Immigrant Success and Wealth Tests: Consequences of the Department of Homeland Security's 2019 Public Charge Rule

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Abstract

The 2019 public charge rule published by the Trump administration has left substantial impacts on public safety net participation for immigrant families. Utilizing data from the Current Population Survey (CPS), I examine the effects of the the updated public charge rule (UPCR) on public safety net participation on citizen children with non-citizen mothers (treatment group), using citizen children with citizen mothers as a control group. I employ a difference-in-differences model to explore the before and after effects of the rule to look at participation rates in Medicaid, SNAP, and lunch subsidies. I find statistically significant results showing that the odds of SNAP participation is approximately 27% lower for the treatment group in comparison with the control group during the years that the UPCR is in effect. Interestingly, I did not find significant results on the effect of the UPCR on Medicaid and lunch subsidy participation. The UPCR exacerbated food insecurity among children living in immigrant households in a time when immigrants were already facing economic hardship as a result of the ongoing COVID-19 pandemic.

Keywords: Public Charge, Public Safety Net Programs

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1 Introduction

The United States of America is often referred to as the “land of opportunity.” The place where one can achieve the American dream. That is, regardless of where you come from, what you look like, or any other social and economic determinants, you can build a successful life. But how much truth does this sentiment hold for immigrants of a low socioeconomic status? Does the American Dream apply to them? Strict rules and regulations on both immigration as well as resources that immigrants may utilize certainly make it difficult for them to achieve success. The public charge rule is one of many regulations that not only deters immigrant success but also presents a danger to their well-being.

The public charge rule has been a federal regulation since 1999 (National Conference of State Legislatures (NCSL), 2021). Designed to limit legal permanent residence status, the rule stipulates that immigrants may be denied such status based on their “past or potential” usage of public safety net programs such as Supplemental Security Income (SSI), Temporary Assistance for Needy Families (TANF), state and local cash assistance programs, and public assistance for long-term care through Medicaid. In 2019, the Department of Homeland Security under the Trump Administration revised the rule to target immigrants suffering from limited resources and support. The list of criteria for which applicants for legal permanent residence could be denied under the updated public charge rule (UPCR) was expanded to also include Supplemental Nutrition Assistance Program (SNAP), non-emergency Medicaid, housing assistance through subsidies and Section 8 vouchers, and government funded long-term care (NCSL, 2021).

There is no question that this rule is targeted towards immigrants of low socioeconomic status. In fact, the Department of Homeland Security published a document outlining the purpose of the new revision to the rule stating that,“through this rule, DHS seeks to better ensure that applicants for admission to the United States and applicants for adjustment of status who are subject to the public charge ground of inadmissibility are self-sufficient, i.e., do not depend on public resources to meet their needs, but rely on their own capabilities and the resources of their family, sponsor, and private organizations" (Federal Register, 2019). Under this guidance, DHS expects applicants for legal permanent residence status to sustain themselves on their own means or acquire external support outside of the government. The UPCR is essentially a "wealth test" for immigrants (Ramirez, 2020).

In this paper, I examine the effects of the UPCR on participation rates of Medicaid, SNAP, and lunch subsidies for US-born children with non-citizen mothers. Medicaid is a joint program between the federal and state governments with eligibility varying by state. Furthermore, although lunch subsidies were neither in the original public charge rule nor the UPCR, I am interested in the spillover effects to determine if these populations discontinued or reduced their usage of other public safety nets after the publication of the new rule. While there have been previous studies done on the impacts of the UPCR, most of them have analyzed the effects on immigrant households in general. My study is centered on citizen children with non-citizen mothers. Furthermore, I employ a model that controls for variables such as state-fixed effects, demographic characteristics, and immigration enforcement activity, all of which are relevant in the literature. My model also includes data from 2020, which was not available at the time that some of the previous studies were completed.

The results of my investigation show that the UPCR has statistically insignificant results on Medicaid participation for US-born children with non-citizen mothers. However, these children are much less likely (approximately 27%) to receive SNAP benefits during the years of the UPCR compared to their counterparts with citizen mothers. They are also less likely (approximately 7%) to receive lunch subsidies, but these results do not carry any statistical significance. Nevertheless, the implications of the UPCR could be burdensome for children and immigrant families and worsen food insecurity.

2 Background

2.1 Direct Effects of the Public Charge Rule

Various studies have been conducted analyzing the impact of the UPCR. One such study was carried out by Urban Institute through their annual Well-Being and Basic Needs Survey (WBNS).[1] The WBNS is a nationally representative, internet-based survey. In 2019, the survey found that 15.6% of adults in immigrant families avoided public safety net programs targeted by the public charge rule (Bernstein, Gonzalez, Karpman, & Zuckerman, 2020). In 2020, this share increased to 17.8% (Bernstein, Gonzalez, Karpman, & Zuckerman, 2021). Benefits that were avoided include Medicaid, the Children's Health Insurance Program (CHIP), SNAP, and housing subsidies. Individuals who reported avoiding participation in these programs did so in order to refrain from jeopardizing their green card status in the future. The authors explain one of the major consequences of the UPCR: "Avoiding medical care and emergency supports necessitated by the pandemic presents risks to adults' and children's well-being and bears consequences for public health and essential industries." They further go on to express the importance of making these changes clear to the immigrant population and ensuring that seeking medical care and other types of support from the government would not put their legal permanent residence status in jeopardy.

Migration Policy Institute (MPI) also investigated the impacts of the public charge rule from 2016-2019 using data from the American Community Survey (ACS) (Batalova, Capps, & Fix, 2020). For non-citizens, participation in SNAP, TANF, and Medicaid declined by 37%, 37%, and 20%, respectively. In comparison, for US-born citizens, these rates declined by 18%, 19%, and 8%, respectively, or roughly one half as much as non-citizens. Similarly, for citizen children with non-citizens living in the household, these take-up rates fell by 36%, 36%, and 18%. Thus, there was an overall reduction in the program take-up by both citizens and non-citizens. MPI provides a possible explanation for the overall reduction, stating that

[1] www.urban.org/policy-centers/health-policy-center/projects/well-being-and-basic-needs-survey

"Citizens and noncitizens alike saw their enrollment in these benefit programs decline during each of the first three years of the Trump administration, most likely because an improving economy reduced the need for assistance."

One of the most concerning aspects of the revisions of the public charge rule is that immigrants and immigrant families are unaware if the rule applies to their future green card status. The rule is ambiguous, and language barriers make it even more difficult for individuals and families to understand it fully. A report completed by the National Immigration Law Center in February 2020 emphasizes that "In many cases, "chilled" populations are not themselves targets of the rule, demonstrating the widespread, spillover harm fear about public charge creates for immigrant communities and members of immigrant families, including those who are already lawful permanent residents or U.S. citizens, as well as for survivors of domestic violence, trafficking, or other serious crimes who are applying for U or T status" (Straut-Eppsteiner, 2020).

2.2 Immigration Enforcement

Immigration enforcement through the U.S. Customs and Immigration Enforcement (ICE) affects Medicaid participation for immigrants. Watson finds that "Immigrants from countries with more undocumented U.S. residents, those living in cities with a high fraction of other immigrants, and those with healthy children are most sensitive to enforcement efforts" in her research study of the chilling effects of immigration enforcement on Medicaid participation (2010). The results show that for a 1% increase in immigration enforcement activity, Medicaid participation decreases by 4.9 percentage points for children. This impact is even greater in magnitude for children of low socioeconomic status. In fact, participation falls by 8.7 percentage points for this group.

Watson also finds that different groups respond more to immigration enforcement activity. For example, Medicaid participation for children under 2 and children under 7 is more likely to be impacted due to immigration enforcement activity than it is for older children.

Additionally, the same holds for married mothers and immigrant mothers from Mexico. According to Watson, approximately “52 percent of the Mexican-born population living in the U.S. is estimated to be undocumented” (Watson, 2010).

