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### **Introduction & Theory Discussion**

The Supplemental Nutrition Assistance Program (SNAP) is the United States federal government's largest anti-hunger program. Formerly known as "food stamps", SNAP benefits aid only the highest need portion of the population. The program is expansive, serving an estimated one in seven Americans in March of 2016. The present program is an entitlement, meaning that everyone who qualifies is guaranteed enrollment. To meet this obligation, SNAP is designed to expand and contract with the economy. SNAP is almost entirely federally funded, with only half of the 7% that goes toward administrative costs coming from state budgets (Center on Budget and Policy Priorities). While states pay very little for the program, because of this contribution, they have significant control over the application and administrative process of SNAP.

Despite SNAP being a federal benefit, state governments have control over how the funds for this program are allocated and how their availability is advertised. States have autonomy in several areas, such as deciding whether to take advantage of time limit waivers, setting requirements for the interview process, determining which assets are to be included when calculating benefits, designating which actions can disqualify individuals from receiving benefits and designing the general business model of the state's program. These areas, amongst others, leave room for considerable state-by-state variation in program outcomes, begging several questions. Are some states implementing SNAP in a more comprehensive way than others? Does the flexibility that SNAP offers to states allow state-level politics to infringe on this federal entitlement?

The purpose of this project is to determine the extent to which partisanship influences the distribution of welfare, such as SNAP. I am interested in discovering if political affiliation of the

state legislature, which has significant control over welfare programs, is related to the reach of SNAP in each state. To this end, I am studying the relationship between party control of the legislature, as a proxy for the political leaning of the state, and enrollment in SNAP to determine if the reach of this federal program is influenced by state politics. This is an important issue, because any qualifying individual or family should be able to access entitlement programs like SNAP. A policy's effectiveness is undermined when its expansiveness is vulnerable to political considerations. Is the flexibility that states are afforded in implementing SNAP at the cost of consistent access to benefits for qualifying persons? If there is a relationship between the dominant political affiliation of a state legislature and benefits enrollment, conventional political wisdom would predict that states with democratic control over the legislature would see higher enrollment in benefits than red states. I hypothesize that this assumption will hold true. To begin to determine its validity, I have gathered data and created a statistical model that will measure the relationship between party control of state legislatures and percentage of the population enrolled in SNAP, controlling for poverty.

#### Data & Methods

The data that I gathered came from the U.S. Department of Agriculture, the U.S. Census and the National Conference of State Legislatures (NCSL). The first pass of my data collection process was a simple Google search. I traced various articles and websites to their government sources before getting a grasp on how to search for the type of data I was looking for. I encountered numerous datasets that were scaled incorrectly for my purposes. For example, I wanted data on individuals, but often first encountered data on households. Ultimately, I extracted and compiled information from four datasets. For the purposes of this project, I used

data only from fiscal year 2015. On the USDA website, I found a dataset on the number of individuals participating in SNAP by state. The dataset was organized by state as well as region, and it specified the monthly participation for each state for fiscal year 2015. I copied and pasted each of the state-wide annual totals into a separate spreadsheet, where I stored all my final data. From the Census, I gathered state-level estimates of the number of individuals living below the poverty line as well as state population estimates. The poverty data was organized by year and state, with additional statistical information about the estimates specified. I copied the 2015 estimates into my final spreadsheet, converting the units from thousands of persons to persons. I also used the annual population estimates in the final dataset. Finally, the NCSL provided me with information on partisan control of each state's legislature. This information was in a PDF, so I recorded each piece of information manually. My final dataset includes six columns: 'state', 'leg\_con' (party in control of legislature), 'pop' (state population), 'num\_poor' (number of individuals below the poverty line), 'SNAP\_num' (number of individuals participating in SNAP), 'perc\_poor' ('num\_poor'/ 'pop'), 'perc\_partic' ("SNAP num"/ "pop"). See Table 1 for a list of variables and their meanings. To tidy the data, I converted the political parties into ID numbers (0 being Republican, 1 being Democrat, and 2 being non-partisan or split) for the leg\_con variable. Excluding the row for the column headers, there are fifty rows, one for each state.

I was highly intentional in selecting these variables. I chose to use the party in control of the legislature as a proxy for a state's political leaning, because the legislature makes policy decisions, including regarding the dispersment of public benefits. The only additional variable that I chose to control for was poverty rate. To keep the model simple, as an initial analysis of

the hypothesis, the only confounding variable I controlled for was poverty rate. Without controlling for poverty, findings on any other variable contributing to SNAP enrollment would be virtually meaningless, since any variation could be explained by differing numbers of in-need persons. I intentionally used the poverty rate instead of a measure for qualifying individuals, because states decide some of the details on program qualifications. Using poverty rate created consistency in comparing states, avoiding the introduction of an additional bias.

