Noncitizen Aid Utilization

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Abstract

This paper addresses the common claim that noncitizens draw heavily from welfare programs using a linear probability model for the usage of various public aid programs, as well as a levels regression on the amount of aid received. Results show that noncitizens use total aid at a rate in excess of their representation in the population, but that there is no significant difference in the amount of benefits received. These models control for many factors, including pre-aid income, age, state of residence, and race. In total means-tested cash and noncash transfers, citizenship reduced the probability of receiving aid by 11.56 percentage points. All but three of the individual programs have coefficients on the citizenship regressor that are not statistically significant below the 10% level.

Introduction

Do people who are not citizens receive more aid than their citizen counterparts? This question is one that has been fiercely debated in US politics. In the late 20th century, the US decided that government assistance should go primarily to citizens, so the Personal Responsibility and Work Opportunity Reconciliation Act was passed in 1996, henceforth the PRWORA or the 1996 Welfare Reform. Signed into law by President Bill Clinton, the reform was intended to lower government spending on welfare reform and shift toward employment-based benefits (Burke, 1996, p.1.). The Aid to Families with Dependent Children (AFDC) supplement was replaced with the Temporary Assistance to Needy Families (TANF) program and jurisdiction over food stamps was passed largely to states, with work requirements also added (Burke, 1996, p.1.). PRWORA also contained language that excludes legal, noncitizen immigrants from receiving federal aid for the first five years they are in the US. This law is an important determinant of aid trends. In theory, few noncitizens should receive assistance. Much of my research is a judgment on the efficacy of this statute and whether it has prevented noncitizens from receiving aid.

I will address this question using data drawn from the Census Bureau's Survey of Income and Program Participation (SIPP). This survey asks respondents about their participation in a wide range of federal and state programs. I use both a linear probability model to determine the difference in usage caused by citizenship status as well as a levels analysis to judge whether citizens or noncitizens receive absolute higher amounts of aid. Much of the existing literature focuses on specific programs or locations. There lacks a nationwide review of noncitizen participation, a gap that my research fills. I control for a wide range of demographic and personal characteristics, including earned income, race, gender, and household size. I perform all regressions at the household level. This includes all beneficiaries of aid without repeating observations. My results indicate that there is only a statistically significant difference in citizenship coefficients on the aggregate benefits linear probability regression and that citizens are less likely to receive aid.

Literature Review

Borjas and Hilton (1996) find that immigrants in 1990 were more likely to receive public assistance than native households, though any gap in cash receipts from the government was limited. In fact, the disparity ended up quite large: "[T]he 8.8 percent of persons residing in immigrant households accounted for 13.8 percent of the cost of the programs, almost 60 percent more than their representation in the population" (Borjas and Hilton, 1996, p.584). They developed a variety of arguments that foreign-born individuals indeed were draining resources. Their research included a wide range of programs, but does not distinguish between foreign-born citizens and noncitizens. Following the passage of PRWORA, this is an important differentiation, as they are treated differently under the law. Thus, my research adds to Borjas and Hilton by separating the population based on citizenship status rather than place of origin. Under current laws, this is a more valuable distinction.

Shortly after the reform act took effect, a report published by the Urban Institute determined that immigrant families suffered higher rates of "hardship" yet received food stamps at lower rates than their native counterparts. Roughly 3,500 families in Los Angeles County and New York City were surveyed, producing results substantially different from the Borjas and Hilton study. Despite immigrant families having poverty rates over double those of native families, immigrant families on average received just half the food stamp benefits (Capps et al., 2002, p.iv). The authors conclude that foreign-born residents (and their native-born children) experienced greater economic struggles. They provide valuable overview of immigrant participation in food stamps but is not nationwide and analyzes a single program. Part of this is a focus on lower-income families as these are the people most in need and most significantly affected by welfare reform.

Oyelere and Oyolola (2016) separate immigrant groups based upon their continent of origin. They find that naturalized immigrants use welfare at lower rates than immigrants who have not yet completed the citizenship process (Oyelere and Oyolola, 2016, p.234). Furthermore, there exist stark differences in welfare receipt dependent upon the origin of the immigrant. This suggests that demographic factors play a large role in determining whether someone receives government assistance. My analysis includes more programs, but does not separate based on country of origin. This more closely mirrors the law, as there is no distinction for noncitizens based on where they are from.