2.3 Medicaid Expansion Effects on Public Safety Net Participation and Educational Outcomes

Medicaid expansion had spillover effects on other public safety net programs. That is, due to expanded eligibility for Medicaid, more people were also eligible for other programs as well (Schmidt, Shore-Sheppard, & Watson 2021). The authors discuss that individuals who were ineligible for Medicaid may have been induced to work less to reduce their earnings to the new eligibility levels. On the contrary, individuals who were already eligible for Medicaid may be induced to work more up to the maximum level that would still deem them eligible for the program. Increased eligibility for Medicaid usually implies increased eligibility in other programs such as SNAP. For TANF, the income limit is much lower than that of Medicaid, so it is unlikely that individuals would be induced to reduce their earnings to that level. For instance, the authors find that an increase in the “income limit from 0 to 138 percent of the poverty level led to a statistically significant change of 0.6 additional SNAP participants per 100 people, a 4 percent increase relative to the mean rate of 15 percent SNAP participation.” Thus, including variables that control for Medicaid expansion in the model is essential as other public safety net programs are affected by it.

Health insurance expansion through both Medicaid and the State Children’s Health Insurance Program (SCHIP) are linked to better educational outcomes for children (Levin & Schanzebach, 2009). Using data available from the National Assessment of Educational Progress (NAEP), the study finds that reading test scores in 4th and 8th grade are found to increase by 0.09 standard deviations for a 50 percentage point increase in eligibility. The researchers note that this outcome could be associated with a better health status at birth which they measure in terms of lower rates of low birth-weight and infant mortality as a result of increased eligibility.

2.4 Implications of the UPCR

There are various implications of the UPCR. In the article "Hunger or Deportation: Implications of the Trump Administration's Proposed Public Charge Rule," authors Bleich and Fleishhacker note three important ones (2019). The most obvious is the reduced usage of public safety net programs and government assistance. Low-income families rely on these programs for sustenance and with millions of people being affected by the UPCR, it is very likely that participation will decline even though the rule has been reversed to the 1999 version by the Biden administration in March 2021 (The White House, 2021). One of the more concerning implications is worsening food insecurity as a result of SNAP being included in the criteria upon which immigrants could be denied their legal permanent residence status. This is especially troubling for citizen children with immigrant parents: "It is common for undocumented immigrants to live in a household that receives SNAP or other safety net programs, because undocumented parents often apply for assistance on behalf of their children." According to the article, approximately 20 million children live in a household with an immigrant parent and most of these children are citizens themselves. Thus, the rule is not only an attack on immigrants, but their family members as well. It would have detrimental effects on people regardless of their citizenship status.

The UPCR could have potentially severe health outcomes for the immigrant population. This is in part due to the fact that subsidies for drug benefits under Medicare Part D are included in the UPCR (Capps, 2018). As studies from the literature have discussed, elderly immigrant individuals in addition to elderly citizen individuals living in immigrant households may potentially avoid these subsidies for drug benefits. This is a result of the fear that immigrant households face in the potential risk of jeopardizing their legal permanent residence status as well as an overall misunderstanding of the rule. Furthermore, in March 2019, Urban Institute conducted interviews of families who reported avoiding public safety net programs out of fear of putting their green card status in jeopardy (Bernstein, McTarnaghan, & Gonzalez, 2019). The interviewees reported using Medicaid for routine check-ups, preventative care, and treatment on chronic conditions such as diabetes. They also disclosed the high cost of medical care in the United States as a reason for avoiding care while being uninsured. Instead, these families had to take out loans or rely on help from extended family members to get their children the care they needed: "One interviewee recalled a neighbor who took on debt to pay for her child's medical care. Another reported that she relies on family members to take her children back to Mexico for more affordable medical care." The consequences of foregoing preventative medical care and routine check-ups can result in dangerous health outcomes for individuals. One study titled "Why People Do Not Attend Health Screenings: Factors That Influence Willingness to Participate in Health Screenings for Chronic Diseases" underlines that "Health screenings can prevent and detect diseases in earlier, more treatable stages. After screening, appropriate preventive treatment is necessary. This would significantly reduce the risks posed by diseases, including disability and early death, and also reduce the cost of medical care" (Chien, Chuang, & Chen, 2020). Thus, avoiding care due to a lack of affordability would not only lead to worse health outcomes, but also be more costly and result in a bigger burden on an already overwhelmed healthcare system in the United States.

There are several consequences of food insecurity on health outcomes for children. One study investigated the association between the two factors using data from the National Health and Nutritional Examination Survey (NHANES) from 2001-2006 (Gundersen & Kreider, 2009). The researchers find that children who are food secure are more likely to have what is considered a healthy weight and also more likely to have a good health status. Another study (Gundersen & ZIliak, 2015) reaffirms these results and finds that "food-insecure children are at least twice as likely to report being in fair or poor health and at least 1.4 times more likely to have asthma, compared to food-secure children." They also report that public safety net programs like SNAP have been useful in reducing food security. Nevertheless, they also find that SNAP does not completely alleviate food insecurity as it still exists among SNAP recipients. They explain several factors that could be leading to this including insubstantial monthly benefit levels from SNAP, barriers to applying and re-applying, and the restrictive eligibility levels where "a substantial portion of food-insecure households have incomes above the gross income limit of 130 percent of poverty," making them ineligible for the program.

3 Data

I utilize data from the Current Population Survey (CPS) to investigate my research question. This data is publicly available to download and analyze through IPUMS. The CPS is a nationally representative, cross-sectional dataset. The sample I collected includes hundreds of thousands of observations from 2017 to 2021. Each row of the data represents an individual and its characteristics and other important variables relevant to the CPS and my investigation. In my study, I filter the dataset to only include US-born children. There are 8,954 US-born children with non-citizen mothers and 117,946 US-born children with citizen mothers from 2017 to 2021 in the CPS.

Other studies investigating the effects of the public charge rule have used the American Community Survey (ACS) as well as Urban Institute's WBNS. ACS data for 2020 was not available at the time I initiated my study. 2020 was the year that the new rule took effect and implementing that into the study would give a better understanding of the magnitude of the impacts as opposed to simply using 2019 when the rule was published. Furthermore, the WBNS is not a dataset that is publicly available and does not have all of the outcomes that I am interested in investigating. Other studies have also utilized the Survey of Income and Program Participation (SIPP), which "collects data and measures change for many topics including: economic well-being, family dynamics, education, assets, health insurance, childcare, and food security."[2] The SIPP is a longitudinal dataset that is nationally repre-

[2] www.census.gov/topics/income-poverty/poverty/guidance/surveys-programs.html

sentative. The benefit of the SIPP being a longitudinal dataset is that it allows researchers to look at the same individuals over time. Thus, it makes it easier to track individuals' usage and participation in public safety net programs.

I also merge in immigration enforcement data from Transactional Records Access Clearinghouse (TRAC) through Syracuse University to control for deportations by state conducted by ICE. Additionally, I collect and merge in immigrant population data from the Pew Research Center and MPI to create proportions of undocumented immigrants deported by state. I discuss the specific adjustments I made to these data in the Model and Methods section.

3.1 Summary Statistics

Table 1: Treatment Group Summary Statistics

	Mean	SD	N
Age	8.411	5.015	8954
Medicaid	.522	.5	8928
SNAP	.269	.443	8954
Lunch Subsidies	.812	.391	6285
Poverty (100%- 124% FPL)	.109	.311	8954
Poverty (125%-149% FPL)	.082	.275	8954
Mother's HS Degree	.292	.455	8954
Mother's BA Degree	.107	.309	8954

Table 2: Control Group Summary Statistics

	Mean	SD	N
Age	8.848	5.05	117946
Medicaid	.304	.46	117452
SNAP	.168	.374	117946
Lunch Subsidies	.56	.496	68227
Poverty (100%- 124% FPL)	.047	.211	117946
Poverty (125%-149% FPL)	.046	.21	117946
Mother's HS Degree	.159	.366	117946
Mother's BA Degree	.163	.369	117946

Looking at the summary statistics of both groups above, there are several data points that stand out. One of the main ones is that members of the treatment group have higher participation rates in public safety nets such as Medicaid, SNAP, and lunch subsidies than their counterparts in the control group. For example, 52.2%, 26.9%, and 81.2% of the treatment group participates in Medicaid, SNAP, and lunch subsidies, respectively, but these shares are only 30.4%, 16.8%, and 56% for the control group. This is interesting because although the treatment group has higher participation rates overall, we will see in the results section that the UPCR has a greater impact on them and they are less likely to utilize these benefits after the publication of the rule.