#### Results

To test my hypothesis, I created a straight-forward linear model. After regressing perc\_partic on leg\_con and perc\_poor (using 'republican' as the baseline), I found a clear linear relationship between party control of the state legislature and the percentage of each state enrolled in SNAP. *Plot 1*, a box and whisker plot of the coefficients for each of the predictors, shows that there is some systematic relationship between party control of state legislatures and enrollment in SNAP. As I hypothesized, the effect of being democratic is larger than either republican or non-partisan/split. According to this model, a state with a democratic state legislature would be estimated to have a 2.29% higher SNAP participation than a republican state. While this might seem like a small percentage increase, when compared with the coefficient of perc\_poor, which is around 0.97%, it seems more impressive. Plot 2 shows the regression lines for each of the party IDs overtop a plot of perc\_poor versus perc\_partic. This visualization makes it clear that the effect of being democratic, when compared to republican or non-partisan/split, is large. The estimate for the coefficients for leg con as democrat and for perc\_poor are also the only two variables that are statistically significant at the 0.05 level (see Table 2).

To test the robustness of the model, I ran a series of tests in R to ensure that none of the statistical assumptions have been violated. Plot 3 is a visualization of the assumption that there is no underlying relationship between the model predictions and its error terms. *Plot 3* looks random, which signifies that the model most likely has not missed a significant variable. In *Plot* 4 and *Plot 5*, randomness is also the goal. These two visualizations are looking for a relationship between each of the independent variables and the error terms of the model. If a relationship were to be found, the assumption that the residuals are randomly distributed would be violated, because there would be some mechanism that has not been explained using the model. Fortunately, there is no clear pattern in either of these plots. The next diagnostic test, depicted in *Plot* 6, is the relationship between the partial residuals and the independent variables. Granted the independent variables in the model are not related, the overlapping of the green and red lines in this plot signifies the existence of a robust relationship between these combined independent variables and participation in SNAP. Further, it is important to test that the error terms of the model are normally distributed. Plot 7 runs a comparison between the quantiles from a true normal distribution against the quantiles from the residuals. Since no points fall outside of the dashed interval in *Plot* 7, the error terms must be normally distributed. Finally, it is important to test for non-constant variance (NCV) as well as multicollinearity. Plot 8 simply plots these two values. For the NCV test, which is the same as the heteroscedasticity test, the result is a p-value. The lower the p-value, in this instance, the more problematic the result, because this statistic signifies the likelihood that the null hypothesis is true. The resulting p-value for this test was just around 0.80, which is very good. The test for multicollinearity is the square-root of the variance inflation factor (VIF). This indicator tests the degree of inflation in the standard errors—the

closer to one the statistic is, the better. This model has a very low result of just around 1.05 for each of the independent variables. The model passes each of the tested assumptions, demonstrating a high level of robustness.

#### Conclusions

This linear model was a successful first round of analysis for further research on partisan influences on social insurance programs. The model supported my hypothesis that states with democratically controlled legislatures would, on average, have a higher percentage enrollment in SNAP than other states. While not all the coefficients for the independent variables had a statistically significant influence on the dependent variable, the effect of the legislature being under democratic control was significant. To gain a better understanding of how partisanship influences SNAP enrollment compared with other factors, it would be productive to include demographic variables, such as race and language spoken at home. It would also be productive to expand the size of the data and see what happens to the strength of the relationship. Perhaps the variables that are not statistically significant on the one-year scale would be on a 10-year scale. Further research could bring in other social insurance programs, like Temporary Assistance to Needy Families, which is said to offer even more flexibility to states than SNAP.