A more recent article published by the US Congressional Research Service in 2014 argues that the poverty rate for noncitizens has remained fairly consistent around 28% since 1995, though this number is nearly triple the rate for naturalized citizens (Wasem, 2014, p.5). Program participation has varied, driven in part by the Great Recession. Between 1995 and 2005, though, the percentage of noncitizens receiving cash assistance, Supplemental Security Income (SSI), Medicaid, or food stamps programs fell steadily. These results fall in line with the early indications that the PRWORA successfully curtailed noncitizen receipt of benefits.

A common explanation of these falling participation rates is the “chilling effects” of broad immigration policy enforcement. Watson (2014) attempts to quantify this effect with a particular focus on take-up rates of Medicaid among children of noncitizens. She finds that during a period of heightened immigration enforcement, participation of citizen children in Medicaid dropped off substantially (Watson, 2014, p.316). She suggests that individuals are dissuaded from applying despite their eligibility. This especially impacts children, who cannot apply for themselves and are often the most vulnerable. While I drop children from my analysis, the chilling effect could explain some of the decline in welfare usage found in the other research.

Overall, the current literature focuses on narrow population groups and on a one or two programs. The literature also lacks much insight regarding the access that noncitizens have to programs compared to citizens. My research adds to the literature by examining the entire noncitizen group and by including many different programs. Most of the literature is also slightly outdated. Thus, my research is a more current, more inclusive study of how citizens and noncitizens use aid.

Data

Data used in this analysis are drawn from Census data, collected in the Survey of Income and Program Participation (SIPP). The SIPP is a panel survey of 14,000 to 52,000 households conducted monthly, including noncitizen households. It measures a broad range of factors related to receipt of aid, including questions regarding food stamp usage, school lunch benefits, and even number of weeks worked the past month. Major programs are covered, so there is little the SIPP lacks in that sense. Respondents are typically interviewed in person when available and must be at least 15 years old, though those below 18 are dropped from my analysis. The data are valuable for my study because they provide a detailed account of what each survey member earns, which programs they participate in, and their demographics.

The specific data used are from Wave 16 of the 2008 Panel. The raw dataset includes over 200,000 observations, with data collection for that wave ending in December, 2013. This is the most recent data available. I chose to use this data because they provide a robust snapshot of current patterns of aid usage. Earlier datasets often have inconsistencies that make it difficult to compare across different panels, such as questions added or omitted year to year.

This dataset has several advantages over its peers, such as the Current Population Survey (CPS), one of the primary alternatives. The CPS focuses on demographics and employment variables, and is the source of most monthly labor force statistics (US Census Bureau, 2016). While the CPS provides a more robust depiction of the labor force, it does not collect information on nearly the range of topics required for this analysis. The SIPP includes many more questions and allows for distinction between different forms of aid and often their levels. It also includes requisite demographic information, such as citizenship, age, and education level.

However, there are some issues with the SIPP data. First, households are interviewed, which leads to variation in the amount of people per household. I eliminated all respondents except the head of household, which limits the effect of household duplication. Though this is necessary, it eliminates the ability to completely determine the aid received by noncitizens. For example, if the head of household is a citizen and the spouse is not, then the benefits going to the noncitizen are not recorded. This is a trade-off that is made to ensure that responses are not counted more than once. Furthermore, the sample size is relatively small when compared to the CPS and other national surveys. After deleting extra months and responses outside those of the head of households, the total observations is reduced to 20,116, with only 4.79% lacking citizenship. However, the value of analyzing all of the programs is quite high.

Descriptive Statistics

Table 1 provides an overview of the aid patterns at the time of the survey, as well as the demographics. In total, there are 20,116 observations.

