Weeding out Needy Households and Welcoming the Better Off? Impacts of Transactional Barriers on SNAP Participation Rates

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April 2021

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Undergraduate Honors Thesis

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*I would like to thank my thesis advisor, Professor David Card for not only his guidance, tips, and encouragement for this thesis but also for teaching me Microeconomics and Econometric foundations.

Abstract

The Supplemental Nutrition Assistance Program (SNAP) was designed to help families in need to purchase the basic necessity of food. Eligibility rules, transaction barriers, and stigma are the three main factors that influence SNAP participation in the United States. This paper analyzes the effects of transaction costs on SNAP take up rates across different household income levels. Transaction costs are different from administrative costs in that transaction costs refer to the barriers applicants face in applying and retaining SNAP benefits such as long wait times, missed interview, and miscommunication. The role of transaction barriers is to validate and confirm a household's eligibility and for households to demonstrate their need through their willingness to go through an extensive application process. My findings suggest that this perception of transaction barriers is not represented in the data and that households in the lower income groups (0-100% of poverty) are more negatively impacted by transaction barriers compared to households earning above poverty.

1. Introduction

The Supplemental Nutrition Assistance Program (SNAP) is one of the largest social programs in the United States serving over 38 million people in 2019 (Hall, 2021). SNAP is a federal program, but the application process, approval, and administering of SNAP are under the jurisdiction of the state. How much a family receives in food assistance depends on the size of the family, the total income, and the makeup of the family. The benefits follow a sliding scale where benefits decrease as household income rises. States differ on eligibility rules, transaction costs, and overall stigma regarding SNAP benefits. A prospective household would apply through a social service office in their county of residence and the office confirms whether or not a household qualifies according to state guidelines. States can vary widely in terms of eligibility rules with some states having asset limits while others don't even check, and some have an income limit of 200% of poverty while others have an income limit of 130% of poverty. Eligibility rules influence SNAP take up rates, but does not explain the complete picture. Transaction barriers serve to filter and validate applicants so that those who are really in need receive benefits. The commonly accepted notion is that households in need would have the willingness to go through the burdensome process of applying and reapplying because of their need. However, my results show that transaction barriers are adversely affecting certain cohorts of families below poverty (100% of FPL) and insignificant for the remaining cohorts, which is contrary to the notion that those in greater need would be more willing to apply for SNAP. This paper will explore the effects of transaction costs on participation rates and how they vary across different groups of individuals in the SNAP qualification spectrum.

2. Current State of SNAP

The long run trend of SNAP enrollment has been steadily increasing in the United States due to many factors such as the lasting impacts of the Financial Crisis and improved application systems that make applying to SNAP easier than before. Traditionally, SNAP and business cycles have a lagged pro-cyclical relationship, but that relationship seemed to break down post Financial Crisis when SNAP participation remained high and did not fall back down as fast as anticipated (Ganong, 2018). Ganong's findings showed that unemployment is estimated to explain about 80% of the increase in SNAP participation, and policy changes such as working requirement waivers and broader eligibility rules explain the remaining 18% of the increase in SNAP (Ganong, 2018). States vary widely in terms of eligibility rules to qualify and to keep SNAP recipiency. One popular requirement that has gained a lot of research attention are work requirements. The overall work requirement applies to 18-60-year-old SNAP recipients where they are required to be employed if they are able, and they cannot purposely quit a job for the sake of qualifying for SNAP assistance (USDA, 2021). Another aspect of the working requirement is the Able-Bodied Adult Without Dependents (ABAWD) requirement where 18-49 year olds without kids under the age of 18 and without disabilities are required to either work 20 hours a week, attend a job training, or volunteer for 20 hours or more. The ABAWD requirement is much stricter and undergoes more stringent review during the recertification process. However, states can apply for waivers through the Federal agency especially when the economic conditions of the state or area are poor due to a recession. The requirements for a state to apply for a waiver is not entirely clear, as states such as California with the largest economy in the U.S has applied and been approved for ABAWD waivers ever since the Great Recession, whereas other states such as Virginia and Texas have reinstated ABAWD requirements a few years after the Financial Crisis. ABAWD requirements have negative effects on SNAP take up rates and contrarian to common beliefs that SNAP recipients do not join SNAP because they do not want to work, the literature suggests that SNAP recipients do not stop working when receiving benefits or when they reach the cutoff age of 50 (Cuffey, 2015). Other requirements are directly related to eligibility such as income, wealth, age, and legal status. SNAP take up is particularly low amongst the elderly and immigrants. Even in states with little to no added restrictions for immigrants, we observe low take up rates in SNAP. There is a myriad of reasons for this observation including language barriers, fear of adversely affecting immigration status, and lack of knowledge about the application process.

3. **Transaction Costs and SNAP:**

Another dimension regarding SNAP participation are the transaction costs involved with applying and retaining SNAP benefits. Applying to SNAP requires of a lot of paper work, interviews, phone calls, and documents. After applying, households are then required to recertify to continue benefits. The frequency in which a household needs to reapply depends on the state's policy. Some states have recertification periods as long as 12 months where others have recertification periods of 3 months. The literature has found that shorter recertification periods decrease SNAP participation rates as the arduous process may discourage recipients from continuing. It is hard to quantify the transaction costs that households face other than individual experience. Studies of San Francisco SNAP recipients found that about half of recertifications fail and lead to a total welfare loss of about 200 dollars per family because of this inconvenience (Homonoff, 2019). Most of the recertification failures are due to transactional mistakes and not because of ineligibility. Homonoff and Somerville observe that the interview date for the recertification had an impact on recertification success. They found that a 1 day delay in the interview date led to a 0.3% increase in a failed recertification leading to an 8.3% increase in likelihood for a failed recertification for those with an interview in the end of the month compared to the beginning of the month. While the majority of those who failed recertification were back on SNAP within 90 days, a 1 day delay in the interview date increased the probability of losing SNAP benefits for the entire year by 0.05% (Homonoff, 2019). This event study gives insight into the transaction barriers that exist but yet are often neglected when making policy decisions because of the natural tendency to think of eligibility rules as the main make or break factor in applying to SNAP.

4. **Who interventions benefit:**

Another phenomenon is related to the notion of targeting. The original intent of SNAP is to help households in most need to receive food benefits. Experiments on elderly participants show that individuals who agreed to receive aid and assistance in applying earned more on average compared to the rest of the sample (Finkelstein, 2018). This experiment had over thirty thousand participants who were put into three groups at random: receive information, receive information and assistance, and a control group. The results showed that SNAP enrollment rates were about 300% higher for the information plus assistance group and 100% higher for the information only group when compared to the control group. The results also show that applicants in the intervention groups were less needy on average, and there were less minorities compared to those that applied from the control group (Finkelstein, 2018). Although assistance was helpful in increasing participation rates, it also showed that assistance in applying can lead to misplaced targeting where those who are in most need are not the ones benefiting from the assistance provided.

5. Current Participation Rates by state:

SNAP participation varies by state with some states like New Mexico with estimated 100% participation and others at around 70% participation (Cunnyngham,2020). There is wide uncertainty in the estimates of SNAP participation and studies usually show a SNAP take-up rate in terms of individuals who are eligible, and in terms of the working poor. In Figure 1 we see the overall proportion of SNAP recipients in a state estimated from Mathematica. SNAP households are also characteristically different from the general public beyond the fact that they earn less on average. Figure 2 is a summary table that includes both individual and household metrics using Current Population Survey(CPS) data from 1996 to 2014. Individual metrics such as citizenship refer to the head of the household and household metrics such as family size refer to the entire household. Some variables that I found interesting were that a higher percentage of SNAP households are led by women, SNAP householders are more likely to report a disability that affects work, and report that they have been absent or not in the labor force.

6. **Data Analysis Vision:**

SNAP participation is mainly centered on three components: eligibility, transaction costs, and stigma. The framework for my data analysis regarding SNAP take-up rates is to understand what is driving differences in SNAP participation across different cohorts of households and states. I want to first test the hypothesis that states with lenient eligibility rules have higher take-up rates than states with more restrictions such as asset limits, strict work requirements, and lower income cutoffs. If this hypothesis seems to be violated for some groups, then it may suggest that transaction costs are playing a factor. Then, I want to explore ways to quantify transactional barriers such as waiting times and recertification period lengths. The reason why I would think that transaction costs are more likely to play a role is because stigma around SNAP in the United States is relatively constant because of the wide use of EBT cards that reduces the opportunity for others in the public to judge those who have SNAP benefits.

7. **Data Description:**

The datasets I used were from the CPS March Survey and Annual Social and Economic (ASEC) Supplement from 1996 to 2014. I chose these years to align with the SNAP policy index data which provides a quantitative measure of transaction costs. The way I computed the SNAP take-up rates was to take the number of households who responded "Yes" to receiving SNAP benefits and multiply by the household size, and divide by the total amount of people in the sample. I also computed the Federal Poverty Level (FPL) values for each household by dividing household income by the official poverty cutoff rate for that household. I split the data into FPL 20% increment buckets from 0% to 200% of FPL and reported the take-up rates in each bucket. I observe a downward trend in participation as the FPL increases which is consistent with the literature and the nature of the program. However, the values from my data are generally lower and different from other estimates of SNAP participation. Most studies compute SNAP participation rates by the number of households who receive SNAP divided by the number of households who qualify. The literature also mentions that CPS data has false negative rates that are around 40% compared to the actual administrative records (Meyer, 2019). The main explanations for this high level of false negative rates (ex. Households indicating not receiving SNAP but actually receiving SNAP) is mainly due to non-response bias where participants do not respond to the questions, and response bias where participants are not comfortable to answer truthfully especially if they are disadvantaged in society (ex. Non-citizen, and low socioeconomic status).

The way I compute participation is mainly focused on different federal poverty levels as it is the main criterion for SNAP recipiency. However, it does not take into account other characteristics such as disabilities and the amount of assets a household has which are also considered when applying to SNAP. Determining the denominator requires inference techniques and cannot be determined solely through survey data. Figure 3 shows the SNAP take up rates for households earning less than 130% of federal poverty level since 130% is the lowest income cutoff across all states. Figure 4 shows the SNAP take up rates amongst the entire population of the state estimated by the Center on Budget Policy and Priorities compared to the CPS data I used. Figure 4 also presents the regression output and scatter plot that shows the moderately strong correlation between the values I computed and the values from the Center on Budget Policy and Priorities. Other variables I chose to include in my models and analysis are age, ownership, household income, public housing, rent subsidy, heat subsidy, the number of units in the structure, the number of couples, mothers, and fathers, sex, race, family size, number of children, type of family, citizenship status, disability status, educational attainment levels, and employment variables. These are the variables that influence eligibility for SNAP and account for barriers that may affect one from applying such as race, state of residence and work status.

8. Cross Classification Model:

The first empirical exercise I applied is to calculate the difference of SNAP participation rates across different FPL buckets between two select states between the years 2016 and 2018 through a cross classification method. I chose to focus on these years instead of 1996 to 2014 because I wanted to focus on a time period of economic stability to control for economic indicators. 2016 to 2018 were years of economic stability as marked by low unemployment and stable GDP growth across all states. The state combinations I chose were Texas and California, and Indiana and California because of California's consistent history of relatively lenient eligibility policies and harsher transaction barriers based off of the USDA transaction barrier index (USDA, 2020). California and Texas both have large economies and population size, but they differ widely in terms of eligibility. Indiana is also another state with less lenient eligibility rules compared to California and I chose to compare these states to see if lenient eligibility rules really improve take-up rates significantly. The goal is to try to limit confounding variables in hopes that the main difference in SNAP-participation rate is due to transaction cost and eligibility rules. As a result, I focused on just U.S citizens for this comparison to remove the potential effects from immigration status because states apply different policies and rules toward immigrant eligibility for SNAP.

