (Activities of Daily Living), functional, activity, or sensory limitation in any interview round. Table 1 lists summary statistics for the main variables used in the analysis. These statistics show clear selection into SNAP by individuals with lower incomes and less education, poorer health status, and higher rates of disability. Importantly, our summary measures indicate that labor Force participation rates among SNAP recipients are lower than among those not receiving benefits.

In our conditional sample, we also control for employment characteristics. These include union status, employer size (less than 25 employees, between 25-99 employees, between 100-500 employees, more than 500 employees), benefits provided by the employer (retirement plan, and paid vacations) and industry indicators.[14]

4. Empirical Results

Before we estimate our main models, we estimate a linear regression model to determine whether the purchasing power of maximum allotment is a strong predictor of SNAP participation. These results are reported in Table 2. The first two columns contain results for the continuous measure of SNAP benefit levels, and the next two columns contain results for the discrete measure of SNAP participation. For both variables, we use the purchasing power of maximum allotment as the instrument. The first stage is calculated for full sample (Panel A) as well as separately for women and men (Panel B, C, respectively). We use MEPS sampling weights, and the standard errors are derived from 300 bootstrap replications that are clustered at the market-level. The F- statistic of IV indicate that the instrument (the purchasing power of maximum

[14] The industry indicators include: 1. natural resources/mining/construction/manufacturing; 2. wholesale and retail trade/transportation and utilities; 3. professional and business services/education, health, and social services; 4. other services/public administration/military/unclassifiable industry.

allotment) is a significant predictor of both discrete measure of SNAP participation, and SNAP benefit level in all three samples. However, the subgroup analysis by gender reveals that this correlation is only powerful by conventional standards the sample of women. The instrument is statistically significant for both samples, but the point estimate of the coefficient is twice as large for women. Moreover, only for women the F-statistic associated with the excluded instrument exceed 10, the conventional minimum standard for the power of a continuous instrument (Stock et al., 2002). Specifically, the F-statistic for women only sample, after controlling for market group and year fixed effects is 46.6 for continuous measure and 37.7 for discrete measure.

In Table 3, we report the marginal effects from our IV model (second column), as well as results from univariate probit model that does not account for the endogeneity of SNAP participation (first column) for comparison purpose. The first 3 columns presents results from continuous measure of SNAP benefit level and the next 3 columns our results for discrete measure of SNAP participation.[15] We continue to present results for the pooled sample, as well as split sample. The marginal effect from non-IV model implies that 100% increase in the amount of benefit is associated with a 1.7 percentage points, (2.9%) reduction in the probability of employment. In contrast, after controlling for the endogeneity of SNAP benefit, we find that doubling the benefit results in a 2.7 percentage points (4.5%) increase in the probability of employment in the pooled sample. The downward bias on the effect of SNAP in the non-IV model is consistent with a negative correlation between lower SES and employment, and a positive correlation between the lower SES and SNAP participation.

[15] The supplementary appendix contains IV results using raw food price in the instrument.

There is a noticeable difference between the labor market effects of SNAP for men and women. Doubling the SNAP benefit increases the probability of employment by 3.3 percentage points (5.8%) for women, but the effect is not statistically different from zero in the sample of men. We find similar results when we estimate the treatment effects. As expected, our estimates from discrete measure of SNAP participation are less precisely estimated, but our qualitative conclusions hold.

Table 4 contains marginal effects of SNAP benefit on weekly work hours using the conditional sample.[16] We report our results for the SNAP treatment effect in Appendix, Table A2. The non-IV results imply that a 100% increase in SNAP benefit amounts reduces the probability of working full time by 0.5 percentage points. These results are completely reversed in sign when the endogeneity of SNAP is taken into account. The marginal effects from IV models for part-time versus full-time employment imply that 100% change in SNAP benefit increases the incentive to work full time by 2.9 percentage points. As in the pooled sample, we find that additional SNAP benefits increase the likelihood of full-time employment when we estimate separate models for men and women.

Table 5 reports the marginal effects of SNAP on employment using the sample of SNAP participants. As expected, 100% additional benefit increases the likelihood of employment by 15 percentage points for SNAP adults. Likewise, we find that increased purchasing power of SNAP significantly raises the likelihood of employment (table 6). These results provide the direct evidence on how variation in the real value of SNAP benefits affects employment decisions.

[16] Employed individuals who had missing hours were dropped from the conditional sample. Those who reported working more than 120 hours per week were also excluded due to concerns over reporting error.