TABLE 1: Descriptive Statistics

Variable		**Population**	**Citizen**	**Noncitizen**
Age	Mean	54.78	55.21	46.23
	Stand. Dev.	16.77	16.83	12.98
HH Income (monthly)	Mean	5,364.72	5,382.44	5,012.76
	Stand. Dev.	5,436.65	5,423.83	5,676.76
Gender	Mean	0.542	0.545	0.468
	Stand. Dev.	0.498	0.497	0.499
Marital Status	Mean	0.513	0.507	0.639
	Stand. Dev.	0.499	0.499	0.481
Citizenship	Mean	0.952		
	Stand. Dev.	0.213		
Education				
No High School	Mean	0.095	0.084	0.316
	Stand. Dev.	0.293	0.277	0.465
High School	Mean	0.392	0.395	0.327

	Stand. Dev.	0.488	0.489	0.469
Some college/Technical	Mean	0.208	0.213	0.115
	Stand. Dev.	0.406	0.409	0.319
College	Mean	0.191	0.194	0.127
	Stand. Dev.	0.393	0.395	0.333
Higher Ed	Mean	0.114	0.114	0.113
	Stand. Dev.	0.318	0.318	0.317
Race				
White (inc. Hispanic)	Mean	0.812	0.818	0.695
	Stand. Dev.	0.391	0.386	0.460
Black	Mean	0.121	0.123	0.090
	Stand. Dev.	0.326	0.328	0.286
Asian	Mean	0.034	0.027	0.179
	Stand. Dev.	0.181	0.161	0.383
Other	Mean	0.032	0.032	0.035
	Stand. Dev.	0.177	0.177	0.185
Hispanic Status	Mean	0.092	0.073	0.480
	Stand. Dev.	0.289	0.259	0.499
HH means-tested transfers %	Mean	0.272	0.258	0.547
	Stand. Dev.	0.445	0.437	0.497
HH in poverty %	Mean	0.135	0.130	0.231
	Stand. Dev.	0.342	0.337	0.421

These statistics are for the householders. On average, noncitizens are younger and more likely to be male. Interestingly, noncitizens experience poverty at nearly twice the rate of the population. However, the average household earned income is higher for noncitizens, despite higher rates of poverty. This could occur due to the substantial difference in terms of education. Noncitizens generally have far less education, with 31.6% not having completed high school. This contrasts with just 8.41% of citizens without a high school diploma. Similarly, 30.9% of citizens have a Bachelor's degree or higher education as opposed to 24.0 % of noncitizens. It is quite likely that this difference in education impacts aid usage substantially. Including education levels in the following regressions will reduce some of the impacts of this relationship.

I will now move onto examining differences in usage of various program. These are simple statistical descriptions and do not make a statement regarding statistical significance.

Rather, these give a general understanding of how the two groups use different types of aid. What is of most interest is if noncitizens use a type of aid at a greater rate than their overall population ratio. It is important to recall that noncitizens represent 4.79% of the population. Found below is a table showing the percentage of respondents who use a program that are not citizens and the percentage of citizens and noncitizens that receive each type of aid. This compares usage between the two groups to analyze which programs each group participates in relatively more often.

TABLE 2: Program Participation Ratios

Program	**% of Recipients who are Noncitizens**	**% of Noncitizens who receive aid**	**% of Citizens who receive aid**
Means-tested cash/noncash	9.65	54.77	25.81
Noncash benefits	9.81	54.67	25.29
Worker's Comp	1.64	0.10	0.31
Welfare Asst.	4.80	0.10	0.18
Child Care Asst.	4.48	0.62	0.67
TANF	4.56	0.73	0.40
Supplemental Unemp.	14.29	0.10	0.03
Energy Assistance	5.83	2.07	1.69
Food Stamps	7.25	15.56	10.02
Social Security	1.11	7.78	34.84
Veteran's Comp	0.73	0.31	2.14
State Unemployment	3.77	0.83	1.07
WIC	13.94	4.15	1.29
Cash Benefits	5.32	8.61	7.71
Clothing Asst.	2.65	0.00	0.12
Government Rent	5.81	1.04	0.85
Federal SSI	4.07	3.42	4.06
Transportation Asst.	2.52	0.41	0.81

Of the eighteen programs included, noncitizens used nine at a rate in excess of their total population representation. These are: total cash/noncash benefits, noncash benefits, Welfare Assistance, supplemental unemployment, energy assistance, Food Stamps, WIC, cash benefits, and government rent. They use less than “their share” of the other ten programs. The most significant gaps in usage are in total benefits, despite significant differences in the individual programs. This is most likely because there are programs that may not be included in the survey. Aside from that, citizens receive far more Social Security benefits from noncitizens. The drivers of these differences are explored further in the regression analyses developed below.