Moreover, a greater proportion of the treatment group are in poverty in comparison with the control group, further emphasizing that the UPCR impacted low-income individuals. We can also see that a lower share of non-citizen mothers hold a bachelor's degree (10.7%) compared to citizen mothers (16.3%). This could partially explain why less members of the control population are taking up programs like Medicaid, SNAP, and lunch subsidies. That is, they are more likely to be ineligible for these government assistance programs if their parents' income levels are higher than the Medicaid eligibility levels. This is expected given that higher degrees usually indicate higher earnings, and thus a less probable chance of being eligible for the programs.

Table 3: Immigration Deportation Z-Score Statistics

Year	Mean	SD
2016	0.436	3.783
2019	0.344	4.249
2020	0.404	4.479

From the immigration deportation z-scores above, immigration enforcement activity was higher on average in the year before the public charge rule. Nevertheless, as I will show in the results section, the magnitude of the UPCR effects on the treatment group are even greater after controlling for immigration enforcement activity. Increased immigration activity induces fear and consequently, immigrant and non-citizen parents may be less likely to partake in government assistance programs.

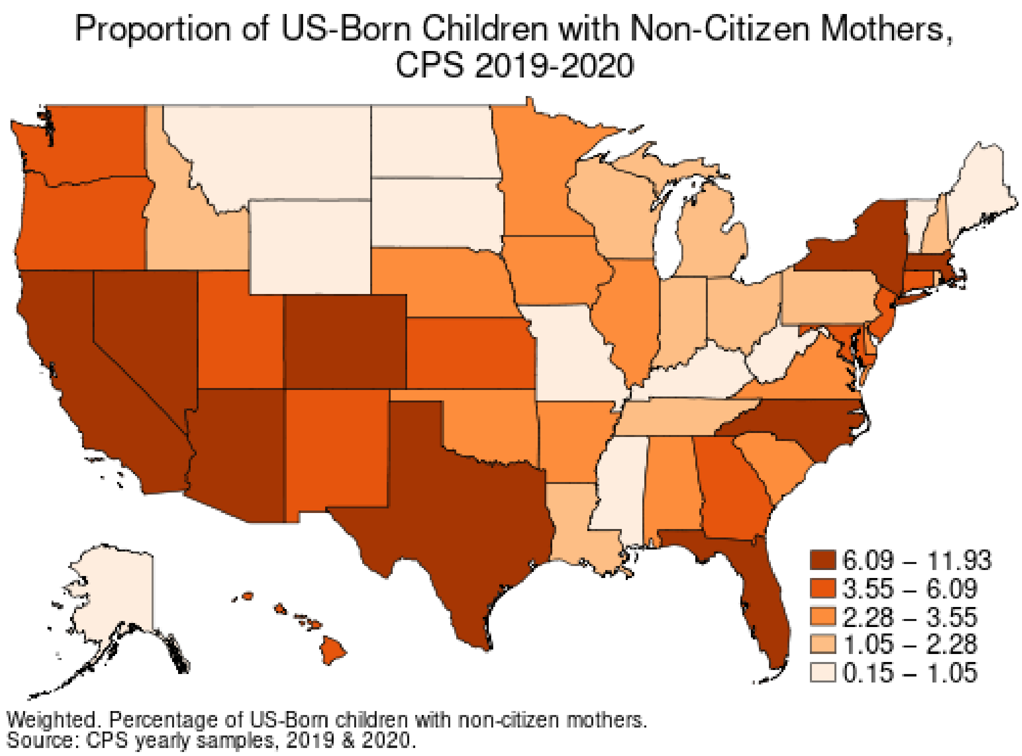

Figure 1: Proportion of Treatment Group by State

Figure 1 is a map I created to understand where in the United States the treatment group is living. The map depicts the proportion of US-born children with non-citizen mothers in each state. The darker shades of orange are states with higher proportions of the treatment group. For example, states like Massachusetts, New York, California, Texas, and Florida have larger shares of this population (6.09% to 11.93%). On the other hand, states such as Maine, Montana, Wyoming, North Dakota, South Dakota, and Kentucky have the lowest proportions of this population (only 0.15% to 1.05%). Overall, the proportion of this population is rather low across across the country.

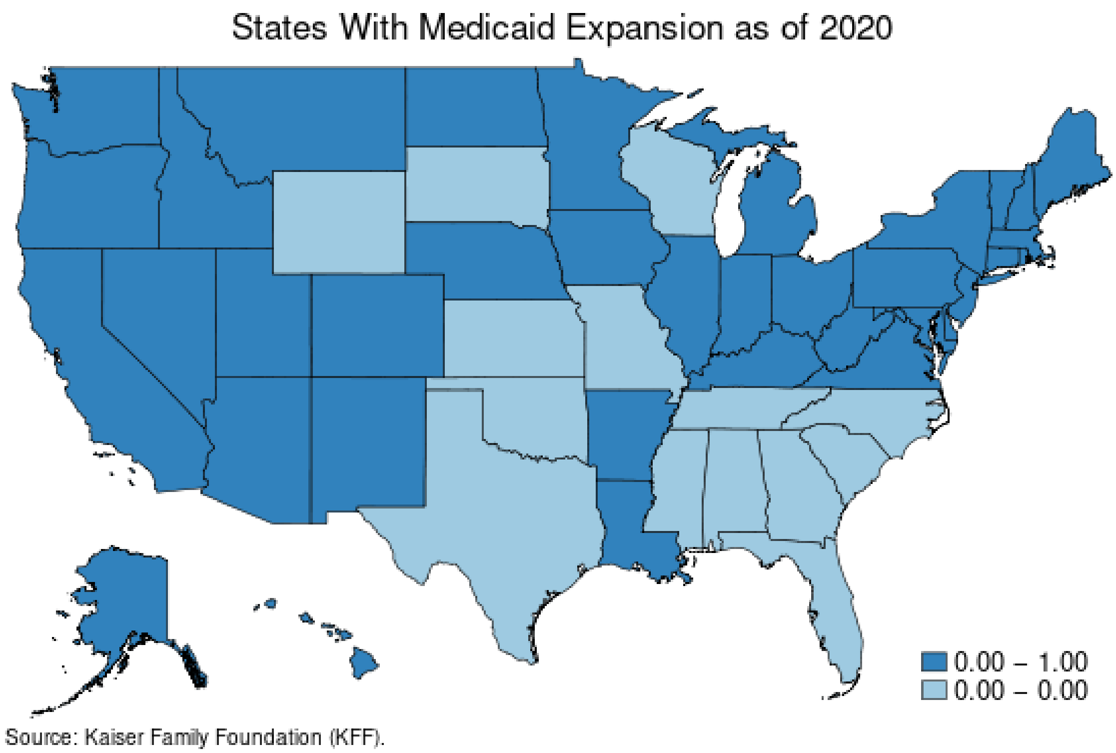

Figure 2: Medicaid Expansion

Figure 2 is a map showing which states adopted Medicaid expansion as of 2020. Medicaid expansion under the Affordable Care Act (ACA) "expanded Medicaid coverage to nearly all adults with incomes up to 138% of the Federal Poverty Level ($17,774 for an individual in 2021)" (Kaiser Family Foundation, 2022). States with the darker shade of blue are the ones that adopted the expansion whereas the lighter shade are the ones that have not. As of 2021, 39 states including DC have adopted the expansion. The 12 states that have not adopted it are: Alabama, Florida, Georgia, Kansas, Mississippi, North Carolina, South Carolina, South Dakota, Tennessee, Texas, Wisconsin, and Wyoming. Medicaid expansion took effect in July 2021 in Oklahoma and August 2021 in Missouri.

