**Understanding the Effect of the Supplemental Nutrition Assistance Program through Quasi-Experimental Methods**

Samuel Michael Thomas and Bikram Karmakar

Department of Statistics, University of Florida

**Author Note**

Samuel Michael Thomas: https://www.linkedin.com/in/samuelthomasds

Bikram Karmakar: https://people.clas.ufl.edu/bkarmakar/

We have no known conflict of interest to disclose.

Correspondence concerning this article should be addressed to sthomas2878@gmail.com or bkarmakar@ufl.edu

**Acknowledgements**

I would first like to thank Dr. Bikram Karmakar for giving me this opportunity. His kindness and guidance have allowed me to grow educationally, professionally, and personally during the last year and a half of working with him. I would also like to thank the University of Florida Statistics Department for its educational opportunities within as well as outside the classroom. Lastly, I would like to thank my friends and family for their help and support throughout my college education.

**Table of Contents**

**Abstract3**

**Introduction4**

**Overview of Methods4**

Instrumental Variables4

Regression Discontinuity Design6

**Introduction4**

**Data7**

**Exploratory Data Analysis9**

**Results12**

Naïve Probit12

Instrumental Variable Method12

Regression Discontinuity Design14

**Conclusion and Discussion17**

**References19**

**Appendix22**

Tables22

Figures25

**Abstract**

The Supplemental Nutrition Assistance Program, or SNAP, is a food assistance program funded by the US federal government whose primary goal is to aid low-income households with the purchase of food. Recently, SNAP has come under pressure due to conflicting scientific evidence of its effectiveness (Nestle, 2019). However, difficulties arise assessing the effectiveness of SNAP due to a strong confounding by indication problem; the program is available only to the poor who are most at risk of food insecurity. In this analysis, the instrumental variable (IV) method and the regression discontinuity design (RDD) method are used on data of 4,826 households produced by the USDA to quantify non-overlapping evidence for the effectiveness of SNAP. In our study, the IV is an individual’s state of residence since states have different regulations for when one must re-register their SNAP eligibility. The RDD method uses the fact that the program is available to individuals just below the federally mandated income threshold, and those slightly above this threshold miss out. Results from the IV analysis state that SNAP use indicates a higher probability of being food insecure. Similar results via RDD were obtained. The recommendation from this paper is that more analysis and validation of methods must be used in order to reach conclusive results.

*Keywords*: SNAP, food insecure, FoodAPS, instrumental variables, regression discontinuity

**Introduction**

The Supplemental Nutrition Assistance Program (SNAP), formerly food stamps, is a program organized by the US Department of Agriculture Food and Nutrition Service to help food insecure American households put healthy, nutritious meals on the table. In 2022, an average of over 41 million Americans utilized SNAP benefits with a total cost of over $119 billion (US Department of Agriculture, 2023). As of 2019, SNAP was the largest food-related welfare program and the third largest welfare program in the US (Nestle, 2019). However, many policy makers have argued over its effectiveness in reducing food insecurity. Because of the scope and cost of the program, it is important to determine the effectiveness of SNAP in reducing food insecurity among American households.

Previous findings have given conflicting results regarding the effect of SNAP on food insecurity. Some have found that those receiving SNAP are more likely to be food insecure (Wilde & Nord, 2005) while others have found no statistical significance between the two (Kostova & Jensen, 2008). Still others have found that those receiving SNAP are less likely to be food insecure (Ratcliffe et al., 2011). The reason why it is so difficult to determine the effectiveness of SNAP is due to its inherent confounding by indication problem; the program is available only to the poor who are most at risk of food insecurity. For this reason, extra steps must be taken during analysis to properly determine the relationship between SNAP and food insecurity.

To analyze the effectiveness of SNAP on food insecurity, this analysis utilizes two quasi-experimental methods. First, a bivariate probit instrumental variable (IV) approach is fit on low-income households to determine SNAP’s relationship with food insecurity. Unique state laws regarding SNAP eligibility are leveraged and used as the instrument in the analysis. The next method involves using a regression discontinuity design (RDD) to analyze the effectiveness of SNAP on food insecurity by using a running variable with a cutpoint that defines SNAP use and eligibility. By using these two methods, causality may be established between SNAP and food insecurity. Thus, it is possible to determine how SNAP reception effects food insecurity.

This paper first starts with an overview of both the instrumental variable and regression discontinuity methods. It then gives an in-depth description of the data. After that, an in-depth exploratory data analysis section is used to give a full understanding of the data. This is followed by IV and RDD results. Lastly, final conclusions and limitations are discussed. All code and data used in the analysis can be found on GitHub at https://github.com/sthomas2878/Thomas-Karmakar-SNAP-Analysis.

**Overview of Methods**

**Instrumental Variables**

First, an instrumental variable (IV) approach is utilized to estimate the effect of SNAP usage on food insecurity for households with income at or below 150% of the poverty threshold. In general, IV approaches are designed to control for confounding variables that may be unmeasured in a survey and analysis. The unique element of the IV method is its use of an instrumental variable, or instrument. A valid instrument must be correlated with the treatment, independent from those unmeasured confounding variables, and only effect the response through the treatment (Baocchi et al., 2014). All these characteristics together allow for a model where the variation in the response is theoretically only influenced via the treatment. Thus, a causal estimate is achieved.

This analysis uses a bivariate probit model with an endogenous dummy variable (Heckman, 1978). Here, there are two different bivariate probit equations. The first stage is:

where if represents receiving SNAP for household i. The second stage is:

where if which represents food insecurity for household i.