Methodology

To analyze whether or not noncitizens are more likely than citizens to receive aid, I will use a linear probability model to predict the likelihood that a respondent receives aid, based on their characteristics. Probit and logit models will be used to support the linear probability model. Then, an Ordinary Least Squares model is used to predict the amount of aid that someone receives, conditional upon them receiving aid. I analyze 18 programs with a binary yes/no response, as well as any receipt of means-tested cash/noncash benefits and poverty status. One issue with the data is that many programs have very low participation rates. For the OLS model, I run regressions for three different programs: public assistance payments, food stamps, and total means-tested transfers. Many different programs fall into this bucket, including food stamps and unemployment insurance.

The regressors in each of the models—whether levels or linear probability—are the same in each case. They include the citizenship status as well as several other demographic variables.[1] Most are dummy variables, such as gender, poverty status, or language spoken at home. To account for differences in how each state administers aid, a dummy variable is included for the respondent's state of residence. The education variable accounts for the effect that changes in schooling have on aid usage. In order to make the regressions more understandable, I created a

[1] The full list of regressors can be found in the Appendix

tiered system for educational attainment. I grouped individuals into five categories: no high school degree, only high school degree, some college or technical school, Bachelor's degree, and graduate or professional degree (Ph.D., J.D., M.D., etc.). The original SIPP data includes 15 levels, including a value for each grade high school. These were removed as the bins were sufficiently small such that I believed the impact was minimal enough to be ignored.

The equations for the regressions are as follows, with the output changed for each program:

1. $\textit{Binary Aid} = \alpha + \beta_1 Cit + \beta_x x + e_i$
2. $\textit{Household Aid Level} = \alpha + \beta_1 Cit + \beta_x x + e_i$

The coefficients for 1., the linear probability model, represent the increase or decrease in likelihood of receiving aid. Variable "x" represents a vector of the control variables, found in the Appendix. In 2., the coefficients are dollar amounts that represent changes in aid receipt based on the change in a certain variable. For example, if the respondent is a citizen, Cit=1, then their predicted amount of aid received changes by β_1.

Results

Armed with this snapshot of current usage, I will create regressions to analyze what factors influence program participation. As described in the Methodology section, this includes a linear probability model, as well as a levels analysis. First is the linear probability model. Table 3 reports the coefficients on citizenship status in each of the program models. In these models, citizenship is recorded as "1," so the values represent the difference in probability that a citizen has of receiving aid compared to a noncitizen, given the same characteristics. Each of the programs is regressed on the same control variables and they are ranked in order of their statistical significance. Therefore, “acquiring” citizenship causes the change shown in the chart.

TABLE 3: Linear Probability Model

Program	**Cit Coefficient**	**Probit**	**Logit**
Means-tested cash/noncash	-0.116***	-0.535***	-0.959***
	0.029	0.118	0.361
Noncash benefits	-0.111***	-0.496***	-0.901***
	0.029	0.103	0.298
Worker's Comp	0.023*	1.374**	3.256**
	0.012	0.484	1.270
Welfare Asst.	-0.007*	1.145*	3.026*
	0.058	0.315	0.709
Child Care Asst.	0.012*	0.902*	2.068*
	0.007	0.087	0.189
TANF Y/N	-0.016	1.650***	3.766***
	0.012	0.774	1.976
Supplemental Unemp.	-0.006	-0.704	-0.908
	0.005	0.903	1.444
Energy Assistance	0.009	0.312	0.645
	0.012	0.078	0.912
Food Stamps Y/N	-0.011	-0.159	-0.263
	0.022	0.427	0.590
Social Security	0.017	0.300	0.546
	0.039	0.299	0.373
Veteran's Comp	0.004	0.074	0.171
	0.012	0.311	0.732
State Unemployment	0.002	0.419	0.886
	0.008	0.243	0.469
WIC	-0.003	0.241	0.510
	0.022	0.257	0.506
Cash Benefits Y/N	0.003	-0.213	-0.521
	0.021	0.120	0.236
Clothing Asst.	0.000	0.000	0.000
	0.003	(omitted)	(omitted)
Government Rent	0.000	0.121	0.358
	0.008	0.202	0.467
Federal SSI	0.000	-0.997	-1.670
	0.014	0.178	0.320
Transportation Asst.	0.000	0.254	0.611
	0.008	0.272	0.647