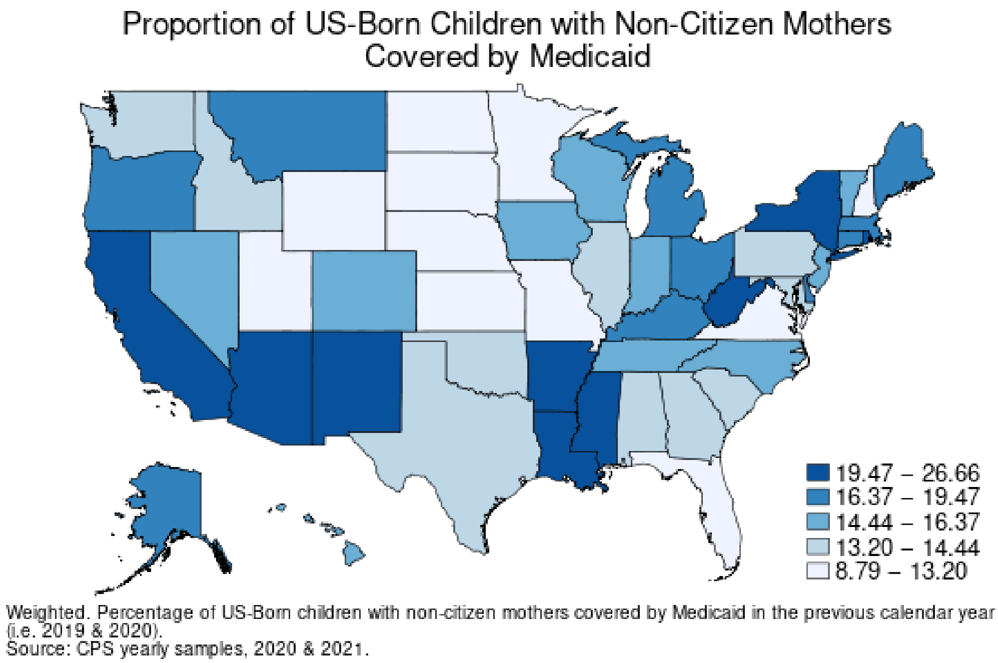

Figure 3: Proportion of Treatment Group Participating in Medicaid by State

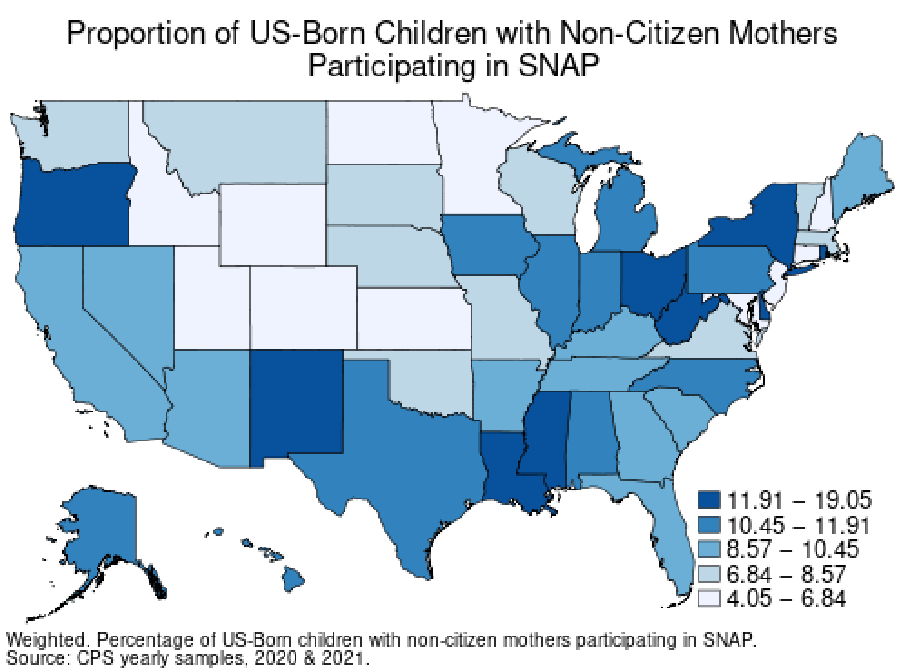

Figure 4: Proportion of Treatment Group Participating in SNAP by State

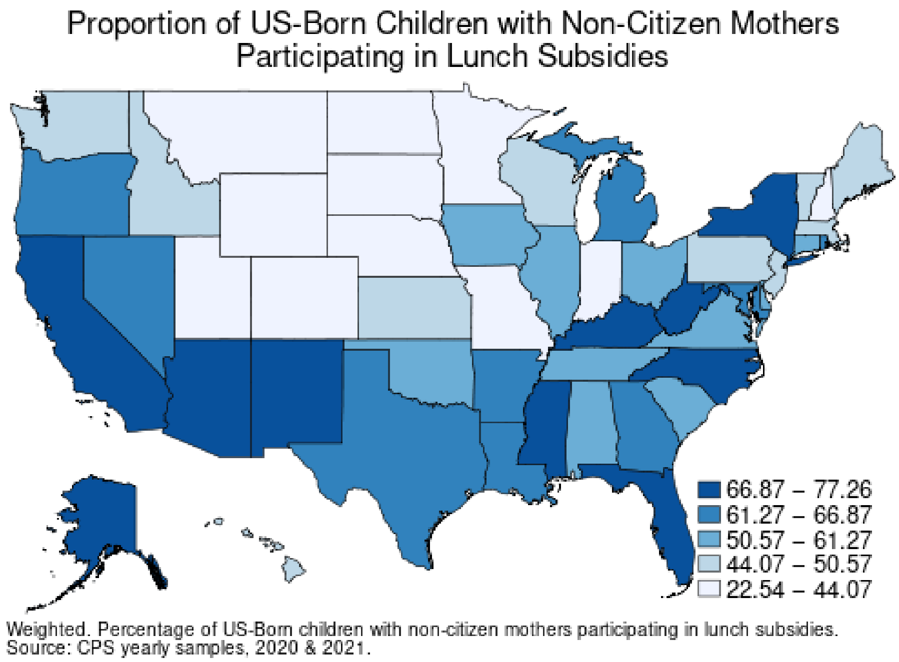

Figure 5: Proportion of Treatment Group Participating in Lunch Subsidies by State

Figures 3, 4, and 5 are maps depicting the proportion of US-born children with non-citizen mothers participating in Medicaid, SNAP, and lunch subsidies in each state.

From Figure 3, we see that the proportion of the treatment group covered by Medicaid across the country ranges from 8.79% to 26.66%. States with the highest proportions of the treatment group being covered by Medicaid include New York, California, Arizona, New Mexico, West Virginia, and Arkansas. All of these states have adopted the Medicaid expansion under the ACA. Furthermore, states like Florida, South Dakota, Wyoming, and Missouri have lower shares of the treatment population with Medicaid coverage. None of these states have adopted Medicaid expansion with the exception of Missouri. The low proportion in Missouri can be explained by the fact that they adopted the expansion in July 2021, so individuals may still be taking time to submit their applications and enroll in the program.

Figure 4 shows that the percentage of the treatment group participating in SNAP ranges from 4.05% to 19.05%. Oregon, New York, New Mexico, Ohio, West Virginia, Louisiana, and Mississippi see the highest participation rates in SNAP from the treatment group. Mississippi is the only state from the previous list that has not adopted Medicaid expansion. Some of the states with the lowest participation rates include Idaho, Wyoming, Utah, Colorado, Kansas, North Dakota, and Minnesota, which is surprising given that all of these states with the exception of Wyoming and Kansas have adopted the expansion. Therefore, it is likely that SNAP participation may not be directly associated with Medicaid participation.

According to Figure 5, the proportion of the treatment group participating in lunch subsidies ranges from 22.54% to 77.26%, showing overall higher proportions than those of Medicaid and SNAP participation. The states with the highest participation rates for lunch subsidies are similar to those of Medicaid coverage including places like New York, California, Arizona, New Mexico, West Virginia, and Kentucky. States with the highest participation rates also include ones that have not adopted the Medicaid expansion such as North Carolina, Mississippi, and Florida. We see lower participation overall in the north-mid-western states in a similar way we see with SNAP participation.