Based off of eligibility alone, I would expect SNAP take up rates to be much higher in California than in Texas and Indiana. The first step in this analysis is to fit a classification model for each state. I fit a random forest model and a logistic model to classify whether or not a household is a SNAP recipient, taking into account a wide range of characteristic variables of the household. This SNAP take-up rate computation will be on the lower end because SNAP households tend to have larger families, and I am computing the proportion of households expected to be on SNAP rather than the proportion of the entire population. The Random Forest Classifier I fitted uses a maximum depth of 10 layers, minimum sample size split of 10, and 3 maximum features. Random forest models can be interpreted as decision trees where the depth is how many “branches” the tree breaks down to, where the higher the number, the greater the risk of overfitting. The maximum number of features and minimum sample split give boundaries to the number of variables and the sample size used at each iteration to form the decision tree. The classification accuracy, false negative rate, false positive rate and the ROC curve are listed in Figure 5. ROC stands for Receiving Operating Characteristic and it shows the performance of the classifier at variable false positive rates. A concave shape is a good sign as it means the classifier performs better than random chance. However, one of the main weaknesses of my classifier are the high false negative rates. The classifier classifies most households as not receiving SNAP benefits because SNAP take up rates are not super high in any specific group as it maxes out at around 50% for families in Low FPL buckets in the CPS data. Another issue is that there are many households with similar characteristics but have different outcome variables, which leads the training set for the model to be unclear for the classifier. To try to mitigate this issue, my sample focuses on households who earn incomes that are less than 200% of federal poverty level. However, the false negative rates are still high because of factors not included in the CPS data like different eligibility policies across different states, non-response bias especially amongst households in the lowest FPL buckets, and the significant false negative rate in the CPS data itself (Meyer, 2019).

After fitting the classification models for each state, I cross apply the models where I apply the classification model for California to Texas and the classification model for Texas to California, and the same combination for Indiana. This provides the hypothetical SNAP participation if California was Texas (Indiana) and if Texas (Indiana) was California in terms of eligibility, transaction, and a wide array of factors. The graph on the left in Figure 5 compares SNAP take up rates in California versus SNAP take up rates if California behaved like Texas (Indiana) in terms of eligibility and transaction. The graph on the right in Figure 5 compares SNAP take up rate in Texas (Indiana) versus SNAP take up rates if Texas (Indiana) behaved like California in terms of eligibility and transaction. The results in Figure 5 are from the Random Forest classifier because of higher accuracy compared to the logistic model. Figure 6 compares the actual take-up rates from the CPS data for the two states of interest.

From the graphs listed in Figure 5, we see an interesting pattern where SNAP participation rates are higher in California for higher FPL level buckets, but lower for very low FPL buckets. When a Texas or Indiana model is applied to California, we observe that the SNAP take up rate would be higher for low FPL households (below 100% of poverty) and lower for high FPL households (above 100% of poverty). When we apply the California model to Texas and Indiana we see that the California model results in higher SNAP take up rates for higher FPL levels and lower take up rates for low FPL levels. The reason why the California model outputs different values for Texas and Indiana is because it is taking in different data and then classifying the outputs. The input into the California model is different when using Indiana and Texas data because of the different characteristics of each state, which leads to a different classification that leads to a different SNAP take-up rate. What we observe in SNAP take up rates amongst low FPL groups is contrary to what we would expect if just taking to account eligibility. One would expect that more lenient eligibility rules for SNAP would increase SNAP take-up rates across all groups of households, but how come California, which has more lenient policies than Texas and Indiana, has lower participation rates for households in lower income buckets? This suggests that other dimensions other than eligibility rules are leading to this difference. To expand on this observation, I utilize the USDA SNAP policy index measurement which includes a transaction index that gives a quantitative measure of transactional barriers for each state.

9. Regressions:

The USDA SNAP policy index includes both weighted and unweighted indexes for transaction, stigma, and eligibility from 1996 to 2014. The USDA also combines all three dimensions into a policy index to construct one concise measure of how lenient a state is in administrating SNAP. I utilize the unweighted transactions cost index which considers three variables that affect transactional barriers: recertification period, online application availability, and simplified reporting. The original index was constructed so that a higher number means that the transaction barrier is low, meaning that it is expected to benefit participation rates (Stacy, 2018). The general trend of the indexes is that states have been more accommodating with indexes increasing over time (Stacy, 2018). The unweighted transaction index is a sum of three variables: Online application availability, short recertification period (1-3 months), and simplified reporting (Stacy, 2018). To make the direction consistent, I converted online application availability to no online application availability, and simplified reporting availability to no simplified reporting availability by negating the variable and adding the max value, which is 1, to reverse the order of magnitudes.

$$No\ online\ application\ availability = -Online\ application\ availability + 1$$

$$No\ simplified\ reporting\ availability = -Simplified\ reporting\ availability + 1$$

I then sum all the variables and normalize these variables by year to make a transaction index. The way to interpret this new transaction index is that a higher value means that the state has more barriers and a lower value means that the state has less barriers.

I then combine the CPS data set from 1996 to 2014 and the normalized transaction cost index and run a regression with SNAP take-up rate as the dependent variable with state fixed effects, transaction cost index, time fixed effects, FPL buckets divided into 20% increments up to 200%, and an interaction term between transaction cost index and FPL buckets as independent variables. If the notion that transaction barriers are put in place to ensure that those who really need the benefits would go through the hassle of applying holds true, I would expect the interaction between the transaction index and federal poverty level to be positive for low income households and turn negative as the federal poverty level bucket increases. From the regression results in Figure 6, I observe that most of the interactions are insignificant at the 10% significance level except for households between 40% and 80% of poverty level. This suggests that transaction costs may have negative and significant impacts on families between 40% to 80% of poverty. These results are inconsistent with the notion that transaction costs weed out families who are not "really" in need, but on the contrary, a certain cohort of families below poverty have SNAP participation rates negatively impacted by transaction barriers. I also observe that higher FPL households seem to not be affected by transaction barriers which is also inconsistent with the notion that transaction barriers discourage higher income and less needy households from applying.

Recertification failure is the most common form of transaction barrier that exists for many households seeking to continue SNAP benefits. I grouped the household level data by state and FPL bucket and took the average duration on SNAP for each group as the outcome variable.

Figure 7 are the results from the ordinary least squares regression where the sample is households who have received SNAP in the year. The results show that all the interactions between Transaction and FPL bucket are negative and significant for all FPL buckets below 160% of poverty. Unlike the regression for SNAP participation, we see that transaction barriers have negative impacts on the duration of SNAP recipiency for all FPL buckets except for the top earners (160-200% of FPL). These findings suggest that a state with more barriers lead to a lower average duration on SNAP per year which gives context to the barrier that many households face in terms of recertification. Losing months of benefits can discourage families from continuing SNAP benefits because of this loss. Analogous to discouraged workers in the labor force, transaction barriers resulting in broken up SNAP recipiency can lead to discouraged beneficiaries.

Instead of grouping by FPL bucket and state, I kept the entire sample at a household level and fitted an ordered logit model where the number of months, 1 to 12, are treated as categorical groups where the logit model classifies the observations into. Figure 9 shows that all the interactions between transaction cost and FPL bucket are insignificant at a five percent significance level for all income levels. This outcome differs from that of the ordinary least squares model aggregated by state, and FPL bucket. This may suggest that on an individual level, transaction barriers do not change the duration a household receives benefits, but on an aggregate level, the average duration on SNAP across SNAP recipients decreases when a household lives in a state with more transactional barriers. This may suggest an accumulation of small differences in SNAP duration across families in a state can lead to a significant difference in terms of the average duration a SNAP household receives benefits.

10. Discussion:

The results from my analysis suggest that states with more transaction barriers adversely impact low FPL households more than higher FPL households. Transaction barriers serve their purpose in validating and confirming a household's need and also serves as a litmus test to show how in need a family is in order to go through the hassle of applying and reapplying. If this purpose held true, we would expect the interaction between transaction barriers and FPL bucket to be positive. However, I observe that it is either negative or insignificant for households below poverty. One example of a major change to transaction cost barriers the United States is the advent of online application forms. Today, most states offer an online application platform for applicants. This policy is an example of a perverse policy that benefits the not as needy but hurts those in most need. Households who earn less than poverty are less likely to own a computer and are less likely to have stable internet access which makes it much more difficult for them to apply than a household at 180% of poverty. Documents can now be uploaded via the online application system which reduces the time needed to travel or send copies of required documents to the social service office. However, even if a very low-income household has internet access, they may not have a smartphone, printer, or scanner to scan documents to upload. This then forces them to mail the documents, or travel to the social service office, putting them at a disadvantage as longer application processes decrease the probability of success due to human error and administrative hiccups as shown in the recertification process in San Francisco (Homonoff, 2019). This means that a higher income household that qualifies for SNAP can successfully apply to SNAP in less time and the processing can go along faster compared to lower income households who qualify for SNAP. A household that has no choice but to travel to the social security office because of their lack of resources is more likely to have to take time off of their job which further reduces their earnings and that tradeoff can deter householders from taking that time off to apply. This is just one example of how transaction barriers do not affect all SNAP eligible households in the same way, and more research and experiments on aspects of transaction are needed to level the transaction barriers across all SNAP eligible households.

11. Limitations:

The USDA SNAP transaction index is limited in that it does not capture all the transaction costs associated with applying and reapplying to SNAP. The transaction index is a weighted average of three factors, whether or not there is an online application, whether or not the recertification period is 1-3 months, and if there is expedited processing available for needy households. If the index was robust, we would expect average SNAP participation in a state to decrease as transaction costs increase. The graphs in Figure 10 plot the relationship between the transaction cost index (adjusted for direction) and participation rates of each state for each FPL bucket. I observe that the relationship is weakly negative, where, as the transaction barrier increases, SNAP participation decreases for all FPL buckets except for Households between 0-20% of poverty, but none of the relationships are statistically significant. I do the same exercise for the duration on SNAP for the year and figure 11 shows that in general, as states have higher transaction costs, the average duration on SNAP per year decreases. This shows that maybe the transaction index provided by the USDA does a better job in explaining the duration of how long a family receives SNAP for a year compared to whether or not a family participates in SNAP. However, this slope is not significant for six out of the ten income groups (21-40% of FPL and 61-160% of FPL).

These two outcomes may suggest two propositions: 1. There is little to no relationship between transaction costs and SNAP participation rates, 2. The index is not a strong measurement of transaction costs due to missing confounding variables in the data. I believe there is stronger support for the latter because the three main factors regarding SNAP participation are eligibility, transaction costs and stigma. Stigma is relatively constant across states especially in recent years due to the introduction of the Electronic Benefits Card which reduces the visibility of SNAP participants to the general public. As a result, we are left with eligibility and transaction costs as the major factors in SNAP participation. In my analysis comparing California and Texas, we see that although California has much more accommodating policies, SNAP participation is much lower for low income households, which suggests that the relationship between transaction cost and participation is negative, and in the case for low FPL households, the negative effects outweigh the benefits of accommodating policies.

A short coming of this transaction cost index is that it uses criterion that is outdated, as most states have the policies that are referred to as lenient policies such as simplified reporting and online application availability. The index does not include further details of the transaction barriers such as wait times, recertification success rate, interview duration, missed interview forgiveness, proximity of social service office, social service office hours, number of required documents, and other barriers. The limited and outdated criteria used to compute the transaction index and the analysis of the current literature leads one to lean toward the proposition that the transaction index is not a strong measure of transaction costs.