***: Significant at <1%, **: Significant at <5%, *: Significant at <10%

The first, household cash/noncash benefits received, is the most statistically significant and reduces the probability by 11.6 percentage points. This is supported by the probit and logit models, which both have significant negative coefficients, as well as the descriptive statistics. Similarly, the coefficient for noncash benefits is significant. These regressions suggest that noncitizens do use more benefits than citizens, but the total gap between the two groups is not explained solely by the citizenship factor. Only three other programs have significant coefficient: worker's compensation, welfare assistance, and child care assistance. However, these coefficients are quite small, all below 3%. Overall participation in these programs is quite low, with less than 1% of citizens and noncitizens participating. Interestingly, the coefficient for TANF receipt is insignificant in the linear probability but is highly statistically significant in both the probit and logit models.

None of the remaining thirteen programs have statistically significant coefficients on citizenship. The most immediate explanation is that these programs have very low absolute participation. While this is true of some—such as clothing assistance, which only 23 people receive—others have substantial amounts of recipients. Food stamps, for example, are received by 15.5% of noncitizens and 10.0% of citizens, but the regression finds no difference caused by citizenship. Thus, citizens and noncitizens must have different characteristics, such as household income or family size.

Throughout these regressions, the impact of citizenship is murky at best. In the most salient category—household cash or non-cash transfer receipt—noncitizens do exhibit an increased likelihood of receiving aid. However, noncitizens do not receive statistically significantly more aid in the vast majority of individual programs. This result is confounding as the two subcategories would seem to create feed into the broader one, but the evidence suggests a minimal impact.

The prior regression gives an understanding of what influences the probability of receiving government assistance, but does not analyze the magnitude of the benefits received. A second regression is thus used to develop a more robust understanding of aid patterns. In Table 4, a dollar amount for the year is the dependent variable, with the same regressors as in the prior regression. The SIPP data lacks substantial information regarding the value of benefits received, as many programs are difficult to quantify. Thus, three programs are analyzed: The regression specifications are found in below:

TABLE 4: Levels Analysis

Program	**Annual Amount**
Public Asst. Payments	5,744.45
Standard Error	4,530.79
Total Means Tested Transfers	-3,367.70
Standard Error	2,977.33
Total Food Stamps	179.82
Standard Error	534.33

***: Significant at <1%, **: Significant at <5%, *: Significant at <10%

These regressions are conditional on receiving some aid. Eliminating the responses of zero increases the robustness of the regression and reduces some of the noise in the data. The magnitude of changes for citizens is quite large in some of these programs. They receive $3,367.70 less per year than their noncitizen counterparts in total transfers. In public assistance, though, citizenship increases the amount of aid by $5,744.45. However, these coefficients are not statistically significant. Citizenship does not seem to inherently affect the amount of aid received.

The combination of these two regressions somewhat improves our understanding of noncitizen usage of government aid, but there is not a clear pattern. In essence, the only statistically significant coefficient of interest was for household cash/noncash transfers binary. These regressions suggest overall that the Welfare Reform Act of 1996 had limited effects in terms of reducing noncitizen Differences in participation between citizens and noncitizens appear fairly small, with noncitizens overall attaining more benefits.

Oaxaca Decomposition

Having developed a regression model, I will further reinforce the model using an Oaxaca decomposition. This is a tool that breaks apart the differences in participation between groups into the portions that a regression explains and does not explain. It uses the means of a variable and the coefficients of the same variables and constructs a sum that equals the differences in the means of the dependent variable. The general form is as follows:

$$\overline{Y_1} - \overline{Y_2} = \hat{\beta}_1(\bar{X}_1 - \bar{X}_2) + \bar{X}_1(\hat{\beta}_1 - \hat{\beta}_2)$$

The subscript 1's and 2's are the different groups, citizens and noncitizens. For my purposes, I will just examine the binary for household cash/noncash benefits received, as this is the most significant and relevant variable. Thus, Y_1 is the percentage of noncitizens receiving aid and Y_2 is the percentage of citizens receiving aid. In this case, Y_1=54.77% and Y_2=25.81%, so Y_1-Y_2= 28.96%. The first term represents the difference caused by unexplained characteristics while the second term is the difference caused by coefficients. Table 5 shows the amount of the gap that is explained by the regression.