3.2 Model and Methods

The main outcomes I am interested in are participation in three public safety net programs for US-born children with non-citizen mothers: Medicaid, SNAP, and lunch subsidies. First, I identify all US-born children with non-citizen mothers as mothers are more likely to make Medicaid enrollment decisions on behalf of the family (Watson, 2010). I use US-born children living in citizen households as a control group as no individuals in an all-citizen household would be affected by the public charge rule. In the IPUMS CPS dataset, the variable caidly identifies Medicaid coverage in the previous year. The same is true for the variables that identify SNAP and lunch subsidy usage in the household. That is, if the census year is 2021, participation for 2020 is identified.

To answer my research question of interest, I run two main models:

1. A model with 2016 as the pre-UPCR year and 2019 and 2020 as the post-UPCR years. This is the model I will discuss throughout the paper as it provides a more complete

picture of the effects, especially noting that the UPCR did not officially go into effect until early 2020.

2. The second model is the same as the first with the exception that 2019 is being used as the post year. The announcement of the UPCR took place in late 2019, but it is possible that families did not make decisions based off of the announcement alone, especially since it went into effect a few months later in the following year. I will include the results of the regression tables in the Appendix section, but will not discuss the results in the main discussion section of this paper.

3.3 Empirical Specification

To understand the effect of the UPCR on U.S.-born children with non-citizen mothers, I employ a difference-in-differences empirical approach. I am analyzing participation rates before and after the implementation of the UPCR for U.S-born children of non-citizen mothers versus U.S.-born children with citizen mothers. The estimation will also control for state-fixed effects, the mother's demographics, and immigration enforcement activity within the child's state of residence. The three outcome variables of interest (participation rates in Medicaid, SNAP, and lunch subsidies) are modeled using the following equation

$$Y_i = \beta_0 + \beta_1 Treatment_i + \beta_2 Time_i + \beta_3 (UPCR_i) + \beta_4 Covariates_i + \epsilon_i \tag{1}$$

where Y_i is the outcome variable of interest, β_0 is a constant term, β_1 characterizes the differential program take-up rate for the treatment population versus the control population, β_2 is the average take-up rate post-UPCR, and β_3 is our parameter of interest - it demonstrates whether children of immigrants had different program take-up behavior than the control population after the rule change. $Treatment_i$ is a dummy variable that takes on the value 1 for U.S.-born individuals with non-citizen mothers and 0 for U.S.-born individuals with citizen mothers. $Time_i$ is a dummy variable that has the value 1 for 2019 and

2020, the years in which the UPCR is published and in effect, respectively. Furthermore, $UPCR_i$ is the interaction of the $Treatment_i$ and $Time_i$ variables, which allows for a better understanding of the causal impact of the revised public charge rule. In other words, when both of these variables take on the value 1, it means that we are looking at the treatment group when the UPCR is in effect. Thus, $\hat{\beta}_1$, the difference-in-differences estimator gives us this causal effect and allows us to better determine a causal relationship between the participation rates in the safety net programs for the treatment group given that the UPCR is in effect. The $covariates_i$ are a vector of controls including the state-fixed effects, demographic characteristics of the mother, and immigration enforcement activity.

I run four models that build upon each other to understand the effect of the UPCR on take-up rates for the treatment group. The first model is a baseline regression difference-in-differences model where the independent variables are the treatment group, the time variable, and the interaction of the two. The interaction of the two variables ultimately reproduces the average value of both and is needed to get the difference-in-differences estimator of the UPCR.

In the second model, I employ the same independent variables as the first model and also control for state-fixed effects. This allows me to control for within-state variation. Some states have adopted Medicaid expansion since 2016, so it is possible to see some variation of Medicaid and other public safety net program participation rates in those places. The state-fixed effects almost perfectly predict whether the state of residence of the child is one that has adopted Medicaid expansion. In fact, in attempting to control for Medicaid expansion and baseline parent eligibility levels for Medicaid, I run into errors of multicollinearity and those variables are dropped from the regression. Therefore, I do not directly control for whether the state has adopted the Medicaid expansion. Instead, I control for the state-fixed effects.

In the third model, I add onto the second model and control for the mother's demographics such as age, Mexican origin, education, and poverty status. As discussed in the background section, controlling for Mexican origin is important as previous studies indicate that nearly half of the Mexican-born population in the U.S. is estimated to be undocumented. Furthermore, education levels are essential in determining the mother's income, which in turn can help predict eligibility. Mothers with increasingly higher degrees such as a bachelor's or a master's degree are expected to have higher incomes and thus exceed the Medicaid eligibility levels. If they do not qualify for Medicaid, it is also likely that they will not qualify for other safety net programs as was also discussed previously.

Lastly, the fourth model builds upon the third one and controls for immigration enforcement within the individual's state of residence. Using a data tool from the Transactional Records Access Clearinghouse through Syracuse University, I collect deportation data by state and year for 2016, 2019, and 2020. The most recent data is only available up to June 2020. In addition to these statistics, I also gather data on immigrant populations by state and year. For the year 2016, I use the Pew Research Center's statistics on immigrant populations by state. For states with less than 5,000 immigrants, Pew leaves their data coded as less than 5,000, bottom-coding their results. In my dataset, I leave it as 5,000 as it is not possible to determine the actual population from that indication alone. This decision does introduce some bias into the immigration enforcement results. Since this data is being used as a denominator for the proportions of undocumented immigrants deported in each state, over-estimating the denominator would lead to smaller proportions overall, and thus an underestimate of immigration enforcement activity. Therefore, I would expect the results to be slightly greater in magnitude if I were to re-code the observations that are less than 5,000 as 50 instead of 5,000. For 2019, I use immigrant population statistics by state from MPI. Since no recent data on immigrant populations by state is available for 2020 and since I expect very little variation from 2019 to 2020, I decide to use 2019 immigrant populations for 2020. Controlling for state-fixed effects partially minimizes the assumption of using 2019 immigrant population data for 2020. With all of this data, I calculate the proportion of immigrants deported in each state for each year. Moreover, due to limited immigration enforcement data in 2020, I create z-scores to deal with issues of scale over time. In order to calculate the z-scores, I first calculate the average of the proportion of immigrants deported in each state for a given year. Then, I subtract the average from each proportion and then divide that difference by the average. The z-scores allow me to determine how many standard deviations the proportion is from the average.

I run each of these four models using a logistic or logit model. I avoid using an OLS difference-in-differences model as the assumptions of OLS are violated. These assumptions are homoskedasticity and the normal distribution of the error terms. One way to fix the violation of the homoskedasticity assumption is to run the regressions with robust standard errors. However, this would not be enough to address the violation of the normality of the error terms [3].

The logit difference-in-differences model is more suitable in determining or predicting the outcome variable. In this model, the coefficients presented in the regression tables represent the log odds. To transform this, we simply exponentiate the coefficient to better grasp the likelihood of an event occurring. Exponentiating the coefficient results in an odds ratio. Let us interpret this ratio. As an example, let x be the odds ratio. When this ratio is greater than 1, it means that the odds of participation is x times higher for the treatment group in comparison to the control group. However, when $x < 1$, it means that the odds are $(1 - x)$ times lower. Consider the case $x = 1$. In this situation, the odds are equal for both groups. [4]

[3] https://stats.oarc.ucla.edu/stata/dae/logistic-regression/

[4] https://health.ucdavis.edu/ctsc/area/Resource$_{L}$*ibrary/documents/logistic−regression−intro−Feb−*2021.*pdf*

4 Results

Table 4: Difference-in-Differences Model: Medicaid

	(1) Simple	(2) State FE	(3) Mother's Demographics	(4) Immigration Enforcement
Treatment	.775***	.775***	.234***	.231***
	(.03)	(.031)	(.036)	(.037)
Time	-.137***	-.129***	.166***	.167***
	(.013)	(.013)	(.016)	(.016)
UPCR	.262***	.254***	.011	.017
	(.045)	(.045)	(.049)	(.049)
Constant	-.743***	-.578***	.146**	.162***
	(.01)	(.042)	(.061)	(.062)
N	126380	126380	87714	87714
Psuedo R^2	.011	.028	.137	.137

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$

We can see in Table 4[5] from the simple model that being a US-born citizen with a non-citizen mother in the years of the UPCR increases the log odds of Medicaid coverage by 26.2%. In other words, the odds of receiving Medicaid coverage is 1.3 times higher for the treatment group than the control group. Incorporating state-fixed effects changes the log odds to 25.4%. These results are statistically significant at the 1% level. However, the log odds reduces to 1.1% and 1.7% when controlling for the mother's demographic characteristics and immigration enforcement activity, respectively. That is, the odds of being covered by Medicaid is 1.011 and 1.017 times higher for the treatment group than the control group.

