What Most Affects the Probability of Receiving Public Assistance? Examining the Effect of Family Background and Educational Attainment on Receiving Public Assistance with Multivariate Regression Analysis

Patricia I. Vargas[1]
Department of Sociology, Oregon State University, 214 Bexel Hall, Corvallis, OR 97331

Abstract
Understanding poverty as a state of being poor with regard to concretely being unable to meet basic needs such as water, food, clothes, shelter, and essential services (e.g., sanitation, health, and education), its concerted study in the United States not only stands tandem with constitutionally upheld values such as equality but is crucial for soundly informing and assessing law, policy, and programs that ensure a robust society. Especially amidst global challenges like COVID-19, it becomes all the more important to understand what factors may most impact movement into and out of poverty. For this project, I examine how family background and educational attainment interact to jointly affect poverty in the United States using data from a nationally representative panel study sponsored by the National Center for Education Statistics (NCES). After proxying poverty with receiving public assistance, I tested 18 independent variables consistent with demographic and family background by conducting a multivariate regression. Ten variables were found to have a statistically significant effect on the probability of receiving public assistance with dependents (under the age of 18), recent unemployment (within the past three years), and being female being among the strongest predictors of receiving public assistance ($p<0.001$). Roughly 36% of the variation in receiving public assistance is explained by the 18 independent variables tested, helping paint poverty with more color. More importantly, these results signal a need to buttress public programs through at least 2023 given the skyrocketing unemployment rate of the 2020 year. Leaders in education, non-profit, and government may ask how, while further research can expand the list of independent variables and/or focus on a single ascribed or achieved status to test varying hypotheses in response to the "causes" of poverty.

Key Words: regression, STATA, poverty, education, family background, quantitative analysis

1. Introduction

A concept more complex than perhaps considered, poverty can evoke a range of thoughts, feelings, and actions such as declaring an "unconditional war on poverty" as 36th United States President Lyndon B. Johnson did in 1964 (Chaudry et al. 2016:1). To begin, we can

[1] Patricia I. Vargas is an Oregon State University '21 alumna with a Bachelor of Science in Sociology rearticulated from the University of California, Los Angeles. She completed this research project as an undergraduate and can be reached at vargasp@lifetime.oregonstate.edu.

premise the topic of poverty ontologically by understanding it as a state of being—a state of being poor with regard to concretely being unable to meet basic needs such as water, food, clothes, shelter, and essential services (e.g., sanitation, health, and education) (Chaudry et al. 2016). The United States' preamble to the Declaration of Independence reminds "that all men are created equal, that they are endowed by their Creator with certain unalienable rights, [and] that among these are Life, Liberty[,] and the pursuit of Happiness" (U.S. 1776). Thinking of the nation the Founding Fathers strived to create, I imagine a nation where "all men" are able to meet their basic needs as they pursue "Life, Liberty[,] and...Happiness." Concerted study of poverty then not only stands in tandem with U.S. American values but becomes crucial for soundly informing and assessing law, policy, and programs to ensure a robust society.

What may most help stave off poverty? As Dr. Robert H. Haveman from the Institute for Research on Poverty at the University of Wisconsin-Madison reminds, "peoples' views [on the causes of poverty] are often mixed with political values" (2018:1). Working full-time (40 hours per week) year-round appears to be the most associated with not being poor (i.e., living above the federal poverty threshold) (Semega et al. 2019:13). However, what additional variables may be a part of the larger causal mechanism for poverty? Here, quantitative analysis can prove insightful. As methods courses cover, "elaboration models" welcome third variables to better assess the strength of initially observed relationships (Babbie 2014:432-449). This paper describes a project that explored just this methodological idea (i.e., moving from something such as a Chi-square analysis to a regression analysis that considers more than three variables—18 variables to be exact).

Proxying poverty with receiving public assistance, I asked: What most affects the probability of receiving public assistance?

2. Background

Poverty in the United States. A complex concept, poverty captures a state of being (i.e., being poor). At its most fundamental form, poverty is being unable to cover basic needs (Chaudry et al. 2016). Thus, in an industrialized country such as the United States where currency is used to obtain goods and services, "money income" becomes a (if not, *the)* greatest signifier for poverty.

It may then come to no surprise that in the United States, poverty is officially measured through its economic dimension (University of Wisconsin-Madison Institute for Research on Poverty 2020). Official poverty is living with a gross "money income" below the respective annually adjusted poverty threshold.

2.1 Federal Measures of Poverty in the United States

2.1.1 Official Poverty Measure

In the United States, poverty has long been measured using the Official Poverty Measure (OPM) developed by economist Mollie Orshansky in 1964. In response to concerns about validity, the U.S. Census Bureau introduced the Supplemental Poverty Measure (SPM) in 2009 (Fox 2019).

