What Factors Make for Successful CalFresh Implementation?

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Abstract

Despite spending more on administrative costs related to the Supplemental Nutrition Assistance Program than any other state in the US, California ranks third to last at connecting working poor households to CalFresh. What does the data suggest in terms of public policy measures that might be taken to increase California's success as a whole? This research uses Ordinary Least Squares (OLS) Modeling to analyze data made publicly available by the California Department of Social Services (CDSS) from 2014-2018 (CalFresh Data Dashboard, 2021) to identify factors that separate successful and unsuccessful implementations of CalFresh at the county level, as measured by Program Reach Index (PRI), a metric that measures access to CalFresh. Most notably, this research finds that counties that are able to enroll people in both CalFresh and Medi-Cal – of which the eligibility requirements are similar – at higher rates typically have higher PRI than counties that have lower rates of this dual enrollment. Moreover, this research suggests that counties with higher churn rates, the rate at which program participants lose CalFresh benefits only to re-enroll within three months, see minimal changes in PRI holding all other independent variables constant, which pushes back on previous literature that suggests that high churn is indicative of inefficient implementation of the program. Overall, this research supports strengthening the alignment and collaboration between the agencies that implement CalFresh and Medi-Cal to increase PRI statewide.

Introduction

In a state that produces more than a third of the country's vegetables and more than two-thirds of the country's fruits and nuts (California Agricultural Production Statistics, 2019), having access to food should not be a struggle anyone has to endure. And yet, in California, about 4.4 million people were estimated to be food insecure – defined as a person "who lacks adequate access to food" – in 2020 (Food insecurity, 2020). One reason for this is that California has far from reached its potential in getting CalFresh, California's implementation of the Supplemental Nutrition Assistance Program, benefits to all those who need it. Despite spending more on administrative costs related to SNAP than any other state in the country, California "ranks third to last in the nation at connecting working poor households to CalFresh [and] last in the nation at connecting seniors to CalFresh" (Botts, 2019).

Moreover, California is one of just twelve states that implements SNAP at the county level versus the state level (Aier, Daniel, & Prabhakar, 2016). Because each county is unique with its own problems, different counties enroll people in CalFresh differently. Likewise, results vary across counties, with enrollment rates of eligible participants ranging widely. Thus, this research aims to use Ordinary Least Squares (OLS) multiple linear regression modeling to find what quantifiable aspects about a county are associated with particularly good and bad implementations of CalFresh. What common factors exist among counties that are very good and very bad at implementing CalFresh at the county level?

To answer this question, this research uses OLS modeling to analyze data from 2014-2018 that was made publicly available by the California Department of Social Services (CDSS). OLS modeling takes one or more Independent Variables (IV) and uses those variables to predict an outcome for the Dependent Variable (DV). How accurate can this modeling be? The accuracy ranges, but for the four models discussed in this paper, R-Squared values range from .9242 to .9482. In other words, the highest-R-squared model is one in which the IV included explain 94.82% of the variation in the Dependent Variable. The Dependent Variable that will be studied is Program Reach Index (PRI) which estimates how many people who are eligible for CalFresh benefits are getting them.

This research uses past topic literature to guide what data to look for as IV in the OLS models. Major documented issues or characteristics of "successful/unsuccessful" CalFresh implementation that might be considered for the purposes of the data analysis conducted in this research paper are listed below:

1. Churn Rates (i.e. unnecessary turnover where someone loses CalFresh benefits errantly usually due to administrative problems only to re-enroll within 30 or 90 days)
2. Food Insecurity Rates
3. Population
4. Gross Domestic Product
5. Average Days to Approve a CalFresh Application
6. English as Second Language Enrollees in CalFresh
7. Active Error Rate of CalFresh Applications
8. Violent Crimes
9. Child Only Households Enrolled in CalFresh
10. Violent Crimes per Capita
11. Food Insecurity Rates

Of these factors at hand, this research focuses in on two main avenues commonly traversed by past topic literature including churn rates and the borrowing of bureaucratic capacity to enroll people in CalFresh and Medi-Cal (of which the eligibility requirements are similar) in the case they are eligible for both. More specifically, this research aims to answer the questions of "Are high churn rates associated with lower PRI values?" and "Are higher dual-enrollment rates in Medi-Cal and CalFresh (DEMC) associated with higher PRI values?" The main findings of this research are that churn rate has a minimal effect on PRI but that DEMC has a significant and very strong relationship with increased PRI rates across California's counties.

Literature Review

Recent literature has used publicly available data to quantify some of these issues (Beck, Danielson, & McConville, 2015) used the Ordinary Linear Squares (OLS) regression approach to predict child enrollment in CalFresh. There are no age restrictions to receive CalFresh benefits and it is estimated that “for every additional $10 in funding for administration relative to each low-income county resident, we estimate an increase of 0.6 percentage points in CalFresh enrollment” (Beck, Danielson, & McConville, 2015).

This research expounds on Beck et. al’s findings in multiple ways, specifically by using more accurate measures of CalFresh’s successes than child enrollment in my OLS analysis – namely Program Reach Index which was invented by the California Department of Social Services. As a December 2015 report from the CDSS argued, looking at child enrollment may be a bad measure of program success, as an estimated 1.77 undocumented adults live in child-only CalFresh households and 1.24 undocumented adults live in non-child-only CalFresh households (CDSS Measure to Estimate Program Access, 2015). Moreover, the CDSS analysis estimated that 94% of child-only CalFresh households are due to citizenship status. This is not to comment on whether undocumented immigrants should receive benefits, but to raise inference issues that arise given this knowledge. Most notably, the CDSS’s analysis above strongly suggests that Beck et. al’s use of child enrollment as a proportion of estimated population is more likely to capture the proportion of undocumented immigrants enrolled out of a county’s population than participation rates of Californians as a whole. Secondly, since undocumented immigrants are not eligible for CalFresh (CDSS Measure to Estimate Program Access, 2015), PRI’s removal of undocumented immigrants as estimated by child enrollment, would be a more accurate indicator of the success of CalFresh if such success is defined by higher values of participants as a proportion of those who are eligible for the program.