[5] See Appendix B for an extended regression table

The results with the inclusion of the mother's demographic characteristics and immigration enforcement are neither significant in magnitude nor in statistical effect.

Table 5: Difference-in-Differences Model: SNAP

	(1) Simple	(2) State FE	(3) Mother's Demographics	(4) Immigration Enforcement
Treatment	.565***	.598***	.165***	.172***
	(.034)	(.035)	(.041)	(.041)
Time	-.062***	-.05***	.352***	.352***
	(.016)	(.016)	(.019)	(.019)
UPCR	.047	.033	-.307***	-.319***
	(.051)	(.051)	(.054)	(.054)
Constant	-1.558***	-1.328***	-.444***	-.477***
	(.013)	(.049)	(.068)	(.07)
N	126900	126900	87959	87959
Psuedo R^2	.005	.02	.125	.126

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$

Table 5 displays the effects of the UPCR on SNAP participation. We can see that from the baseline model as well as the one with the state-fixed effects, the odds of the treatment group receiving SNAP benefits is only approximately 1.04 times higher than the control group. However, after adding in the mother's demographics and immigration enforcement activity, the odds of U.S.-born children with non-citizen mothers receiving SNAP benefits are 26.4% and 27.3% lower compared to US-born children with citizen mothers. These results are statistically significant at the 1% level and critical in regards to effect sizes.

Table 6: Difference-in-Differences Model: Lunch Subsidies

	(1) Simple	(2) State FE	(3) Mother's Demographics	(4) Immigration Enforcement
Treatment	1.263***	1.165***	.555***	.556***
	(.042)	(.043)	(.051)	(.051)
Time	.532***	.56***	.979***	.979***
	(.016)	(.016)	(.022)	(.022)
UPCR	.194***	.183**	-.075	-.076
	(.071)	(.072)	(.078)	(.078)
Constant	-.085***	-.097*	.79***	.786***
	(.012)	(.051)	(.078)	(.08)
N	74512	74512	53304	53304
Psuedo R^2	.028	.059	.194	.194

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$

Additionally, Table 6 displays the results of the model with lunch subsidies as the outcome variable. Columns (1) and (2) show that the odds of lunch subsidy participation for US-born children with non-citizen mothers are approximately 1.2 times higher than the control group. This is statistically significant at the 1% level. Nevertheless, the magnitude of the effect worsens for the treatment group when we control for the mother's demographics and immigration enforcement activity. That is, the odds of participation are approximately 7.23% lower for the treatment group compared to the control group post-UPCR. These results, however, are not statistically significant.

4.1 Robustness Checks

I run several tests to check the robustness of the models I have employed.

The first check I performed is on the bottom-coding of the Pew Research Center's estimates of undocumented immigrants living in the United States. The Pew Research Center bottom-coded the undocumented immigrant population estimates in 2016 for four states: Maine, Montana, Vermont, and Washington. Their populations were listed as "less than 5,000." In my original model, I coded these populations as 5,000, which would be an underestimate of the actual proportion of deportations within these states. Therefore, in the robustness check, I re-code these four states to have a population of 50 undocumented immigrants to understand what would happen from a potential over-estimated or more accurate representation of the proportion of deportations. I do not find any significant changes with regards to magnitude or statistical impact. The results of this robustness check can be found in Appendix C.1.

Another check I perform is to run difference-in-difference-in-differences (DDD) regressions to analyze the effects of the UPCR on the treatment group in states that did not adopt Medicaid expansion under the ACA. 14 states had not adopted the expansion as of 2020.[6] My assumption is that we would see lower rates of public safety net participation across the non-expansion states for the treatment group. Surprisingly, however, I find the exact opposite results. The treatment group is more likely to participate in public safety net programs in non-expansion states after the publication of the UPCR. The effect sizes are the most substantial for Medicaid and SNAP participation. The results of this triple difference regression is presented for each outcome in Tables 7-9 below:

[6] Refer back to the description under Figure 2 to see which states did not adopt the expansion as of 2020

Table 7: Triple Difference Model: Medicaid

	(1) Simple	(2) State FE	(3) Mother's Demographics	(4) Immigration Enforcement
Treat	.826***	.812***	.304***	.302***
	(.036)	(.037)	(.042)	(.042)
Time	-.135***	-.125***	.18***	.179***
	(.015)	(.016)	(.02)	(.02)
Non-Exp	.004	-.236***	-.196**	-.2***
	(.023)	(.062)	(.077)	(.077)
UPCR	.257***	.246***	-.032	-.028
	(.053)	(.054)	(.059)	(.059)
Time · Non-Exp	-.006	-.015	-.05	-.043
	(.029)	(.03)	(.036)	(.037)
Treat · Non-Exp	-.181***	-.129*	-.251***	-.253***
	(.067)	(.069)	(.074)	(.074)
Triple Difference	.032	.037	.159	.162
	(.098)	(.099)	(.108)	(.108)
Constant	-.744***	-.332***	.368***	.383***
	(.012)	(.043)	(.063)	(.064)
N	126380	126380	87714	87714
Pseudo R^2	.012	.028	.137	.137

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$

Table 8: Triple Difference Model: SNAP

	(1) Simple	(2) State FE	(3) Mother's Demographics	(4) Immigration Enforcement
Treat	.615***	.674***	.256***	.262***
	(.041)	(.042)	(.047)	(.047)
Time	-.051***	-.036*	.362***	.368***
	(.019)	(.019)	(.023)	(.023)
Non-Exp	.16***	-.242***	-.218**	-.209**
	(.028)	(.071)	(.086)	(.086)
UPCR	-.026	-.042	-.404***	-.414***
	(.061)	(.061)	(.065)	(.065)
Time · Non-Exp	-.036	-.05	-.032	-.051
	(.035)	(.035)	(.042)	(.043)
Treat · Non-Exp	-.178**	-.256***	-.313***	-.311***
	(.077)	(.078)	(.082)	(.082)
Triple Difference	.239**	.254**	.325***	.32***
	(.11)	(.111)	(.117)	(.117)
Constant	-1.604***	-1.06***	-.206***	-.241***
	(.015)	(.049)	(.069)	(.071)
N	126900	126900	87959	87959
Pseudo R^2	.005	.02	.126	.126

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$

Table 9: Triple Difference Model: Lunch Subsidies

	(1) Simple	(2) State FE	(3) Mother's Demographics	(4) Immigration Enforcement
Treat	1.261***	1.147***	.572***	.572***
	(.049)	(.051)	(.058)	(.058)
Time	.531***	.56***	.977***	.977***
	(.019)	(.02)	(.026)	(.026)
Non-Exp	.141***	-.613***	-.559***	-.558***
	(.027)	(.077)	(.098)	(.098)
UPCR	.21**	.207**	-.082	-.082
	(.084)	(.085)	(.092)	(.092)
Time · Non-Exp	.005	.001	.008	.006
	(.035)	(.036)	(.047)	(.047)
Treat · Non-Exp	.014	.062	-.06	-.06
	(.094)	(.096)	(.104)	(.104)
Triple Difference	-.062	-.081	.025	.024
	(.157)	(.158)	(.17)	(.17)
Constant	-.126***	.515***	1.348***	1.344***
	(.015)	(.057)	(.084)	(.086)
N	74512	74512	53304	53304
Pseudo R^2	.029	.059	.194	.194