2.1.2 Supplemental Poverty Measure

The Supplemental Poverty Measure (SPM) "extends the official poverty measure by taking into account government benefits and necessary expenses, like taxes, that are not in the official measure" (U.S. Census Bureau 2017). In other words, while the OPM only looks at cash resources, the SPM goes a step further by also "includ[ing] noncash benefits" and "subtract[ing] necessary expenses ([inclusive of] taxes and medical [costs])" (Fox 2018).

It can be noted that the SPM has been well received and most recently, an improved SPM was released in September 2021 using new methodology voted upon the year prior in September 2020 (U.S. Census Bureau 2021a).

2.2 Declining Poverty in the United States (pre-COVID)

Regarding poverty trends, "the official poverty rate in 2020 was 11.4 percent with 37.2 million people in poverty. This was a 1.0 percentage-point increase from 10.5 percent in 2019, which was the lowest rate observed since estimates were initially published in 1959. It was also the first annual increase in the poverty rate following five consecutive annual declines" (Shrider et al. 2021:14).

Pre-COVID, Dr. Liana E. Fox from the U.S. Census Bureau comparatively graphed poverty in the United States for the past 11 years (i.e., from 2009 to 2019) using both the OPM and the SPM, with a general recent decline emerging as a pattern (Fox 2020:6). A review of U.S. Census Bureau Current Population Reports confirms that poverty gradually declined in the United States for five consecutive years, from 14.9 percent in 2014 to 10.5 percent in 2019 using the OPM and from 15.3 percent in 2014 to 11.7 percent in 2019 using the SPM (Short 2015:14; Fox 2020:6).

2.2.1 Official Poverty Rate post-COVID

The first half of the 2020 year saw a skyrocketing number of unemployment claims that very well alluded to "the increase in poverty [that] coincided with the 2020 recession associated with the COVID-19 pandemic" (Long 2020; Long and Van Dam 2020; Shrider et al. 2021:14). Needless to say, and perhaps as a result of quick action at all levels (local, state, and national), "the increase [in the poverty rate] associated with the 2020 recession (1.0 percent)" was less than the "the increase in the poverty rate during the Great Recession (1.9 percent)" (Shrider et al. 2021:14).

2.2.2 Supplemental Poverty Measure post-COVID

Different legislation was introduced, passed, and enacted to curb poverty during the unique times of an epidemic evolving into a pandemic. In response to the COVID-19 pandemic, the Coronavirus Aid, Relief, and Economic Security (CARES) Act (2020) was the first legislation passed by the United States Congress and signed into law by the 45th United States President Donald J. Trump on March 27, 2020 to provide Americans with economic relief in the form of a stimulus (Taylor et al. 2020). After the CARES Act (2020), the Consolidated Appropriations Act (2021) and the Coronavirus Response and Relief Supplemental Appropriations (CRRSA) Act (2021) were passed by Congress and signed into law on December 27, 2020 (California Department of Education 2021). Later, the American Rescue Plan (ARP) Act (2021) was signed into law by the 46th United States President Joseph R. Biden on March 11, 2021 to further provide federal relief during the pandemic (Sullivan 2021; California Department of Education 2021).

As a result of legislation that "provided households with additional income in the form of stimulus payments, expanded unemployment, SNAP, and pandemic electronic benefits transfer (P-EBT) benefits" during the COVID-19 pandemic, "poverty [was] estimated to be lower using the SPM [(9.1 percent)] than using the [OPM (11.4 percent)]" "for the first time in the history of the SPM" (Fox and Burns 2021:7, 13).

2.3 Public Assistance in the United States

Public assistance first emerged in the United States after the Great Depression and under 32nd United States President Franklin D. Roosevelt in the 1930s (Social Security Administration 1997).

Now in day, public assistance includes social welfare programs and social insurance programs. As United States government agencies note, "some of the major federal, state, and local social welfare programs are: Supplemental Security Income (SSI), Supplemental Nutrition Assistance Program (SNAP), Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), Temporary Assistance for Needy Families (TANF), and General Assistance (GA)"; while "some of the major federal, state, and local social insurance programs are: social security (self and on behalf of a dependent child), Department of Veterans' Affairs benefits (except Veteran's pension), unemployment insurance compensation, and workers' compensation" (U.S. Census Bureau 2021b).

3. Methodology

Quantitative Analysis. This project grew from examining the effect of two variables on household poverty status with a Chi-square analysis in SPSS using nationally representative data from a panel study sponsored by the U.S. Census Bureau to examining the effect of 18 variables on receiving public assistance, a proxy for poverty, with multivariate regression analysis in STATA with using nationally representative data from a panel study sponsored by the National Center for Education Statistics (NCES).