4.1. Robustness Checks

We conduct several robustness checks of our main results. First, we re-estimate all of our models after excluding ABAWDs. These individuals face stricter work requirements and time limitations as a qualification for receiving assistance. When we exclude ABAWDs from the sample, we find similar results. This suggests that our results are not driven by this sub-population.

In order for this model to generate consistent estimates of the impact of SNAP participation and employment outcomes, the instrument must be excludable. However, the exogeneity of instruments is difficult to validate. In order to see whether our estimates are robust to different plausible instruments, we use another source of identification. State-level variables from the SNAP policy database have been widely used in the literature as instruments for SNAP participation (See, for example, Meyerhoefer and Pylypchuk 2008, Yen et al. 2008, Ratcliffe et al. 2011, Gregory and Deb 2015, Almada, McCarthy and Tchernis 2016). We use simplified reporting requirements as the excluded instrument in the regressions. The 2002 Farm Bill gave states the discretion to extend simplified reporting requirements to households with non-earned income, referred to as expanded simplified reporting. Many states also lengthened reporting intervals to 4, 5 or 6 months for 12 month certification periods. We only distinguish between states that adopted any form of simplified reporting and those that did not. Tables 7 shows the marginal effects of SNAP on the probability of SNAP participation for both discrete and continuous specifications. Under simplified reporting, SNAP households must only report income changes that occur during the reporting period if they result in total countable income rising above 130 percent of the poverty level. The F-statistic of IV indicate that simple reporting

requirements are a highly significant and substantial predictor of SNAP participation measures. These suggest that SNAP participation increases work incentive.

5. Potential Mechanism

Our results suggest that participation in SNAP leads to higher rates of employment and more working hours. Two potential explanations for this result are work requirements linked to the SNAP and the ability to pay for job-related expenses. Major categories of such expenses include transportation and child care. The high cost of child care can be an impediment to taking a job among low income households with children. Since SNAP participation frees up income for nonfood expenditures, participant households may face fewer challenges in terms of arranging safe and reliable child care. According to the U.S. Census Bureau, the percentage of income that poor families with employed mothers spend on child care is four times more than that of other working parents. While child care subsidies help defray these costs for some low-income families, only a small proportion of eligible families receive them. To help buffer the impact that out-of-pocket child care expenses can have on family food budgets, Congress in 1980 created a separate SNAP deduction for dependent care expenses. This allows SNAP recipients to deduct dependent care expenses required for work from income when calculating SNAP benefits. The deduction allows for both licensed child care as well as informal or alternative types of care as long as another member of the food stamp household does not provide it. Similarly, household members caring for elderly or disabled adults who are financially dependent upon the household member even if they live in the same household may also be eligible for the dependent care deduction. While any household with out-of-pocket dependent care expenses is eligible for the deduction, the group most likely to claim it is single-parent households with children where the parent is employed.

We use data from Early Childhood Longitudinal Study, Kindergarten Class (ECLS-K) to empirically examine whether children in SNAP households are more likely to receive care from non-parental sources. The ECLS-K is a nationally representative survey of children entering kindergarten in the 1998–1999 school year conducted by the National Center for Educational Statistics of the U.S. Department of Education (Institute of Education Sciences, 2009). The data were collected on children entering full-day and part-day kindergarten in either a public or private school. The ECLS-K collected information from children, their parents, teachers and their schools, using a variety of methods. Parents were surveyed by a trained interviewer over the phone, and teachers and school administrators completed paper and pencil surveys.

Data were collected during the fall and spring of kindergarten (1998–1999), fall and spring of first grade (1999–2000), the spring of third grade (2002), the spring of fifth grade (2004), and the spring of eighth grade (2007), but not all of those waves are useful for this analysis. We include the fall kindergarten, the spring 1st, 3rd, and 5th grades, because information on child care arrangements are recorded only for these four waves. The spring kindergarten wave does not include information on child care, so we use that wave only to extract certain time-invariant characteristics of children, such as their race and ethnicity

Parents in the ECLS-K are interviewed about their participation in SNAP, and the data also contain various measures of child care. These include a binary measure indicating whether the child receives care from a child care center or from a non-parental arrangement, current relative, or non-relative. We use these four measures and estimate a recursive bivariate probit model to determine whether SNAP households are more likely to utilize non-parental child care services. The first equation in the model predicts SNAP participation and the second equation predicts whether the child receives any non-parental care. The instrument we use to identify

SNAP participation is a variable that indicates whether the SNAP recipient's state of residence expands categorical eligibility rules, also known as broad-based categorical eligibility (BBCE).[17] Under BBCE, states can opt to set a gross income limit higher than the SNAP Federal limit and waive, or relax, the SNAP Federal asset test. The set of control variables includes: child age, gender, race/ethnicity (White, Black, Hispanic, and Other), population density of residence (urban, suburban, and rural), number of household members under age 18, the age of parents (if they live in the household), the log of total family income normalized by the square root of household size, and the years of education of the most educated parent.