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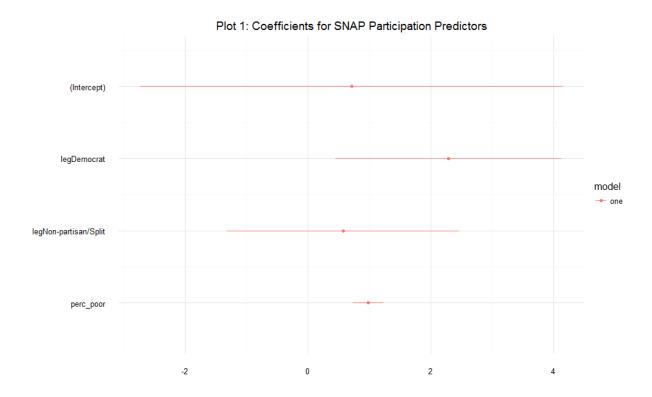
# <u>Appendix</u>

Table 1: Model Variables

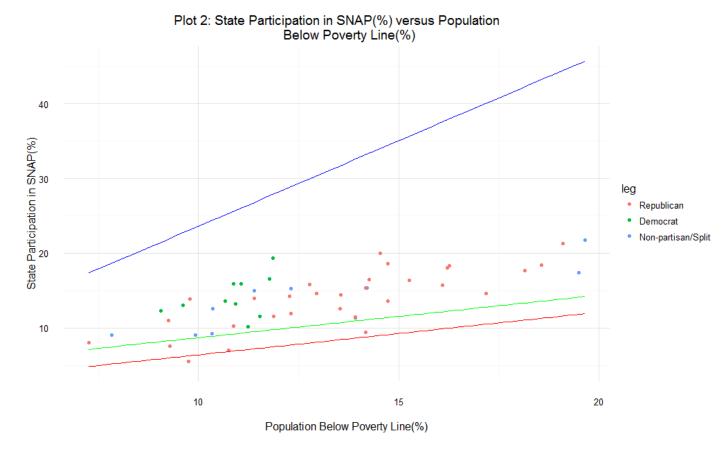
Table 1: Variables		
Name	Meaning	
state	state	
leg_con	political party in conrol of state's legislature	
pop	state's population	
num_poor	number of individuals below poverty line living in the state	
SNAP_num	number of individuals enrolled in SNAP in the state	
perc_poor	the percentage of people living below the poverty line	
perc_partic	the percentage of the state's population participating in SNAP	

Table 2: Regression Table

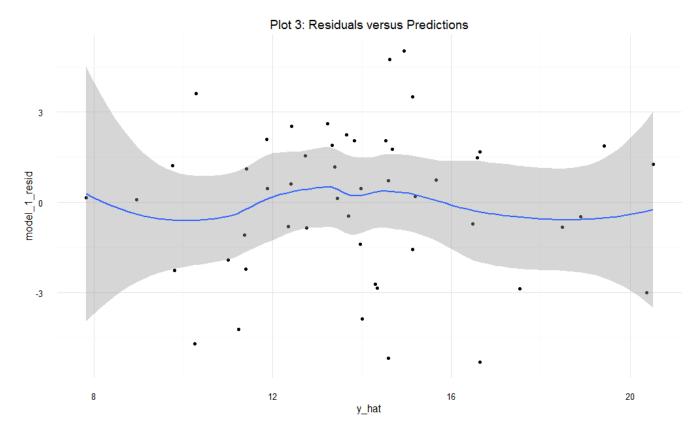
Table 2: Regression table			
	Participation in SNAP		
Constant (Republican)	0.7073 (0.6887)		
Democrat	2.2900 (0.0187*)		
Split/Non-partisan	0.5701 (0.5575)		
Percent in Poverty	0.9792 (5.62e-10***)		
Observations	50		
p-values in parenthesis			



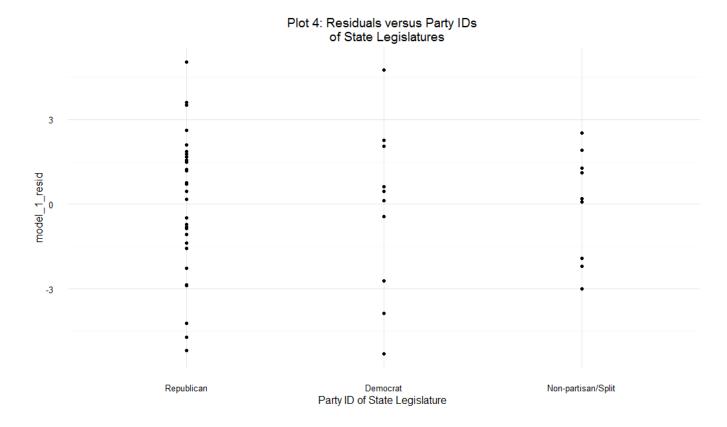
Plot 1: Dot & Whisker Plot of the residuals for the linear model