3.1 The Educational Longitudinal Study

The data for this project comes from the 2002 and 2012 Education Longitudinal Study (ELS), a federal panel study sponsored by the National Center for Education Statistics (NCES). The 2002 ELS consists of a nationally representative sample of "10th graders in 2002" (NCES 2021). "Surveys of students, their parents, math and English teachers, and school administrators" are collected and "students [are] followed throughout [their] secondary and postsecondary years" (NCES 2021).

Broadly, the ELS looks at "students' trajectories from the beginning of high school into postsecondary education, the workforce, and beyond," including "the different patterns of college access and persistence that occur in the years following high school completion." The purpose of the ELS, in part, is to inform the development and evaluation of educational policy by gathering data on Social Background, Home Educational Support System, School and Classroom Characteristics, Postsecondary Education Choice and Enrollment, Employment, and Outcomes (NCES 2021).

More specifically, the ELS:2002 has four major data components: (1) a base-year interview, (2) a first follow-up interview, (3) high school transcript data collection, and (4) a second follow-up interview (Bozick and Lauff 2007).

During the spring 2002 term, 15,400 eligible selected high school sophomores from a “nationally representative probability sample of about 750 public, Catholic, and other private schools” completed a base-year questionnaire. Two years later, during the spring 2004 term, 15,000 students from the sample of eligible high school seniors completed the first follow-up interview. Almost one year later, during the winter 2005 term, at least one high school transcript was collected for the 14,900 eligible students who had graduated. About two years later, during the 2006 year, 14,200 students from the sample of eligible high school graduates completed the second follow-up interview (Bozick and Lauff 2007). Furthermore, six years after students graduated high school, a third follow-up data collection, inclusive of post-secondary transcripts, was completed in 2012 (NCES 2021).

Because this project focused on the joint effect of family background and educational attainment on receiving public assistance, the third follow-up data collection from ELS:2012 was used, resulting in a sub-sample of 4,150 respondents.

3.2 Variables Examined

Conducting a multivariate regression analysis consisted of working with 19 variables overall: one dependent variable and 18 independent variables.

3.2.1 Dependent Variable Proxy for Poverty

Poverty was proxied with receiving public assistance and coded as a nominal variable using the following binary: 1=yes and 0=no. The rationale behind selecting receiving public assistance as a proxy for poverty is that by default, every person who receives public assistance has met the official poverty threshold. In other words, anyone who receives public assistance is economically poor by federal standards. The only limitation is that the opposite does not hold true: not everyone who is economically poor receives public assistance (e.g., some people do not apply). Thus, proxying poverty with receiving public assistance does not capture the everyone who is economically poor.

3.2.2 Independent Variables Consistent with Demographic Details, School Background, and Family Background

Using qualitative research on, (and existential knowledge of), the proxy for poverty, 18 independent variables consistent with demographic details, school background, and family background were focused upon for their perceived predictiveness of receiving public assistance.

First, I sifted through 57 pages of the ELS:2012 follow-up questionnaire and highlighted 76 potential independent variables. Second, from these 76 potential independent variables, I selected 20 variables from the NCES ELS:2002 and ELS:2012 for “ideal types”: sex, race, being Hispanic, educational attainment, student debt, marital status, number of dependents (age < 18), employment status, recent unemployment (within the past three years), housing arrangement, family composition, number of siblings, parents’ educational attainment, family income, parents’ English fluency, higher education savings, school type, school urbanicity, school free-lunch rate, and school college-going rate. Third, and lastly, I discussed the selected 20 variables with my faculty mentor, Dr. Shelley Nelson, and concluded by deciding upon 18 to serve as my independent variables. Dr. Nelson and I agreed on clustering variables by region to account for regional differences and data was run in STATA on Tuesday, May 12, 2020.

3.3 Binary Logistic Regression Model
Specifically, data was run using binary logistic to predict the probability of receiving public assistance as a function of the independent variables in the model. In other words, a mathematical transformation of probabilities was used into a new variable called logit to model the probability of receiving public assistance as a linear function of the independent variables (Crowson 2021:18). *Figure 1* visually summarizes this.

$$\text{logit}(\text{receiving public assistance}) = \ln\left(\frac{\text{pr}(\text{receiving public assistance})}{1 - \text{pr}(\text{receiving public assisstance})}\right)$$
$$= \ln\big(\text{odds }(\text{receiving public assistance})\big) = b_0 + b_1X_1 + b_2X_2 + \cdots + b_kX_k$$

Figure 1. Logit link function that captures the probability of receiving public assistance considering multiple explanatory variables.