The variable represents the vector of dummy variables used for the instrument. The instrument in this analysis is census region. There are 4 census regions that are defined by the US Census Bureau (2021). These include the Northeast, Midwest, South, and West regions. Each census region is made up of states that each have different policies regarding the reception of SNAP benefits (US Department of Agriculture, 2019). These policy differences affect food insecurity only through SNAP reception. Thus, they may be used as an instrumental variable. Unfortunately, due to the security requirements of the survey data, individual state-level data is not provided. However, census region-level data is available and used as the instrument.

Next, the variable represents the vector of economic and demographic exogeneous variables that are included in the analysis. These include both continuous and dummy variables for income, age, immigration status, race, ethnicity, education, number of children, number of adults, sex, disabled, and rural.

Both and are the error terms in the first and second equation, respectively. Here, it is assumed that both error terms draw from independent normal distributions with mean 0 and variance 1.

**Regression Discontinuity Design**

The other method used in this paper is a regression discontinuity design (RDD). The introduction of RDD was by Thistlethwaite and Campbell (1960) to investigate the effect of a treatment that is determined by a cutoff point of a running variable. A crucial idea behind the design is that those who are just below the cutpoint are similar to those who are just above the cutpoint. Therefore, the only difference between the two groups is the treatment, and the effect of the treatment may be studied as in a randomized experiment (Lee & Lemieux, 2010). It is important to also look at RDD because IV requires a strong instrument. For this reason, RDD can circumvent this limitation and give supplementary evidence to the original IV analysis.

Previous literature has determined that low-income households are defined as those that are at or below 150% of the poverty threshold (Ratcliffe, 2011). Because SNAP eligibility and reception changes at that point, it then follows that percent of the poverty threshold can be used as a running variable, with a cutpoint of 150%, to determine the effect of SNAP eligibility and reception on food insecurity. Furthermore, graphical analysis (Figure 21, 22) confirms the eligibility of using a cutpoint of 150%.

One important consideration for RDD is that individuals in between groups are more likely to be similar around the cutpoint than those far from the cutpoint. For this reason, it is necessary to carefully select a bandwidth in order to look at the proper quantity of data near the cutpoint. In this analysis, the Imbens and Kalyanaraman (2012) bandwidth was used.

Finally, an important assumption of RDD is that there is no manipulation of the running variable around the cutpoint in order to change treatment status. In order to test for this assumption, the McCrary (2008) Test was utilized.

There are two different types of RDD commonly used: sharp and fuzzy (Hahn et al., 2001). A sharp RDD assumes that one side of the cutpoint receives a treatment, and the other side receives the other treatment. In this case, however, many households below the cutpoint do not receive SNAP while some above the cutpoint do receive SNAP (Figure 22). For this reason, it is necessary to use a fuzzy RDD. Both a parametric and non-parametric approach are explored.

In a fuzzy RDD, the resulting effect that is estimated is called the Local Average Treatment Effect (LATE). This effect is interpreted as the difference in the response between the two groups around the cutpoint. In the fuzzy design, this effect takes into consideration the “take-up” of the treatment to achieve an accurate estimate (Lee & Lemieux, 2010).

Fuzzy RDD takes advantage of an instrumental variable approach in order to account for the non-deterministic nature of treatment use (Lee & Lemieux, 2010). This leads to the following first stage equation (The World Bank, n.d.) with SNAP:

where if household i is below the cutpoint and receives the treatment. Then, the second stage equation is:

where if household i is food insecure, and measures the LATE.

The variable if household i is SNAP eligible or a SNAP receiver. Further, represents a function of the percent poverty of household i. Gelman and Imbens (2019) recommended that this be a local linear or smooth function with order 1 or 2. represents the same exogeneous variables as in the IV model except for monthly income. Note that and are mean 0 errors specific to the RDD models.

**Data**

Individual and household-level data for the analysis comes from the National Household Food Acquisition and Purchase Survey (FoodAPS). This survey was co-sponsored by the USDA’s Economic Research Service (ERS) and Food and Nutrition Service (FNS). Data was collected from a nationally representative sample of 4,826 households between April 2012 and January 2013 (USDA Economic Research Service, 2021).

The data contains information regarding quantities and prices of all foods purchased by all household members over a seven-day period. Further, the data contains information about the eating occasions by all household members.

The interview process started with an initial screening phase to determine the eligibility of the household. Then, an initial, computer-assisted in-person survey was conducted with the primary respondent, deemed as the “main food shopper or meal planner in the household” (USDA Economic Research Service, 2016a). After the initial interview, all household members were asked to track all food acquisitions and meals eaten for the next seven days. Additionally, during this seven-day period, the primary respondent was asked to conduct three separate phone interviews with the interviewer to report food acquisitions. Once the seven-day period was complete, the interviewer conducted a final computer-assisted in-person interview. Additionally, the primary respondent filled out a feedback form and received the incentives.

Household characteristics include SNAP participation, food security, income, and other demographic characteristics. Further, household information regarding access to food and nutritional knowledge is included in the data.

This analysis was conducted at the household level using only publicly available information. The following economic household characteristics from the data were used:

* ADLTFSCAT – Adult food security status
* REGION – Census region
* RURAL – Household is in a rural Census tract
* INCHHAVG\_R – Monthly household average income
* SNAPNOWHH – Anyone in household is receiving SNAP benefits
* POVTHRESH\_HH – 2012 monthly poverty threshold for household of this size and composition
* SNAPNOWHH – Anyone in household is receiving SNAP benefits
* ELIG\_UNITS1 – Number of eligible SNAP units formed in household in model run 1

Note that ELIG\_UNITS1 is calculated using the Microanalysis of Transfers to Households (MATH) SIPP+ Microsimulation Model (USDA Economic Research Service, 2016b). This model was built by Mathematica Policy Research, who were contracted by ERS to conduct the survey. The model is built upon data from the Survey of Income and Program Participation (SIPP), government rules that determine eligibility, and estimation models which consider SNAP rules. This model was then run on the FoodAPS data to determine whether households were eligible for SNAP participation. Model run 1 considered SNAP-eligibility on a household level with earnings as reported. This is consistent with how the analysis in this paper was run – on a household level utilizing as reported earnings.