Another limitation is the data itself. The CPS data has a high false negative rate in that some households do not respond or they do not respond in a way that reflects their true situation (Meyer, 2019). Fitting a classification model on data that has a false negative rate of about 40% when compared to administrative records will lead to results that are not entirely accurate and potential leads to large measurement bias due to the nature of the data.

The largest limitation in my analysis is potential omitted variable bias. Although I included many household and economic variables, it is likely I missed other variables such as duration of unemployment and city unemployment rate that could explain SNAP participation rates in a specific state. This potential omitted variable bias will bias the interaction terms of interest.

12. Next Steps

I would like to expand on this research by trying to use instrumental variables, differences in differences, or other inference techniques to prove causality. I could not find an instrument that would relate to transaction cost without affecting SNAP participation directly and did not observe parallel trends in state participation with a defining event that could have affected SNAP take up rates related to transaction cost. This would be more likely to achieve if I could link survey data with administrative records from social security offices across the United States and this linkage will help reduce the high false negative rates when just relying on survey data alone. I would also like to do interviews with administrators of SNAP and other SNAP participants to hear more about their perspective on transaction barriers and what they experience on a day to day basis regarding transaction barriers because my perspective in this thesis has largely been my personal experience in applying and recertifying for SNAP benefits. This broader perspective will give me greater insight and ideas in what policies can be implemented to ensure families in need are receiving the benefits they need to thrive. I would also like to dig deeper into factors that influence participation rather than just cherry-picking variables mentioned in the literature, to improve my classification performance to provide sounder quantitative comparisons of the impact on transactional barriers on SNAP take up rates across different cohorts of households.

13. Conclusion:

The literature on SNAP has put a heavy emphasis on eligibility and how different aspects of eligibility rules affect SNAP participation. Eligibility plays a significant role in SNAP participation, but does not explain the complete picture. In this paper, I focus on transaction barriers which are the costs associated with applying and reapplying for SNAP benefits such as wait times, administrative error, and required documentation. From comparing SNAP participation rates between California and Texas and California and Indiana, I observe that although California has more accommodating eligibility rules compared to Texas and Indiana, SNAP take up rates are lower for households at lower poverty levels in California. Objectively, households at lower percentage levels of poverty are in more need of SNAP benefits compared to households above poverty (Income cutoffs range between 130% to 200% of poverty). My findings suggest that accommodating policies may lead to a lack of targeting, and limit access to those who are in need of SNAP benefits. The role of transactional barriers is to verify a household's eligibility and filter applicants based off of demonstrated need. In other words, the hypothesis is that transactional barriers should have a positive interaction with income level for households at low poverty levels and a negative interaction with income level for households earning a higher level of income. However, my findings suggest that the original intent of transactional barriers is not supported by the data, as there is no evidence that very low-income households are demonstrating their need via the application process, nor that better off households are deterred from applying. This suggests that the transaction barriers are adversely impacting households at lower levels of poverty more than households in higher levels of poverty, which challenges the original intent of SNAP in providing benefits and support for those in most need.

Figures

Figure 1: Estimates of SNAP participation rates from Mathematica

Source: Cunnyngham,Karen [2020] Empirical Bayes Shrinkage Estimates of State Supplemental Nutrition Assistance Program Participation Rates in Fiscal Year 2015 to Fiscal Year 2017 for All Eligible People and Working Poor People.

	All eligible people			Working poor people		
	FY 2015	FY 2016	FY 2017	FY 2015	FY 2016	FY 2017
Alabama	84	86	84	78	81	83
Alaska	83	73	76	67	58	59
Arizona	72	74	76	61	65	66
Arkansas	73	73	69	65	68	67
California	69	71	71	58	59	57
Colorado	72	80	80	60	74	62
Connecticut	91	91	92	70	71	76
Delaware	100	100	100	86	88	96
District of Columbia	99	97	96	62	66	44
Florida	90	93	90	76	77	83
Georgia	84	86	86	72	76	71
Hawaii	88	85	84	74	70	75
Idaho	84	83	79	78	81	79
Illinois	100	100	100	83	84	85
Indiana	85	78	74	75	76	69
Iowa	87	89	92	78	83	87
Kansas	74	77	71	67	80	65
Kentucky	82	75	75	73	68	72
Louisiana	77	84	85	68	77	73
Maine	89	92	97	79	84	94
Maryland	94	92	89	73	70	69
Massachusetts	85	91	92	59	64	64
Michigan	100	98	94	89	92	89
Minnesota	82	83	81	77	81	78
Mississippi	84	83	77	72	71	70
Missouri	88	87	85	75	79	76
Montana	82	88	90	71	85	79
Nebraska	71	81	78	66	79	71
Nevada	81	85	86	74	77	81
New Hampshire	80	81	76	68	73	68
New Jersey	79	82	81	65	65	70
New Mexico	100	100	100	92	98	100
New York	87	92	93	76	79	83
North Carolina	82	87	77	74	83	68
North Dakota	60	63	63	53	61	54
Ohio	86	85	81	79	82	80
Oklahoma	79	82	84	67	73	72
Oregon	100	100	100	91	94	95
Pennsylvania	93	98	99	83	90	96
Rhode Island	100	100	100	83	88	97
South Carolina	81	80	80	74	75	74
South Dakota	83	82	82	77	81	78
Tennessee	95	92	92	81	80	81
Texas	70	74	75	66	71	63
Utah	69	71	70	62	66	58
Vermont	100	100	100	88	92	97
Virginia	73	76	76	65	71	66
Washington	100	100	96	87	88	82
West Virginia	96	97	92	87	88	98
Wisconsin	99	94	95	89	90	91
Wyoming	58	57	52	53	57	47
United States	83	85	84	72	75	73

Figure 2: Characteristic Summary comparing households on SNAP and households not on SNAP

Source: Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V8.0

Characteristic Summary	Non-SNAP Households	SNAP Households
% Own a home	71.57	30.23
% in Public Housing	1.93	18.1
% Receiving Rent Subsidy	0.74	10.03
% Receiving Heat Subsidy	1.3	24.3
% with Female as Head of Family	44.79	67.96
% Non-Citizens	5.29	8.1
% of Head of Household in Labor Force	68.52	45.44
% of Head of Household holding a Union job	2.18	0.54
Family Size	2.41	2.88
Number of Children 5 years old or younger	0.13	0.33
% of Head of Household being Absent from Work in past year	41.55	70.15
% of Head of Households with Disability that Affects Work	10.81	34.22
% of Head of Households with Hispanic Origins	6.72	14.98
% of Head of Households with College Education	57.61	29.57
Age of Householder	50.34	44.58

Figure 3: SNAP take-up rates amongst families earning less than 130% of poverty

Source: Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V8.0

State	2016	2017	2018
Alabama	47.06	46.34	46.38
Alaska	26.21	47.86	42.31
Arizona	62.22	51.09	43.53
Arkansas	35.44	46.28	35.9
California	42.18	39.73	32.99
Colorado	54.79	36.36	30.25
Connecticut	37.42	65.44	48.65
Delaware	42.62	48.37	44.53
District of Columbia	58.45	48.31	43.62
Florida	44.34	41.02	40.53
Georgia	55.35	45.03	39.90
Hawaii	45.37	38.57	32.73
Idaho	43.71	54.10	40.24
Illinois	49.88	52.16	42.6
Indianna	52.06	44.76	39.29
Iowa	47.5	36.14	47.40
Kansas	48.48	41.94	29.09
Kentucky	49.83	51.92	41.28
Louisiana	48.20	51.41	43.27
Maine	52.24	59.44	58.57
Maryland	48.03	49.67	44.7
Massachusetts	46.47	34.68	47.71
Michigan	50.31	55.37	38.72
Minnesota	55.24	47.06	58.6
Mississippi	54.13	47.4	35.49
Missouri	54.84	37.21	45.45
Montana	45.9	42.22	36
Nebraska	68.32	44.81	48.21
Nevada	41.79	45.75	32.5
New Hampshire	51.69	36.45	43.27
New Jersey	45.65	41.74	35.74
New Mexico	59.26	48.06	42.49
New York	54.48	43.98	42.73
North Carolina	55.78	50.12	51.58
North Dakota	35.48	34.56	42.44
Ohio	55.31	56.6	58.68
Oklahoma	38.7	45.99	38.18
Oregon	61.95	54.69	56.34
Pennsylvania	54.76	45.05	46.54
Rhode Island	43.4	56.9	48.37
South Carolina	49.82	63.46	45.71
South Dakota	53.09	55.17	41.86
Tennessee	59.85	54.64	38.77
Texas	39.76	40.96	34.22
Utah	50.86	41.18	26.8
Vermont	58.42	50.97	32.68
Virginia	37.35	40.6	34.86
Washington	57.36	47.79	41.52
West Virginia	59.91	56.56	55.48
Wisconsin	49.42	54.23	46.58
Wyoming	31.34	40.72	37.23

Figure 4: SNAP take up rates (%) over the entire state population compared with numbers from Center on Budget Policy and Priorities

Sources: Lauren Hall [2021] A Closer Look at Who Benefits from SNAP: State-by-State Fact Sheets

Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V8.0

State	**2016**	**2017**	**2018**	**2018 from CBPP**	**2018 minus 2018 from CBPP**
Alabama	15.02	14.23	10.64	16	-5.36
Alaska	7.31	9.96	10.88	13	-2.12
Arkansas	11.30	13.06	9.92	12	-2.08
California	11.26	10.81	8.59	10	-1.41
Colorado	11.58	6.15	5.67	8	-2.33
Connecticut	9.35	12.05	6.81	11	-4.19
Delaware	8.52	13.92	9.36	15	-5.64
District of Columbia	14.54	14.95	10.09	16	-5.91
Florida	13.71	11.55	12.12	14	-1.88
Georgia	16.64	12.90	10.67	15	-4.33
Hawaii	13.91	11.29	8.05	12	-3.95
Idaho	10.53	11.47	8.86	9	-0.14
Illinois	12.77	12.23	8.49	14	-5.51
Iowa	11.11	8.61	9.40	11	-1.60
Kansas	10.92	9.52	7.51	8	-0.49
Kentucky	15.67	15.37	10.37	14	-3.63
Louisiana	15.22	16.51	14.57	19	-4.4
Maine	13.68	15.49	14.07	13	1.07
Maryland	10.45	10.96	9	11	-2
Michigan	12.31	10.71	8.37	13	-4.63
Minnesota	7.80	9.22	10.21	8	2.21
Mississippi	17.60	15.38	13.03	17	-3.97
Missouri	11.49	11.12	10.85	12	-1.15
Montana	9.18	9.44	7.22	11	-3.78
Nebraska	9.97	9.98	9.25	9	0.25
Nevada	11.65	9.57	8.85	15	-6.15
New Hampshire	6.96	5.72	4.46	6	-1.54
New Jersey	8.36	7.99	7.57	9	-1.43
New Mexico	18.20	17.31	16.46	22	-5.54
New York	11.56	11.08	10.90	14	-3.10
North Carolina	14.80	13.37	12.45	13	-0.55
North Dakota	6.8	6.01	7.93	7	0.93
Ohio	14.26	13.58	11.11	12	-0.89
Oklahoma	11.02	13.10	9.8	15	-5.2
Oregon	16.47	15.15	14.74	15	-0.26
Pennsylvania	10.10	11.43	10.87	14	-3.13
Rhode Island	11.70	12.07	13.19	N/A	N/A
South Carolina	14.68	15.29	11.75	13	-1.25
South Dakota	12.15	11.62	8.83	10	-1.17
Tennessee	16.42	17.12	9.02	14	-4.98
Texas	10.61	11.46	9.42	13	-3.58
Utah	9.43	9.26	5.13	6	-0.87
Vermont	13.19	9.99	7.08	12	-4.92
Virginia	9.10	8.72	6.41	9	-2.59
Washington	16.78	13.58	9.54	12	-2.46
West Virginia	17.81	16.45	15.47	18	-2.53
Wisconsin	12.10	11.12	8.78	11	-2.22
Wyoming	6.13	6.66	5.34	5	0.34

Correlation between SNAP Participation Rate Estimates in 2018 from CPS and Center on Budget Policy and Priorities Across Entire State Population.