4. Results

4.1 Multivariate Regression Analysis
After proxying poverty with receiving public assistance, a majority of variables were found to predict receiving public assistance at the 0.05 level (minimum). Ten variables have a statistically significant effect on the probability of receiving public assistance with dependents (age < 18), recent unemployment (within the past three years), and being female being among the strongest predictors of receiving public assistance ($p < 0.001$).

4.1.1 Unstandardized Regression Slopes (or Logits) Interpreted
Of the 18 independent variables examined, five variables are positive and significant predictors of the probability of receiving public assistance, five variables are negative and significant predictors of the probability of receiving public assistance, and eight variables are not statistically significant different from zero. *Table 1* visually summarizes this.

Being female is a positive and significant predictor of the probability of receiving public assistance (b = 0.450, *s.e.* = 0.120, Wald Z = 3.777, p < 0.001). *Marital status* is a positive and significant predictor of the probability of receiving public assistance (b = 0.139, *s.e.* = 0.059, Wald Z = 2.345, p = 0.019). *Number of dependents (age <18)* is a positive and significant predictor of the probability of receiving public assistance (b = 1.268, *s.e.* = 0.066, Wald Z = 19.208, p < 0.001). *Employment status* is a positive and significant predictor of the probability of receiving public assistance (b = 0.142, *s.e.* = 0.024, Wald Z = 5.827, p < 0.001). *Recent unemployment (within the past three years)* is a positive and significant predictor of the probability of receiving public assistance (b = 0.916, *s.e.* = 0.069, Wald Z = 13.216, p < 0.001).

Educational attainment is a negative and significant predictor of the probability of receiving public assistance (b = -0.294, *s.e.* = 0.051, Wald Z = -5.755, p < 0.001). *Parents' educational attainment* is a negative and significant predictor of the probability of receiving public assistance (b = -0.070, *s.e.* = 0.024, Wald Z = -2.969, p = 0.003). *Parents' income* is a negative and significant predictor of the probability of receiving public assistance (b = -0.111, *s.e.* = 0.015, Wald Z = -7.366, p < 0.001). *School type* is a negative and significant predictor of the probability of receiving public assistance (b = -0.082, *s.e.*

= 0.014 Wald Z = -5.713, $p < 0.001$). *School college-going rate* is a negative and significant predictor of the probability of receiving public assistance (b = -0.115, *s.e.* = 0.046, Wald Z = -2.485, p = 0.013).

Table 1. Binary logistic regression model for receiving public assistance.

Variable [a]	Raw Coefficient [b] (b)	Odds Ratio [c] (e^b)
BYSEX	0.4499	1.568 ***
BYRACE	-0.0785	0.924
BYSTLANG	-0.0037	0.996
F3ATTAINMENT	-0.2942	0.745 ***
F3FEDDUE3	0.0000	1.000
F3MARRSTATUS	0.1392	1.149 *
F3D19A	1.2677	3.553 ***
F3EMPSTAT	0.1416	1.152 ***
F3C07	0.9157	2.499 ***
BYFCOMP	0.0007	1.001
BYSIBHOM	0.0265	1.027
BYPARED	-0.0698	0.933 **
BYINCOME	-0.1106	0.895 ***
BYPLANG	0.1952	1.216
BYSCTRL	-0.0819	0.921 ***
BYURBAN	-0.1126	0.894
BY10FLP	0.0401	1.041
F1A19A	-0.1149	0.891 *

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$. N = 4150.
[a] BYSEX represents being female, BYRACE represents race, BYSTLANG represents being a native English speaker, F3ATTAINMENT represents educational attainment, F3FEDDUE3 represents student federal loan debt, F3MARRSTATUS represents marital status, F3D19A represents number of dependents (age <18), F3EMPSTAT represents employment status, F3C07 represents recent unemployment (within the past three years), BYFCOMP represents family composition, BYSIBHOM represents number of in-home siblings, BYPARED represents parents' educational attainment, BYINCOME represents parents' income, BYPLANG represents parents' English language fluency, BYSCTRL represents school type, BYURBAN represents school urbanicity, BY10FLP represents school free-lunch rate, and F1A19A represents school college-going rate.
[b] Raw coefficient, or *b,* is used determine factor change.
[c] Odds ratio, or e^b, is the factor change in odds for unit increase in X.