Results for this model are reported in Table 8. We do not find any statistically significant impact of SNAP participation on relative care or child care center, but we do find that children in SNAP households are 4.3 percentage points more likely to receive care from informal arrangements. Informal care refers to minimally regulated care provided by neighbor or extended family member looking after a child outside school hours. Importantly, this type of child care qualifies for the SNAP dependent care deduction.

6. Conclusion

In this article, we present evidence on the work incentive effects of SNAP participation, the largest transfer program in the U.S. safety net. This paper makes an important contribution to the literature on work incentives of social welfare programs. In order to identify the employment effects of the SNAP, we use a quasi-experimental research design. Contrary to the perception that SNAP significantly reduces incentives to work, we find that SNAP increases the likelihood of employment among low income households. In addition, we find that SNAP

[17] When we use ECLS_K data, we are not able to use the purchasing power of maximum allotment as an instrument for SNAP enrollment, since the ECLS_K data does not contain information on the county of residence.

increases the probability of working full time. It is likely that higher labor supply among SNAP households is driven by work requirements imposed in SNAP and the ability to afford job related expenses such as child care. Our subgroup analyses indicate that the effects of SNAP on employment are concentrated among women, which is consistent with the importance of SNAP to child care affordability. We test this hypothesis using ECLS-K data, and find that SNAP households are more likely to use informal child care than non-participating SNAP eligible households.

We believe that our study has important implications for public policies. First, we provide foundational analysis necessary to understand how low paid workers react to SNAP participation, and insight into how states can structure the design of policies that address the negative consequences of SNAP participation. Second, these findings are relevant to recent policy debates discussing making work requirement a condition of Medicaid eligibility, and serve as a test of whether work regulations are fulfilling their purpose.[18] In addition, our study provides insight into how states can structure their policies and procedures to ensure that eligible households better manage the high costs of dependent care. For many years, the dependent care deduction was capped at $175 per month per dependent ($200 per child), well below the out-of-pocket costs that many low-income families must pay for care. The farm bill, which went into effect October 1, 2008, allows households to deduct the full amount of eligible dependent care costs incurred. This, in turn, enables households whose dependent care expenses exceed the former caps to receive larger SNAP benefits. Our results suggest that deductions for dependent care can be an effective way to boost labor force participation and hours worked among low-paid workers.

[18] Available at https://www.wsj.com/articles/after-linking-work-to-food-stamps-maine-seeks-same-with-medicaid-1492162202.

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Table 1) Descriptive Statistics by SNAP participation status

	Non-SNAP		SNAP	
	Mean	Std. dev.	Mean	Std. dev.
Age 18-29	0.282	0.004	0.357	0.006
Age 30-39	0.175	0.003	0.250	0.006
Age 40-50	0.212	0.004	0.220	0.005
Age 51-64	0.329	0.003	0.173	0.006
White	0.625	0.009	0.440	0.015
Hispanic	0.185	0.008	0.214	0.016
Black	0.139	0.006	0.304	0.015
Other race	0.051	0.003	0.042	0.005
Married	0.519	0.006	0.288	0.011
Number of children under 5	0.212	0.006	0.623	0.019
Number of children 6-17	0.482	0.011	1.084	0.026
HH size	2.586	0.020	3.494	0.049
Any senior member	0.197	0.004	0.104	0.004
Any disabled member	0.102	0.003	0.201	0.006
North east	.0165	0.007	0.175	0.011
Midwest	0.205	0.008	0.220	0.012
South	0.393	0.011	0.396	0.016
West	0.236	0.010	0.208	0.015
Urban	0.804	0.009	0.767	0.014
Female	0.523	0.003	0.636	0.006
Less than High School	0.241	0.004	0.469	0.008
High School	0.321	0.005	0.354	0.007
Some college or above	0.430	0.007	0.166	0.006
Missing education	0.008	0.001	0.011	0.002
Ln(income earned by other members/ sqrt(size))	6.650	0.048	4.431	0.072
Good MH all rounds	0.385	0.004	0.378	0.007
Excellent MH all rounds	0.235	0.004	0.145	0.005
Poor/ fair MH	0.127	0.003	0.277	0.007
Excellent MH all rounds	0.488	0.005	0.358	0.007
Poor health all rounds	0.097	0.002	0.221	0.006
Poor health some rounds	0.214	0.004	0.407	0.007
Excellent health some rounds	0.342	0.004	0.227	0.005
Excellent health all rounds	0.140	0.003	0.081	0.004
Good health all rounds	0.444	0.004	0.374	0.006
Any disability	0.055	0.002	0.125	0.005
State level per capita income/100	36.294	0.186	35.433	0.213
State level poverty rate	12.950	0.097	13.514	0.114
State level bachelor attainment	26.656	0.156	26.050	0.162
State level housing price	1.647	0.010	1.534	0.008
Price parity index	99.681	0.284	98.604	0.319
Consumer price index	196.273	0.307	196.523	0.555
Max allotment/TFP	1.841	0.013	2.437	0.031