Next, the following variables were computed from some of the household characteristics listed above:

* BINADLTFSCAT – Adult food security status
  + 0 – Food Secure (ADLTFSCAT = 1 or ADLTFSCAT = 2)
  + 1 – Food Insecure (ADLTFSCAT = 3 or ADLTFSCAT = 4)
* PERCENT\_POVERTY – Income as a percentage of 2012 monthly poverty threshold for household of this size and composition
  + (INCHHAVG\_R / POVTHRESH\_HH) \* 100

Next, demographic data was collected from the individual-level variables collected during FoodAPS (USDA Economic Research Service, 2016a). Note that only individuals considered to be a part of the primary respondent’s family (FAMMEMBER = 1) were used to calculate demographic data. In the data, the primary respondent is given a value of PNUM = 1. The following variables were computed and used in the analysis:

* PR\_AGE\_R – Approximate midpoint of primary respondent’s age group
* NCIMMIGRANT\_ANY – Anyone in the household is a non-citizen immigrant
  + Derived from USCITIZEN = 0 (May need to add a note about this)
* PROP\_WHITE – Proportion of household members that are White
* PROP\_BLACK – Proportion of household members that are Black
* PROP\_OTHER – Proportion of household members that are not White or Black
* HISPANIC – Proportion of household members that are Hispanic
* PR\_EDUCCAT – Primary respondent’s highest level of completed education
* NCHILDREN – Number of children in the household
* NADULTS – Number of adults in the household
* PR\_SEX – Sex of the primary respondent
* DISABLED – Any member of the household is disabled
  + According to FoodAPS, disabled persons are defined as follows:
    - Individuals under age 60 and either
      * An SSI Recipient or
      * Nor working or not in school because of disability and is receiving a disability-based benefit

After creating all new variables and data cleaning, there remained 4,808 of the original 4,826 households. Households that did not make it into the final dataset for analysis either refused to respond or responded as ‘Don’t know’ to most necessary categories. Finally, the 2,046 households in the dataset at or below 150% of the poverty threshold were used for the IV analysis.

**Exploratory Data Analysis**

As previously mentioned, 4,808 households from the FoodAPS dataset (USDA Economic Research Service, 2021) were used for this analysis. In this section, we break down each variable.

1. Response – Food Security

The FoodAPS data provides a variable called ADLTFSCAT that measures food security of each household. For the purposes of this analysis, ADLTFSCAT has been condensed into a binary variable represented by BINADLTFSCAT. Figure 1 and Figure 2 show barplots with counts of both food insecurity variables.

The majority of households have high food security. This is followed my marginal security, low security, and very low security. This is further represented in the binary version of the variable where 3470 households are food secure versus 1338 food insecure households.

1. Endogenous Variable – Receiving SNAP

The endogenous variable used in the instrumental variable analysis is a binary variable that indicates whether anyone in the household is receiving SNAP benefits. Of the 4,808 households in this analysis, 3,232 are not receiving any SNAP benefits, and 1,576 households are receiving SNAP benefits (Figure 3). Further, of those not receiving SNAP benefits, 628 are reported to be food insecure, or 19.4%. On the other hand, of those receiving SNAP benefits, 710 are reported to be food insecure, or 45.1% (Figure 4).

1. Instrument – Region

Next, is the REGION variable. Due to security and privacy regulations, the only geographic information provided in the publicly available dataset are the 4 census regions. These 4 regions are Northeast, Midwest, South, and West. The states which are included in each region can be seen in Figure 5.

In this data, the region with the most households is the South with 1777 (Figure 6). This is followed by the Midwest with 1168 households, the West with 1051 households, and the Northeast with 812 households. Breaking down the regions further by receiving SNAP, the South has the largest proportion of its households receiving SNAP (Figure 7). They are followed closely by the West and the Northeast. Last is the Midwest.

Next, breaking the regions down by Food Security (Figure 8), it appears that the South also has the highest rate of food insecurity followed again by the West. Interestingly, the Midwest has the third highest rate of food insecurity, and the Northeast has the lowest rate of food insecurity. This is a flip from the order of proportion of SNAP benefit receivers where Midwest receives the least amount of SNAP benefits and Northeast the second least.

1. Exogenous Economic Variables

The first exogenous economic variable is whether a household is in a rural area or not. The FoodAPS survey follows the Census Bureau's urbanized area definition. A household is considered rural if it is in a census tract with a geographic centroid in an area with less than or equal to 2,500 people (USDA Economic Research Service, 2016b).

3,503 households in this dataset are not in rural Census tracts as opposed to 1,305 households that are (Figure 9). Breaking down by receiving SNAP (Figure 10), the majority of households in both rural and urban areas do not receive SNAP benefits. Further, the proportion of households receiving SNAP benefits is slightly higher in non-rural areas than rural areas. A similar phenomenon is seen when breaking down rurality by food security (Figure 11). However, the proportion of food insecure non-rural households and food insecure households is slightly larger than the difference in the proportion of non-rural SNAP households and rural SNAP households.

Figure 12 gives the breakdown of region by rural. Each region has a different proportion of rural households. The South has the highest proportion of rural households, followed by the Midwest, Northeast, and West. In fact, the South has a proportion of rural households that is over twice the proportion of the West.