TABLE 5: Household Cash/Noncash Oaxaca Decomposition

Noncitizen	0.547	
Citizen	0.258	
Difference	0.289	
Explained	0.264***	91.70%
Unexplained	0.024	8.30%

***: Significant at <1%, **: Significant at <5%, *: Significant at <10%

This shows that 91.7% of the variance is due to coefficients. Only 8.3% is a result of unobservable characteristics. This strengthens the results of the linear probability model for household cash/noncash benefits, specifically that lack of citizenship increases the probability of receiving aid by roughly 11 percentage points. Unfortunately, the Oaxaca decomposition does not evaluate the impact of a single variable, so it is unclear how much of the difference is caused by citizenship alone. With many regressors, the Oaxaca decomposition is likely to show high levels of explanation.

Conclusion

Using data from the Census's Survey of Income and Program Participation (SIPP) from 2013, I constructed statistical overview of noncitizen receipt of government assistance as well as several regression models. Through this analysis, I have found that noncitizens do use aid at a rate exceeding their representation in the population. They also receive cash and non-cash transfers approximately 11% more often than their citizen counterparts. However, there could be trends or characteristics of the two groups that are not captured in the data, and thus are left out of the regression. Feelings and sentiment are not reflected in this data.

Whether noncitizens are entitled to this aid or if they "should" receive it is a question outside the scope of this analysis. What I have done does not include any measure of what individuals pay in to the welfare system, so I cannot discuss this aspect of the issue. Across all regressions, though, the impact of citizenship is unclear. They seem to be more likely to receive aid, but receive the same amount of aid. This difference could result from noncitizens lacking awareness of the benefits they could receive or is simply a result of missing data. Overall, my research suggests that if the goal of the PRWORA was to reduce noncitizen participation, then it spears somewhat unsuccessful.