	Coefficient	**Standard Error**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	0.0210	0.012	1.793	0.080	-0.003	0.045
2018 Estimates from CPS	1.0468	0.117	8.985	0.000	0.812	1.281

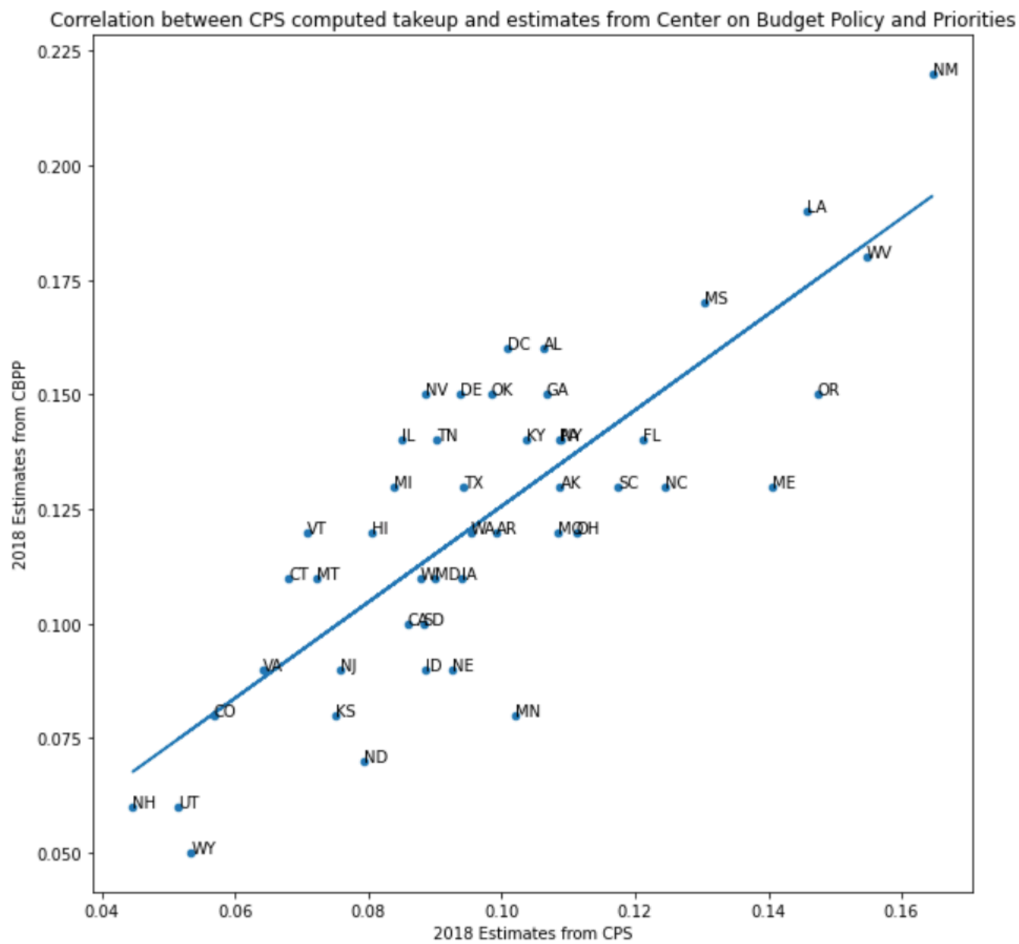
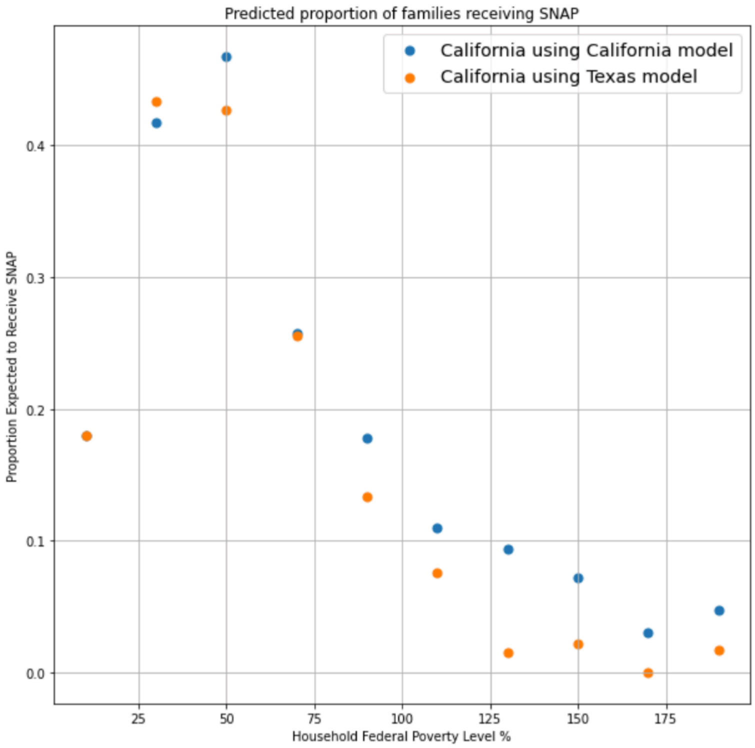
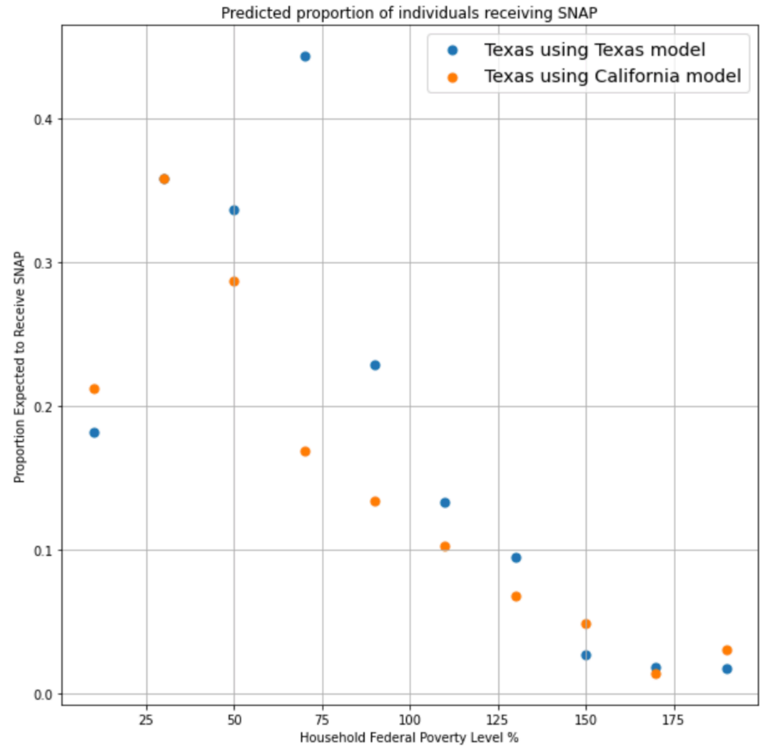
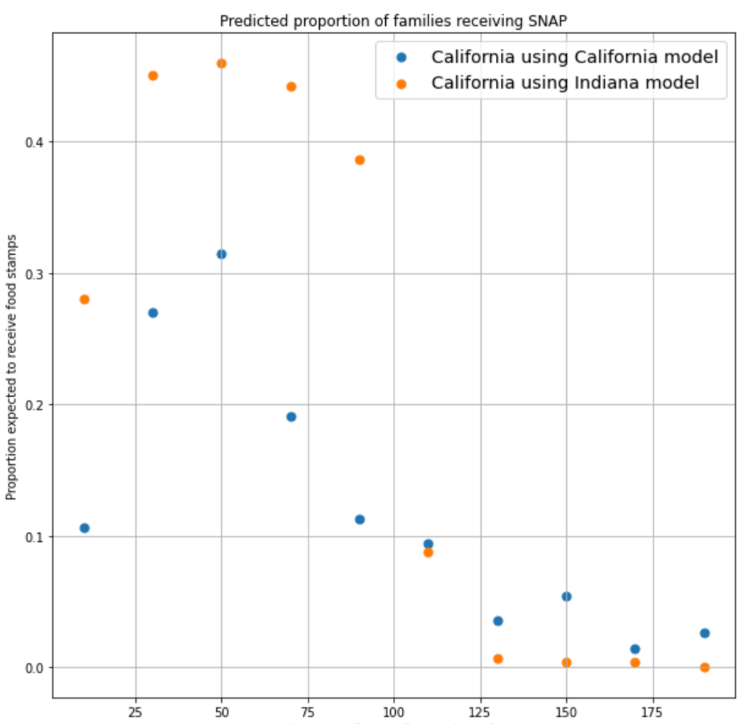


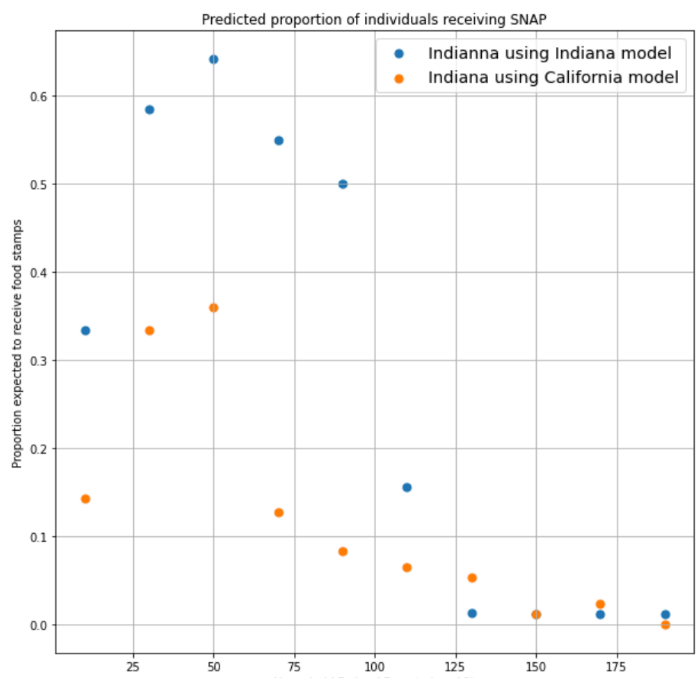
Figure 5: Cross Classification for SNAP participation rates

Source: Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V8.0


Predicted proportion of families receiving SNAP
California using California model
California using Texas model
Proportion Expected to Receive SNAP
Household Federal Poverty Level %


Predicted proportion of individuals receiving SNAP
Texas using Texas model
Texas using California model
Proportion Expected to Receive SNAP
Household Federal Poverty Level %