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$

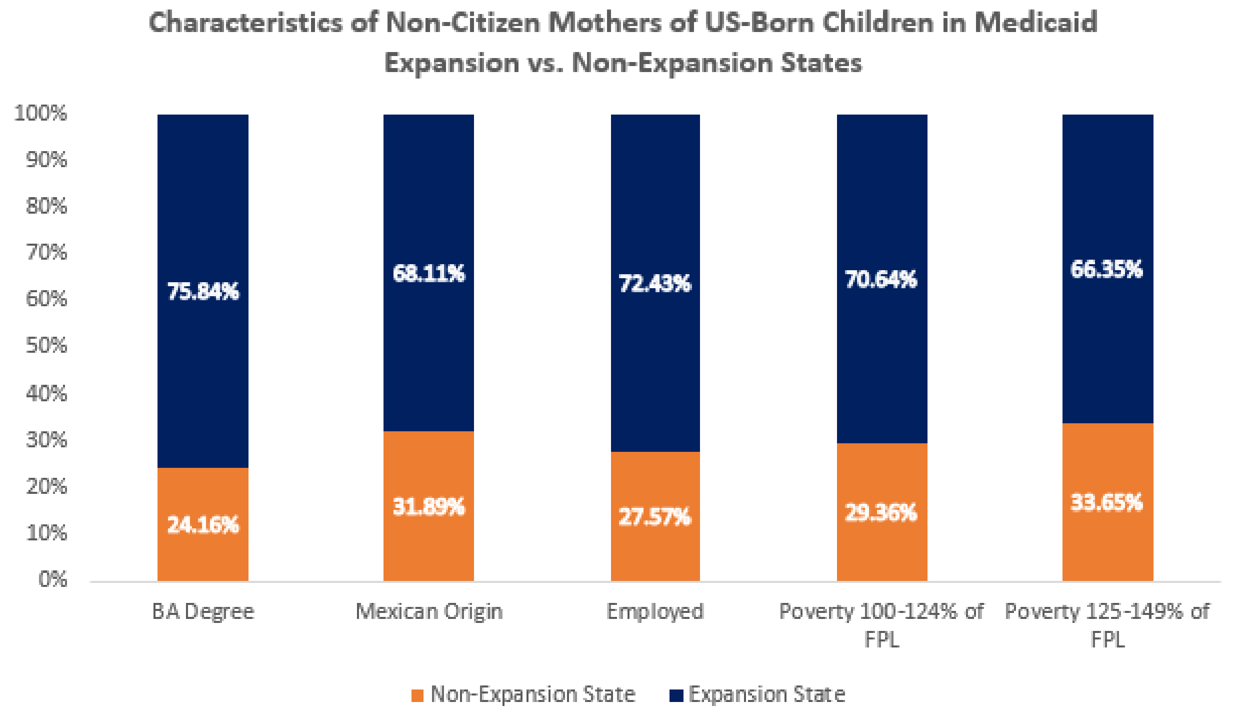

Figure 6

To understand the reasoning behind these results, I run some summary statistics of the control variables for the treatment group living in expansion and non-expansion states. Before I discuss these results that are displayed in Figure 6 above, I want to first point out that 29.13% (2,608 children) of the treatment group live in expansion states. Among US-born children with non-citizen mothers, mothers have lower rates of bachelor's degrees and employment in non-expansion states vs. expansion states. Furthermore, within the treatment group, we see lower rates of poverty and lower proportions of mothers who are of Mexican origin within the non-expansion states. Overall, the non-expansion states are less immigrant friendly with non-expansion states having higher probabilities of immigration enforcement activity. Taking all of this into consideration, the results of the DDD regressions may be a consequence of sampling issues with there being more members of the treatment group living in expansion states than non-expansion states. Additionally, it could be a result of seeing more mothers of Mexican origin living in expansion states. From the literature review, we know that approximately half of the Mexican-born population living in the U.S. is estimated to be undocumented, so we might expect to see higher rates of withdrawal from public safety net programs from this population. Lastly, these results may simply be a result of unexplained variability or randomness within the dataset.

Moreover, I perform a robustness check of the SNAP results from Table 5. I further investigate the results of this model as it is the one where the treatment group experienced the most detrimental impacts. SNAP is a federally funded public safety net program designed to provide nutritional support for low-income families (Center on Budget and Policy Priorities, 2019). Most of the eligibility criteria are determined at the federal level, but states do hold some discretion in some of the factors that go into determining qualification and benefit levels. Average and monthly benefit levels vary by household size. Additionally, certification periods for SNAP differ by demographics. For instance, elderly and disabled people have longer certification periods. In this robustness check, I add in additional variables into columns 2-4 of the model, where I control for the percentage of households with children participating in SNAP by state as well as the average certification period (in months) by state. In order to avoid issues of multicollinearity, I run these regressions without controlling for state-fixed effects. I find trivial changes with regards to statistical significance and magnitude between this robustness check and the original models presented in the results section. Since there are no significant changes, I display these results in Appendix C.2.

5 Discussion

From the results above, we do not see any statistically significant impacts of the UPCR on Medicaid or lunch subsidy participation for the treatment group. We do however notice substantial effects of the UPCR on SNAP participation with children from the treatment group being approximately 27% less likely to receive SNAP. The sharp reduction in usage during the years of the UPCR is very concerning for some of the reasons mentioned during the background section. These children are already more likely to face higher rates of poverty than their peers in the control group. Additionally, although the effect of the UPCR on lunch subsidy participation was not statistically significant, it is important to note that children in the treatment group are still approximately 7% less likely to receive lunch subsidies in comparison with children with citizen mothers. Without having some sort of assistance from the government, citizen children with non-citizen mothers could be facing food insecurity at home as well as at school.

Additionally, the UPCR was officially published right before the start of the COVID-19 pandemic, where many immigrant families faced job losses, furloughs, etc. Many lost the means to support their families and the children in those families. A study by MPI highlights some of the consequences of the pandemic on the immigrant labor force: "The total employed population fell by 5.2 million, with immigrants accounting for 28 percent of this decline (1.5 million people)—a disproportionately large share, given they made up 17 percent of the labor force before the pandemic. The percentage decline in the number of working immigrants was greater than that of U.S.-born workers over this period, and for men the decline was twice as large" (Capps, Batalatova, & Gelatt, 2021). As mentioned previously, worsening food insecurity could have detrimental impacts on children's development, health, and educational outcomes. Children with non-citizen mothers would fall behind and face more difficulty and issues in regards to these areas than their peers would.

6 Conclusion

The implications of the UPCR, although not always statistically significant, are still significant in magnitude for citizen children with non-citizen mothers, specifically with regards to SNAP participation. While investigations into the consequences of the UPCR are essential, it is equally important for governments at the federal, state, and local levels to communicate that the public charge rule has been reversed to its 1999 version, so they understand and know the list of criteria for which they could be deemed a public charge, and thus risk their green card status.

There are limitations to my investigation. One is data availability. Immigration deportation data from TRAC may not be completely up to date with official records from U.S. Immigration and Customs Enforcement. I believe that the number of deportations may be underestimated in each state and year as one study by Watson found that immigration enforcement increased during the Trump administration relative to the years directly prior to it (2021). Additionally, deportations were not the main tactic used by the Trump administration in enforcement. It was the use of detention. According to Watson's article "Immigrant Deportations During the Trump Administration," "the average number of individuals in immigration detention each day was 28,000 in 2015 and 50,000 in 2019, far exceeding historical patterns." Furthermore, there is no way to identify undocumented immigrants through the CPS. Although undocumented immigrants are typically not eligible for public safety net programs, households with undocumented immigrants may have faced substantial impacts from the UPCR.

The costs of the UPCR are important to consider. The most concerning is the exacerbation of food insecurity among immigrant households, which could lead to poor health outcomes, and a greater demand for medical care. The healthcare system would take on a greater burden as a result of having to provide emergency care for individuals who fear enrolling in Medicaid or other forms of government-funded health insurance like Medicare. For the well-being of immigrant families and the continued existence of the American Dream, it is essential for policymakers to move away from this rule altogether and determine a new procedure in determining the issuance of green cards to immigrants. The rule even in its 1999 version is still detrimental for immigrant families who need government assistance to support their economic, social, and physical health and well-being.

