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The Supplemental Nutrition Assistance Program and Childcare

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THE SUPPLEMENTAL NUTRITION ASSISTANCE PROGRAM AND CHILDCARE

BY

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This thesis is approved as a creditable and independent investigation by a candidate for the Master of Science in Economics degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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This thesis is dedicated to those individuals who helped me put a staple in this paper, in word or in deed.

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CONTENTS

ABBREVIATIONS

SNAP	Supplemental Nutrition Assistance Program
ARRA	American Recovery and Reinvestment Act of 2009
ATUS	American Time Use Survey
CPS	Current Population Survey
FFS	Food Security Supplement
FSP	Food Stamp Program
WIC	Women Infants and Children
CPI	Consumer Price Index
OLS	Ordinary Least Square
2SLS	Two-Stage Least Square

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ABSTRACT

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This paper attempts to analyze the effects of subsidized food dollars on the amount of daily childcare in households. More specifically, households in the low income category are of interest because they are the most likely to receive food subsidies. There has been a political debate recently in the United States which argues over the appropriate level of subsidies, if any. More importantly, food insecurity is an issue in the world; many do not know where will the next meal come from. This paper provides statistical evidence that food subsidies in the form of the Supplemental Nutrition Assistance Program (SNAP) have a positive effect on the amount of childcare in which enrolled households engage. Childcare is measured in minutes per day, and SNAP assistance is measured in dollar assistance. These effects are analyzed both before and after the increases to SNAP benefits provided by the American Recovery and Reinvestment Act of 2009 (ARRA). Through the review of related literature, this paper will show that authors in the discipline that have done studies related to food economics and childcare argue that children who receive more childcare are better off later in their lives. Also, other authors show that SNAP enrollment can decrease food insecurity.

Statistical analysis in this paper is done using combined datasets from the Current Population Survey and the American Time Use Survey and the STATA© statistical package. Regression analysis and statistical hypothesis tests are the main tools for

determining statistical significance. Models reported are an ordinary least square model and a two-stage least square model. Both are included in this paper because the statistical tests for endogeneity of the of the main explanatory variable do not provide evidence to support which model is more appropriate for the approximation of the partial effect of SNAP on childcare.

The main conclusion found from these statistical tests is that childcare is positively affected at the household level by subsidized food dollars from SNAP. An implication is that increasing the magnitude of food subsidies in other forms may also have a positive impact on childcare at the household level. Future studies ought to examine the effects of other food subsidies in order to determine their viability in aiding with time households can spend in childcare.

INTRODUCTION

A current worldwide economic issue is food insecurity where households wonder where their next meal will come from. In order to counteract food insecurity, the United States government has enacted several food subsidy programs. The question for economists is whether those food subsidies actually combat food insecurity and the residual effects that occur inside a household. One of the negative externalities of food insecurity is a decrease in the quantity of daily childcare that households can engage in. This phenomenon occurs for several reasons as household adults make economic decisions to reduce food insecurity that may crowd out time spent in daily childcare. Food subsidies aim to reduce food insecurity, and one of the outcomes to households could be an increased magnitude of average daily childcare by household adults. This paper examines the specific economic question whether food subsidies increase the time that households engage in daily childcare.

Through the course of the literature review, this paper will provide evidence that there are many positive aspects from children receiving more childcare in the household. However, most of these aspects are intangible and difficult to measure. It should not be trivialized that time spent in childcare provides intangible benefits. The results of this paper may provide evidence that food subsidies could be further pursued by policy makers to allow more households to experience the positive externalities.

The new knowledge derived from this study could be used to further examine the effects of food subsidies in the short run and restructure government budgets for a greater number of households to be better off in the long run. The contribution to the economic knowledge stock can also be applied to other types of subsidies. Government agencies engage in subsidies beyond food, and this paper may provide a starting point for which to examine how subsidies can have positive effects outside their intended goals.

BACKGROUND

Households are restricted several ways when it comes to eligibility including their resources, income, allowable deductions, and employment. SNAP defines a household as everyone who lives together and purchases and prepares meals together. These rules are either adjusted or ignored when the application includes a household member that is elderly or disabled. As far as SNAP is concerned, an elderly person is any person 60 years of age or older. A disability is more difficult to determine so there is a set of considerations by SNAP to decide if a person is disabled. A person is considered disabled if they:

- Receive federal disability or blindness payments under the Social Security Act
- Receive state disability or blindness payments
- Receives a disability retirement benefit from a governmental agency because of a permanent disability under the Social Security Act
- Receives an annuity under the Railroad Retirement Act and is eligible for Medicare
- Are a veteran who is totally disabled, permanently housebound, or in need of regular aid
- Are a surviving spouse or child of a veteran who is receiving VA benefits and is considered to be permanently disabled

There are upper limits on the amount of a household's resources. There are some exceptions and exclusions to resources. The more exclusions, the more likely a household qualifies for SNAP. A household may have up to $2,250 in deposits or cash, called countable resources. This is increased to $3,250 if the household has at least one person older than 60 years old or disabled. Certain resources are not counted, such as the value of the house or a lot. Also, resources of people who receive Temporary Assistance for Needy Families and pension plans are non-countable. Assets such as vehicles in possession are handled on a state-by-state basis. In some states, the value of the household's primary vehicle is excluded from assets. In other states, the market value of all household vehicles are considered as non-excludable. A third way states handle vehicles is the total exclusion of their value from household resources. The remaining states exempt household vehicles with higher values than the SNAP standard of $4,650 from the fair market value to determine the countable resource value of the vehicle.

Perhaps the most important stipulation in determining eligibility for SNAP benefits in this paper is household income. Table 1 lists the allowable household income based on the number of people living in the household at the time of SNAP registration.

Table 1. SNAP Income Qualifications.

Household Size	Gross monthly income (130 percent of poverty)	Net monthly income (100 percent of poverty)
1	$1,276	$981
2	$1,726	$1,328
3	$2,177	$1,675
4	$2,628	$2,021
5	$3,078	$2,368
6	$3,529	$2,715
7	$3,980	$3,061
8	$4,430	$3,408
Each additional member	$451	$347

In order to receive SNAP benefits, a household's income must not exceed the values in Table 1. These income requirements are from October of 2015 and are valid through September of 2016. Households must meet these requirements unless all members in the household are receiving Temporary Assistance for Needy Families, Supplemental Security Income, or any general subsidized assistance in some states.

Gross income is a household's total income and non-excluded income before any allowable deductions. Net income in the gross income less the allowable deductions. A special note, the net income limits are higher in Alaska and Hawaii, but the Continental United States, the District of Columbia, and all territories follow the above guidelines for income. Most households need to meet both the net and gross income requirements to qualify, but households with at least one elderly person or at least one person who is receiving some types of disability payments needs only to meet the net income requirements. There are several deductions to income that are allowed by SNAP:

- A 20% deduction from earned income
- A standard deduction of $155 for households with three or less people
- A standard deduction of $168 for households with four or more people
- A dependent care deduction when needed for work, training, or education
- Medical expenses for elderly or disabled household members that are more than $35 for the month if they are not paid by insurance or some other benefactor
- Legally owed and outstanding child support payments
- Some states allow homeless households the amount of $143 for shelter costs
- Excess shelter costs that are more than half of the household's income after the other deductions

- Allowable costs include the cost of fuel to heat and cook, electricity, water, fees for basic telephone, rent/mortgage payments, and taxed on the home
- Shelter deductions cannot exceed $504 unless one person in the household is elderly or disabled

Once a household is determined to be SNAP eligible, there are caps to the amount of benefits a household may receive. The benefits received by households are referred to as allotments and apply to when the household applies for SNAP. The net monthly income of the household is multiplied by .3 and the product is subtracted from the maximum allotment for the household size to find the household's allotment. The 30% is assumed to be the amount that households will allocate toward food from their own income. Again, the following table has values which are applicable to the contiguous states, the District of Columbia, and territories held by the United States and are current through September of 2016:

Table 2. SNAP Monthly Allotments.

People in Household	Maximum Monthly Allotment
1	$ 194
2	$ 357
3	$ 511
4	$ 649
5	$ 771
6	$ 925
7	$ 1,022
8	$1,169
Each additional person	$ 146

Employment requirements also apply to receiving SNAP benefits. These requirements include registering for work, not voluntarily quitting a job or asking for a reduction of hours, not voluntarily rejecting a job when offered, and participation in employment and training programs to be determined at the state level. Omission of any of these requirements can result in disqualification from SNAP. Also, nondisabled adults without dependents are required to work or be part of a work program for a minimum of 20 hours per week for more than three months in a continuous 36-month period. Table 3 contains the average enrollment, average benefit per person per day in dollars, and the magnitude of aggregate funds dedicated to SNAP:

Table 3. SNAP Figures for Select Years.

Supplemental Nutrition Assistance Program Participation and Costs					
(Data as of March 4, 2016)					
Fiscal Year	Average Participation	Average Benefit Per Person	Total Benefits	All Other Costs	Total Costs
	Thousands	Dollars Per Day	Millions ($)		
2005	25,628	3.10	28,567.88	2,504.13	31,072.01
2006	26,549	3.16	30,187.35	2,715.72	32,903.06
2007	26,316	3.21	30,373.27	2,800.25	33,173.52
2008	28,223	3.41	34,608.40	3,031.25	37,639.64
2009	33,490	4.18	50,359.92	3,260.00	53,619.92
2010	40,302	4.46	64,702.16	3,581.30	68,283.47
2011	44,709	4.46	71,810.92	3,875.56	75,686.49
2012	46,609	4.45	74,619.34	3,790.34	78,409.68
2013	47,636	4.44	76,066.32	3,806.01	79,872.32
2014	46,664	4.17	69,998.84	4,182.82	74,181.66
2015	45,767	4.23	69,655.43	4,326.81	73,982.24

The American Recovery and Reinvestment Act of 2009 contains several governmental budget changes and resource allocations. One such change is the increase of monthly benefit levels of SNAP by an average of 15% and easing the constraints on SNAP eligibility for unemployed adults without children. Its intention is to decrease food insecurity through the SNAP channel and to provide jobs to those who were searching but still unemployed. Through these two intermediate targets, the long-run aim is to boost purchasing power of recipients of SNAP and thus stimulate the economy with their added capacity to engage in market transactions. Originally, SNAP was set to receive $20 billion over the five years following 2009. ARRA also allocated $300 million to states in order to aid with the administrative costs of SNAP for the fiscal year following 2009. There are several other provisions of ARRA:

- Increasing the Thrifty Food Plan and maximum monthly allotments by an average of 13.6%
- Increase the minimum monthly benefit from $14 to $16
- Eliminated the three month per three year time limit set on SNAP benefits for adults who had no children and did not have a disability
    - Still required to comply with the State Employment and Training Programs
- Increasing state administrative funding for SNAP operations by $145 million in 2009 and $150 million in 2010

The reasoning behind increasing SNAP benefits as part of ARRA is that SNAP benefits are liquid and are therefore quickly injected back into the economy through market transactions. These purchases would not be possible without receiving SNAP benefits that ease the household budget constraint of SNAP recipients, meaning that these households have more disposable income with which to engage in market activity.

However, due to legislation since 2009, the $20 million increase in SNAP from ARRA has been diminished. The Health, Hunger-Free Kids Act of 2010 reauthorized the United States Department of Agriculture's child nutrition programs and shorted the end date for ARRA to increase SNAP benefits from 2019 back to 2013. In addition, funding allocated for Medicaid, education, and jobs crowded out ARRA increases to SNAP monthly benefits as of 2014. The effects of ARRA on SNAP are seen in Table 4.