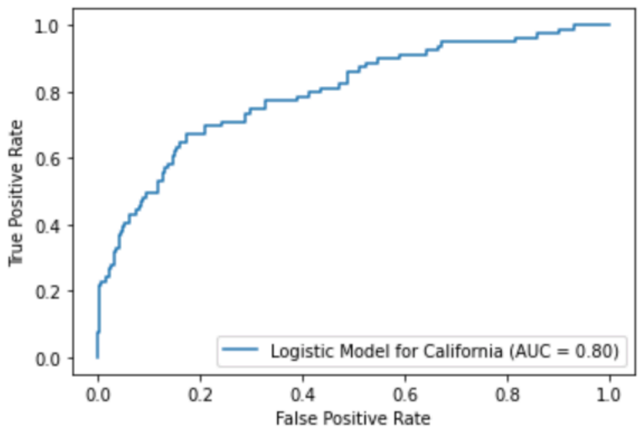

Predicted proportion of families receiving SNAP
California using California model
California using Indiana model
Proportion expected to receive food stamps
Household Federal Poverty Level %


Predicted proportion of individuals receiving SNAP
Indianna using Indiana model
Indiana using California model
Proportion expected to receive food stamps
Household Federal Poverty Level %

Accuracy,False Negative, and False Positive Rates for Logistic Classifier applied to California

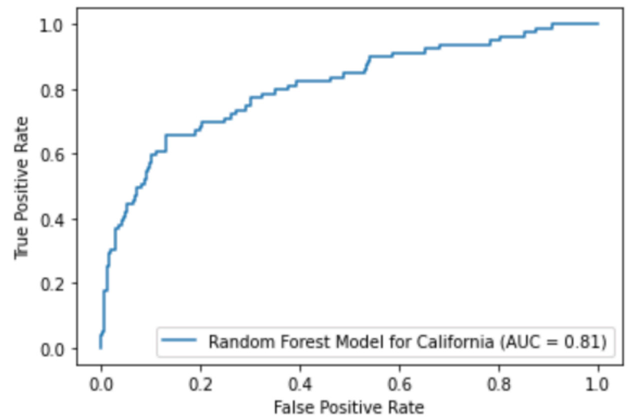
Accuracy	False Negative Rate	False Positive Rate
0.834191549667128	0.6663920399611098	0.04039373026749675

False Positive Rate



Accuracy,False Negative, and False Positive Rates for Random Forest Classifier applied to California

	Accuracy	False Negative Rate	False Positive Rate
0	0.8367556522312306	0.7155510766683029	0.025001039084303768

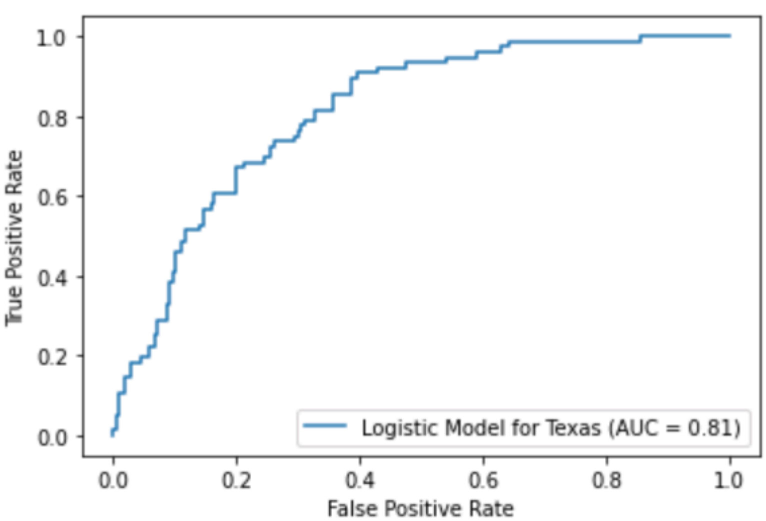


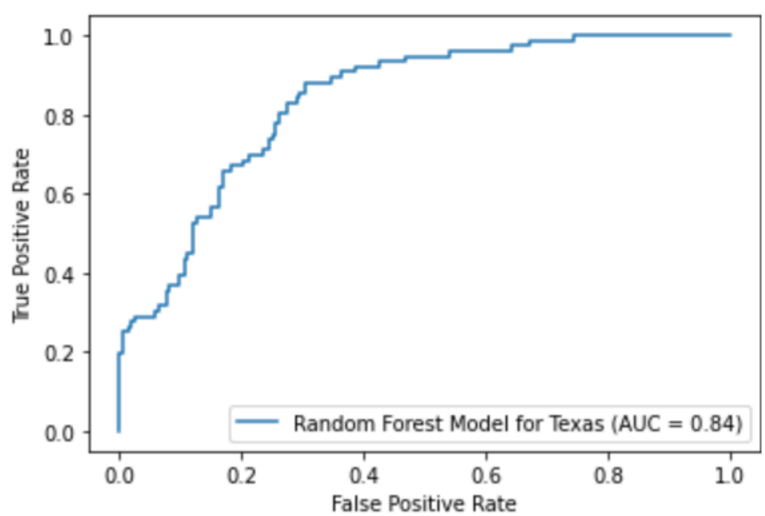
Accuracy,False Negative, and False Positive Rates for Logistic Classifier applied to Texas

Accuracy	False Negative Rate	False Positive Rate
0.7946473896381825	0.5570393251305292	0.08346753564482132

Accuracy,False Negative, and False Positive Rates for Random Forest Classifier applied to Texas

	Accuracy	False Negative Rate	False Positive Rate
0	0.7889911909620265	0.6818986943121766	0.04836921079906252



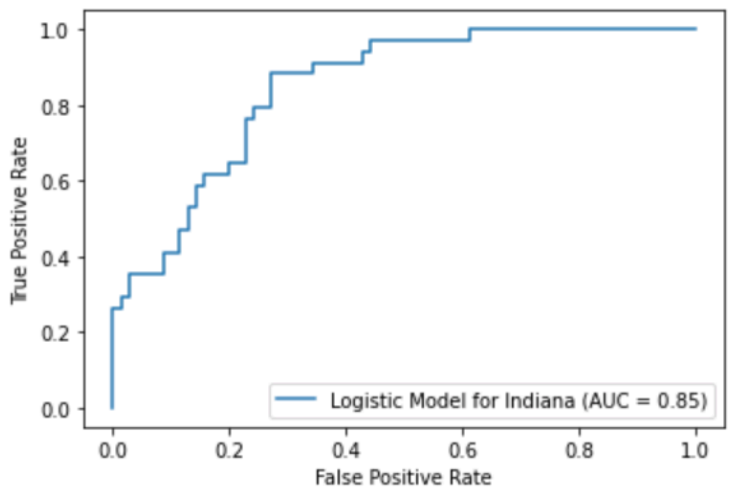


Accuracy,False Negative, and False Positive Rates for Logistic Classifier applied to Indiana

Accuracy	False Negative Rate	False Positive Rate
0.7884615384615384	0.4609907120743034	0.10695992401874754

Accuracy,False Negative, and False Positive Rates for Random Forest Model applied to Indian

	Accuracy	False Negative Rate	False Positive Rate
0	0.8096153846153846	0.5145046439628483	0.05981145775263423



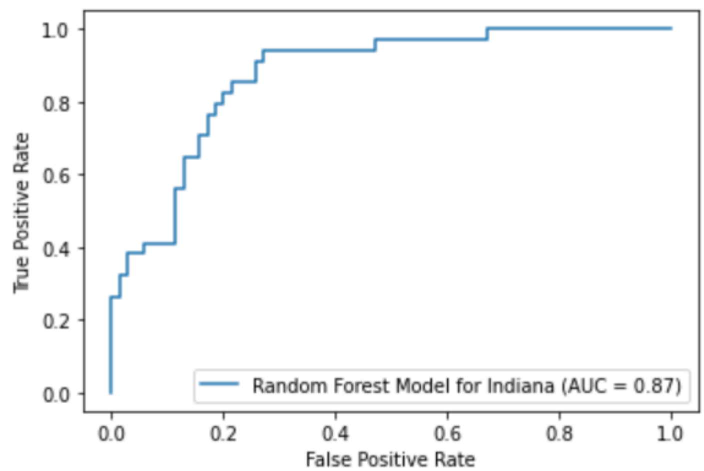
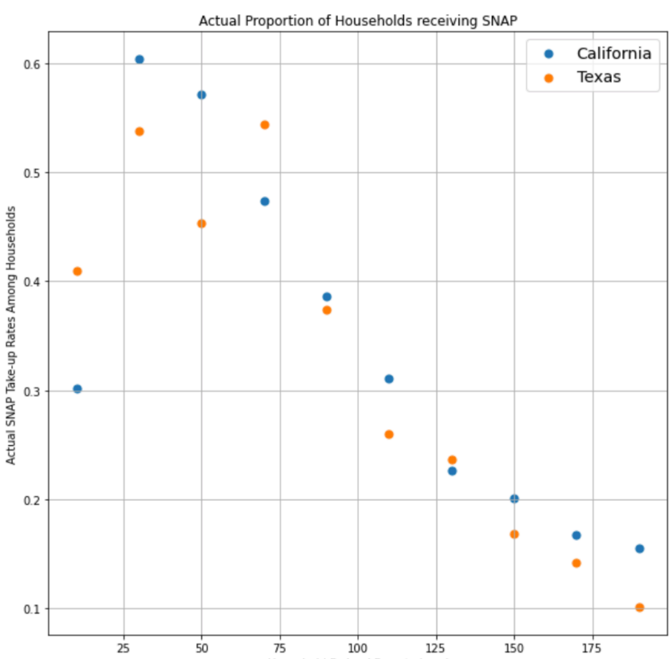


Figure 6: Actual Data for California and Texas without Cross Applying Years 2016-2018

Source: Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V8.0



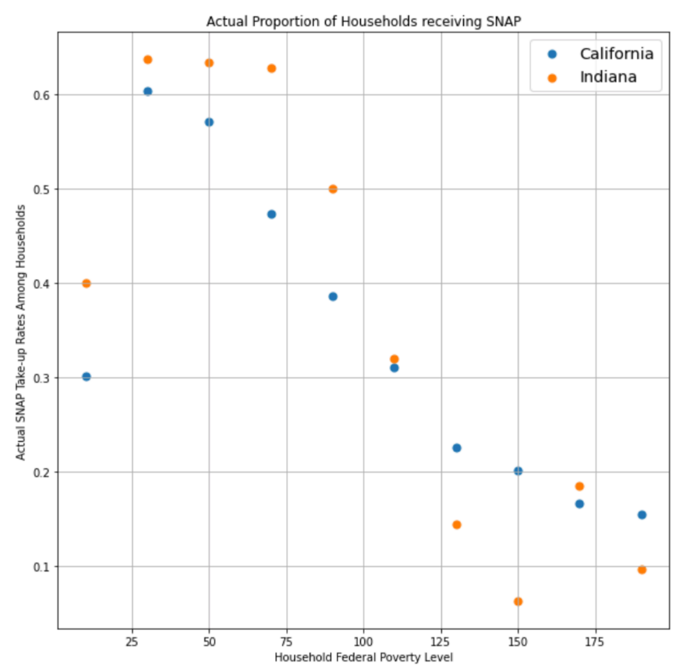


Figure 7: Ordinary Least Squares Regression with SNAP take-up rate as dependent variable

Source: Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V8.0

Dep. Variable:	SNAP Take-up Rate	**R-squared:**	0.683
Model:	OLS	**Adj. R-squared:**	0.679
Method:	Least Squares	**F-statistic:**	207.7
No. Observations:	9754		