Although the slope for *race* is negative, it was not statistically significant different from zero (b = -0.079, *s.e.* = 0.118, Wald Z = -0.664, p = 0.506). Although the slope for *being a native English speaker* is negative, it was not statistically significant different from zero (b = -0.004, *s.e.* = 0.050, Wald Z = -0.074, p = 0.941). Although the slope for *student federal loan debt* is positive, it was not statistically significant different from zero ($b < 0.001$, *s.e.* < 0.001, Wald Z = -1.511, p = 0.131). Although the slope for *family composition* is positive, it was not statistically significant different from zero (b = 0.001, *s.e.* = 0.047, Wald Z =

0.016, $p = 0.988$). Although the slope for *number of in-home siblings* is positive, it was not statistically significant different from zero ($b = 0.026$, *s.e.* = 0.038, Wald $Z = 0.701$, $p = 0.483$). Although the slope for *parents' English language fluency* is positive, it was not statistically significant different from zero ($b = 0.195$, *s.e.* = 0.119, Wald $Z = 1.634$, $p = 0.102$). Although the slope for *school urbanicity* is negative, it was not statistically significant different from zero ($b = -0.113$, *s.e.* = 0.078, Wald $Z = -1.444$, $p = 0.149$). Although the slope for *school free-lunch rate* is positive, it was not statistically significant different from zero ($b = 0.040$, *s.e.* = 0.031, Wald $Z = 1.313$, $p = 0.189$).

4.1.2 Odds Ratios Interpreted

Of the 10 statistically significant independent variables, five explanatory variables have a factor change greater than 1.00, meaning odds increase with increase on the predictor. The remaining five explanatory variables have a factor change less than 1.00, meaning odds decrease with increase on the predictor. *Figure 2* graphically summarizes these findings.

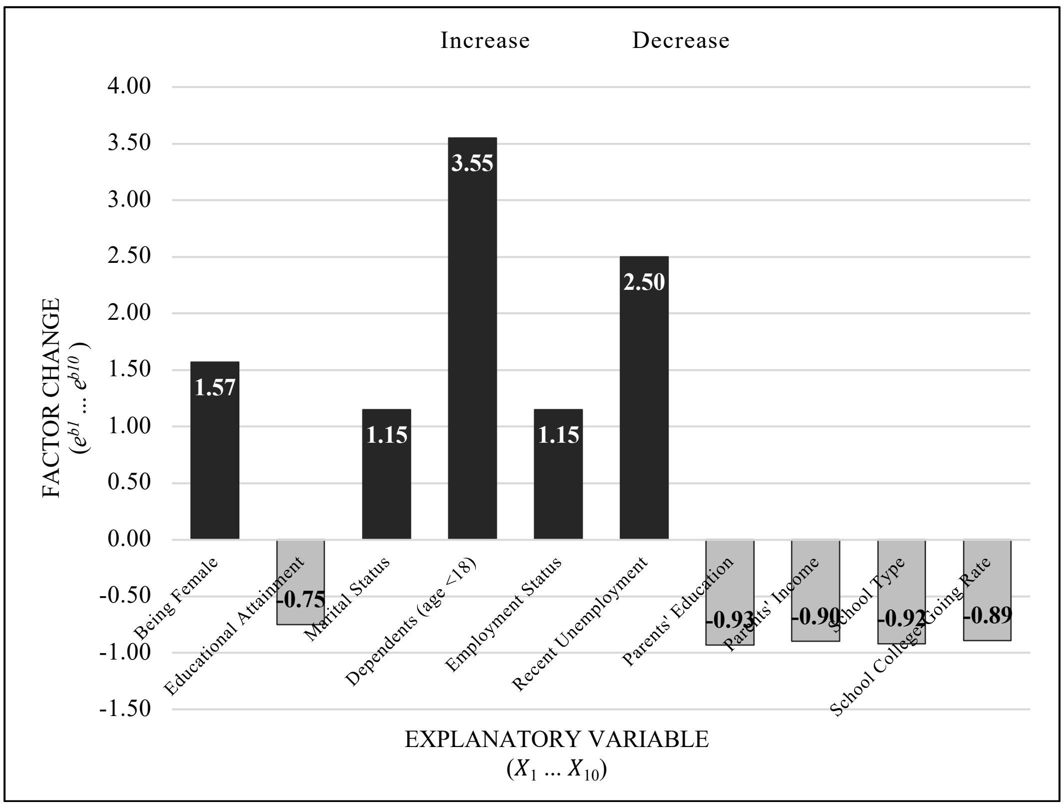

Figure 2. Factor change in predictive probabilities of receiving public assistance. Note: All e^b values are positive; negative signage only used to visually communicate decrease. Data source: National Center for Education Statistics (NCES), Education Longitudinal Study (ELS), 2002 and 2012.