Table 4. ARRA Increase to SNAP per Day.

ARRA Household Increase to SNAP	
Household size	Daily Increase
1	$0.80
2	$1.47
3	$2.10
4	$2.67
5	$3.17
6	$3.80
7	$4.20
8	$4.80
9+	$0.60/person

LITERATURE REVIEW

Berger and Black (1992) examine the effects of childcare subsidies on the decisions of low-income mothers and on the quality of care that children in these situations receive. These authors use survey data from families living in Kentucky that were enrolled in Louisville's 4C (Community Coordinated Childcare) and Kentucky's Title XX Purchase of Care subsidy programs. Louisville's 4C program includes female-led households with income not more than 80% of the state median family income at the time of the study. Title XX is limited to an even smaller subset of low-income female-led households including only households with incomes not more than 60% of the state median family income at the time of the study. The authors selected these two programs because of the stratification in percentages of state median income to allow for analysis across income levels even in low-income households and because of the many similarities the two programs have in terms of qualifications and requirements. The authors are interested in the requirement that children must be placed in licensed day care centers, which must satisfy Kentucky standards for safety and health. The authors obtained their data through phone interviews administered to groups of recipients, or potential recipients on waiting lists for either subsidy program in the summer of 1989.

To analyze the impact of the subsidy on single mothers' labor supply decisions, the authors employ multiple regression analysis using the same right-hand-side variables to attempt to explain hours worked and employment:

$$
\begin{aligned}
&hours\ worked \\
&\quad = \beta_0 + \beta_1 mother\ is\ black + \beta_2 mother's\ age \\
&\quad + \beta_3 age\ of\ youngest\ child + \beta_4 mother'schooling \\
&\quad + \beta_5 mother\ lives\ in\ an\ urban\ area + \beta_6 number\ of\ children \\
&\quad + \beta_7 receiving\ a\ subsidy + \beta_8 \log(wage) + \varepsilon
\end{aligned}
$$

$$
\begin{aligned}
&employment\ status \\
&\quad = \beta_0 + \beta_1 mother\ is\ black + \beta_2 mother'sage \\
&\quad + \beta_3 age\ of\ youngest\ child + \beta_4 mother'schooling \\
&\quad + \beta_5 mother\ lives\ in\ an\ urban\ area + \beta_6 number\ of\ children \\
&\quad + \beta_7 receiving\ a\ subsidy + \beta_8 \log(wage) + \varepsilon
\end{aligned}
$$

Berger and Black (1992) conclude from surveys that those receiving either subsidy responded with higher levels of satisfaction with their childcare arrangements, as the effect of the subsidy on satisfaction was statistically significant. The authors also report statistical evidence that receiving a subsidy increases employment by 11.7% for single mothers. There is no statistical evidence to support an effect on hours worked as the result of receiving a subsidy.

Tekin (2007) examines the effects of the price of childcare and wages on part-time and full-time employment decisions of single mothers and the choice to pay for childcare by single mothers. The author notes that there is literature to support that an increase in the cost of organized childcare has a negative effect on labor participation of single mothers, but there has been no agreement in the economics discipline as to the price elasticity of childcare on employment. The author obtains data from the 1997 National Survey of America's Families (NSAF). Importantly, this survey contains information on childcare subsidies. Less vital, but still important, is the fact that these data come after large welfare reform legislation in the early and mid-1990s. To be eligible for federal childcare subsidies, the household income could not exceed 85% of the state median income for families of the same size and whose parent(s) are working. The model presented by Tekin (2007) is a single decision-maker framework where the single mother has three choices: 1) whether to work, then to work part-time or full-time, 2) whether to pay for childcare, and 3) whether to receive a childcare subsidy if they do decide to pay for childcare. The mother's indirect utility function is expressed:

$$V_i = \boldsymbol{X}\beta_i + \alpha_{Pi}P_s^* + \alpha_{PTi}W_{PT} + \alpha_{FTi}W_{FT} + \varepsilon_i, \quad i = 1, \ldots, J$$

where W represents the wage rates for part-time and full-time employment, P^* is the hourly price of childcare in market s, $\boldsymbol{X}$ is the vector of preferences that do not vary across alternatives, and β's and α's are the parameters to be estimated by regression analysis. This model demonstrates how a single mother will respond to the three decision criteria presented. From this framework, Tekin (2007) determines that a higher price of childcare reduces utility to the mother, a higher part-time wage increases utility to the mother if she works part-time, a higher full-time wage increases utility to the mother if she works full-time, and a higher childcare subsidy increases utility to the mother when she chooses to receive a subsidy. The author notes that using state dummy variables as identifying instruments in either wages or in childcare costs would be invalid if location affects preferences, and therefore decision-making, of single mothers. However, there are no alternatives that are theoretically justified in order to estimate the equation parameters.

Tekin (2007) concludes that there is statistical evidence to support the claim that increasing childcare subsidy dollars increases the employment participation of single mothers in both part-time and full-time categories. The author notes that these results do not provide information about the relative cost-effectiveness of childcare subsidies and do not answer the question of which subsidy would lead to the greatest amount of labor force participation by single mothers. One main conclusion from this paper is that, even though both categorical estimates are statistically significant, single mothers working full-time are more sensitive to wage increases than part-time working single mothers. Another conclusion is that subsidies related to childcare are likely to have a greater impact on labor force participation by single mothers than wage subsidies for respective subsets. The childcare price elasticity on employment found in this paper is smaller than that of similar studies done previously, namely Blau and Hagy (1998), Michalogoulos and Robins (2000), and Blau and Robins (1998).

Gustafsson and Stafford (1992) attempt to demonstrate the effects of specific childcare arrangement decisions made by parents on the well-being of children. These authors argue that this relationship cannot be properly analyzed in the United States because the number, type, quality, and diversity of childcare arrangements makes patterns unmeasurable because to do so would require scalar weights to deflate and decompose the heterogeneity of different childcare options. To get around these data issues, the authors analyze data from Sweden. Sweden has a homogeneous childcare system because of national standards for operation. The authors argue that Sweden’s childcare market provides better inferences about the effects of childcare options and well-being because of the homogeneity of the arrangements. Sweden also provides a unique opportunity to study price variation as the price for homogenous childcare differs across regions.

The authors use data collected in a national survey for 1984 from the National Central Bureau of Statistics combined with municipality data on childcare fees for the same year published by Svenska Kommunförbundet. There model is as follows:

$$U = U(Child\ well - being, Standard\ of\ living)$$

Child well-being is specified as a function of time spent in childcare by parents and money spent on household goods for the benefit of household children. The standard of living is defined as a function of money spent on goods other than for the benefit of household children. The authors note that subsidies lead to increased use of childcare outside the home and increased market participation of parents. However, the loss of in-home child well-being need not mean the loss of child well-being altogether. That is to say, the well-being gained from using out-of-home childcare may be greater in magnitude than well-being lost from in-home childcare.

Gustafsson and Stafford (1992) conclude that price responsiveness to using the childcare structure in Sweden allows for analysis to demonstrate the extent to which subsidies in a particular municipality influences participation in these markets. They also conclude that the net impact on the labor supply is close to zero because much of the response to subsidies comes from the substitution effect of public for private childcare, as subsidies in public childcare increases. The authors note that their analysis is limited due to diversity of family situations not including wage, income, and subsidy rate for a particular municipality. These differences lead to out-of-home childcare decisions that are attributed to lurking variables or irrational decision-making in choosing childcare.

Hill and Stafford (1980) analyze parental time devoted to childcare during their preschool years to discover if differentials in social class or education of parents leads to the transmission of income disparity intertemporally. The authors argue that intergenerational wealth transfers through parental time spent on childcare that affects the particular cognitive development of children during their preschool years. The Time Use Survey is used to determine the time allocated by parents to childcare. The following is a set of equations used to determine deviations H_{it} from the mean annual hours of housework for a woman with no children:

$$H_{it} = \beta_0 + \sum \beta_n CH_{nit} + \alpha_{it}$$

$$\alpha_{it} = \Pi_1 Z_{1it} + \Pi_2 Z_{2it} + \varepsilon_{1it}$$

or simplified:

$$H_{it} = \beta_0 + \sum \beta_n CH_{nit} + \Pi_1 Z_{1it} + \varepsilon_{2it}$$

$$\varepsilon_{2it} = \Pi_2 Z_{2it} + \varepsilon_{1it}$$

The deviation from the mean number of hours spent on housework increases with the number of children in the household, CH_{it}, which is divided into age groups of the children CH_n including babies, preschoolers, grade-schoolers, and high-schoolers. Z_1 is the vector of observed variables that are known to alter the number of hours a mother spends in childcare. Z_2 is the vector of unobserved variables that alter the number of hours a mother spends in childcare.

Hill and Stafford (1980) conclude that, because there are substantial per-child differences in care across all levels of parental education and income, their results are only circumstantial in determining the lifetime achievement of children based on their care early in life. However, the authors argue that their findings suggest that more-educated parents spend more time in childcare with their children than less-educated parents. More-educated parents provide more market outputs to society and more time inputs for their children as the children develop before leaving the home. The authors suggest, though their results are only circumstantial, that this relationship may account for certain types of higher functioning later in life by the child in the labor market and interpersonal relationships. Finally, the authors conclude that equal educational opportunity could provide societal benefits in subsequent generations.

Datcher-Loury (1988) demonstrates a connection between time spent by mothers in childcare and the corresponding children's outcomes as adults. The author cites Michael (1973) that the amount of time spent in childcare increases with the financial resources available to the parents and notes that the effect of schooling in economic literature is uniformly positive. Datcher-Loury (1988) uses data from the University of Michigan Panel Study of Income Dynamics to analyze the effects of a mother's time spent in childcare on their children's years of schooling. In this framework, the child makes the decision to pursue schooling partly based on their care early in life and partly based on the magnitude of financial investment made, if any, by the parent with their perception of schooling quality. The framework assumes that the child would choose the school where the marginal cost of the investment is equal to the marginal benefit of the schooling. The dataset used provides information on annual hours of housework time spent by mothers but does not directly specify the time spent in childcare. The author uses a variant of the method used by Hill and Stafford (1980) to get at time spent in childcare. Based on this model, the author reasons that differences in the mean value of α_{it} across time includes individual-specific variations in time mothers spend in childcare. Datcher-Loury (1988) uses this metric as a proxy variable for time spent in childcare by mothers not explicitly included in the dataset and uses the following model:

$$\alpha_i = \beta_0 + \beta_1 \#Child(0-2) + \beta_2 \#Child(3-5) + \beta_3 \#Child(6-13) + \beta_4 \#Child(14-17) + \beta_5 Mother's\ schooling + \beta_6 Father's\ schooling + \beta_7 Lives\ in\ south + \beta_8 Parents\ expect\ college + \beta_9 Mother'shourly\ wage + \beta_{10} Other\ income(father's\ income\ and\ nonlabor\ income) + \beta_{11} Years\ as\ female\ head\ of\ household + \varepsilon_i$$

The author then uses the estimates for α_i as a parameter in a model to predict the years of schooling a child will have based on maternal childcare received before leaving the home.

$$Schooling_i = X_i\delta_1 + \delta_2\alpha_i + \varepsilon_{3i}$$

Schooling of a child is a function of maternal childcare estimated above and the vector X_i which includes years of both father's and mother's years of schooling, whether the father was a white collar worker during the period, mean real family income, whether the mother was less than 19 when she birthed the first child, whether the parents expected their child to attend college, number of siblings, and maternal employment. The last two variables are commonly used proxies for childcare time spent by mothers. To avoid inconsistency and bias with ordinary least square estimates, an instrumental variable approach was used in the multiple regression analysis. However, the differences in errors between OLS and IV are found to be insignificant.