Monthly average income is the other exogenous income variable used in the IV analysis. The monthly average income is the sum of average income per member in dollars. For households that did not report their income, the income is imputed using the average of 5 imputations.

The distribution of incomes is very right-skewed (Figure 13). The mean is $3761.19 with a standard deviation of $3697.41. Also, the 25th, 50th, and 75th quantiles are $1440, $2660, and $4795.32, respectively. One thing to note is that 98 households reported an income of $0.

Breaking down income by receiving SNAP, the 25th, 50th, and 75th quantiles are all lower for those receiving SNAP compared to those not receiving SNAP. Specifically, the median income for households receiving SNAP benefits is $1551.71 versus $3500.00 for those not receiving SNAP (Figure 14). However, there is overlap regarding income for those receiving SNAP and those not receiving SNAP. This trend is very similar between households that are food secure and food insecure (Figure 15). Interestingly, the median of food insecure households is $1701.49 compared to a median of $3220.00 for households that are food secure. Hence, we see that the median income for food insecure households is higher than those receiving SNAP benefits.

As far as region goes, there are differences, in the distribution of income between different regions (Figure 16). The median income of Northeast, Midwest, South, and West is $3289.50, $2688.50, $2323.00, and $2965.67, respectively. Because of these differences in income by region, it is important that region is included in the analysis.

1. Exogenous Demographic Variables

Table 1 breaks down the mean and standard deviations of the exogenous demographic variables. The mean age of primary respondents was 46 years old with a standard deviation of 16.8 Interestingly, both the 50th and 75th percentiles are 47.5. Next, on average, the racial makeup of households was 69.3% White, 14.8% Black, and 15.8% other races. Further, 19.9% of household members are Hispanic while 80.1% are non-Hispanic.

The mean number of children in a household was 0.89 with a standard deviation of 1.25. The mean number of adults in a household was 1.85 with a standard deviation of 0.95. Interestingly, there were 9 households that had 7 or more adults and 1 household that had no adults.

Next, 12.9% of households had at least one member that was considered a non-citizen immigrant. Additionally, 8% of households, or 334 households have a disabled member.

In terms of education, 53% of primary respondents had completed more than high school, 28.8% had completed high school only, and 17.3% completed less than high school.

Next, 73.5% of primary respondents were female with the rest being male. This is a curious finding because 25.7% of households with male respondents receive SNAP while 35.3% of households with female respondents receive SNAP. Further, 26.2% of households with male respondents are food insecure versus 28.4% of female respondents being food insecure, a 2-percentage point difference. It is possible the reason for the discrepancy in the proportion of female and male respondents may be due to the survey design itself.

1. Receiving SNAP vs SNAP eligible

The last graph of interest in the exploratory data analysis section is the mosaic plot of households that are receiving SNAP versus those that are SNAP eligible (Figure 17). Interestingly, 234 households are not eligible for SNAP, but are receiving SNAP. In comparison, 2008 households are not eligible nor receiving SNAP.

Among households that are eligible to receive SNAP, 1342 are receiving SNAP in comparison to 1224 that are not receiving SNAP. This equates to 52.3% of households that are eligible to receive SNAP benefits are utilizing them.

This result is important during the regression discontinuity analysis. Because there are so many households that do not receive SNAP even when they are eligible for benefits, it is necessary to use a fuzzy design. This design is a specific use case for when the main treatment, in this case SNAP use, is not perfectly adhered to by all participants.

**Results**

**Naïve Probit**

First, it is important to look at the results of the model regressing our endogenous variable, receiving SNAP onto our response food insecurity for households at or below 150% the poverty threshold. This is a probit model that also includes all exogeneous variables. The results can be seen on the right side of Table 2.

Most importantly, receiving SNAP has a positive, significant effect in the model. Hence, keeping all else constant, those who receive SNAP benefits are more likely to be food insecure. As previously discussed, the goal of SNAP is to provide nutritional assistance to those who are in need. The very nature of SNAP presents a phenomenon of self-selection by food insecure households to use SNAP. This is precisely in line with the program’s target in helping those particular food insecure households. Therefore, our model validates the thought process that households who use SNAP are more likely to be food insecure than those that do not. For these reasons, it is necessary to use an instrumental variable technique in order to account for the endogeneity of SNAP.

Other positive, significant variables include disabled, number of adults, and education less than high school. Keeping all else constant, households with disabled members are more likely to be food insecure. Similarly, households with more adults are more likely to be food insecure and households where the primary respondent has less than a high school level of education are more likely to be food insecure, keeping all else constant.

Lastly, the first order term of age is positive, while the second order term of age is negative. This means that keeping all else constant, households with an older primary respondent are more likely to be food insecure.

**Instrumental Variable Method**

In Model 1, all demographic variables were included as exogeneous variables. Additionally, income was included as an exogeneous variable. The instrumental variable is a set of indicator variables representing each region. These exogeneous variables and indicator variables were fit on receiving SNAP.

Then, the predictions from this fit were used alongside the same exogeneous variables to fit the next probit model on the binary version of food insecurity. Note that the standard errors needed to be calculated differently than a usual probit model in order to account for the instrumental variable approach. This was all done using the ivtools package in R (Sjolander, 2022). Further, the subset of 2,046 households at or below the 150% poverty threshold were used for the IV analysis, as this is the study population of interest.

The results of both fits can be seen in Table 2. The results for the first model indicate that all indicators for region are significant at a 95% confidence level. Further, the coefficient for each region is negative indicating that a household in the Northeast, keeping all other economic and demographic variables constant, is most likely to receive SNAP. This is an interesting result because in the exploratory data analysis section, the Northeast ranked third among all regions for the proportion of its population receiving SNAP benefits.