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Appendix

A 2019 as Post-UPCR Year in Model

Table 10: Difference-in-Differences Model: Medicaid

	(1) Simple	(2) State FE	(3) Mother's Demographics	(4) Immigration Enforcement
Treatment	.775***	.784***	.228***	.225***
	(.03)	(.031)	(.038)	(.038)
Time	-.17***	-.165***	.142***	.143***
	(.015)	(.016)	(.02)	(.02)
UPCR	.161***	.15***	-.114*	-.104*
	(.057)	(.057)	(.063)	(.063)
Constant	-.743***	-.588***	.131*	.157**
	(.01)	(.051)	(.071)	(.073)
N	86506	86506	65698	65698
Psuedo R^2	.011	.027	.134	.134

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$

Table 11: Difference-in-Differences Model: SNAP

	(1) Simple	(2) State FE	(3) Mother's Demographics	(4) Immigration Enforcement
Treatment	.565***	.608***	.12***	.125***
	(.034)	(.036)	(.043)	(.043)
Time	-.249***	-.241***	.172***	.17***
	(.02)	(.02)	(.024)	(.024)
UPCR	-.067	-.073	-.438***	-.454***
	(.068)	(.068)	(.073)	(.073)
Constant	-1.558***	-1.267***	-.291***	-.334***
	(.013)	(.06)	(.081)	(.084)
N	126900	126900	87959	87959
Psuedo R^2	.005	.02	.125	.126

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$

Table 12: Difference-in-Differences Model: Lunch Subsidies

	(1) Simple	(2) State FE	(3) Mother's Demographics	(4) Immigration Enforcement
Treatment	1.263***	1.174***	.552***	.551***
	(.042)	(.043)	(.052)	(.052)
Time	.316***	.336***	.746***	.747***
	(.018)	(.019)	(.026)	(.026)
UPCR	.263***	.259***	.009	.012
	(.088)	(.089)	(.097)	(.097)
Constant	-.085***	-.125**	.88***	.889***
	(.012)	(.059)	(.088)	(.09)
N	52814	52814	40606	40606
Psuedo R^2	.025	.06	.196	.196

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$

The tables presented in this section are the results of the model with 2019 as the post UPCR year. The coefficients should be interpreted the same way as they were in the Results section of the paper (logit difference-in-differences model).

B Extended Regression Tables from Results Section

Table 13: Difference-in-Differences Model: Medicaid

	(1) Simple	(2) State FE	(3) Mother's Demographics	(4) Immigration Enforcement
Treatment	.775***	.775***	.234***	.231***
	(.03)	(.031)	(.036)	(.037)
Time	-.137***	-.129***	.166***	.167***
	(.013)	(.013)	(.016)	(.016)
UPCR	.262***	.254***	.011	.017
	(.045)	(.045)	(.049)	(.049)
Mother's Age			-.007***	-.007***
			(.001)	(.001)
Mother HS Degree			.244***	.245***
			(.018)	(.018)
Mother AA Degree			-.112***	-.112***
			(.035)	(.035)
Mother BA Degree			-1.16***	-1.16***
			(.023)	(.023)
Mother MA Degree			-1.523***	-1.523***
			(.036)	(.036)
Mother Mexican Origin			.414***	.414***
			(.029)	(.029)
Mother's Employment			-.631***	-.631***
			(.016)	(.016)
Poverty (100-124% FPL)			1.11***	1.11***
			(.033)	(.033)
Poverty (125-149% FPL)			.942***	.943***
			(.033)	(.033)
Immigration Enforcement				.016
				(.013)
Constant	-.743***	-.578***	.146**	.162***
	(.01)	(.042)	(.061)	(.062)
N	126380	126380	87714	87714
Psuedo R^2	.011	.028	.137	.137

Standard errors are in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

Table 14: Difference-in-Differences Model: SNAP

	(1) Simple	(2) State FE	(3) Mother's Demographics	(4) Immigration Enforcement
Treatment	.565***	.598***	.165***	.172***
	(.034)	(.035)	(.041)	(.041)
Time	-.062***	-.05***	.352***	.352***
	(.016)	(.016)	(.019)	(.019)
UPCR	.047	.033	-.307***	-.319***
	(.051)	(.051)	(.054)	(.054)
Mother's Age			-.01***	-.01***
			(.001)	(.001)
Mother HS Degree			.175***	.175***
			(.02)	(.02)
Mother AA Degree			-.195***	-.195***
			(.041)	(.041)
Mother BA Degree			-1.465***	-1.465***
			(.032)	(.032)
Mother MA Degree			-1.923***	-1.922***
			(.055)	(.055)
Mother Mexican Origin			.085**	.085**
			(.033)	(.033)
Mother's Employment			-.695***	-.695***
			(.018)	(.018)
Poverty (100-124% FPL)			.807***	.806***
			(.032)	(.032)
Poverty (125-149% FPL)			.521***	.521***
			(.034)	(.034)
Immigration Enforcement				-.034**
				(.014)
Constant	-1.558***	-1.328***	-.444***	-.477***
	(.013)	(.049)	(.068)	(.07)
N	126900	126900	87959	87959
Psuedo R^2	.005	.02	.125	.126

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$

Table 15: Difference-in-Differences Model: Lunch Subsidies

	(1) Simple	(2) State FE	(3) Mother's Demographics	(4) Immigration Enforcement
Treatment	1.263***	1.165***	.555***	.556***
	(.042)	(.043)	(.051)	(.051)
Time	.532***	.56***	.979***	.979***
	(.016)	(.016)	(.022)	(.022)
UPCR	.194***	.183**	-.075	-.076
	(.071)	(.072)	(.078)	(.078)
Mother's Age			-.013***	-.013***
			(.001)	(.001)
Mother HS Degree			.248***	.248***
			(.026)	(.026)
Mother AA Degree			-.169***	-.169***
			(.046)	(.046)
Mother BA Degree			-1.121***	-1.121***
			(.028)	(.028)
Mother MA Degree			-1.51***	-1.51***
			(.04)	(.04)
Mother Mexican Origin			.618***	.618***
			(.043)	(.043)
Mother's Employment			-.61***	-.61***
			(.022)	(.022)
Poverty (100-124% FPL)			1.568***	1.568***
			(.056)	(.056)
Poverty (125-149% FPL)			1.38***	1.38***
			(.054)	(.054)
Immigration Enforcement				-.004
				(.017)
Constant	-.085***	-.097*	.79***	.786***
	(.012)	(.051)	(.078)	(.08)
N	74512	74512	53304	53304
Psuedo R^2	.028	.059	.194	.194

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$

C Robustness Checks

C.1 Bottom Coding

Table 16: Difference-in-Differences Model: Medicaid

	Immigration Enforcement
Treatment	.236***
	(.036)
Time	.16***
	(.017)
UPCR	.006
	(.049)
Constant	.16***
	(.061)
N	87714
Pseudo R^2	.137

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$

Table 17: Difference-in-Differences Model: SNAP

	Immigration Enforcement
Treatment	.164***
	(.041)
Time	.356***
	(.019)
UPCR	-.305***
	(.054)
Constant	-.451***
	(.069)
N	87959
Pseudo R^2	.125

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$

Table 18: Difference-in-Differences Model: Lunch Subsidies

	Immigration Enforcement
Treatment	.556***
	(.051)
Time	.976***
	(.022)
UPCR	-.077
	(.078)
Constant	.796***
	(.078)
N	53304
Pseudo R^2	.194

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$

C.2 SNAP Program: Certification Period and Proportions of Households with Children

Table 19: Difference-in-Differences Model: SNAP

	(1) Simple	(2) SNAP Factors	(3) Mother's Demographics	(4) Immigration Enforcement
Treatment	.565***	.565***	.149***	.153***
	(.034)	(.035)	(.04)	(.04)
Time	-.062***	-.059***	.346***	.339***
	(.016)	(.016)	(.019)	(.019)
UPCR	.047	.045	-.305***	-.311***
	(.051)	(.051)	(.054)	(.054)
Constant	-1.558***	-2.003***	-.608***	-.549***
	(.013)	(.065)	(.085)	(.086)
N	126900	126900	87959	87959
Pseudo R^2	.005	.006	.114	.115

Standard errors are in parentheses: *** $p < .01$, ** $p < .05$, * $p < .1$