	Coefficient	**Standard Error**	**t**	**P> |t|**
Intercept	0.0982	0.009	10.346	0.000
Transaction Index	-0.0004	0.005	-0.070	0.945
Hispanic	0.0006	0.001	1.020	0.308
Above HS Education	-0.0012	0.000	-2.579	0.010
Disability that Affects Work	-0.0014	0.001	-2.600	0.009
Non-Citizen	-0.0018	0.001	-2.351	0.019
Public Housing	0.0026	0.001	3.371	0.001
Rent Subsidy	0.0029	0.001	2.550	0.011
Heat Subsidy	0.0130	0.001	18.427	0.000
Gender	0.0006	0.000	1.515	0.130
Labor Force	-0.0033	0.002	-2.196	0.028
Class of Worker	0.0002	7.15e-05	3.489	0.000
Own a Home	-0.0029	0.000	-7.734	0.000
Asset Limit	-0.0401	0.010	-3.920	0.000
0-20% of FPL	0.3435	0.009	40.402	0.000
21-40% of FPL	0.4583	0.008	54.511	0.000
41-60% of FPL	0.4039	0.008	49.396	0.000
61-80% of FPL	0.3164	0.008	37.668	0.000
81-100% of FPL	0.2333	0.008	28.644	0.000
101-120% of FPL	0.1518	0.008	19.991	0.000
121-140% of FPL	0.0834	0.007	11.561	0.000
141-160% of FPL	0.0519	0.007	7.440	0.000
161-180% of FPL	0.0285	0.007	4.154	0.000
181-200% of FPL	0.0115	0.007	1.673	0.094
0-20% of FPLxTransaction	0.0111	0.007	1.619	0.105
21-40% of FPLxTransaction	0.0067	0.007	1.004	0.315
41-60% of FPLxTransaction	-0.0120	0.007	-1.802	0.072
61-80% of FPLxTransaction	-0.0137	0.007	-2.070	0.039
81-100% of FPLxTransaction	-0.0051	0.007	-0.772	0.440
101-120% of FPLxTransaction	-0.0031	0.007	-0.465	0.642
121-140% of FPLxTransaction	-0.0052	0.007	-0.783	0.433
141-160% of FPLxTransaction	-0.0110	0.007	-1.635	0.102
161-180% of FPLxTransaction	-0.0075	0.007	-1.100	0.272
181-200% of FPLxTransaction	-0.0062	0.007	-0.897	0.370

Notes: OLS model with State and Time fixed effects using a Transaction index

Figure 8: Ordinary least squares regression with the fraction of year on SNAP as the dependent variable

Source: Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V8.0

Dep. Variable:	Fraction of Year receive SNAP	**R-squared:**	0.697	
Model:	OLS	**Adj. R-squared:**	0.694	
Method:	Least Squares	**F-statistic:**	222.3	
No. Observations:	9754	**AIC:**	-1.684e+04	
Df Residuals:	9653	**BIC:**	-1.612e+04	
Df Model:	100			
	Coefficient	**Standard Error**	**t**	**P> |t|**
Intercept	0.0525	0.011	4.886	0.000
Transaction index	0.0114	0.005	2.264	0.024
Hispanic	0.0006	0.000	1.419	0.156
Above HS Education	-0.0012	0.000	-3.300	0.001
Disability that Affects Work	-0.0005	0.000	-1.091	0.275
Non-Citizen	-0.0013	0.001	-2.156	0.031
Public Housing	0.0043	0.001	6.990	0.000
Rent Subsidy	0.0052	0.001	5.870	0.000
Heat Subsidy	0.0108	0.001	19.528	0.000
Gender	-0.0005	0.000	-1.632	0.103
Labor Force	-0.0021	0.001	-1.754	0.080
Class of Worker	0.0002	5.59e-05	3.004	0.003
Own a Home	-0.0017	0.000	-5.756	0.000
Asset Limit	-0.0475	0.008	-5.814	0.000
0-20% of FPL	0.2666	0.010	27.879	0.000
21-40% of FPL	0.3541	0.010	37.264	0.000
41-60% of FPL	0.3219	0.009	34.281	0.000
61-80% of FPL	0.2953	0.010	31.074	0.000
81-100% of FPL	0.2293	0.009	24.535	0.000
101-120% of FPL	0.1420	0.009	15.692	0.000
121-140% of FPL	0.0714	0.009	8.050	0.000
141-160% of FPL	0.0469	0.009	5.319	0.000
161-180% of FPL	0.0238	0.009	2.716	0.007
181-200% of FPL	0.0079	0.009	0.887	0.375
0-20% of FPLxTransaction	-0.0182	0.006	-3.107	0.002
21-40% of FPLxTransaction	-0.0141	0.006	-2.458	0.014
41-60% of FPLxTransaction	-0.0210	0.006	-3.692	0.000
61-80% of FPLxTransaction	-0.0290	0.006	-5.127	0.000
81-100% of FPLxTransaction	-0.0351	0.006	-6.193	0.000
101-120% of FPLxTransaction	-0.0355	0.006	-6.276	0.000
121-140% of FPLxTransaction	-0.0226	0.006	-3.984	0.000
141-160% of FPLxTransaction	-0.0174	0.006	-3.041	0.002
161-180% of FPLxTransaction	-0.0109	0.006	-1.869	0.062
181-200% of FPLxTransaction	-0.0040	0.006	-0.666	0.505

Notes: OLS model with State and Time fixed effects using a Transaction index7

Figure 9: Ordinal logistic regression with number of months on SNAP as the dependent variable

Source: Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V8.0

	Coefficient	t-Statistic
Number of Months on SNAP		
Transaction Cost	-0.0185	-0.44
Asset Limit	-0.490***	-4.31
Above HS Education	-0.221***	-10.24
Disability that Affects Work	0.198***	7.74
Non-Citizen	0.0231	0.57
Public Housing	0.521***	17.67
Rent Subsidy	0.577***	15.37
Heat Subsidy	0.338***	13.84
Gender	0.208***	9.84
Hispanic Origin	0.100**	3.04
Class of Worker	-0.0232***	-8.23
Labor Force	-0.250***	-4.10
Own a Home	0.0445	1.92
0-20% of FPL	0.00126	0.02
21-40% of FPL	0.170**	2.79
41-60% of FPL	0.207***	3.57
61-80% of FPL	0.287***	5.12
81-100% of FPL	0.185***	3.32
101-120% of FPL	-0.112*	-1.99
121-140% of FPL	-0.337***	-5.87
141-160% of FPL	-0.465***	-7.84
161-180% of FPL	-0.553***	-8.94
181-200% of FPL	-0.626***	-9.68
0-20% of FPLxTransaction	0.0586	0.96
21-40% of FPLxTransaction	-0.0389	-0.72
41-60% of FPLxTransaction	-0.0194	-0.38
61-80% of FPLxTransaction	-0.0461	-0.94
81-100% of FPLxTransaction	-0.0158	-0.33
101-120% of FPLxTransaction	-0.0644	-1.30
121-140% of FPLxTransaction	-0.0879	-1.72
141-160% of FPLxTransaction	0.0196	0.36
161-180% of FPLxTransaction	-0.0641	-1.13
181-200% of FPLxTransaction	-0.0235	-0.39
/		
2 Months	-3.977***	-38.61
3 Months	-2.985***	-29.81
4 Months	-2.318***	-23.35
5 Months	-1.990***	-20.10
6 Months	-1.795***	-18.15
7 Months	-1.376***	-13.93
8 Months	-1.281***	-12.98
9 Months	-1.156***	-11.72
10 Months	-1.053***	-10.68
11 Months	-0.966***	-9.79
12 Months	-0.921***	-9.34)
N	61574	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 10: Robustness check for transaction cost index on SNAP take-up

Source: Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren.

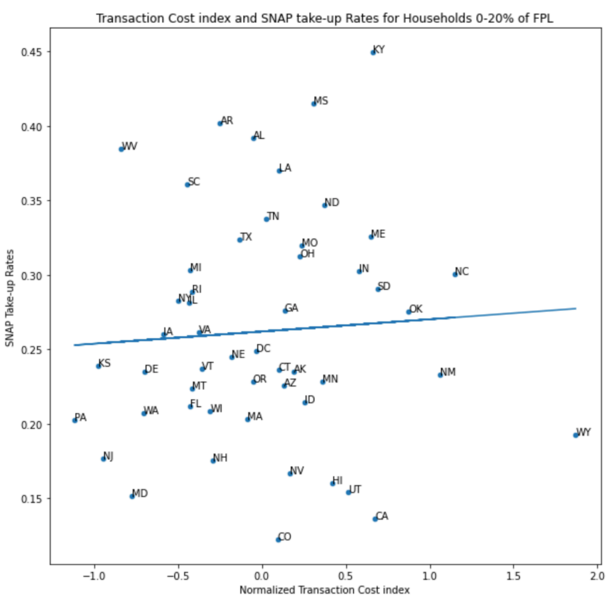
Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset].

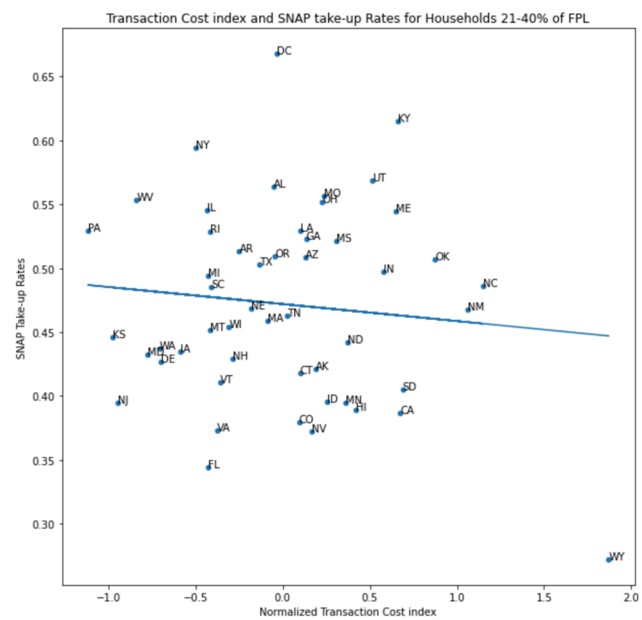
Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V8.0

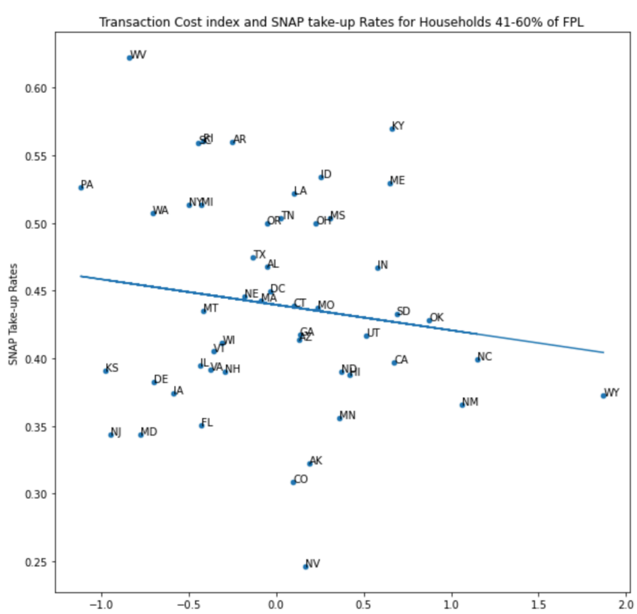
Table 3: SNAP Participation Rates by State, Regressed on Transaction Cost Index