Next, we see that monthly average income is a significant variable at the 95% level. Additionally, the negative coefficient indicates that keeping all else constant, households with higher income are less likely to receive SNAP benefits. This follows as SNAP exists for the benefit of lower income households.

The demographic variables that are significant at the 95% level with a negative coefficient are the squared term of primary respondent age and whether a household member is a non-citizen immigrant. The rules surrounding non-citizen immigrants receiving SNAP benefits are much different than those that apply to citizens (US Department of Agriculture, 2013). Because of these rules, it makes sense that non-citizen immigrants are less likely to receive SNAP benefits in comparison to citizens with the same characteristics.

The demographic variables that are significant at the 95% level with a positive coefficient are the proportion of Black household members, the education levels, number of children, number of adults, sex of primary respondent being female, and if there is a disabled member of the household. The variables such as number of children and number of adults follows as more people in the household means more mouths to feed and therefore more likelihood of receiving SNAP benefits. Further, education levels seem to follow as well because respondents with less completed education are likely worse off and more likely to need SNAP benefits.

Curiously, primary respondent sex being female is a significant variable with 73.5% of households having a female respondent. After looking back into the data, it appears that 25% of male respondents receive SNAP whereas 35% of female respondents receive SNAP benefits. Hence, even after controlling for all other variables, there is still a significant effect for female respondents.

The results for the second stage model indicate a positive, significant estimate for those receiving SNAP benefits. In other words, keeping all other variables constant, those who receive SNAP benefits are more likely to be food insecure. This result comes even after controlling for other economic and demographic variables. This result is nearly the same as the original model without using the instrumental variable technique. The difference is that the coefficient for SNAP in the original model is 0.194 in comparison to a coefficient of 1.031 in the IV model. Further, the standard error for the original model is 0.0623 compared to 0.414 in the IV model. Hence, we see a larger coefficient in the original model, but a larger standard error in the IV model.

The other significant variables with the same sign of coefficient are the squared age term, proportion of Black household members, education less than high school, and disabled member in the household.

A new, significant variable is the first order age term. Additionally, the number of children is still significant, but has flipped signs. Now, keeping all else constant, households with more children are less likely to be food insecure. Further, we see in this fit that monthly income is a nonsignificant, positive coefficient. This is perhaps most surprising as the results here state that there is no statistical relationship between income and food security, which is against general consensus of previous research (Wilde & Nord, 2005; Ratcliffe et al., 2011). A possible reason for this is that income effect is captured by the estimates in the first stage because there exists a strong correlation between income and receiving SNAP in the first stage of the IV model.

In comparison to the naïve probit model, the signs for significant variables are the same. However, the IV model does introduce two new significant variables in proportion of Black members in the household and number of children. On the other hand, the number of adults was significant in the naïve probit model but is not significant in the IV model.

There do exist validation tests with respect to IV analysis. However, most widely available tests focus on continuous outcomes. Further, recent literature has found that these tests do not work for probit IV models (Li et al., 2022). Other literature has found some validation tests for probit IV analysis (Frazier et al., 2020), but these tests are not readily available in the software packages used during this analysis. Further probit IV analysis of this dataset must focus on the validity of region as an instrument in order to verify the usage of probit IV.

**Regression Discontinuity Design**

For the regression discontinuity design, the running variable that was studied was percent poverty. This is because there is no clear guideline for SNAP eligibility solely based on household income. SNAP eligibility also takes household size and composition into account. For this reason, percent poverty was used as the running variable of interest. Importantly, percent poverty was derived from the 2012 monthly poverty threshold for each household’s size and composition. For this reason, size and composition is now taken into account when determining a cutpoint.

Further, a cutpoint of 150% was used for this study. According to Ratclife et al. (2011), 150% of the poverty threshold represents a low-income household. Further, from graphical analysis (Figure 21, 22), 150% appears to be an accurate cutpoint for both SNAP eligible households and SNAP receiving households.

The regression discontinuity design can be used in either a sharp setting or a fuzzy setting. In a sharp setting, all units on one side of the cutpoint use the same treatment, and all units on the other side of the cutpoint use the other treatment. From Figure 17, however, only 47.7% of units who are eligible to use SNAP are not using SNAP. Similarly, of those who are not eligible for SNAP, about 10% are receiving SNAP. Figure 21 and Figure 22 give further evidence for the use of a fuzzy RDD because there are households that are receiving the treatment which are above the cutpoint as well as households that are not receiving the treatment who are below the cutpoint. For this reason, two fuzzy RDD analyses were conducted with one using SNAP eligibility as the treatment and the other using SNAP reception as the treatment. All RDD analysis was conducted using the rddtools package (Stigler & Quast, 2016) in R.

1. Log Transform

One of the main diagnostic tests to check that a regression discontinuity design can be used on the data is called the McCrary (2008) Test. This test checks to see if there is manipulation of the running variable by households to qualify for a certain treatment. In this case, households may purposely lower their percent poverty in order to qualify for SNAP. Failure of this test would then violate assumptions to accurately estimate the results of RDD.

First, the McCrary test was computed on the original percent poverty variable (Figure 18). The results can be seen below in Table 3. A p-value of almost zero was obtained, rejecting the null that the density is continuous around the cutpoint of 150. Unfortunately, this invalidates any results obtained by the RDD models with the original percent poverty variable.

However, a natural log transformation of percent poverty (Figure 20) yields encouraging results (Figure 19). After transformation, the McCrary Test produces a p-value of 0.09, which fails to reject the null hypothesis. Hence, it can be concluded that the running variable is continuous around the cutpoint, which after transformation is 5.01. All analysis using RDD going forward is completed using the log transformed running variable and cutpoint.