Note: Means are weighted to be nationally representative.

Table 2) Linear First-Stage among SNAP-Eligible Adults

	(1)		(2)		
	Coefficient	F-statistic	Coefficient	F-statistic	observations
Panel A: Full-sample	1.376***	27.77	0.211***	25.20	62,065
	(0.261)		(0.042)		
Panel B: Women only	1.630***	46.65	0.242***	37.70	36,180
	(0.239)		(0.039)		
Panel C: Men only	0.901***	7.02	0.141**	6.81	25,885
	(0.340)		(0.054)		

(1) The outcome variable is the log of SNAP benefit
(2) The outcome variable is SNAP participation status.

Note: Standard errors in parentheses. Bootstrap standard errors based on 300 iterations are corrected for clustering at the market group level.
Significance level: ***p < 0.01. **p < 0.05. *p < 0.1.

Table 3) Marginal Effects of SNAP on Employment among SNAP-Eligible Adults

	(1)			(2)		
	Non-IV	IV	Mean dep.	Non-IV	IV	Mean dep.
Panel A: Full-sample	-0.017***	0.027***	0.589	-0.106***	0.038***	0.589
	(0.001)	(0.004)		(0.008)	(0.007)	
Panel B: Women only	-0.018***	0.033***	0.565	-0.116***	0.055***	0.565
	(0.001)	(0.005)		(0.009)	(0.007)	
Panel C: Men only	-0.017***	0.010	0.618	-0.107***	-0.003	0.618
	(0.002)	(0.009)		(0.013)	(0.012)	

(1) The endogenous variable is the log of SNAP benefit
(2) The endogenous variable is SNAP participation status.

Note: Standard errors in parentheses are adjusted for the complex design of the MEPS for the non-IV models. For IV models, bootstrap standard errors based on 300 iterations are corrected for clustering at the market group level. Significance level: ***p < 0.01. **p < 0.05. *p < 0.1.

Table 4) Marginal Effects of Log of SNAP Benefit on Working Hours (Sample of Working Adults)

	hour<30	(hour<40 & hour>=30)	hour>=40
Panel A: non-IV (continuous)			
Full-sample	0.004***	0.001***	-0.005***
	(0.001)	(<0.001)	(0.001)
Women	0.006***	0.001	-0.007***
	(0.001)	(<0.001)	(0.002)
Men	0.004***	0.002***	-0.006***
	(0.001)	(<0.001)	(0.002)
Panel B: IV			
Full sample	-0.022***	-0.007***	0.029***
	(0.003)	(0.001)	(0.004)
Women	-0.025***	-0.005***	0.030***
	(0.004)	(0.001)	(0.005)
Men	- 0.014***	-0.006***	0.020***
	(0.004)	(0.002)	(0.005)

Note: Standard errors in parentheses are adjusted for the complex design of the MEPS for the non-IV models. For IV models, bootstrap standard errors based on 300 iterations are corrected for clustering at the market group level. Significance level: ***p < 0.01. **p < 0.05. *p < 0.1.

Table 5) Marginal Effects of the Log of SNAP Benefit on Employment among SNAP Participants

	Non-IV	IV	F-statistic	Mean	Observations
Panel A: Full-sample	-0.002	0.153***	22.09	0.43	22,859
	(0.006)	(0.044)			
Panel B: Women only	-0.006	0.137***	33.52	0.42	14,839
	(0.007)	(0.053)			
Panel C: Men only	0.001	0.049	9.55	0.45	8,020
	(0.008)	(0.178)			

Note: Standard errors in parentheses are adjusted for the complex design of the MEPS for the non-IV models. For IV models, bootstrap standard errors based on 300 iterations are corrected for clustering at the market group level. Significance level: ***p < 0.01. **p < 0.05. *p < 0.1.