For every one unit increase in *number of dependents (age <18)*, the predicted odds of receiving public assistance is multiplied by a factor of 3.55. [Since we are multiplying odds by 3.55 per unit increase on the predictor, this must mean our odds are increasing with increase on the predictor]. For *recent unemployment (within the past three years)*, the predicted odds of receiving public assistance is multiplied by a factor of 2.50. [Since we are multiplying odds by 2.50 per unit increase on the predictor, this must mean our odds are increasing with increase on the predictor]. For *being female*, the predicted odds of receiving public assistance is multiplied by a factor of 1.57. [Since we are multiplying odds by 1.57 per unit increase on the predictor, this must mean our odds are increasing with increase on the predictor]. For every one unit increase in *marital status*, the predicted odds of receiving public assistance is multiplied by a factor of 1.15. [Since we are multiplying odds by 1.15 per unit increase on the predictor, this must mean our odds are increasing with increase on the predictor]. For every one unit increase in *employment status*, the predicted odds of receiving public assistance is multiplied by a factor of 1.15. [Since we are multiplying odds by 1.15 per unit increase on the predictor, this must mean our odds are increasing with increase on the predictor].

For every one unit increase in *educational attainment*, the predicted odds of receiving public assistance is multiplied by a factor of 0.75. [Since we are multiplying odds by 0.75 per unit increase on the predictor, this must mean our odds are decreasing with increase on the predictor]. For every one unit increase in *school college-going rate*, the predicted odds of receiving public assistance is multiplied by a factor of 0.89. [Since we are multiplying odds by 0.89 per unit increase on the predictor, this must mean our odds are decreasing with increase on the predictor]. For every one unit increase in *parents' income*, the predicted odds of receiving public assistance is multiplied by a factor of 0.90. [Since we are multiplying odds by 0.90 per unit increase on the predictor, this must mean our odds are decreasing with increase on the predictor]. For every one unit increase in *school type*, the predicted odds of receiving public assistance is multiplied by a factor of 0.92. [Since we are multiplying odds by 0.92 per unit increase on the predictor, this must mean our odds are decreasing with increase on the predictor]. For every one unit increase in *parents' educational attainment*, the predicted odds of receiving public assistance is multiplied by a factor of 0.93. [Since we are multiplying odds by 0.93 per unit increase on the predictor, this must mean our odds are decreasing with increase on the predictor].

Lastly, approximately 36% of the variation in receiving public assistance is explained by the 18 independent variables tested.

5. Conclusions and Implications

Combining the top three predictors found to significantly increase the probability of receiving public assistance at the 0.001 level, families appear to be the most susceptible to moving into and out of poverty during and post- COVID-19. More specifically, results highlight single mothers who have experienced recent unemployment (within the past three years) as one of the most vulnerable groups in the United States, gravely needing public assistance to meet basic needs. Thus, these findings affirm the existence of many social programs like the National School Lunch Program (free/reduced lunch); Women, Infants, and Children (WIC); and the Supplemental Nutrition Assistance Program (SNAP), underscoring just how vital they are for meeting the needs of a diverse society.

Further, this research uniquely helps project societal needs as they relate to the COVID-19 pandemic. With recent unemployment (within the past three years) standing as the second strongest predictor of receiving public assistance and a record number of unemployment claims being filed during the last 2020 year, we can infer that there, too, will be an increase in the number of people receiving public assistance—through at least 2023.

The probability of receiving public assistance more than doubles if someone has experienced unemployment even just once in the past three years. Thus, logic follows that the probability of receiving public assistance more than doubled for the 23.1 million people who experienced unemployment in April 2020, a record high in the history of unemployment at 14.7 percent (Bureau of Labor Statistics 2020).
Leaders in government, education, and the non-profit sector must therefore continue to lead with strength, direction, and purpose. Now, with at least one year having lapsed since the beginnings of the pandemic, legislation has been passed, vaccines have been created, and new protocols have been adapted to ensure the safety of people, communities, and the United States at large.

The number of COVID-19 legislation passed and enacted is an example of how public assistance plays a vital role in ensuring the United States continues to thrive as a robust society. "Stimulus payments, expanded unemployment, SNAP, and pandemic electronic benefits transfer (P-EBT) benefits" helped several households and as a result, "for the first time in the history of the SPM, poverty [was] estimated to be lower using the SPM [(9.1 percent)] than using the [OPM (11.4 percent)]" (Fox and Burns 2021:7, 13). Further, as a result of action at all levels—local, state, and federal—"the increase [in the poverty rate] associated with the 2020 recession (1.0 percent)" did not reach "the increase in the poverty rate during the Great Recession (1.9 percent)" (Shrider et al. 2021:14).

Reflecting, I believe our nation's Founding Fathers would commend collective efforts and action in response to the pandemic, and stand proud to see its people continuing to rise, thrive, and carry onward in the pursuit of "Life, Liberty[,] and...Happiness."