All models included all the demographic variables used in the IV analysis, region, and rural as covariates. Additionally, all models used the Imbens-Kalyanaraman (2012) Optimal Bandwidth for RDD. The bandwidth for all models using log percent poverty as the running variable was calculated to be 0.609.

1. SNAP Eligible Treatment

The non-parametric fit yielded a Local Average Treatment Effect (LATE) of -0.0098 (Table 4). However, the standard error was 0.011, which gave a z-value of -0.8862 and therefore a p-value of 0.3755. At the 95% confidence level, this result is not statistically significant. Further, even when using different bandwidths, the LATE is not significant at the 95% level as shown in Figure 23.

Next, a first order parametric fit using a probit link was used. The parametric fit yielded a LATE of 0.0056 with a standard error of 0.019 (Table 4). This result yields a p-value of 0.7699. A second order parametric fit gives similar results as shown in Figure 24.

That being said, using a different cutpoint for both the non-parametric and parametric estimates can lead to very different results. However, slight changes in the cutpoint of 5.01 do not lead to any changes in significant estimates.

These results together indicate that there is no statistically significant relationship between being SNAP eligibility and food insecurity. Hence, those who are SNAP eligible around the cutpoint of 5 are just as likely to be food insecure as those who are not SNAP eligible around the cutpoint. In other words, there is no statistically significant difference between the two groups around the cutpoint.

1. SNAP Reception Treatment

The non-parametric fit using SNAP reception as the treatment gave a LATE of 0.0918, with a standard error of 0.011 (Table 4). Hence, the z value is 8.292, and the p-value is near zero. Therefore, those who receive SNAP around the cutpoint are more likely to be food insecure than those who do not receive SNAP.

Further, the first order parametric fit gives a similar result of a positive LATE of 0.2819, with a standard error of 0.016 (Table 4). This yields another p-value near zero. Once again, the RDD using SNAP reception as the treatment gives a conclusion that those who receive SNAP around the cutpoint are more likely to be food insecure than those who do not receive SNAP.

Curiously, however, this result holds for any changes in bandwidth and order for the parametric and non-parametric estimates (Figure 25). Perhaps most importantly, the result holds for any cutpoint between 4 and 6 in both the non-parametric and parametric estimates (Figure 26).

The reason why this result holds for every cutpoint is that there may be some self-selection bias occurring. Those households who truly are in desperate need for food will seek out SNAP benefits. For this reason, these households are more likely to be food insecure.

**Conclusion and Discussion**

During this analysis, quasi-experimental methods were used in order to determine the effectiveness of the Supplemental Nutrition Assistance Program (SNAP). Econometric and statistical analysis of this problem suffers from the bias created by the general nature of the problem that SNAP sets out to solve (Ratcliffe et al., 2011). Those who require SNAP are likely going to be more food insecure than those who do not need SNAP. For this reason, it is necessary to use a quasi-experimental method, such as IV, to establish causality between SNAP and food insecurity.

The first naïve probit regression of food insecurity on SNAP and other exogeneous factors for households at or below 150% the poverty threshold found that receiving SNAP has a significant, positive effect on food insecurity (Table 2). Hence, those who receive SNAP are more likely to be food insecure. For the probit instrumental variable model, the first stage estimate of SNAP reception indicated all the instruments, regions, as being significant. Further, income is a very important indicator of SNAP reception. Then, during the second stage, SNAP had a positive, significant estimate (Table 2). Hence, those who receive SNAP benefits are more likely to be food insecure.

The next analyses conducted were non-parametric and parametric fuzzy regression discontinuity designs to analyze food insecurity using log percent poverty as the running variable. All models used log(150) as the cutpoint. The first analysis used SNAP eligibility as the treatment (Table 4). Both non-parametric and parametric estimates do not produce a statistically significant Local Average Treatment Effect (LATE), meaning those who are SNAP eligible around the cutpoint are just as likely to be food insecure as those who are not SNAP eligible around the cutpoint. The second analysis used SNAP reception as the treatment (Table 4). Both non-parametric and parametric estimates yielded a positive, significant LATE. Therefore, those that receive SNAP around the cutpoint are more likely to be food insecure than those who do not receive SNAP.

There are still many limitations when it comes to different parts of the analysis. There exist some standard validation tests with respect to IV analysis using a continuous response. However, literature has found that these validation methods do not work for probit IV models (Li et al., 2022). While recent work has found some validation tests for probit IV (Frazier et al., 2020), these tests are not readily available in the software packages used for this project (R, Python). For this reason, important tests like instrument validity cannot be verified currently.

As far as the results themselves, many may suffer due to selection bias that comes as a result of the nature of the program. Because SNAP specifically focuses on households in need of nutritional assistance, those that receive SNAP as a group are likely fundamentally different than those that do not receive SNAP. Although the IV addresses this issue, the RDD does not. This is potentially a reason why the results of the RDD using SNAP reception as the treatment point to those using SNAP as being more food insecure around the cutpoint.

Ideally, further analysis can and should be conducted using this data, especially with regards to the IV methods. As more research is conducted and more validation tests become readily available in statistical software, more accurate results can be acquired with regards to the effectiveness of SNAP. Policy decisions can then be made to reflect these results and the lives of those in need can improve.

**References**

Baiocchi, M., Cheng, J., & Small, D. S. (2014). Instrumental variable methods for causal

inference. *Statistics in medicine*, *33*(13), 2297-2340.

Frazier, D. T., Renault, E., Zhang, L., & Zhao, X. (2020). Weak identification in discrete choice

models. *arXiv preprint arXiv:2011.06753*.

Gelman, A., & Imbens, G. (2019). Why high-order polynomials should not be used in regression

discontinuity designs. *Journal of Business & Economic Statistics*, *37*(3), 447-456.