Table 6) Marginal Effects of Variation in SNAP Purchasing Power on Employment among SNAP Participants

		Observations
Panel A: Full-sample	0.098**	22,859
	(0.036)	
Panel B: Women only	0.112***	14,839
	(0.039)	
Panel C: Men only	0.020	8,020
	(0.066)	

Note: Bootstrap standard errors in parentheses based on 300 iterations are corrected for clustering at the market group level.
Significance level: ***p < 0.01. **p < 0.05. *p < 0.1.

Table 7) Marginal Effects of SNAP on Employment Instrumented with Simplified Reporting

	(1)	(2)	F-statistic	Observations
Panel A: Full-sample	0.034***	0.060***	21.34	88,214
	(0.004)	(0.008)		
Panel B: Women only	0.040***	0.081***	19.3	51,614
	(0.003)	(0.006)		
Panel C: Men only	0.019**	0.010	25.70	36,600
	(0.008)	(0.012)		

(1) The endogenous variable is the log of SNAP benefit
(2) The endogenous variable is SNAP participation status.

Note: Standard errors in parentheses are corrected for clustering at the state level.
Significance level: ***p < 0.01. **p < 0.05. *p < 0.1.

Table 8) Marginal Effect of SNAP Participation on the Use of Non-parental Child Care

	non-parental care	Formal care	Informal care	Relatives
Panel A: non-IV	-0.041*	-0.005	0.012	-0.042*
	(0.023)	(0.015)	(0.011)	(0.023)
Panel B: IV	-0.082	-0.043	0.039*	-0.016
	(0.122)	(0.042)	(0.020)	(0.073)
Observations	6459	6459	6459	6459

Note: Standard errors for IV models are corrected for clustering at the state level.
Significance level: ***p < 0.01. **p < 0.05. *p < 0.1.

Appendix

Table A1) First Difference Estimate of Purchasing Power of SNAP Benefit on Employment Status among Continuously Participant Adults

	Allotment/TFP
Full-sample	-0.084
	(0.057)
Women only	-0.130
	(0.078)
Men only	<-0.001
	(0.079)

Note: Standard errors are corrected for clustering at the market group level.
Significance level: ***p < 0.01. **p < 0.05. *p < 0.1.

Table A2) Marginal Effects of SNAP on Employment among SNAP Eligible Sample Using Raw Food Price

	(1)			(2)		
	Non-IV	IV	Mean	Non-IV	IV	Mean
Panel A: Full-sample	-0.017***	0.023***	0.589	-0.106***	0.028***	0.589
	(0.001)	(0.004)		(0.008)	(0.008)	
Panel B: Women only	-0.018***	0.031***	0.565	-0.116***	0.050***	0.565
	(0.001)	(0.005)		(0.009)	(0.009)	
Panel C: Men only	-0.017***	0.001	0.618	-0.107***	-0.005	0.618
	(0.002)	(0.009)		(0.013)	(0.012)	

(1) The endogenous variable is the log of SNAP benefit
(2) The endogenous variable is SNAP participation status.

Note: Standard errors are corrected for clustering at the market group level.
Significance level: ***p < 0.01. **p < 0.05. *p < 0.1.

Table A3) Marginal Effects of SNAP Participation on Work Hours (Conditional Sample)

	hour<30	(hour<40 & hour>=30)	hour>=40
Panel A: non-IV (discrete)			
Full-sample	0.051***	0.013***	-0.064***
	(0.008)	(0.002)	(0.009)
Women	0.067***	0.010***	-0.077***
	(0.011)	(0.001)	(0.012)
Men	0.050***	0.017***	-0.067***
	(0.010)	(0.003)	(0.013)
Panel B: IV (discrete)			
Full sample	-0.171***	-0.049***	0.220***
	(0.022)	(0.006)	(0.028)
Women	-0.186***	-0.036***	0.223***
	(0.025)	(0.004)	(0.029)
Men	- 0.116***	-0.046***	0.161***
	(0.034)	(0.011)	(0.045)

Note: Standard errors are corrected for clustering at the market group level.
Significance level: ***p < 0.01. **p < 0.05. *p < 0.1.