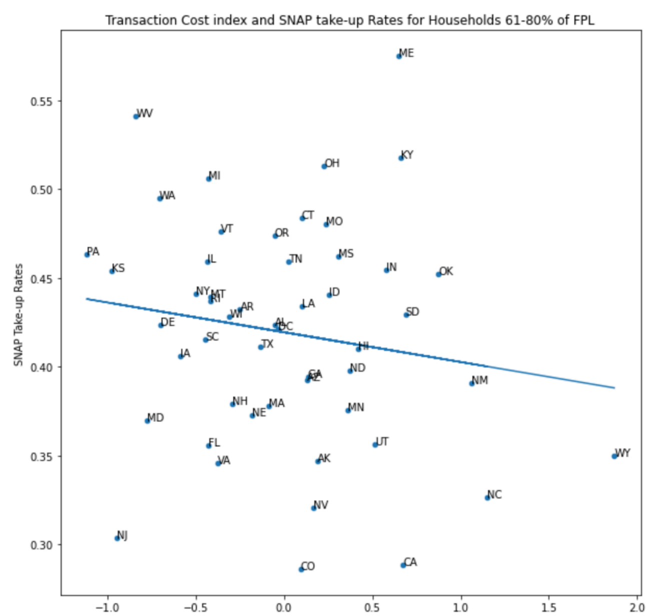
Federal Poverty Level	0-20%	21-40%	41-60%	61-80 %	81-100%	101-120%	121-140%	141-160%	161-180%	181-200%
const	0.2619***	0.4719***	0.4395***	0.4194***	0.3390***	0.2333***	0.1524***	0.1169***	0.0856***	0.0662***
	(0.0108)	(0.0106)	(0.0108)	(0.0089)	(0.0085)	(0.0066)	(0.0053)	(0.0042)	(0.0034)	(0.0028)
Normalized Transaction Cost index	0.0082	-0.0133	-0.0188	-0.0168	-0.0106	-0.0094	-0.0051	-0.0060	-0.0004	-0.0004
	(0.0183)	(0.0181)	(0.0184)	(0.0151)	(0.0144)	(0.0112)	(0.0091)	(0.0072)	(0.0059)	(0.0047)
R-squared	0.0041	0.0109	0.0209	0.0246	0.0110	0.0141	0.0065	0.0143	0.0001	0.0002
R-squared Adj.	-0.0163	-0.0093	0.0009	0.0047	-0.0092	-0.0060	-0.0138	-0.0059	-0.0203	-0.0202

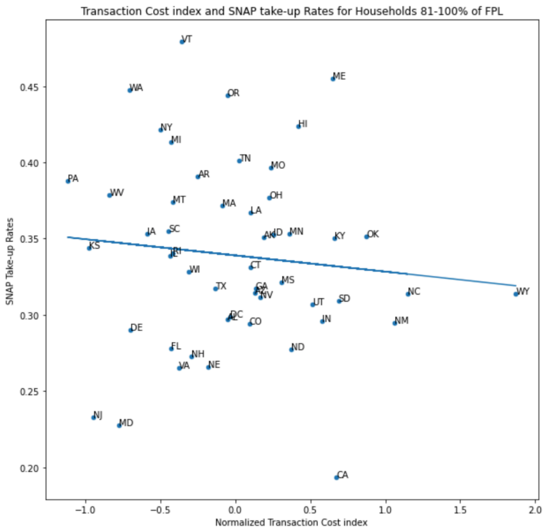
Notes:* = significant at 10% level, ** = 5 % level, *** = 1% level

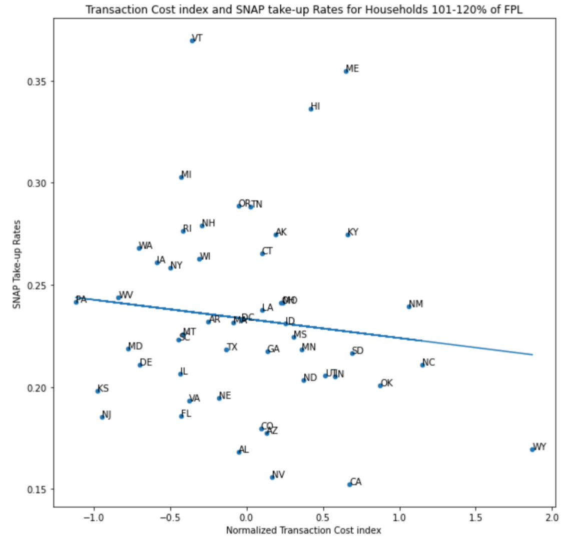


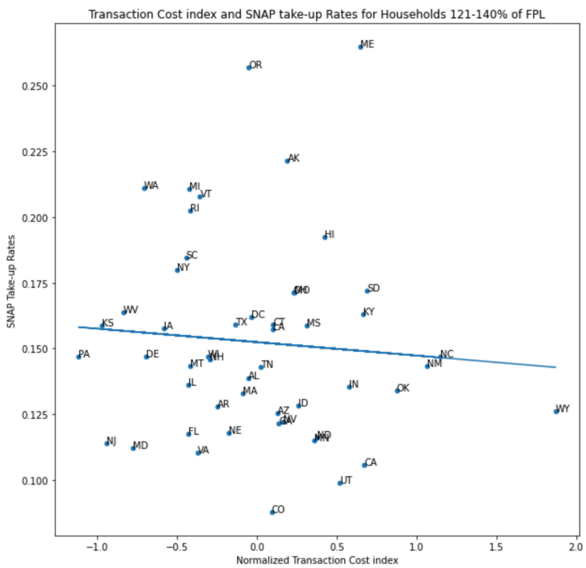


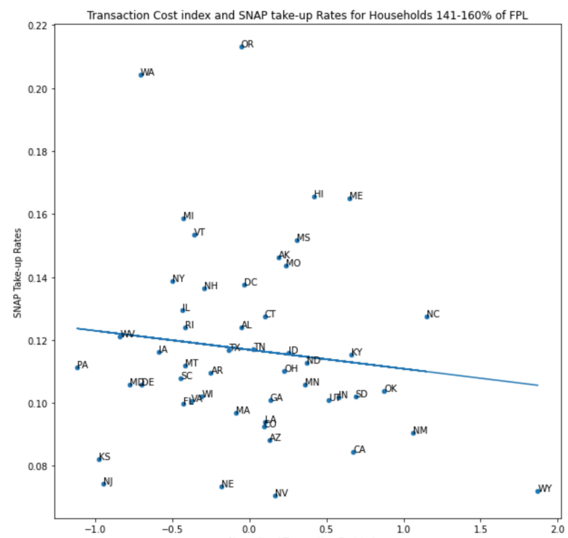


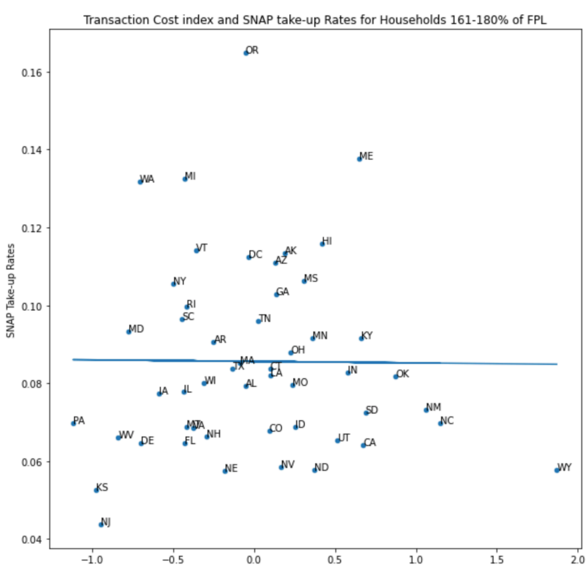



Transaction Cost index and SNAP take-up Rates for Households 81-100% of FPL
SNAP Take-up Rates
Normalized Transaction Cost index
0.20
0.25
0.30
0.35
0.40
0.45
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0


Transaction Cost index and SNAP take-up Rates for Households 101-120% of FPL
SNAP Take-up Rates
Normalized Transaction Cost index
0.15
0.20
0.25
0.30
0.35
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0


Transaction Cost index and SNAP take-up Rates for Households 121-140% of FPL
SNAP Take-up Rates
Normalized Transaction Cost index
0.100
0.125
0.150
0.175
0.200
0.225
0.250
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0


Transaction Cost index and SNAP take-up Rates for Households 141-160% of FPL
SNAP Take-up Rates
Normalized Transaction Cost index
0.08
0.10
0.12
0.14
0.16
0.18
0.20
0.22
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0


Transaction Cost index and SNAP take-up Rates for Households 161-180% of FPL
SNAP Take-up Rates
Normalized Transaction Cost index
0.04
0.06
0.08
0.10
0.12
0.14
0.16
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0

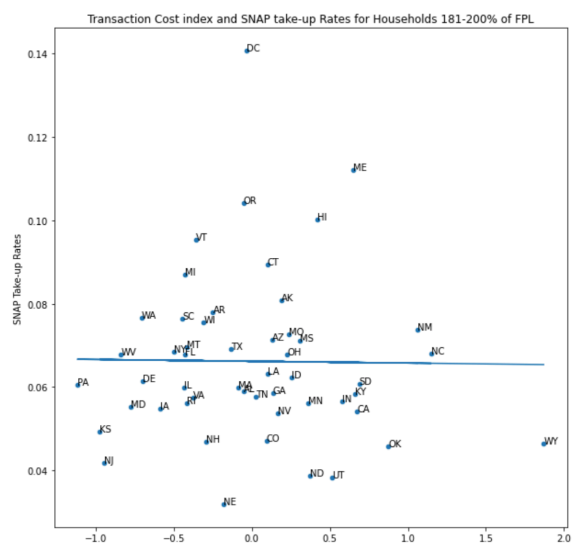

Transaction Cost index and SNAP take-up Rates for Households 181-200% of FPL
SNAP Take-up Rates
Normalized Transaction Cost index
0.04
0.06
0.08
0.10
0.12
0.14
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0

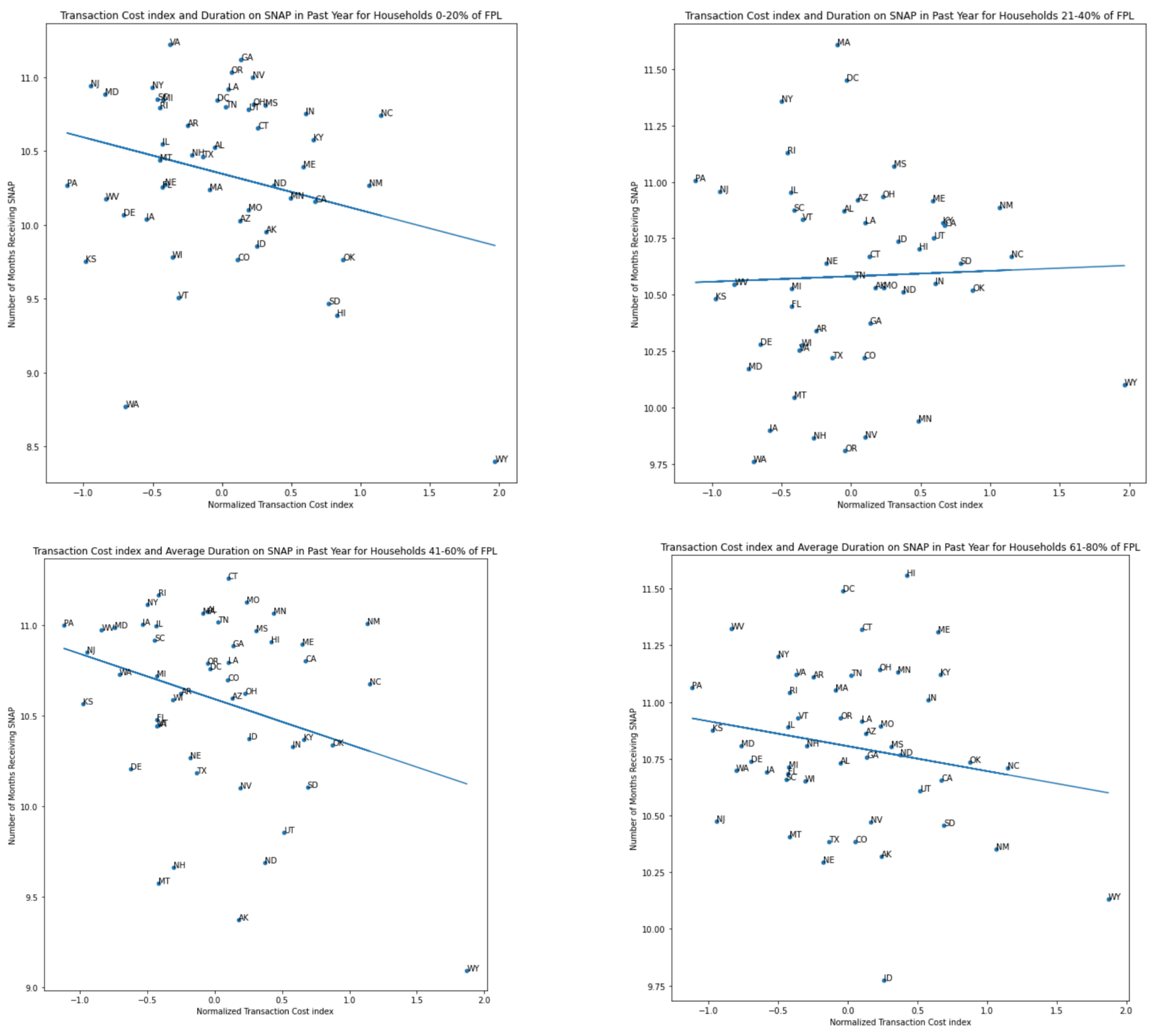
Figure 11: Robustness check for transaction cost index on SNAP duration