Hahn, J., Todd, P., & Van der Klaauw, W. (2001). Identification and estimation of treatment

effects with a regression-discontinuity design. *Econometrica*, *69*(1), 201-209.

Heckman, J. J. (1978). Dummy Endogenous Variables in a Simultaneous Equation System.

*Econometrica*, *46*(4), 931–959. https://doi.org/10.2307/1909757

Imbens, G., & Kalyanaraman, K. (2012). Optimal bandwidth choice for the regression

discontinuity estimator. *The Review of economic studies*, *79*(3), 933-959.

Kostova, S., & Jensen, H. H. (2008). Food Assistance Programs and Outcomes in the Context of

Welfare Reform. *Social Science Quarterly*, *89*(1), 95–115.

http://www.jstor.org/stable/42956258

Lee, D. S., & Lemieux, T. (2010). Regression Discontinuity Designs in Economics. *Journal of*

*Economic Literature*, *48*(2), 281–355. http://www.jstor.org/stable/20778728

Li, C., Poskitt, D. S., Windmeijer, F., & Zhao, X. (2022). Binary outcomes, OLS, 2SLS and IV

probit. *Econometric Reviews*, *41*(8), 859-876.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design:

A density test. *Journal of econometrics*, *142*(2), 698-714.

Nestle, M. (2019). The Supplemental Nutrition Assistance Program (SNAP): history, politics,

and public health implications. *American journal of public health*, *109*(12), 1631-1635.

Ratcliffe, C., McKernan, S. M., & Zhang, S. (2011). How much does the Supplemental Nutrition

Assistance Program reduce food insecurity?. *American journal of agricultural*

*economics*, *93*(4), 1082-1098.

Sjolander, A., Dahlqwist, E., & Martinussen, T. (2022). ivtools [Computer software].

https://cran.r-project.org/web/packages/ivtools/ivtools.pdf

Stigler, M., & Quast, B. (2016). rddtools: A toolbox for regression discontinuity in R [Computer

software]. The Graduate Institute, Maison de la paix, Geneva,

Switzerland.https://qua.st/rddtools/

Tampa International Airport. (n.d.). *US Census Regions* [MAP]. Tampa International Airport.

https://www.tampaairport.com/us-census-regions

The World Bank. (n.d.) *Regression Discontinuity*. The World Bank. Dimewiki.

https://dimewiki.worldbank.org/Regression\_Discontinuity

Thistlethwaite, D. L., & Campbell, D. T. (1960). Regression-discontinuity analysis: An

alternative to the ex post facto experiment. *Journal of Educational psychology*, *51*(6),

309.

US Census Bureau. (2021, October 8). Geographic Levels. *Census.gov*.

https://www.census.gov/programs-surveys/economic-census/guidance-

geographies/levels.html

US Department of Agriculture. (2013, September 4). SNAP Policy on Non-Citizen Eligibility.

*Food and Nutrition Service U.S. Department of Agriculture*.

https://www.fns.usda.gov/snap/eligibility/citizen/non-citizen-policy

US Department of Agriculture. (2019, June 27). State Options Report. *Food and Nutrition*

*Service U.S. Department of Agriculture*. https://www.fns.usda.gov/snap/waivers/state

options-report

US Department of Agriculture. (2023, March 10). SNAP Data Tables. *Food and Nutrition*

*Service U.S. Department of Agriculture*. https://www.fns.usda.gov/pd/supplemental-

nutrition-assistance-program-snap

USDA Economic Research Service (2016, November). Codebook: FoodAPS Individual Public

Use File faps\_individual\_puf. *National Household Food Acquisition and Purchase*

*Survey (FoodAPS).*

USDA Economic Research Service (2016, November). Codebook: Household-Level Public Use

File faps\_household\_puf. *National Household Food Acquisition and Purchase Survey*

*(FoodAPS)*

USDA Economic Research Service. (2021). *FoodAPS National Household Food Acquisition and*

*Purchase Survey* [Data Set]. https://www.ers.usda.gov/data-products/foodaps-national-

household-food-acquisition-and-purchase-survey/

Wilde, P., & Nord, M. (2005). The effect of food stamps on food security: A panel data

approach. *Review of Agricultural Economics*, *27*(3), 425-432.

**Appendix**

**Table 1: Summary of Household Demographic Characteristics for All Households and Those Receiving SNAP**

Table

Description automatically generated

**Table 2: Estimates of the Two IV Model Fits and Naïve Probit Fit**

A picture containing text, receipt, screenshot

Description automatically generated

Note: Standard errors are presented in parenthesis. Sample includes 2,046 households in the dataset at or below 150% the poverty threshold. \*\*\* p < 0.001, \*\* p < 0.01, \* p < 0.05.

**Table 3: Results of McCrary Test on Percent Poverty and Log Percent Poverty**

A picture containing text

Description automatically generated

**Table 4: Regression Discontinuity Design (RDD) Results for SNAP Eligible and SNAP Receiver Treatments**

Table

Description automatically generated

Note: Standard errors are presented in parenthesis. Non-parametric estimates are from a local linear, first-order model. \*\*\* p < 0.001, \*\* p < 0.01, \* p < 0.05.

Chart, treemap chart

Description automatically generated

Figure 1: Barplot of food security status by household. Households that with low or very low food security are considered food insecure while high or marginal security is considered food secure.

Chart, bar chart

Description automatically generated

Figure 2: Barplot of household responses to food security level.

Chart, treemap chart

Description automatically generated

Figure 3: Barplot of households receiving SNAP during the survey.

Chart, bar chart

Description automatically generated

Figure 4: Barplot of households receiving SNAP by food security status.