Acknowledgements

Thank you to Dr. Shelley L. Nelson (faculty in the Department of Sociology in the School of Public Policy, College of Liberal Arts at Oregon State University [OSU]) for her quality mentorship. I am grateful for the hours dedicated outside of SOC 316: Methods II – Quantitative Analysis to support me as an undergraduate student during the Spring 2020 quarter term. I am glad I was encouraged to expand my research project from a Chi-square analysis into a multivariate regression analysis and introduced to the National Center for Education Statistics (NCES) Educational Longitudinal Study (ELS) and STATA along the way. Thank you to Dr. Brian Fuller (faculty in the Department of Sociology in the School of Public Policy, College of Liberal Arts at Oregon State University) for his feedback in a preceding paper written in SOC 315: Methods I – Research Design during the Winter 2020 quarter term as well.

Thank you, at large, to the Department of Sociology in the OSU School of Public Policy, College of Liberal Arts, and thank you to the OSU President's Commission on the Status of Women for supporting me with an award to present this research at four annual meetings and conferences, including the American Statistical Association (ASA) 2021 Symposium on Data Science and Statistics.

Thank you to former professors from my transfer institution, the University of California, Los Angeles (UCLA)—Dr. Vivian Lew (faculty in the Department of Statistics at the UCLA) and Dr. Edward R. Geiselman and Dr. Rajesh Nandy (faculty in the Department of Psychology at UCLA). Thank you to Dr. Nihal Kaylor-Makhyoun (faculty in the Department of Psychology at Los Angeles Valley College), as well as thank you to my mathematics teachers from the Los Angeles Unified School District (LAUSD)—Mr. Roque Montañez, Mr. Bill Shaw (Shawbillion), and Mr. Joe Morgan.

Thank you to friends and family—Jasmine Melgar, Evelin Melgar, Mirna del Carmen Hernández, and Monica Gonzalez.

Lastly, thank you to the National Center for Education Statistics (NCES) for making the Educational Longitudinal Study (ELS) datasets from the 2002 and 2012 panels available for university faculty and students. Writing, presenting, and publishing nationally representative findings would not have been possible without the ability to use data from NCES ELS 2002 and ELS 2012 panels to conduct quantitative research.

References

Babbie, Earl. 2014. *The Practice of Social Research, Fourteenth Edition*. Boston, MA: Cengage.

Bozick, Robert, and Erich Lauff. 2007. *Education Longitudinal Study of 2002 (ELS:2002): A First Look at the Initial Postsecondary Experiences of the High School Sophomore Class of 2002*. National Center for Education Statistics (NCES), Institute of Education Sciences, NCES 2008-308. Washington, DC: U.S. Department of Education. 1-55. Retrieved November 10, 2021 (https://nces.ed.gov/pubs2008/2008308.pdf).

Bureau of Labor Statistics. 2020. Unemployment rate rises to record high 14.7 percent in April 2020. Washington, DC: Bureau of Labor Statistics. Retrieved November 10, 2021 (https://www.bls.gov/opub/ted/2020/mobile/unemployment-rate-rises-to-record-high-14-point-7-percent-in-april-2020.htm).

California Department of Education. 2021. "Federal Stimulus Funding." Sacramento, CA: California Department of Education. Retrieved November 10, 2021 (https://www.cde.ca.gov/fg/cr/index.asp).

Chaudry, Ajay et al. 2016. *Poverty in the United States: 50-Year Trends and Safety Net Impacts*. Washington DC: Office of the Assistant Secretary for Planning and Evaluation (ASPE). Retrieved November 10, 2021 (https://aspe.hhs.gov/system/files/pdf/154286/50YearTrends.pdf).

Crowson, Mike. 2021. "Binary Logistic Regression using Stata Syntax." *University of Oklahoma*.

Fox, Liana E., and Kalee Burns. 2021. *The Supplemental Poverty Measure: 2020*. U.S. Census Bureau, Current Population Reports, P60-275. Washington, DC: U.S. Government Printing Office. 1-37. Retrieved November 10, 2021 (https://www.census.gov/content/dam/Census/library/publications/2021/demo/p60-275.pdf).

Fox, Liana E. 2020. *The Supplemental Poverty Measure: 2019*. U.S. Census Bureau, Current Population Reports, P60-272. Washington, DC: U.S. Government Printing Office. 1-32. Retrieved November 10, 2021 (https://www.census.gov/content/dam/Census/library/publications/2020/demo/p60-272.pdf).