Source: Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V8.0

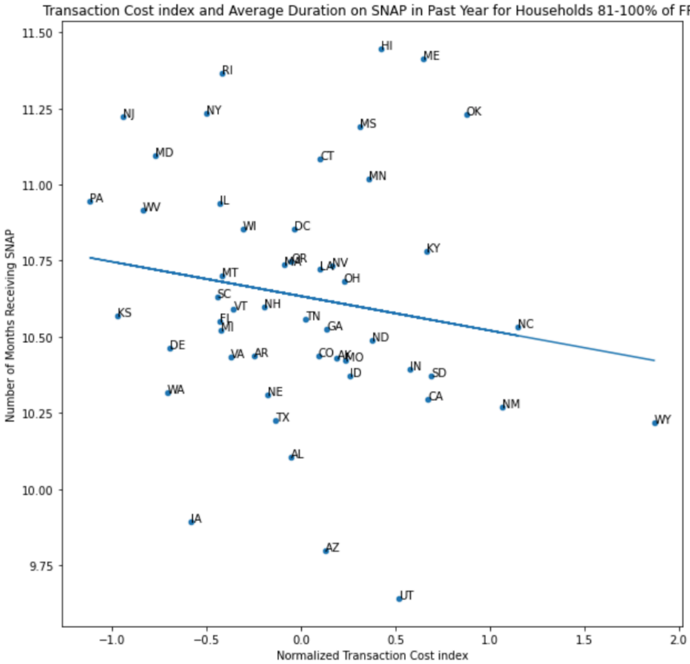
Table 4: Average Months on SNAP by State Regressed on Transaction Cost Index

Federal Poverty Level	0-20%	21-40%	41-60%	61-80%	81-100%	101-120%	121-140%	141-160%	161-180%	181-200%
const	10.3465***	10.5817***	10.5902***	10.8053***	10.6335***	10.0005***	9.5057***	9.2730***	8.9576***	8.6181***
	(0.0795)	(0.0597)	(0.0665)	(0.0487)	(0.0558)	(0.0827)	(0.0929)	(0.1047)	(0.1140)	(0.1469)
Normalized Transaction Cost index	-0.2466*	0.0241	-0.2503**	-0.1098	-0.1128	-0.2348	-0.2506	-0.0772	-0.4222**	-0.4948**
	(0.1308)	(0.0999)	(0.1128)	(0.0825)	(0.0951)	(0.1402)	(0.1589)	(0.1782)	(0.1834)	(0.2415)
R-squared	0.0677	0.0012	0.0914	0.0349	0.0279	0.0542	0.0483	0.0038	0.0976	0.0789
R-squared Adj.	0.0486	-0.0192	0.0728	0.0152	0.0081	0.0349	0.0289	-0.0165	0.0791	0.0601

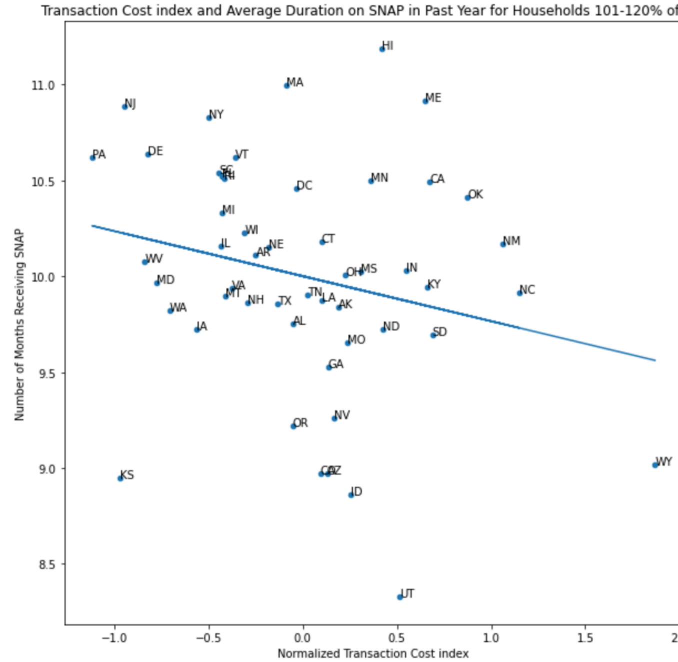
Notes:* = significant at 10% level, ** = 5 % level, *** = 1% level



Transaction Cost index and Average Duration on SNAP in Past Year for Households 81-100% of FPL

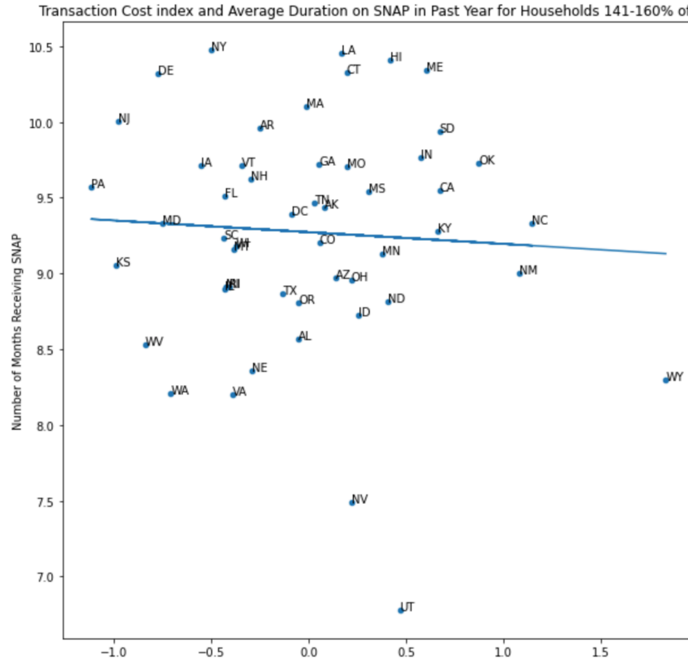


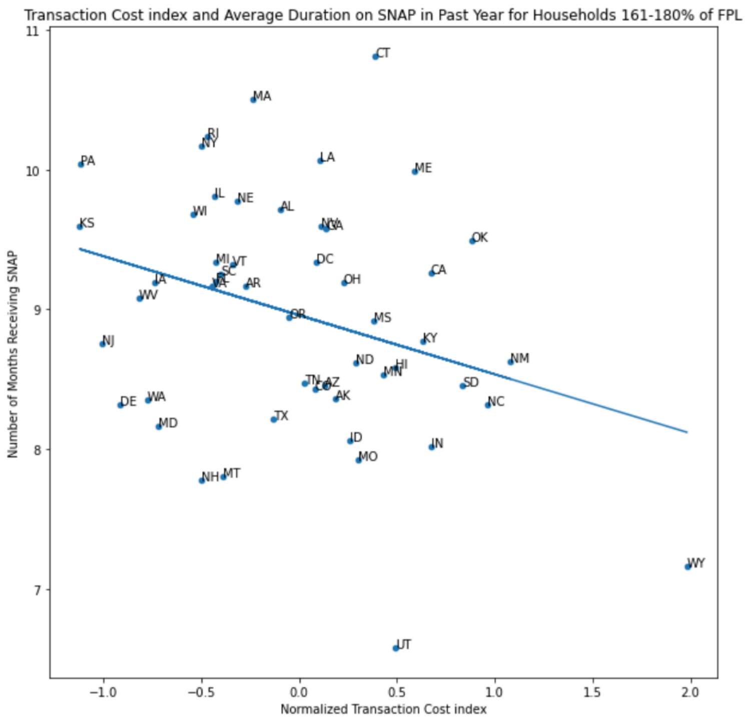
Transaction Cost index and Average Duration on SNAP in Past Year for Households 101-120% of FPL

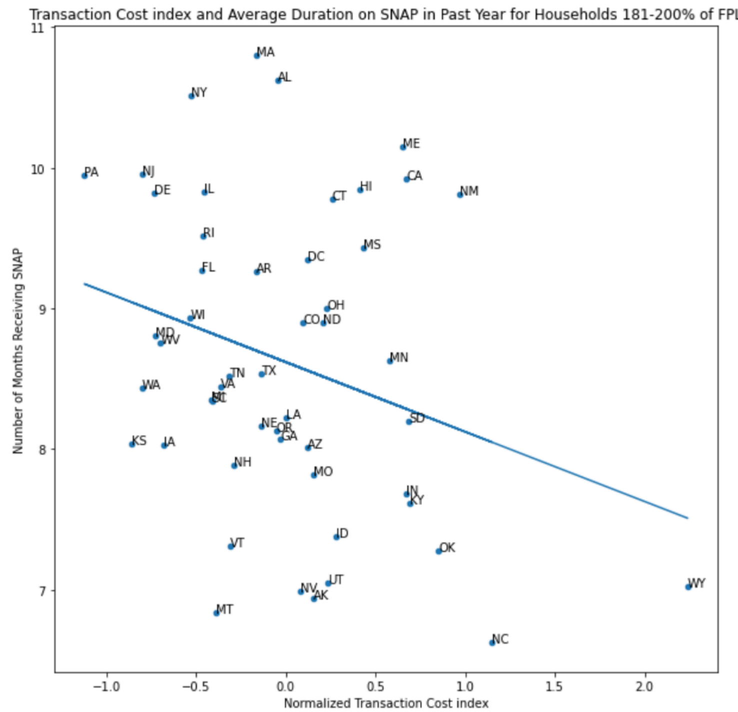


Transaction Cost index and Average Duration on SNAP in Past Year for Households 121-140% of FPL

Transaction Cost index and Average Duration on SNAP in Past Year for Households 141-160% of FPL




Transaction Cost index and Average Duration on SNAP in Past Year for Households 161-180% of FPL
Number of Months Receiving SNAP
Normalized Transaction Cost index
11
10
9
8
7
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0


Transaction Cost index and Average Duration on SNAP in Past Year for Households 181-200% of FPL
Number of Months Receiving SNAP
Normalized Transaction Cost index
11
10
9
8
7
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0

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