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Appendix

Exhibit 1: Full Cash/Noncash Benefits Received Binary Regression, with comments

Household Cash/Noncash Benefits Received Binary	**Coefficient**	**Standard Error**
Constant	0.129**	0.060
Citizenship Status (1=Citizen)	**-0.116*** **	**0.030**
Race		
Black alone	0.085***	0.008
Asian alone	-0.008	0.018
Other	0.048***	0.013
Hispanic Origin	0.056***	0.012
Born in the US (1=Yes)	0.034	0.028
Gender (1=Female)	-0.006	0.007
Marital Status (1=Married)	-0.060***	0.020
Age	-3.25E-3***	0.001
Age^2	2.10E-5**	0.000
Education (0=No High School Degree)		
High School Diploma	-0.058***	0.009
Some College/Technical School	-0.068***	0.009
College Degree	-0.109***	0.010
Higher Education	-0.119***	0.011
Poverty Status	0.116***	0.008
Total Person Income	-1.34E-5***	0.000
Total Person's Earned Income	1.94E-5***	0.000
Total HH Income	7.75E-6***	0.000
Total HH Earned Income	-1.81E-5***	0.000
Lifetime Armed Forces Service	-0.007	0.008
Gov. Savings Bond Owned	-0.027***	0.009
IRA or Keogh Account Owned	-0.043***	0.006
Savings Account Owned	-0.046***	0.005
Mutual Funds Owned	0.002	0.009
Stocks Owned	-0.011	0.008
US Govt. Securities Owned	0.057**	0.027
Mortgage Held	0.010	0.032
Rental Property Owned	-0.022**	0.010
Business Owned	0.006	0.008
Had Work-Limiting Disability	0.041***	0.012
Had Work-Preventing Disability	0.095***	0.014
Spent Time Laid-Off this Month	0.017	0.019
Spent Time Looking for Work	0.082***	0.013
Paid by the Hour (1=Yes)	0.043***	0.006
How the Respondent Became a Citizen (0=Born in the US)		
Naturalized	0.072**	0.029
Through you or your spouse"s military service in U.S. Armed Forces	-0.001	0.071
Adopted by U.S. citizen parent or parents	-0.032	0.116
Born in a U.S. Island Area or born in the United States	0.000	(omitted)
Born abroad of U.S. citizen parent or parents	0.000	(omitted)
Family Type (0=Married Household)		
Male householder	0.115***	0.023
Female householder	0.139***	0.021
Male householder nonfamily household	0.006	0.021
Female householder nonfamily household	0.040*	0.022
Group Quarters	0.028	0.046
Number of People in Household	0.093***	0.002
Continued to the right		
***: Significant at <1%, **: Significant at <5%, *: Significant at <10%		
N=20,116		
Adjusted R-Squared: 49.02%		
Continued	**Coefficient**	**Standard Error**
Language Spoken at Home		
Spanish	0.061***	0.023
French (include Creole)	0.086**	0.042
German	-0.076*	0.043
Slavic languages (Polish, Russian, Serbo-Croatin, Bosnian, Yugosl..)	0.081**	0.040
Other Indo-European languages (Greek, Italian, Portuguese, Hindi,..)	0.008	0.032
Chinese, Mandarin, Cantonese	0.034	0.035
Tagalog, Philipino	0.095**	0.047
Vietnamese	0.024	0.051
Other Asian languages (Japanese, Korean)	-0.005	0.045
Other And Unspecified Languages	0.000	(omitted)
Speak Language Other than English (1=Yes)	-0.005	0.020
State of Residence		
Alaska	0.193***	0.056
Arizona	0.000	0.022
Arkansas	0.042	0.028
California	0.026	0.019
Colorado	-0.026	0.025
Connecticut	0.047*	0.028
Delaware	-0.016	0.046
DC	0.088	0.054
Florida	0.025	0.020
Georgia	0.035*	0.021
Hawaii	0.037	0.048
Idaho	0.132***	0.035
Illinois	0.038*	0.021
Indiana	0.014	0.021
Iowa	0.067**	0.028
Kansas	0.010	0.031
Kentucky	0.032	0.026
Louisiana	0.058**	0.025
Maine	0.071*	0.036
Maryland	0.033	0.023
Massachusetts	0.073***	0.022
Michigan	0.020	0.022
Minnesota	0.016	0.024
Mississippi	0.049*	0.027
Missouri	0.006	0.021
Montana	0.106**	0.042
Nebraska	0.009	0.035
Nevada	-0.019	0.036
New Hampshire	0.014	0.036
New Jersey	-0.017	0.021
New Mexico	0.143***	0.033
New York	0.071***	0.020
North Carolina	0.027	0.021
North Dakota	-0.022	0.046
Ohio	-0.018	0.021
Oklahoma	0.049*	0.027
Oregon	0.052*	0.027
Pennsylvania	0.030	0.021
Rhode Island	0.170***	0.052
South Carolina	0.047*	0.025
South Dakota	0.024	0.049
Tennessee	0.030	0.022
Texas	0.034*	0.019
Utah	-0.006	0.032
Vermont	0.131**	0.056
Virginia	0.002	0.020
Washington	0.047**	0.021
West Virginia	0.030	0.031
Wisconsin	0.039*	0.021
Wyoming	0.098*	0.053

The full regression for receipt of any cash/noncash transfer includes over twenty regressors. I included many different variables in an attempt to capture as much of the difference as possible. In lieu of country-or-origin data, language spoken at home is used as a proxy. Both Spanish- and French-speaking households used more aid, but German-speaking households were less likely to. Education has a strong intuitive impact on reducing transfers. Interestingly, Alaskan respondents were more likely to receive aid by 19.3 percentage points and in a statistically significant manner. The drivers behind state aid usage are unfortunately not captured in the data and are most likely the result of enforcement policies and other subtler factors. However, no state has a statistically significant negative coefficient, which suggests that policies are fairly consistent. The single largest non-state coefficient with significance is for single female heads of households, at 13.9%. I also included some asset variables in an attempt to control for accumulated wealth. Unfortunately the data lack a concrete way to determine the actual amount of assets owned, but the binary variables serve a valuable role nonetheless and are quite significant. Finally, as mentioned earlier, the coefficient on citizenship is negative and strongly significant.