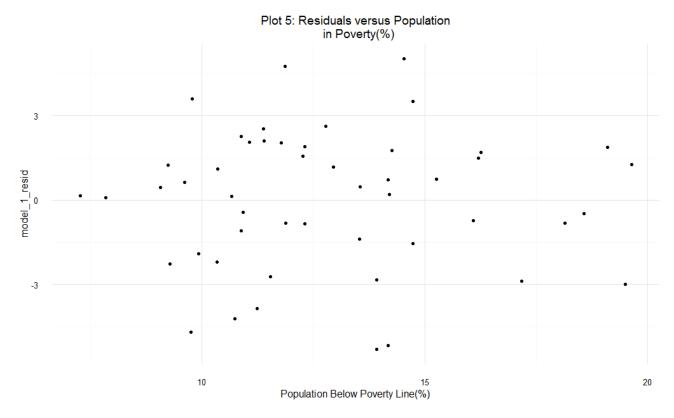
Plot 2: Linear regressions of each factor of 'leg\_con' (Republican, Democrat, Non-partisan/Split) on SNAP participation, controlling for poverty



 $Plot \ 3: \ Residuals \ for \ the \ linear \ model \ versus \ predictions \ to \ test \ randomness \ of \ error \ terms \ around \ a \ predicted \ value \ assumption$ 

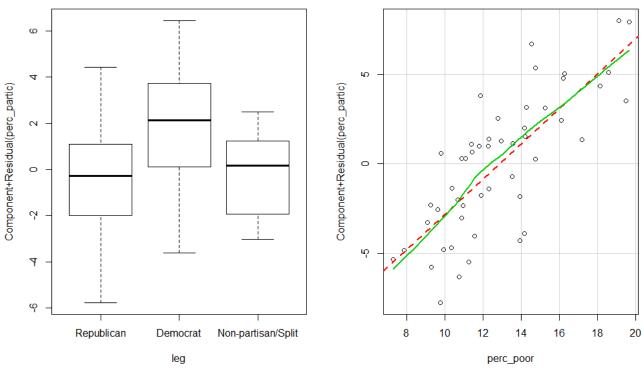


 $Plot\ 4:\ Residuals\ for\ the\ model\ versus\ each\ factor\ of\ `leg\_con'\ (Republican,\ Democrat,\ Non-partisan/split)\ to\ test\ the\ randomness\ of\ an\ error\ around\ an\ independent\ variable\ assumption$ 



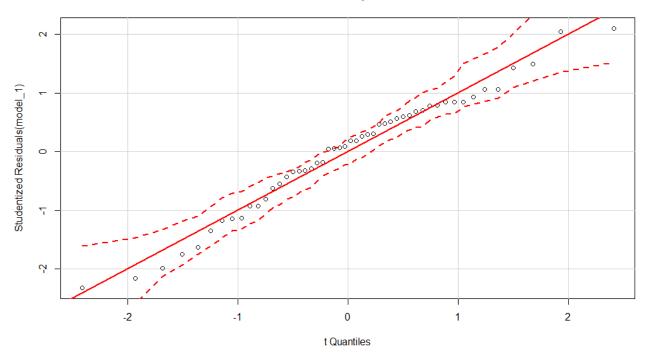
 $Plot \ 5: Residuals \ for \ the \ model \ versus \ 'perc\_poor' \ to \ test \ the \ randomness \ of \ error \ around \ an \ independent \ variable \ assumption$ 

Plot 6: Component + Residual Plots

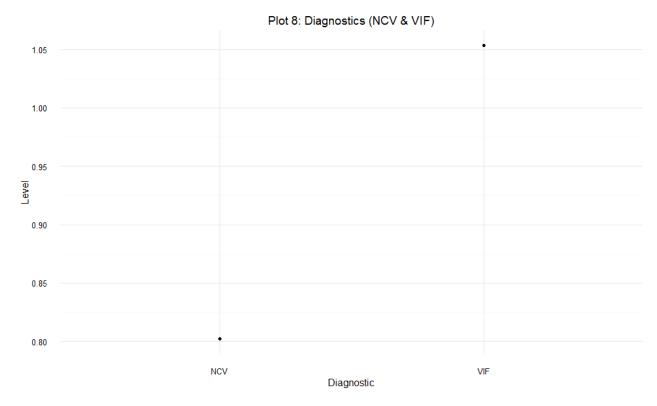


Plot 6: Partial residuals versus independent variables ('leg\_con' and 'perc\_poor')

Plot 7: Normality of Errors



Plot 7: Testing normality of errors assumption



 $Plot \ 8: \ Visualizing \ the \ results \ for \ non-constant \ variance \ (p-value) \ and \ multicollinearity (sqrt (VIF))$