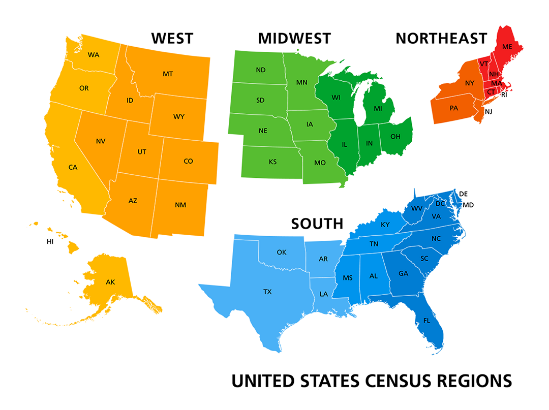


Figure 5: Map depicting the states that are in each census region (Tampa International Airport, n.d.).

Chart, bar chart

Description automatically generated

Figure 6: Barplot showing the quantity of households in each region. Each number represents the count of households in each region.

Chart, treemap chart

Description automatically generated

Figure 7: Mosaic plot of households receiving SNAP benefits broken down by region. The South has the greatest proportion of households receiving SNAP (37.5%) followed by the West (33.7%), Northeast (30.9%), and Midwest (26.1%).

Chart, treemap chart

Description automatically generated

Figure 8: Mosaic plot of household food security status broken down by region. The South has the greatest proportion of food insecure households (32.5%) followed by the West (31.1%), Midwest (22.4%), and Northeast (21.1%).

Chart, bar chart, treemap chart

Description automatically generated

Figure 9: Barplot of quantity of households in the dataset that are classified as rural.

Chart, treemap chart

Description automatically generated

Figure 10: Mosaic plot of households receiving SNAP broken down by rural. The percentage of rural households receiving SNAP is 31.0% while the percentage of non-rural households receiving SNAP is 33.5%.

Chart, treemap chart

Description automatically generated

Figure 11: Mosaic plot of household food security status broken down by rural. The percentage of food insecure rural households is 24.6% while the percentage of food insecure non-rural households is 29.0%.

Chart, treemap chart

Description automatically generated

Figure 12: Mosaic plot of rural households broken down by region. The South has the highest proportion of rural households (36.1%), followed by the Midwest (28.4%), Northeast (23.8%), and West (13.2%).

Chart, histogram

Description automatically generated

Figure 13: Histogram of average monthly household income. The median average monthly household income is $2660.

Chart, box and whisker chart

Description automatically generated

Figure 14: Boxplots of household monthly income broken down by households receiving SNAP. The median income for households not receiving SNAP is $3500.00 while it is $1551.71 for those receiving SNAP.

Chart, box and whisker chart

Description automatically generated

Figure 15: Boxplots of household monthly income broken down by household food security status. The median income for food secure households is $3220.00 while food insecure households have a median income of $1701.49.

Chart, box and whisker chart

Description automatically generated

Figure 16: Boxplots of household monthly income broken down by region. The region with the highest median income is the Northeast ($3289.50), followed by the West ($2965.67), Midwest ($2688.50), and South ($2323.00).

Chart, treemap chart

Description automatically generated

Figure 17: Mosaic plot of households receiving SNAP by SNAP eligibility. About 10.4% of households who are not eligible for SNAP are receiving SNAP benefits while 52.3% of households who are eligible for SNAP receive SNAP benefits.

Chart, scatter chart

Description automatically generated

Figure 18: Density plot for estimations of Percent Poverty. This plot is used for the McCrary test and shows the discontinuity in the data at the cutpoint. Hence, the null hypothesis of no discontinuity is rejected.

Chart, scatter chart

Description automatically generated

Figure 19: Density plot for estimations of Log Percent Poverty. This plot is used for the McCrary test and shows the lack of discontinuity around the cutpoint. Therefore, the test fails to reject the null hypothesis, and the RDD analysis may continue.

Chart, histogram

Description automatically generated

Figure 20: Density plot of Log transform of Percent Poverty. The Log Percent Poverty transform is much more normally distributed with a slight peak around 0 due to many households earning 0 monthly income. The median log percent poverty is 5.17.

Chart, scatter chart

Description automatically generated

Figure 21: Jitter plot of SNAP Eligible Households against Log Percent Poverty. The red, vertical line represents the cutpoint in the RDD analysis of log(150). While the cutpoint does a good job discriminating households that are SNAP eligible, no cutpoint will do it perfectly. Therefore, it is necessary to use a fuzzy design.

Chart, scatter chart

Description automatically generated

Figure 22: Jitter plot of SNAP Receiving Households against Log Percent Poverty. The red, vertical line represents the cutpoint of log(150) used for the RDD analysis. Again, the cutpoint does a good job discriminating between the two groups, but no cutpoint will do a perfect job, so a fuzzy design is necessary.

Chart, line chart

Description automatically generated

Figure 23: Plot of LATE based on the bandwidth for the non-parametric fuzzy design using SNAP Eligibility as the treatment. In this case, any change in the bandwidth does not yield a statistically significant LATE.

Chart, line chart

Description automatically generated

Figure 24: Plot of LATE based on the bandwidth for the different ordered parametric fuzzy design using SNAP Eligibility as the treatment. Apart from the 0th order, any change in the bandwidth does not yield a statistically significant LATE.

Chart, line chart

Description automatically generated

Figure 25: Plot of LATE based on the bandwidth for the different ordered parametric fuzzy design using SNAP Reception as the treatment. Every bandwidth for every order yields a positive, statistically significant LATE.

Chart, line chart

Description automatically generated

Figure 26: Plot of LATE based on cutpoint for the 1st order parametric fuzzy design using SNAP Reception as the treatment. All cutpoints produce a positive, statistically significant LATE.