Datcher-Loury (1988) concludes that maternal childcare time increases with maternal home productivity and decreases with rising opportunity costs of increasing potential wages. The author also concludes that maternal childcare time increases children's years of schooling supported by statistical evidence. This paper limits the dataset to mothers who have at least twelve years of schooling. The outcomes found in this paper may differ because of variance in maternal home productivity across educational groups. The fourth conclusion is that the existence of sibling children in the same age group or one age group older has negative effects on the years of schooling for a particular child. However, these findings are generally small and nearly statistically insignificant.

Kohler, Behrman, and Skytthe (2005) explain that both being in partnerships with a significant other and having children increases utility to the parents. To do this, the authors analyze the debate on the validity of conceptual framework that states: "Partner + Children = Happiness." This framework makes two key assumptions, the first is that agents do not have misconceptions about the impacts of partnerships and fertility on their happiness, and the second is that these agents make conscious and informed decisions when it comes to these choices. By fertility, the authors note that there is an emphasis on biological children, not those attained from adoption or any other avenue. The above simple equation is challenged on the grounds that happiness is primarily determined by genetic factors that affect personality and other predispositions. Proponents on this side of the debate, typically psychologists, argue that chance events severely affect happiness, but do not persist to affect long-run happiness. That is to say that happiness is relatively stable over an individual's lifetime, but there are deviations based on life events that affect only the short-run.

The authors of this paper control for data limitations by using a dataset from Denmark that includes monozygotic twins that were asked survey questions about their relative well-being and their socioeconomics and demographic experiences. This dataset is used to control for certain unobserved endowments and genetic predispositions that would affect happiness were the respondents genetically different. Based on this, causal interpretations can be made from the data on the relative well-being of agents based on their partnership status and if they have children.

The data used in from the Danish Twin Registry, a nationwide database established in 1954 and the first in the world. The Registry conducted a survey in 2002 on twins that were born between the years on 1931 and 1982 addressing issues of health, socioeconomic characteristics, number of biological children and age at which the parent had their first child, and partnership behaviors including the number of and age at which the respondent was married. The survey was arranged to measure subjective well-being by having the respondents rank their satisfaction with their lives from “very satisfied” to “not satisfied at all” for two different age groups, 25 to 45 and 50 to 70 years of age. The authors use these two age groups to demonstrate categories of individuals who are and are not in their childbearing years. The authors note that Scandinavian countries have decreased the importance of the distinction between marriage and cohabitation, and the twin survey treats the two relationship arrangements the same under the name “partnership” in the data.

A problem in estimating causal relationships between partnerships and fertility on happiness is that unobserved endowments may be endogenous. Using the twin dataset, the authors are able to control for the unobserved endowments using a differential approach in their regression equation from one twin to the other. The authors argue that twins share the same genetic endowments and socioeconomic upbringing that affect emotional predispositions to happiness. This way, the causal effects of differences in partnership arrangements and fertility on subjective happiness is exogenous in multiple regression analysis. The model for twin *i* in pair *j* is as follows:

$$Happiness_{ij} = \beta_0 + \beta_1 Partner_{ij} + \beta_2 Fertility_{ij} + \mu_j + \varepsilon_{ij}$$

where *Partner* refers to partnership behavior of twin i, and *Fertility* refers to fertility behavior of twin i, μ is the unobserved endowments that are common to twins in pair j, and ε is a randomly distributed variable that reflects other unobserved factors of happiness not described in the regression equation. The differential regression equation is then as follows:

$$\Delta Happiness_j = \beta_1 \Delta Partner_j + \beta_2 \Delta Fertility_j + \varepsilon_j$$

where the Δ terms are differentials in twin pair j. Without using a differential approach, the estimates of β_1 and β_2 are biased, especially in survey data.

Kohler, Behrman, and Skytthe (2005) conclude that parental happiness is influenced little by the normal variables such as income, education, and occupation. Instead, happiness seems to depend most on personality characteristics, genetic predispositions, and socioeconomic background. Partnership status is a primary aspect of subjective happiness for both men and women in both age ranges. An important finding, first-born children have a larger effect on subjective happiness of parents than subsequent children. Also, fertility does not seem to affect the happiness gained by parents from their partnership arrangement. The authors note that first-born children before the parents' age of 21 reduces subjective happiness in the long run.

Kenney (2008) demonstrates that children in households with pooled income from both a mother and a father are less likely to experience food insecurity when the finances are exclusively allocated by the mother. The author bridges a gap in the literature where the gender of the parent who controls the household finances is a determining factor of the food security of the children in that household. Data for this study comes from two components of the Fragile Families Child Wellbeing study: the Core Survey and the In-Home Survey.

Kenney (2008) answers two test questions, the first being whether children are more or less food secure when the mother controls the finances in low-income and moderate-income two-parent households in the United States. The second question is a test that measures sensitivity in a child's food security to their father's involvement in the allocation of finances. The author notes that there are two possible reasons for variations in food security based on the gender of the parent who controls the finances. The first is that opposite-gendered parents make different choices in the type of food they buy, particularly children's food. A father may be have less knowledge of what types of child-specific foods are needed to best provide nutrition to children, leading to a quality deficiency in the food that is purchased. Alternatively, fathers may simply misallocate the appropriate amount of household resources to food, leaving a quantity deficiency for the children to eat.

Multiple regression analysis is used to test the author's hypotheses that gender matters in resource allocation of household resources for food security subject to the following models:

$$\begin{aligned} &Any\ child\ food\ insecurity \\ &\quad = \beta_0 + \beta_1 \boldsymbol{Management\ of\ household\ resources} \\ &\quad + \beta_2 \boldsymbol{Household\ characteristics} + \beta_3 \boldsymbol{Mother's\ characteristics} \\ &\quad + \beta_4 \boldsymbol{Father's\ characteristics} + \varepsilon \end{aligned}$$

$$\mathit{Child\ food\ insecurity\ index} =$$

$$= \beta_0 + \beta_1 \boldsymbol{Management\ of\ household\ resources}$$
$$+ \beta_2 \boldsymbol{Household\ characteristics} + \beta_3 \boldsymbol{Mother's\ characteristics}$$
$$+ \beta_4 \boldsymbol{Father's\ characteristics} + \varepsilon$$

The author first determines the existence, if any, of food insecurity based on the first equation. Then the extent of the food insecurity is determined in the second equation using the standard USDA children's food security scale as the dependent variable, a continuous measure demonstrating the severity of food insecurity of a child. All the variable names listed in the equations above are vectors containing groupings of related variables. *Management of household resources* represents five dummy variables that determine which parent controls the household resources and the extent to which there is joint control. *Household characteristics* represents the household-poverty ratio, material hardship index, if the household is receiving WIC or food stamps, the proportion of the household income attributed to the mother, if the parents are cohabitating, the number of adults in the household, the number of children in the household, and the relationship quality index. *Mother's characteristics* represents age, race, foreign born, existence of substance abuse, and existence of a child(ren) with another partner. *Father's characteristics* represents the existence of substance abuse, existence of a child(ren) with another partner, existence of violence toward mother, and extent of involvement in childcare.

Kenney (2008) concludes that the probability of a child experiencing food insecurity is more likely in low-income and moderate-income households when the father makes allocation decisions, either in full or in part. The results of this study support with statistical evidence that children are more likely to be food secure when the mother makes resource allocation decisions autonomously from the father. In some model variants, the likelihood of food insecurity is 2.5 times as high when the father is the exclusive decision maker.

The author notes that women, particularly in the United States, are perceived as being held more accountable for food than men. This study supports this gender stereotype with statistical evidence. Mothers are more likely to spend money on food when they are making allocation decisions, leading to greater food security for the children in the household. The author expected to find that increasing the father's involvement in childcare would increase food security, but the results did not support this hypothesis. Kenney (2008) reasons that fathers often engage in childcare activities of young children to keep them out of the way of the mother while she is engaging in food preparation, meaning that gender roles in the household still point to the mother bearing most of the burden of providing food security. The author acknowledges a shortcoming in the dataset as it only includes heterosexual parents living in urban areas with at least one preschool age child that the parents care for jointly. A possible extension of this paper would be to examine particular food subsidy programs that focus on nutrition of children so that even when the father makes allocation decision, the probability of food insecurity is decreased.

Frongillo, Jyota, and Jones (2006) aim to determine if participation in the Food Stamp Program (FSP) leads to outcomes in a child's performance in school and health, namely reading, mathematics, weight gain, and social skills. The FSP is one of several federal food assistance programs in the United States, the main goal of which is to reduce food insecurity. The authors note that participation in these subsidy programs is by self-selection and it is therefore difficult to distinguish between a causal effect of the programs that would reduce food insecurity and the selection effects of choosing to be a participant. Longitudinal data over a four year period of childhood development is used in the place of cross-sectional data in order to tease out the magnitudes of the causal and selection effects and reduce bias.

Data for this study comes from the Early Childhood Longitudinal Study-Kindergarten cohort from 1998 to 1999, which is a nationally representative sample for analysis. The USDA's Household Food Security Survey Module is used as the measure for food insecurity. Mathematics and reading scores were measured in kindergarten and again in the third grade. Heights and weights were also recorded. Social skills were measured using teacher evaluations of the children for a variety of behaviors that capture social skills, learning abilities, and self-control. The authors employ a differential model to test their hypotheses based on the following equations:

$$\Delta score_{3-K} = \beta_0 + \beta_1 \Delta \boldsymbol{covariates}_{3-K} + \beta_2 \Delta food\ insecurity_{3-K} + \beta_3 \Delta FSP\ participation_{3-K} + E$$

$$\Delta score_{3-K} = \beta_0 + \beta_1 \Delta \boldsymbol{covariates}_{3-K} + \beta_2 \Delta composite\ need_{3-K} + \beta_3 \Delta FSP\ participation_{3-K} + \beta_4 \Delta FSP\ participation_{3-K} * \Delta composite\ need_{3-K} + E$$

The composite need in the second equation is a continuous measure for material hardship, and β_4 is the coefficient for the interaction term between participation in the Food Stamp Program and material hardship. *Covariates* is a vector representing the differentials in reading and mathematics scores, height and weight, and social skill development measures.

Frongillo, Jyota, and Jones (2006) conclude that children in households that started to engage in FSP participation had less weight gain than children in households that had ceased FSP participation, contrary to the expected result of the authors. However, this result is not statistically significant. The results show an increase in academic measures of children participating in FSP. The authors reason that this could be the result of improved quality or quantity of nutritious food. However, there is not enough evidence to support a causal relationship between FSP participation and better nutrition, only that FSP increases the availability of nutritional substances.

Nord and Golla (2009) estimate the effects of the Supplemental Nutritional Assistance Program (SNAP), previously FSP, on the food security of those participating in the program. The authors note that there is a data anomaly whereby food insecurity is more prevalent in households that participate in SNAP than other qualifying households that do not. They reason that those households that enroll in SNAP are more likely to enroll when they are in desperate in their need for food and these observations are not taken into account by econometricians and data analysts. Nord and Golla (2009) claim to provide, in greater detail, information on the timing of household enrollment in SNAP based on their level of food insecurity at the time of their initial participation. To handle this selection data issue, the authors analyze the months following enrollment into SNAP instead of before.