Fox, Liana E. 2019. *The Supplemental Poverty Measure: 2018*. U.S. Census Bureau, Current Population Reports, P60-268(RV). Washington, DC: U.S. Government Printing Office. 1-33. Retrieved November 10, 2021 (https://www.census.gov/content/dam/Census/library/publications/2019/demo/p60-268.pdf).

Fox, Liana E. 2018. "What Is the Supplemental Poverty Measure and How Does It Differ From the Official Measure?" Washington DC: U.S. Census Bureau. Retrieved November 10, 2021 (https://www.census.gov/newsroom/blogs/random-samplings/2018/09/what_is_the_suppleme.html).

Haveman, Robert. 2018. "Causes of Poverty." Madison, WI: University of Wisconsin-Madison. Retrieved November 10, 2021 (https://www.irp.wisc.edu/wp/wp-content/uploads/2018/07/1a-Teaching-Poverty-2018-Haveman-Causes-of-Poverty.pdf).

Long, Heather. 2020. "U.S. now has 22 million unemployed, wiping out a decade of job gains." *Washington Post*, April 16. Retrieved November 10, 2021 (https://www.washingtonpost.com/business/2020/04/16/unemployment-claims-coronavirus/).

Long, Heather, and Andrew Van Dam. 2020. "U.S. unemployment rate soars to 14.7 percent, the worst since the Depression era." *Washington Post*, May 08. Retrieved November 10, 2021 (https://www.washingtonpost.com/business/2020/05/08/april-2020-jobs-report/).

National Center for Education Statistics (NCES). 2021. "Educational Longitudinal Study of 2002 (ELS:2002)." Washington DC: U.S. Department of Education. Retrieved November 10, 2021 (https://nces.ed.gov/surveys/els2002/).

Pituch, K.A., & Stevens, J.P. (2016). *Applied multivariate statistics for the social sciences*. New York: Routledge.

Semega, Jessica et al. 2019. *Income and Poverty in the United States: 2018*. U.S. Census Bureau, Current Population Reports, P60-266(RV). Washington, DC: U.S. Government Printing Office. 1-77. Retrieved November 10, 2021 (https://www.census.gov/content/dam/Census/library/publications/2019/demo/p60-266.pdf).

Short, Kathleen. 2015. *The Supplemental Poverty Measure: 2014*. U.S. Census Bureau, Current Population Reports, P60-254. Washington, DC: U.S. Government Printing Office. 1-22. Retrieved November 10, 2021 (https://www.census.gov/content/dam/Census/library/publications/2015/demo/p60-254.pdf).

Shrider, Emily A. et al. 2021. *Income and Poverty in the United States: 2020*. U.S. Census Bureau, Current Population Reports, P60-273. Washington, DC: U.S. Government Printing Office. 1-83. Retrieved November 10, 2021 (https://www.census.gov/content/dam/Census/library/publications/2021/demo/p60-273.pdf).

Social Security Administration. 1997. *Social Security Programs in the United States*. Social Security Administration, Office of Research, Evaluation and Statistics, SSA Publication No. 13-11758. Retrieved November 10, 2021 (https://www.ssa.gov/policy/docs/progdesc/sspus/sspus.pdf).

Sullivan, Kate. 2021. "Biden signs historic $1.9 trillion Covid-19 relief law." *CNN*, March 11. Retrieved November 10, 2021 (https://www.cnn.com/2021/03/11/politics/biden-sign-covid-bill/index.html).

Taylor, Andrew et al. 2020. "Trump signs $2.2T stimulus after swift congressional votes." *Associated Press*, March 27. Retrieved November 10, 2021 (https://apnews.com/article/donald-trump-financial-markets-ap-top-news-bills-virus-outbreak-2099a53bb8adf2def7ee7329ea322f9d).

University of Wisconsin-Madison Institute for Research on Poverty. 2020. "How Is Poverty Measured." Madison, WI: University of Wisconsin-Madison. Retrieved November 10, 2021 (https://www.irp.wisc.edu/resources/how-is-poverty-measured/).

U.S. Census Bureau. 2021a. "Improvements to the Census Bureau's Supplemental Poverty Measure for 2021." Washington DC: U.S. Census Bureau. Retrieved November 10, 2021 (https://www.census.gov/topics/income-poverty/supplemental-poverty-measure/library/working-papers/topics/potential-changes.html).

U.S. Census Bureau. 2021b. "About Public Assistance." Washington DC: U.S. Census Bureau. Retrieved November 10, 2021 (https://www.census.gov/topics/income-poverty/public-assistance/about.html).

U.S. Census Bureau. 2017. "Measuring America: How the U.S. Census Bureau Measures Poverty." Washington DC: U.S. Census Bureau. Retrieved November 10, 2021 (https://www.census.gov/library/visualizations/2017/demo/poverty_measure-how.html).