Data for this study comes from USDA food security surveys with supplementary sections to the Current Population Survey conducted by the U.S. Census Bureau from

2001 to 2006. The authors hypothesize that SNAP eases the burden of food insecurity in the months after beginning enrollment in the subsidy. Each household is assessed over a two year period in order to decompose the timing effects of self-selection into the program. Statistical tests are performed using logistic regression with food insecurity of each year, respectively, as dependent variables to determine if SNAP reduced food insecurity over the time of enrollment. The authors note that SNAP enrollment may have seasonal pattern that would distort the results, so the model uses household member composition and annual household income as controls.

$$
\begin{aligned}
Food\ insecurity_{Year\ 1} &= \beta_0 + \beta_1 Months\ before\ SNAP + \beta_2 Months\ before\ SNAP^2 \\
&+ \beta_3 \boldsymbol{Household\ composition} + \beta_4 \boldsymbol{Household\ income} + \varepsilon
\end{aligned}
$$

$$
\begin{aligned}
Food\ insecurity_{Year\ 2} &= \beta_0 + \beta_1 Months\ before\ SNAP + \beta_2 Months\ before\ SNAP^2 \\
&+ \beta_3 \boldsymbol{Household\ composition} + \beta_4 \boldsymbol{Household\ income} + \varepsilon
\end{aligned}
$$

Household composition is a vector that represents the number of adults in the household, and the number of children in the household, and the absence of either parent. *Household income* is a vector that represents different levels of income as a percentage to the poverty line.

Nord and Golla (2009) conclude that food insecurity increases for households seven or eight months leading up to their entry to the SNAP program. After enrolling in SNAP, drastic food insecurity decreased, but then remained stable for the next ten months. This demonstrates the self-selection hypothesis and a causal relationship between decreasing food insecurity and SNAP enrollment. The authors note that there is a possibility that the causal relationship may be threatened if SNAP acts as a marker for households that have recently experienced drastic food insecurity. These marked households may experience an increase in food security due to some other externality associated with being enrolled in the SNAP program or that their food insecurity function has a positive first derivative and a negative second derivative after becoming participants in the program.

Burgstahler, Gundersen, and Garasky (2012) seek to determine if SNAP participation increases obesity in children to those enrolled in the program. This study expands on previous studies because it controls for household financial stress, which can be a cause of childhood obesity. Financial stress, the authors argue, causes changes in the behavior of the parents and alters the environment in which children develop. Gatasky et al. (2009) demonstrate that exposure to household stress is correlated with childhood obesity by avenues of subconscious psychological responses that influence changes in diet and exercise. One of the hypotheses of this study is that participation in SNAP reduces the amount of household level financial stress that can negatively affect children and in turn cause weight gain. The model is as follows using two-stage least square multiple regression methodology:

$$Childhood\ obesity_{ij} = \alpha + \beta SNAP_i^* + \lambda Financial\ stress_i + \gamma \boldsymbol{X}_i + \varepsilon_i$$

and

$$SNAP_i = \alpha + \lambda Financial\ stress_i + \gamma \boldsymbol{Z}_i + \varepsilon_i$$

The data for this study comes from the Survey of Household Finances and Childhood Obesity in 2009 to 2010, a survey which focuses particularly on financial stress. The observations are composed of low-income metro and non-metro counties in

Illinois, Iowa, and Michigan. Survey data are collected in two phases, first by phone interviews and second by mailed surveys measuring height and weight of children of households participating in SNAP. The authors note that this dataset is useful because it has stratified levels of financial stress, county level SNAP participation rates, and children's height, weight, and a derivation of body mass index percentiles. The measure of financial stress is derived from the survey data with six specific objective questions about day-to-day living limited to time spent in the household. This makes for discrete measures of financial stress (from 1 to 6), which are then used as weights for the stress experience.

The authors use geographic information from the dataset about the county of residence for particular participants in SNAP as an instrumental variable for the SNAP variable in the analysis. Their reasoning is that high SNAP participation rates for a particular county ought to be highly correlated with an individual household's decision to enroll in SNAP because the level of the negative stigma associated with receiving food subsidies is diminished relative to that in counties with low SNAP participation rates. Also, there would be more outreach of the SNAP program in counties with high participation and more availability of information about the program and receiving of its benefits. SNAP participation rates are affected greatly by factors such as unemployment rate, median income, percentage of population in respective minorities, and county-level need for food subsidies to decrease food insecurity. These are also used as controls in the model.

The vectors $\boldsymbol{X}$ and $\boldsymbol{Z}$ refer to standard sets of covariates that are common in literature including education level, household income, health insurance status, race, ethnicity, household size, and marital status. The sample data are restricted to households that qualify to receive SNAP benefits, however, not all qualifying households will choose to enroll for the SNAP program. Because the study is on children in particular, the authors also remove observations where the only children in qualifying households are under the age of two as there is no general consensus about how to uniformly measure body mass index in children of that age. Before drawing conclusions, the authors test the validity of their instrumental variables for SNAP. Based on the Sargan chi-squared statistic and the Basmann chi-squared statistic, the tests provide no statistical evidence that the chosen instruments are invalid or introduce endogeneity.

Burgstahler, Gundersen, and Garasky (2012) conclude that SNAP participation is negatively associated with obesity in children in low-income households in counties in Illinois, Iowa, and Michigan. These results are found both before and after controlling for household financial stress. This study was pursued in response to other studies done that showed evidence suggesting that SNAP led to childhood obesity, but these results show evidence to disprove those assertions and support the opposite claim, that SNAP enrollment decreases childhood obesity for participating households. The authors note possible extensions would be to consider the relationships between financial stress using longitudinal data to tease out dynamic relationships over time. This research would be enriched by using a larger dataset with more observations from a larger geographic region. Lastly, the dataset used in this study was limited to those households that would likely be experiencing financial stress. The get a more general picture, the data should be allowed to include observations from households that are not perceived by the researchers as being predisposed to financial stress.

Nord and Prell (2011) aim to demonstrate that food security of households with incomes within 130% of the poverty level (SNAP eligible) increased from 2008 to 2009 with most of the increase attributed to the American Recovery and Reinvestment Act of 2009. To conduct their study, the authors analyze data on SNAP participation, food insecurity, household spending on food, and household characteristics from the Current Population Survey (CPS) Food Security Supplement (FSS). The annual FSS survey augments the monthly CPS survey conducted by the USDA. The survey is administered by the U.S. Census Bureau. In 2009, 46,000 households participated in the survey and consisted of civilian, noninstitutionalized people in the United States. The following table shows how monthly SNAP benefits are increased by ARRA from 2008 to 2009 from Nord and Prell (2011).

Table 5. Maximum Monthly SNAP benefits pre-ARRA and post-ARRA

Number of People in the SNAP Household	Pre-ARRA in fiscal 2009	Post-ARRA	Arra increase in mazimum monthly SNAP benefits
1	$176	$200	$24
2	$323	$367	$44
3	$463	$526	$63
4	$588	$668	$80
5	$698	$793	$95
6	$838	$952	$114
7	$926	$1,052	$126
8	$1,058	$1,202	$144

Data on SNAP participation, SNAP benefits, food spending, and food security in December 2009 are compared to the corresponding statistics for December 2008. The 2009 data was collected about eight months after ARRA went into effect so there would be households that would have gone through the eight month survey period completely since ARRA was enacted. Several income categories are analyzed in this study including all low-income households, low-income households that were participating in SNAP, and households whose income exceeds the maximum for SNAP enrollment but is less than the U.S. median income. Multivariate regression methods with controls for changes in income, employment, and other household characteristics are employed to analyze the partial effects from 2008 to 2009.

The authors examine three interrelated outcomes: SNAP participation, food expenditures, and food security. These outcomes are then tested for consistency against the desired outcomes of the ARRA increases to SNAP. The effects of the low-income households are compared to the effects of households that the authors define as “near SNAP eligible”, meaning that their income exceeds 150% of the poverty line but does not exceed 250% of the poverty line. In this way, the near SNAP eligible households are not low-income but are still well below the national median income. The authors analyze data from 2001 to 2009 to capture some pre-recession data as well as post-ARRA data for a broad cross-section of economic environmental factors. Data complications occur in the form of the self-selection bias inherent with SNAP enrollment and under-reporting of SNAP participation of households enrolled due to the perceived negative stigma of receiving SNAP benefits.

The key variables in this study are income, low-income and near-SNAP-eligible status, SNAP participation, Thrifty Food Plan-adjusted food expenditures, and food security. Unadjusted multivariate comparisons are used and employ medians instead of means because medians provide more robust measurement errors, which is particularly relevant to food expenditure data. These are mostly used as a naïve baseline. Adjusted multivariate comparisons are used to account for any household-specific circumstances independent of ARRA’s increase to SNAP benefits from year to year. These models control for income, employment and labor force status, household composition and structure, presence of an elderly person(s), race and ethnicity, citizenship status, education level of the most highly educated adult in the household, metropolitan residential status, and geographic region. Difference-in-difference comparisons are also employed in this study to control for factors that are not-household specific from year to year independent of ARRA’s increase to SNAP benefits. The authors note that a change in food prices could affect food security to a household but would have nothing to do with the household specifically, thus skewing the results.

Nord and Prell (2011) conclude that food security of low-income households improved from 2008 to 2009. Their results suggest that ARRA’s increase to SNAP benefits was a substantial factor for the decrease in food insecurity between the two years in the study. This result is further supported because households with income that exceeds the level of SNAP eligibility did not see a decrease in food insecurity between 2008 and 2009. Another conclusion of this study is that SNAP enrollment demonstrates a decrease in food insecurity. The authors decomposed the changes in food security related to SNAP enrollment between two factors that work in opposing directions. Firstly, there is a self-selection bias to SNAP enrollment. Second, households with a greater disparity between their resources and their needs are more likely to enroll in SNAP to diminish the gap to cover their needs. Because of these two forces, the evidence that ARRA decreased food insecurity to those enrolled in SNAP is to be considered a vast improvement in the effectiveness of the program. The authors note that their findings question the adequacy of SNAP benefits before ARRA because of the large, positive effect suggested by the study that ARRA had on reducing food insecurity. The authors suggest that “adequacy” is difficult to define with a national food supplement program as different regions have different local food prices, different household needs, and each household’s capacity to manage their resources is different. However, the overall conclusion is that SNAP benefits prior to 2009 still have a substantial benefit to households who received SNAP benefits.

In aggregate, the literature supports that childcare is important, not only to the well-being of the children, as cited in Gustafsson and Stafford (1992), but also in the level of market output that the parents provide, as supported by Tekin (2007) and Berger and Black (1992). Hill and Stafford (1980) demonstrate that the quality of childcare greatly affects the potential market participation and output of children, so a high standard of childcare is important to the ability of children to become productive members of society in adulthood. Datcher-Loury (1988) supports the findings of Hill and Stafford (1980) and shows that not only does quality childcare allow for productivity increases later in life, but when the mother is the primary childcare provider, her nonmarket productivity increases. Kohler, Behrman, and Skytthe (2005) demonstrate that children are positive attributes to the utility of parents.

Food insecurity can be reduced, as demonstrated by Nord and Golla (2009) and Nord and Prell (2011), by enrollment in the Supplemental Nutritional Assistance Program, both before and after 2009, and by the mother of the household making resource allocation decisions as it comes to food based on the findings of Kenney (2008). Not only can food insecurity be reduced by enrollment in SNAP, formerly the Food

Stamp Program, but the nutritional value of the food available to children in this program increases as demonstrated by Frongillo, Jyota, and Jones (2006). In addition to Frongillo, et al. (2006), Burgstahler, Gundersen, and Garasky (2012) provide statistical evidence that SNAP enrollment is negatively associated with childhood obesity to those children enrolled. Overall, childcare is important, which can be augmented with a subsidy like SNAP in order to provide food security and increased nutritional availability to children.

No previous research examines the effect of SNAP enrollment directly on non-pecuniary household resource allocation decisions, including the childcare provided to children by household adults. This paper contributes by showing a positive statistical relationship between enrollment in SNAP and nonmarket work done by parents that benefits children in the household.

CONCEPTUAL FRAMEWORK

Consider that individual households have utility functions that are an aggregation of the utility of all household members that are increasing in consumption and leisure:

$$U = f(C, L)$$

This utility function *U* is optimized by the household in order to maximize utility, constrained by the household's budget constraint:

$$C = w(T - L) + V$$

where *C* is consumption by the household of goods spent in dollars, *T* is total hours in the time period of the analysis, *L* is hours of leisure, *w* is the wage rate, and *V* is other household income earned in *(T-L)* hours. Other household income includes infusions, like subsidies, to the household's income. The constraint is increasing in *V*. Thus, any other income shifts the budget constraint out, allowing for greater levels of consumption and leisure when the model is solved. Leisure hours also include non-market activities, work or otherwise. To be a non-market work activity, the household agent does not receive a wage for work being done, typically household work. Rearranging the budget constraint yields the following equation:

$$wT + V = C + wL$$

This algebraic transformation is useful because it shows how much a household would produce in terms of wages if all available hours were used for work. This rewritten budget constraint also shows that every hour of leisure costs *w*, the wage rate. The constrained maximization problem can be solved using a Lagrange multiplier approach:

$$max\Omega = U(C, L) + \lambda(wT + V - C - wL)$$

However, there may also exist a perceived negative stigma from SNAP enrollment which diminished the utility of the household. Since the stigma, *W*, is dependent on SNAP enrollment, *W* is a function of SNAP. The stigma is added to the Langrangian as follows:

$$max\Omega = U(C,L) - W(S) + \lambda(wT + V - C - wL)$$

It is important to note that households can have more than one wage-receiving agent. These cases can be expanded mathematically to accommodate that different household agents can receive differing wage rates by adjusting the household budget constraint, but the process to the solution remains the same. The Lagrangian method chooses the levels of consumption and leisure that maximize household utility subject to the budget constraint. It stands to reason that neither using all hours for work nor using all hours for leisure optimizes the objective function.

In order to have money for consumption, agents in a household need to do market work in order to earn a wage. Working, in itself, is assumed to provide disutility to agents, who derive their utility from the consumption the working provides. The assumption that work provides disutility would not hold if the agents experience greater utility from working than from the wages their hours working provide.

The utility function for households can be expanded to accommodate the inclusion of household children and is as follows:

$$U = f[C, L, WB(C,L)]$$

where *WB* is the well-being of the household children, defined as follows:

$$WB = f(C,L)$$

WB is a function of *C*, household consumption, and *L*, the amount of leisure household adults spend on household children. Children attain a higher state of well-being as more nonmarket hours of the household's adults are spent on them. For this reason, the household utility function for households with children is increasing in *WB*.

Next, consider a household with children that receives a subsidy in the form of SNAP benefits, the constraint is the same except *S* is added to *V to* specify that at least part of other income in the constraint is in the form of a subsidy.

$$C = w(T - L) + V + S$$

Receiving a subsidy eases the household budget constraint and allows a household to achieve a greater level of utility in equilibrium since the constraint is increasing in both *V* and *S*. The constrained maximization problem is again solved with the Lagrange multiplier approach with the expanded objective function and the rewritten budget constraint:

$$max\Omega = U[C, L, WB(C, L)] - W(S) + \lambda(wT + V + S - C - wL)$$

The central question in this framework is how the well-being variable in households with children is affected when at least part of other income is in the form on a subsidy. More narrowly, how does receiving SNAP benefits, a subsidy, affect the well-being of children in the household?

EMPIRICAL MEASUREMENT

The data for this analysis are from the American Time Use Survey (ATUS) merged with data from the Current Population Survey Food Security Supplement (CPS) using years 2005 to 2013. Both of these surveys are conducted by the Bureau of Labor Statistics (BLS). The Food Security Supplement portion of the CPS collects information regarding household food expenditure, food assistance participation, food security, ways that households cope with food security, and household concern about food insecurity.

The universe for the CPS includes households that are above 185% of the poverty line and below. Households that are deemed to be food insecure are then asked the supplementary questions pertaining specifically to food. Interviewers direct their questions toward the member of the household who buys and prepares the food, if possible. There are approximately 60,000 households that are surveyed every month. About one-eighth of the households exit the sample each month after their eighth CPS interview attempt.

ATUS aims to measure how Americans divide their time during a typical day for all of life's activities. One such activity that people spend time on is childcare. Demographic information is also attained during the survey process. ATUS covers all American residents that are at least fifteen years of age, excluding active military and those institutionalized in nursing homes, permanent rehabilitation facilities, and prisons. The ATUS sample is drawn from the CPS so the universe for the two datasets is the same.

The ATUS sample is a three-stage stratified selection process from the CPS. The first selection stage is a reduction of the CPS oversample in the less-populated states. The

CPS has a reliability requirement for each state, meaning that less-populated states are allocated a larger proportion of the national CPS sample than they would get with national reliability requirement. This increases the reliability of the estimates at both state and national levels. ATUS does not have a state reliability requirement. To improve the efficiency of the national estimates, the CPS sample is subsampled to derive the ATUS sample which is distributed across states approximately equal to the proportion of the national population each state represents.

The second selection stage stratifies households based on various demographic characteristics of the households including race/ethnicity, age and presence of children, and the number of adults in households without children. Sampling rates vary across strata. To increase the reliability of time-use data, the eligible households with a Hispanic or non-Hispanic black households are oversampled. To ensure appropriate measures of childcare, households with children are also oversampled. To accommodate the oversampling of households with children, households without children are undersampled.

In the final selection stage, an eligible person from each household selected from the second stage is randomly selected to be the designated person for ATUS. Eligibility is defined as a member of a civilian household at least 15 years of age. All eligible persons within a sample household have an equal probability of being selected as the designated person for ATUS.

After 2003, the ATUS sample was reduced by 35% in order to bring costs down to an acceptable amount based on the annual survey budget. The same proportion of each stratum was removed in order to make the reduction. This somewhat reduced the accuracy of the estimates for the smaller groups, but the precision loss was eased as the group size increased. Since 2003, response rates have averaged 54.7% on an annual basis. Secondary activities are defined by ATUS as activities that are done concurrently with a more important, or primary, activity. With the exception of childcare, no secondary activities are compiled by the ATUS.

The ATUS, and therefore the CPS, is edited after the raw data collection in order to produce usable datasets. The most common edit is to deal with item nonresponses, missing variables in otherwise completed questionnaires. Simply ignoring missing values leads to biased estimates in analysis. To handle missing data, a response is imputed one of three ways in order to make full questionnaires and complete datasets. The BLS discloses that imputation can lead to overstatement of the precision of estimates. The first imputation method is relational imputation which infers the missing value based on characteristics from others in the same household. Most commonly, this edit is used to fill in demographic information. The second imputation method is longitudinal assignments which uses the final month of CPS data to determine whether a value exists and what assignment the value should be given. This is typically used on labor force edits. The final imputation method is hot-deck allocation which implies missing values using records with similar characteristics. This is similar to relational imputation but not using data from within the same household and is most commonly used on labor force edits where longitudinal assignments cannot be used. The edits that are shared by both the CPS and the ATUS are labor force status edits, industry/occupation edits, and earnings edits. The edits that differ in the CPS and the ATUS are household demographic edits and school enrollment edits.

The subsample used for the regression analysis limits the sample to households that have household income below 130% of the poverty line for each year in the time series. Because the poverty line is determined by how many residents are in the household of a particular respondent, the poverty line increases as the number of household residents increases. The poverty line also moves depending on the current economic climate in any particular year. Therefore, respondents with the same number of residents in their house and the same household income in different years are not guaranteed to both be part of the subsample in this process. In this paper, the subsample of those below 130% of the poverty line is coded in STATA© as sample130. This subsample was chosen because respondents need to be within 130% of the poverty line as one of the qualifications for receiving SNAP benefits. In order to determine 130% of the poverty line, the Consumer Price Index (CPI) is used to deflate each year in the time series using 2013 as the base year.

MODEL

The dependent variable used in this model is the minutes of daily childcare that respondents spend in primary childcare with their own children that are living in the same house and are not classified as adults. Primary childcare is defined by the CPS as time spent actively participating in activities with children, individuals who are less than 18 years old, or taking care of their basic needs. Changing diapers and playing games with children are examples of primary childcare. This differs from secondary childcare which CPS defines as time respondents spend with their children but are not actively engaging in activities with the child. An example would be watching television while a child plays in the same room.

The explanatory model employs some basic demographic information as right-hand-side variables including age and sex. Age is an integer variable with discrete values. Sex is coded as a dummy variable where a value of 0 is male and a value of 1 is female. If these dummy values were to be scaled up by one, they would not affect the interpretation of the estimates because they would still be binary in nature. Marital status is included in the model with four interaction variables that incorporate the existence of children and the involvement of the spouse. Other variables included are employment status and the existence of multiple jobs. The two are related, but distinctly different. Clearly, if the employment status of a respondent is unemployed, that same respondent will not be able to have multiple jobs. It stands to reason that if a respondent does not have a job, that respondent cannot have more than one job. The income variable is measured as the midpoint of the stratified categories of the average household income. Household size is the number of people living in a respondent’s household. The variables about employment relate to childcare through the avenue of the need of a respondent to outsource their childcare to daycare centers. Likewise, the income variable has explanatory power for respondents' ability to pay a center for childcare. The summary statistics are reported in Table 6.

Table 6. Descriptive Statistics.

Variable	**Definition**	**Full Sample**		**Subsample**	
variable name	*STATA© coding*	*N*	*Mean (Std.Dev.)*	*N*	*Mean (Std.Dev.)*
childcare	daily childcare (minutes)	1,186,760	31.7635 (79.3943)	783,136	32.6098 (80.0868)
snapdoll	SNAP assistance ($)	47,321	14.9589 (69.6135)	8,317	67.1445 (136.3850)
age	age of respondent	1,186,760	46.5943 (17.6618)	783,136	46.5241 (17.6699)
sex	0 if male 1 if female	1,186,760	0.5634 (0.4960)	783,136	0.5637 (0.4959)
marrwsp	1 if respondent is married and living with spouse, 0 otherwise	1,186,760	0.4960 (0.5000)	783,136	0.4795 (0.4996)
marrwosp	1 if respondent is married and living without spouse, 0 otherwise	1,186,760	0.0142 (0.1183)	783,136	0.0155 (0.1236)
marrwspchild	1 if respondent is married, has household, children and living with spouse, 0 otherwise	1,186,760	0.2924 (0.4549)	783,136	0.2946 (0.4558)
marrwospchild	1 if respondent is married, has household, children and living without spouse, 0 otherwise	1,186,760	0.0052 (0.0719)	783,136	0.0057 (0.0753)
empstat	0 if employed 1 if unemployed 2 if not in the labor force	1,186,760	0.6965 (0.9261)	783,136	0.7006 (0.9259)
multjobs	0 if no 1 if yes	1,186,760	0.0602 (0.2379)	783,136	0.0597 (0.2370)
income	midpoint of the categories of the average household income (in $10,000)	1,077,176	6.3146 (5.7682)	769,499	6.5266 (6.1356)
hhsize	number of people living in respondent's household	56,449	2.7478 (1.5287)	10,424	2.7998 (1.819)
ARRA1	ARRA assistance 0 if year<2009, 1 otherwise	1,186,760	0.3997 (0.4898)	783,136	0.5526 (0.4972)

The main explanatory variable in this framework is the number of dollars of SNAP benefits received by respondents. ARRA is a dummy variable for the existence of the ARRA increase to SNAP benefits. Ultimately, the simple OLS regression equation takes the form:

$$\begin{aligned} childcare_i = \ & \beta_0 + \beta_1 snapdoll + \beta_2 age + \beta_3 sex + \beta_4 marrwsp + \beta_5 marrwosp \\ & + \beta_6 marrwspchild + \beta_7 marrwospchild + \beta_8 empstat + \beta_9 multjobs \\ & + \beta_{10} hhsize + \beta_{11} income + \varepsilon_i \end{aligned}$$

where β_0 is the constant and ε_i is the error term. Any $\beta > 0$ will increase average expected minutes of daily childcare while any $\beta < 0$ will decrease average expected minutes of daily childcare. Based on the hypothesis that SNAP will increase childcare, $\beta_1 > 0$ is expected. Because the dependent variable is measured in minutes and the main explanatory variables are measured in dollars, small coefficients are expected since the incremental values of the variables are small. The interpretation of the main explanatory variables then is that an increase of $1 in subsidies changes daily childcare minutes by the β coefficient's magnitude.

The interaction variables are multiplicative products of different dummy variables related to childcare. In this framework, the interaction variables are marrwsp, marrwosp, marrwspchild, and marrwospchild. Marrwsp is defined as a respondent being married and the spouse is present in the household. Marrwosp is defined as a respondent being married and the spouse is absent from the household. Marrwspchild and marrwospchild follow the same definition except with the inclusion of the presence of household children. These variables take on a value of 1 if all the components are satisfied for the particular interaction set, 0 otherwise. This is because if any one component of the interaction is unsatisfied, that piece takes on a value of 0 and is multiplied through the entire variable, resulting in 0. For a particular respondent, some of the interaction variables may turn to 0. Depending on the sign of the corresponding β coefficient, this may increase or decrease the respondent's expected minutes of childcare per day. At this point, potential data issues will be examined and discussed.

Heteroskedasticity refers to the phenomenon where there is increased variance, σ^2, in the error term, ε_i, across values of an explanatory variable. Formally, heteroskedasticity is defined:

$$Var(\varepsilon|x) \neq \sigma^2$$

One of the consequences of heteroskedasticity is incorrect standard errors. Therefore, any confidence intervals or statistical tests of coefficients are incorrect as well. Because of the survey structure related to the collection process of the data being used for this model and with this process of analysis, there is nothing that can be done to fix any heteroskedasticity if it exists in the data. Using the survey (svy) command in STATA© implies that the data being used are collected by a survey. Using this particular command, the error terms are adjusted to accommodate for the survey collection method.

Endogeneity refers to variables that lead to biased and inconsistent estimates for different reasons. Most prevalent are omitted variables that are relevant to the regression, measurement errors, and simultaneity. The last refers to a situation where a specific independent variable explains the dependent variable, but the presumed dependent variable also explains the independent variable. In other words, the two simultaneously explain changes in the other. This causes the estimates in the model to be biased and inconsistent. One way to correct endogeneity is to use an instrumental variable estimator.

In this study, those who receive SNAP benefits may be deciding to enroll for reasons that impact childcare simultaneously. First, an adult may be able to sustain themselves on a limited diet that may not be nutritious. However, a parent may feel as though their child should not experience food insecurity even if the parent themselves is capable of doing so. Since SNAP is one way to reduce food insecurity, households with children, and therefore those that engage in childcare, may be more likely to enroll in SNAP than households where no children are present. In this way, SNAP enrollment could be endogenous to a model that estimates childcare.

Another plausible reason why SNAP and childcare are endogenous is that having more children increases the household's food demand, which could put strain on the household's budget. This could cause some households with many children to fall to a level of income where they are SNAP eligible. Since there are many children in the household, the household adults will most likely be spending more time in daily childcare on average than households with fewer children. In this way, SNAP enrollment may be endogenous to having many children and engaging in more daily childcare on average.

An instrumental variable, z_i, is correlated with the endogenous variable, but is otherwise exogenous. Good instrumental variables are highly correlated with the endogenous explanatory variable, x_i, and uncorrelated with the error term, u_i. In this paper, the variable that is under suspicion of being endogenous is snapdoll and the instrument(s) are ARRA and ARRA1. The instruments ARRA and ARRA1 are formally defined as follows:

$$ARRA1 = 0 \; if \; year < 2009$$

$$ARRA1 = 1 \; if \; year \geq 2009$$

$$ARRA = ARRA1 * snapdoll$$

The final condition for instrumental variables is that the instrument does not belong in the original regression equation. Variables that belong in the regression equation that are used as instruments introduce omitted variable bias. The formalized versions of these the relationships are defined as follows:

$$Corr(z, x) \neq 0$$

$$Corr(z, u) = 0$$

If these conditions are met, the instrumental variable is valid. ARRA is related to SNAP because one part of the ARRA was explicitly to increase the level of SNAP benefits. Because of this, ARRA and snapdoll should shift in the same direction at the same time. In addition, ARRA does not have any direct impact on childcare, so it is exogenous to the model. For these reasons, ARRA is an acceptable instrument for the snapdoll variable in this study. There are different statistical tests that test for evidence of endogeneity and valid instrumental variables.

The Hausman test for endogeneity is used in an OLS regression in which endogeneity is in question. The Hausman test provides statistical evidence a variable is exogenous. Similar to the Sargan test, the null hypothesis for the Hausman test is exogeneity and the alternative hypothesis is endogeneity. The assumption in this endogeneity test is that the variable is exogenous.

In order to perform a Hausman test, the first step is to run the OLS model including the instrument and the potential endogenous variable as right-hand-side variables. Then predict fitted values for the possible endogenous variable and the residuals from the OLS model. In a second-stage regression, the predicted values for the potential endogenous variable are used in place of the variable itself. From this point, the instrument is kept out, the possible endogenous variable is put back into the regression, and the predicted residuals are used as another right-hand-side variable. A test for significance of the residual coefficient is a test of exogeneity. The magnitude of the test statistic in this case is irrelevant for comparison to other models after the p-value is calculated because of varying degrees of freedom.

The Sargan test for validity is used in a two-stage least square instrumental variable regression when there are more instrumental variables than potential endogenous variables. The Sargan test suggests instruments are valid by providing statistical evidence that they are uncorrelated with the predicted residuals. The null hypothesis for the Sargan test is that the instrumental variables are uncorrelated with the predicted residuals and are therefore valid. The alternative hypothesis is that the instrumental variables are correlated with the predicted residuals, and the estimates they provide are statistically invalid. It is important to note that because the null hypothesis is validity of the instruments, the assumption is that the instruments being used in the overidentification are valid.

In order to perform a Sargan test, the first step is to run the OLS model including the instruments and predict the residual values. These residuals are then regressed on the same right-hand-side variables as the OLS. In essence, the dependent variable has been replaced with the predicted residuals. The resulting estimates from this regression are then tested for statistical significance with a Sargan test statistic. The test determines whether the reduced form regression estimates are statistically different from zero. The degrees of freedom are calculated by subtracting the number of instruments that are overidentifying the suspected endogenous variable less one for the endogenous variable itself. In this instance, there are two instrumental variables for one potential endogenous variable so there is one degree of freedom. The magnitude of the test statistic in this case is irrelevant for comparison to other models after the p-value is calculated because of varying degrees of freedom. Though the Sargan test can provide statistical evidence to support the exogeneity of overidentified instrumental variables, it cannot indicate which of the instruments is most valid.

There are some shortcomings for the models reported in the previous section. There are models that include two instrumental variables, ARRA1 and ARRA. The latter of these two is not used in a separate model as a single instrument because of how it is defined. Not only does only take on a value of 1 starting in 2009 like ARRA1 does, but it also only takes on a value of 1 when there is SNAP enrollment. In this way, ARRA is a function of the potentially endogenous variable:

$$ARRA = ARRA1 * snapdoll$$

Therefore, it may not meet the criteria for being an acceptable instrumental variable as it is not only correlated with the potential endogenous variable but is defined as a function of the variable it is intended to instrumentalize. This could lead to endogenous correlation between the instrument and the potentially endogenous variable instead of exogenous correlation. However, ARRA is included in the analysis and reported in this paper because of the Sargan test for validity for overidentified 2SLS models. The Sargan test failed to reject the null hypothesis of valid instruments. Therefore, the overidentified model has statistical evidence to show that it is valid, even with one of the instruments being defined as a function of the potentially endogenous variable snapdoll.

This paper utilizes both an OLS model and a 2SLS model in order to estimate the partial effect of snapdoll on daily childcare. Based on the Hausman and Sargan tests, respectively, OLS is statistically valid. Both models are reported in this paper because the p-values associated with the Hausman and Sargan test statistics are close to the threshold of statistical significance for rejecting the null hypothesis of exogeneity at the 90% significance level, or a critical alpha value of $\alpha = 0.1$. This implies that the statistical evidence provided by either model is moderate, not strong. Also, the statistical tests, though they provide evidence that both models are valid, do not suggest which best portrays the intended partial effect of snapdoll on average daily childcare.

RESULTS

This chapter reports the results of all the statistical models used for analysis to investigate the effects on daily childcare, interprets coefficients, and shows which coefficients were found to be statistically significant. Table 7 lists the results found in the OLS models, and Table 8 lists the results found in the 2SLS models. Note that in Table 8, the variable listed snapdoll has been instrumented.

Model 1 in Table 7 is the simplest naive OLS regression relationship between minutes spent in childcare on a daily basis and the magnitude of SNAP assistance received by a household. This regression uses the larger sample from the ATUS before restricting the subsample to only include households that are SNAP eligible based on household income. The maximum household income for SNAP eligibility is at or below 130% of the poverty line, so the subsample includes households whose income does not exceed 130% of the poverty line. The coefficient for snapdoll implies that for every additional dollar of SNAP assistance, the household is able to engage in another 0.0993631 minutes, about six seconds, of childcare per day. Put another way, an additional $10 of assistance allows for another minute spent in daily childcare, on average.

Model 2 in Table 7 is the naive OLS regression relationship between minutes spent in childcare on a daily basis and the magnitude of SNAP assistance received by a household that is restricted to the subsample which only includes households that are SNAP eligible based on household income. The coefficient for snapdoll implies that an additional dollar of SNAP assistance, the household is able to engage in another

0.1332499 minutes of childcare per day. Put another way, an additional $7.50 of assistance allows for another minute spent in daily childcare, on average.

Model 3 in Table 7 is the OLS regression which includes all the right-hand-side independent variables from the general form in the previous section. The coefficient for snapdoll would imply that for every additional dollar of SNAP assistance, ceteris peribus, the household is able to engage in another 0.07 minutes of childcare per day. The specific form as the result of the OLS model is given as follows:

$$\begin{aligned} childcare_{OLS} = {} & 9.251968 + (0.0716397 * snapdoll) - (0.7339277 * age) \\ & + (22.42056 * sex) - (5.655668 * marrwsp) \\ & - (8.615675 * marrwosp) + (51.50522 * marrwspchild) \\ & + (23.15323 * marrwospchild) + (3.382499 * empstat) \\ & - (13.08805 * multjobs) + (3.887812 * hhsize) - (3.741196 \\ & * income) \end{aligned}$$

The coefficient for age implies that an additional year of age of the respondent, ceteris peribus, the household averages 0.74 fewer minutes of childcare per day than the average household. The coefficient for sex implies that for female respondents, ceteris peribus, the household averages 22.42 more minutes of childcare per day than the average household. The coefficient for marrwsp implies that for households where the respondents are married, ceteris peribus, the household averages 5.66 fewer minutes of childcare per day than the average household. The coefficient for marrwosp implies that for households where the respondents are married but not together, ceteris peribus, the household averages 8.62 fewer minutes of childcare per day than the average household. The coefficient for marrwspchild implies that for households where the respondents are married and there is at least one child in the home, ceteris peribus, the household averages 51.51 more minutes of childcare per day than the average household. The coefficient for marrwospchild implies that for households where the respondents are married but not together and there is at least one child in the home, ceteris peribus, the household averages 23.15 more minutes of childcare per day than the average household. The coefficient for empstat implies that for respondents that are employed, ceteris peribus, the household averages 3.38 more minutes of childcare per day than the average household. The coefficient for multjobs implies that for respondents with at least two jobs, ceteris peribus, the household averages 13.09 minutes fewer of childcare per day than the average household. The coefficient for hhsize implies that for every additional person in the household, ceteris peribus, the household averages 3.89 more minutes of childcare per day than the average household. The coefficient for income would imply that for every additional dollar in household income, ceteris peribus, the household averages 3.74 fewer minutes of childcare per day than the average household.

In Model 3, the intercept is statistically significant at the 90% level. Age, marrwospchild, and income are statistically significant at the 95% level. Snapdoll, sex, marrwsp, marrwosp, marrwspchild, empstat, multjobs, and hhsize are statistically significant at the 99% level.

Table 7. OLS Results.

Variable	**(1)**	**(2)**	**(3)**
Intercept	30.65662*** (0.37749)	23.85713*** (1.08899)	9.251968* (5.10838)
snapdoll	0.0993631*** (0.00530)	0.1332499*** (0.01027)	0.0716397*** (0.01038)
age	—	—	-0.7339277** (0.06661)
sex	—	—	22.42056*** (2.06495)
marrwsp	—	—	-5.655668*** (1.43264)
marrwosp	—	———	-8.615675*** (2.65575)
marrwspchild	—	—	51.50522*** (3.74415)
marrwospchild	—	—	23.15323** (11.91468)
empstat	—	—	3.382499*** (1.31808)
multjobs	—	—	-13.08805*** (4.76407)
income	—	—	-3.741196** (1.96572)
hhsize	—	—	3.887812*** (0.95487)
n	47,321	8,317	8,317
R-squared	0.0074	0.0488	0.1752
Prob – F	0.0000	0.0000	0.0000

* significant at the 90% level
** significant at the 95% level
***significant at the 99% level

Model 4 in Table 8 is the 2SLS regression which includes all the right-hand-side independent variables from the general form in the previous section and uses ARRA1 as an instrumental variable for snapdoll. The coefficient for snapdoll would imply that for every additional dollar of SNAP assistance, ceteris peribus, the household averages 0.06 fewer minutes of childcare per day. However, this coefficient is not statistically significant. The specific form as the result of the 2SLS model is given as follows:

$$\begin{aligned} childcare_{2SLS} = \ & 16.51178 - (0.06163 * snapdoll) - (0.86168 * age) \\ & + (25.05667 * sex) - (9.73768 * marrwsp) \\ & - (12.59329 * marrwosp) + (53.75938 * marrwspchild) \\ & + (31.46213 * marrwospchild) + (4.404867 * empstat) \\ & - (13.5589 * multjobs) + (7.775969 * hhsize) - (9.29017 * income) \end{aligned}$$

In Model 4, marrwospchild and income are statistically significant at the 95% level. Age, sex, marrwsp, marrwosp, marrwspchild, empstat, multjobs, and hhsize are statistically significant at the 99% level. The main explanatory variable snapdoll is not statistically significant.

Model 5 in Table 8 is the overidentified 2SLS regression which includes all the right-hand-side independent variables from the general form in the previous section and uses ARRA1 and ARRA as instrumental variables for snapdoll. This model is overidentified because there are two instruments for the same potentially endogenous variable. The coefficient for snapdoll would imply that for every additional dollar of SNAP assistance, ceteris peribus, the household averages 0.05 more minutes of childcare per day. The specific form as the result of the 2SLS model is given as follows:

$$\begin{aligned} childcare_{2SLS} = {} & 10.46092 + (0.049192 * snapdoll) - (0.755201 * age) \\ & + (22.85954 * sex) - (6.335431 * marrwsp) \\ & - (9.278053 * marrwosp) + (51.8806 * marrwspchild) \\ & + (24.53688 * marrwospchild) + (3.55275 * empstat) \\ & - (13.16646 * multjobs) + (4.53529 * hhsize) - (4.665248 \\ & * income) \end{aligned}$$

In Model 5, marrwospchild and income are statistically significant at the 95% level. Snapdoll, age, sex, marrwsp, marrwosp, marrwspchild, empstat, multjobs, and hhsize are statistically significant at the 99% level.

Table 8. 2SLS Results.

Variable	(4)	(5)
Intercept	16.51178* (7.40024)	10.46092** (5.13061)
Snapdoll	-0.063163 (0.09784)	0.049192*** (0.01322)
age	-0.86168*** (0.11457)	-0.755201*** (0.06785)
sex	25.05667*** (2.96138)	22.85954*** (2.09715)
marrwsp	-9.73768*** (3.33772)	-6.335431*** (1.42753)
marrwosp	-12.59329*** (3.99450)	-9.278053*** (2.65578)
marrwspchild	53.75938*** (4.18495)	51.8806*** (3.75489)
marrwospchild	31.46213** (13.29260)	24.53688** (11.85374)
empstat	4.404867*** (1.49508)	3.55275*** (1.32406)
multjobs	-13.5589*** (5.02857)	-13.16646*** (4.78152)
income	-9.29017** (4.63204)	-4.665248** (2.04169)
hhsize	7.775969*** (3.04084)	4.53529*** (0.99538)
n	8317	8317
R-squared	0.1331	0.1740
Prob - F	0.0000	0.0000

* significant at the 90% level
** significant at the 95% level
***significant at the 99% level

The Hausman test for endogeneity for Model 3 resulted in a universal F-statistic of 2.0200 with an associated p-value of 0.1558. Since the null hypothesis is exogeneity, this test failed to reject the null hypothesis at the 90% significance level. The conclusion is that there is statistical evidence to show that snapdoll is exogenous in OLS Model 3.

The Sargan test for validity for the overidentified Model 5 resulted in a Sargan-statistic of 2.2349 with an associated p-value of 0.1349. Since the null hypothesis is validity, this test failed to reject the null hypothesis at the 90% significance level. The conclusion is that there is statistical evidence to show that instruments in the overidentified Model 5 are valid for estimating the partial effect on daily childcare.

DISCUSSION

The estimated models indicate that, with few exceptions, expected signs of coefficients based economic intuition hold. The following paragraphs provide some speculation and interpretation as to the positive and negative magnitudes of the coefficients in the models.

Models 1 and 2 are included only to show the naïve regression estimates between the main explanatory variable snapdoll and the dependent variable childcare. However, these are only included as a baseline to start from. It should be understood that the coefficients maybe biased as many relevant variables are omitted.

Model 3 has a higher R-squared value than the two previous OLS models. This stands to econometric reason that adding right-hand-side variables in OLS necessarily increases the R-squared, or fit of the model. Model 3 also has the highest R-squared value of any of the models reported in this paper. Snapdoll has a positive coefficient, as expected, because receiving a food subsidy allows parents to work less and stay in the household more to engage in more daily childcare, on average. As stated earlier, the relatively small magnitude of the coefficient is related to the small incremental values of the units of the dependent variable, namely minutes.

Age shows a negative coefficient. This could be because younger parents are more likely to spend more time in the household to stay with their children. It could also be true that younger parents are more likely to have fewer children and may feel the need to stay closer to a firstborn child as opposed to a third- or fourth-born child. Sex has a large, positive coefficient. This is because of the way the variable is coded in STATA©

with female being the larger discrete value. This coefficient suggests that women engage more in childcare than men, on average.

Marrwsp shows a negative coefficient. Intuition would lead to the possible conclusion that having a spouse in the home means that the parents can split time in childcare. Therefore, a negative coefficient would make sense. Marrwosp showed a larger negative coefficient than households where the spouse is still in the household. Again, economic intuition would lead to the conclusion that single parents must spend more time in other activities other than childcare. In this scenario, the single parent needs to work more in order to provide income enough to pay for food, taking time away from potential childcare. Marrwspchild is the largest coefficient in magnitude and the largest positive coefficient in Model 3. Combining the pieces of the coded multi-interaction variable, it makes sense that the presence of a child means that there is more childcare taking place in the household. Marrwospchild is positive with a smaller magnitude with the related variable where the spouse is still in the household. Following the logic from above, the presence of a child allows for more childcare and being a single parent may force the parent to work more, taking time away from childcare.

Empstat has a positive coefficient. Being employed allows for an increase in childcare. This could be from the security of having a job as opposed to the time involved in searching for a job that could take away from childcare. Multjobs has a negative coefficient meaning that having more than one job takes time from childcare. This makes sense because trying to work more with several jobs takes time away from being in the household and therefore potential time spent engaging in childcare. Income has a negative coefficient. It could be true that households with more income are more likely to pay for childcare outside of the household because they have the financial ability to do so. This would crowd out childcare time spent in the household. The final variable is hhsize which has a positive coefficient. This is because more people in the household means that there are more individuals who can engage in childcare throughout the day. In addition, more household members likely means that children are present. This can take the form of a stay-at-home spouse or living with older generations of family members that stay in the household for longer periods during the day. Regardless of which avenue the extra childcare occurs, having more people in the household leads to the result of more time spent in daily childcare on average.

Model 4 is the 2SLS model and the only model reported where the main explanatory variable snapdoll has a negative coefficient. However, the coefficient is statistically insignificant. Actually, snapdoll in Model 4 is the only variable in any of the models reported that is not statistically significant at the 90% level. Because of the statistical insignificance, the confidence interval includes 0. This means that even though the coefficient is negative, it is possible that the coefficient is 0 or is even positive. Therefore, the negative coefficient has little explanatory power in explaining the magnitude of childcare. So the partial effect, though possessing the wrong sign, can essentially be ignored when drawing conclusions.

Age has a negative coefficient. Similar to above, this could be because younger parents are more likely to stay in the household to stay with their children. It could also be true that younger parents are more likely to have fewer children and may feel the need to stay closer to a firstborn child as opposed to a third- or fourth-born child. Sex has a large, positive coefficient that is greater in magnitude than Model 3. The sign is because of the way the variable is coded in STATA© with female being the larger discrete value. This coefficient suggests that women, on average, are more likely to engage in daily childcare than men, the same conclusion as above.

Marrwsp shows a negative coefficient. Intuition similar to above would lead to the possible conclusion that having a spouse in the home means that the parents can split time in daily childcare. Marrwosp should a larger negative coefficient than households where the spouse is still in the household, which again is true in Model 4. Again, economic intuition would lead to the possible conclusion that single parents may need to take on more burden when it comes to providing household income. Marrwspchild is the largest coefficient in magnitude and the largest positive coefficient in Model 4, but not as large as the coefficient in Model 3. Combining the pieces of the coded multi-interaction variable, it makes sense that the presence of a child means that there is more daily childcare taking place in the household. Marrwospchild is positive with a smaller magnitude with the related variable where the spouse is still in the household. Following the logic from before, the presence of a child allows for more childcare and being a single parent may force the parent to work more, taking time away from time spent in daily childcare.

Empstat has a positive coefficient. Being employed allows for an increase in daily childcare, on average. Multjobs has a negative coefficient meaning that having more than one job takes time from daily childcare. This makes sense because trying to work more with several jobs takes time away from being in the household and therefore potential time spent engaging in daily childcare. Income has a negative coefficient. The speculation as to why an income decreases daily childcare is explained above. The final variable is hhsize which has a positive coefficient. Regardless of which avenue the extra childcare occurs, having more people in the household leads to more time spent in daily childcare, on average.

Model 5 is the overidentified 2SLS model. Snapdoll has a positive coefficient, as in every model except Model 4. Age shows a negative coefficient. The speculations above ought to be similar to above for the previous models. The sign is because of the way the variable is coded in STATA© with female being the larger discrete value.

Marrwsp shows a negative coefficient. Intuition similar to above would lead to the possible conclusion that having a spouse in the home means that the parents can split time in daily childcare. Marrwosp should a larger negative coefficient than households where the spouse is still in the household, which again is true in Model 5. The explanation is similar to the previous models. Marrwspchild is the largest coefficient in magnitude and the largest positive coefficient in Model 5, but not as large as the corresponding coefficients in the previous models. Marrwospchild is positive with a smaller magnitude with the related variable where the spouse is still in the household. Following the logic from before, the presence of a child allows for more childcare and being a single parent may force the parent to work more, taking time away from daily childcare, on average.

Again here, empstat has a positive coefficient. Being employed allows for an increase in daily childcare, on average. Multjobs has a negative coefficient meaning that having more than one job takes time from daily childcare, on average. The rationale is the same from the previous models. Income, again, has a negative coefficient. The speculation as to why an income decreases childcare is explained above. The final variable is hhsize which has a positive coefficient. Regardless of which avenue the extra childcare occurs, having more people in the household leads to more time spent in daily childcare, on average.

For a supplementary investigation, the subsample was restricted to include only households that are SNAP eligible and have children. SNAP eligibility, again, is defined at households that are below 130% of the poverty line. The presence of household children consists of those children whose parents live in the same household. By restricting the sample with two qualifiers, these results control for white noise that may have affected the key variables in the study thus far, specifically by those households that are SNAP eligible that do not have children. The following table shows descriptive statistics. Notice that the interaction variables that included children, marrwspchild and marrwospchild, are now excluded as any variation in these variables is now explained by marrwsp and marrwosp, respectively. The only difference between the first pair of interaction variables and the second pair is the presence of children in the household, which all households do in this subsample. The inclusion of both pairs is redundant. Also note that the observations for each variable have decreased, reflecting the second qualifier to the sample. The estimation results pertaining to Model 6 and Model 7 are in Table 10.

Table 9. Descriptive Statistics for with Child Subsample.

Variable	**Definition**	**Subsample with child**	
variable name	*STATA coding*	*Obs.*	*Mean (Std. Dev.)*
childcare	daily childcare (minutes)	650,580	41.08495 (88.00602)
snapdoll	SNAP assistance ($)	27,998	22.17748 (85.46133)
age	age of respondent	650,580	44.46106 (17.17129)
sex	1 if male 2 if female	650,580	0.566255 (0.49559)
marrwsp	1 if respondent is married and living with spouse, 0 otherwise	650,580	0.5138953 (0.49981)
marrwosp	1 if respondent is married and living without spouse, 0 otherwise	650,580	0.0144702 (0.119419)
empstat	0 if employed 1 if unemployed 2 if not in the labor force	650,580	0.6700283 (0.91188)
multjobs	0 if no 1 if yes	650,580	0.0596499 (0.23684)
income	midpoint of the categories of the average household income (in $10,000)	630,133	6.919729 (6.323024)
hhsize	number of people living in respondent's household	37,066	2.781606 (1.55813)
ARRA1	ARRA assistance 0 if year<2009, 1 otherwise	650,580	0.729134 (0.44441)

The model to be tested is the same as presented before in this paper with childcare being the dependent variable and the magnitude of dollars of SNAP benefits received by respondents being the main explanatory variable. The right-hand-side variables are the same less the two redundant variables. The equation takes the following general form:

$$childcare_i = \beta_0 + \beta_1 snapdoll + \beta_2 age + \beta_3 sex + \beta_4 marrwsp + \beta_5 marrwosp + \beta_6 empstat + \beta_7 multjobs + \beta_8 hhsize + \beta_9 income + \varepsilon_i$$

All of the econometric principles explained before still apply.

In this subsample, the Hausman test for endogeneity is performed on the OLS regression. The Hausman test provides statistical evidence to support that the main explanatory variable snapdoll is exogenous to the model in this subsample. The universal F-statistic for the OLS model is 0.3700 with an associated p-value of 0.5449. The null hypothesis is exogeneity, so this test failed to reject the null hypothesis at the 90% significance level. Thus, there is strong statistical evidence to show that all variables in the OLS Model 6 are exogenous.

Model 7 is an exactly identified instrumental variable 2SLS model for comparison that uses the correctly coded, and therefore valid, ARRA1 as an instrument for snapdoll. The same rationale for SNAP benefits possibly being endogenous and ARRA1 being a valid instrument applies as above. An overspecified 2SLS model was tested, but the Sargan test for validity came back with an associated p-value of 0.0000, providing strong statistical evidence that the model was invalid. For this reason, the overspecified model is not reported for this subsample.

In Model 6, the intercept, empstat, multjobs, income, and hhsize are significant at the 95% level. Age, sex, and marrwsp are statistically significant at the 99% level. The main explanatory variable snapdoll is also statistically significant at the 99% level. Marrwosp is not statistically significant. For the OLS model, the child-contingent subsample differs from Model 3 reported above most notably in marrwsp which changed sign and is statistically significant with a greater positive magnitude than its counterpart in Model 3. Most likely, this is due to the exclusion of the now redundant marrwspchild. Marrwosp is still negative but is no longer statistically significant. Snapdoll has a slightly smaller negative coefficient but did not lose statistical significance compared to Model 3. This would imply that the existence of household children slightly increases the average expected minutes of daily childcare, which stands to reason. If there are children, there is more childcare, on average. Age has a slightly smaller negative magnitude but is now more statistically significant. The coefficient for sex increased in positive magnitude, but the standard error more than doubled. The statistical significance remains the same at in Model 3, however. Being female increases average childcare per day by a greater magnitude when the subsample is contingent on the existence of children. Empstat is larger in positive magnitude but lost some statistical significance. Multjobs increased in negative magnitude, but the error term is almost twice as large causing it to lose some statistical significance compared to Model 3. Income became greater in negative magnitude at the same level of statistical significance. Hhsize change sign from positive to negative and is still statistically significant. The intercept nearly tripled in positive magnitude and had a doubling of its error term but gained statistical significance in relation to Model 3.

In Model 7, the intercept, empstat, multjobs, and hhsize are statistically significant at the 95% level. Age, sex, and marrwsp are statistically significant at the 99% level. The main explanatory variable snapdoll as well as marrwosp and income are not statistically significant. For the 2SLS model, the child-contingent subsample differs from Model 4 reported most notably in marrwsp which changed sign and is statistically significant with a greater positive magnitude than its counterpart in Model 4. Again, this is likely due to the exclusion of marrwspchild. Marrwosp changed sign, but is no longer statistically significant. Snapdoll became smaller in negative magnitude and is still statistically insignificant. The coefficient for age became slightly smaller in negative magnitude but remains at the same level of statistical significance. The coefficient for sex became about 50% larger than in Model 4, but has almost twice the standard error. Sex has the same level of statistical significance. Hhsize changed from positive to negative and is still statistically significant. Empstat became slightly larger in positive magnitude but lost some significance. Multjobs became slightly larger in negative magnitude but lost some significance. Income's negative coefficient became smaller and is now statistically insignificant. The intercept is twice as large as in Model 4.

On balance, limiting the sample to only include households with children shifted the marriage interaction variables on a greater scale in absolute magnitude than the other right-hand-side variables. This phenomenon could be that the included marriage variables are now reflective of the two other marriage interaction variables that were contingent on childcare before the restriction of the subsample. The only variable that changed sign with any statistical significance is the size of the household. This could reflect that some households may have several additional household adults but no children. The households meeting that description are now excluded from the subsample contingent upon children. In this way, households with several household adults and no children could have been adding significant white noise to the estimates for childcare before the restricted subsample analysis.

Table 10. With Child Subsample Results.

Variable	**(6)**	**(7)**
intercept	26.33998** (11.96072)	33.82541** (16.76443)
snapdoll	0.0564669*** (0.01195)	-0.0126403 (0.11515)
age	-.6860414*** (0.14368)	-.7524238*** (0.17417)
sex	36.27843*** (4.55638)	37.66865*** (5.25713)
marrwsp	36.18515*** (4.88367)	34.4397*** (5.62852)
marrwosp	-3.619867 (11.80367)	-2.747514 (11.89139)
empstat	5.743416** (2.38187)	6.12733** (2.45636)
multjobs	-18.54542** (8.00615)	-18.75308** (8.15846)
income	-5.447587** (2.70083)	-8.943996 (6.56721)
hhsize	-2.072558** (1.33775)	-0.4184277** (3.11279)
n	3889	3889
R-squared	0.0599	0.0487
Prob - F	0.0000	0.0000

* significant at the 90% level
** significant at the 95% level
***significant at the 99% level

This exercise in limiting the subsample is one of the ways this study can be expanded. By limiting the sample to control for white noise and removing redundant variables, the estimates from the models are more likely to reflect the actual relationship between variables of interest. In this case, limiting the sample to being contingent upon the existence of children made for several sign and significance changes. Other extensions include using different linear approximations to attain estimates with more controls. One such way to achieve this is with a difference-in-difference model to control for changes in the overall economic environment over time instead of only controlling for changes in specific household observations over time.

CONCLUSION

The most important take away from this study is that there is evidence that enrollment in the Supplementary Nutrition Assistance Program increases the amount of time that parents can engage in childcare with their children in the household. Through the course of the literature review, SNAP is shown to decrease food insecurity and make for more successful children, both sociologically and economically, later in their lives. Multiple models are reported because it is impossible to determine which is most appropriate for determining the partial effect of SNAP enrollment on childcare. That being said, there is statistical evidence that both provide valid econometric arguments in favor of Model 5.

Future studies could potentially examine the differences between the proposed models to determine which is most appropriate for the estimation. Along those lines, other food subsidies whose aim is to decrease food insecurity could be examined in a similar framework as the one presented in this paper to determine their viability in increasing the amount of childcare that parents are able to take part in each day. Another potential study that could come from the conclusions in this paper could be to examine the requirements to enroll in SNAP. Specifically, investigating if food insecurity could be decreased in a broader range of people is certainly worth studying, especially if there are positive aspects such as increased daily childcare.

The conclusions in this paper suggest that increasing the magnitude of SNAP dollars is beneficial to household childcare and food security. By continuing this framework to investigate other food subsidies, the overall magnitude of subsidized food dollars could be increased. This would lead to children who are better off later in life even though they were raised in low income households and experienced some food insecurity, which the literature shows gives them a disadvantage later in life. Political debates, adverse selection, and moral hazard aside, there is statistical evidence to support that increasing the magnitude of food subsidies is beneficial for children experiencing food insecurity.

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