The CDSS conducted initial investigations of correlations between factors about counties and PRI in a 2014 article but were ultimately disappointed in the results. They note, “Neither unemployment nor poverty rates are strongly correlated with participation rates. However, analysis of data on individuals speaking a language other than English pointed to the state’s population of low-income unauthorized immigrants as a likely component of differences in participation”(Methodology for Measuring Neighborhood Access to CalFresh, 2014). These factors will be analyzed in this research either at a year-based level for a one-year period if such data is available or at a multi-year period, if possible. OLS, the method used in this research, should capture a similar metric of correlation that the CDSS appears to have attempted to analyze in their 2014 study. That is, the Pearson correlation coefficient, called R, is an important component of determining the success of an OLS model. R-squared (i.e. the value received when squaring R) tells how much of the variation in the dependent variable is explained by the model (e.g. an R-squared of .6 means that 60% of the variation in the dependent variable is explained by the predictors in the OLS model).

In the policy recommendations literature, scholars have proposed ways to increase participation and prevent losing eligible participants due to administrative errors (Aier, Daniel, & Prabhakar, 2016) concluded on-demand interviews were the best way to increase program participation, but that trade-offs existed between highest potential increases of participation and administrative feasibility. The SF-Marin Food Bank (CALFRESH CHURN: WHAT IS IT, AND HOW DO WE FIX IT?, 2017) concluded that minimizing the issue of “churn” – which they define as when an “eligible recipient unexpectedly loses CalFresh benefits ... only to re-enroll within one to three months" – can be done by modernizing the online CalFresh experience. Given that churn rates at the 30- and 90-day level are publicly available, it could be helpful to see if this claim is supported by the data. In other words, do counties with higher churn rates (i.e. potentially more inefficient counties) have lower PRI values? Does having to process more unnecessary applications that should be processed as recertifications lead to a county being able to enroll less of the other CalFresh-eligible members of their population.

Some legislation has also attempted to increase CalFresh reach, most notably two bills introduced by San Francisco Senator Scott Wiener, Senate Bills 285 and 882, and one by Los Angeles Senator Kevin de León, Senate Bill 1002. SB285 would have required enrollment thresholds for each county by 2024 and for the state to develop a new metric to better track who is getting CalFresh at a local level and who is not (Wiener, 2019). SB882 would have simplified the application process for seniors and have created a firm timeline by when all Californians would be allowed to certify or recertify for CalFresh benefits over the phone. Both of Wiener's bills died in committee (SB-882 CalFresh., 2020).De León's bill, SB1002, was vetoed by Governor Jerry Brown in 2014 but would have made clear that a county may renew a person's Medi-Cal eligibility should they be enrolled in CalFresh and would have required that the California Department of Social Services seek federal approval such that one's Medi-Cal enrollment could grant them eligibility for CalFresh (León, 2014).

Aligning the Department of Social Services and Department of Health Services eligibility determinations process by borrowing the administrative capacity of each from the other was argued to make the process of application and recertification for Medi-Cal and CalFresh benefits more efficient for Californians. This might make sense as the eligibility for the programs are quite similar. Everitt (2014) explains that "More than 90 percent of individuals eligible for CalFresh are also eligible for Medi-Cal." Because of this overlap, it may be worth investigating if higher dual-enrollment rates in Medi-Cal and CalFresh are highly correlated with higher PRI rates. (Call, Jensen, & Tracy, 2019) hint at this relationship writing, "It is common for counties with PRIs above 90% to have a dual enrollment (in Medi-Cal and CalFresh) rate at or near 50%." It could be helpful to investigate this relationship to see if an OLS model supports the inclusion of a dual enrollment rate.

In summary, this research aims to test common theories supported by previous topic literature to see which claims (straightforwardly asserted to be linked to higher enrollment rates or ones insinuated by authors such as legislators) are supported by the CDSS's publicly available data. This research should provide valuable insights from a data analysis perspective and can help shape future discourse on areas in which can be future studied to increase enrollment rates. For example, given that the OLS model in this research suggests variable X is positively correlated with higher levels of PRI (i.e. on average, higher levels of X are associated with higher levels of PRI), it may be helpful for the CDSS to further explore variable X as a possible way to increase PRI. However, this is not to say that the data analysis perspective is an end-all-be-all. Because this is an observational study that analyzes past data but doesn't include experimental aspects such as giving certain counties a "treatment" to see how they affect PRI in those counties, causal claims cannot be made about the factors analyzed in this research. Instead, they provide nonetheless important insights into what factors in the past were associated with successful implementations of CalFresh as measured by PRI for the different counties in California.

Methodology

To investigate the research question at hand, I used publicly available data published by CDSS as the main source of data. The CDSS' CalFresh Data Dashboard contains data from recent years including Program Reach Index estimates and number of people eligible for CalFresh in a county, among other variables. Program Reach Index (PRI) is the main outcome variable that will be studied to answer the research question as a metric of how many people who are eligible for CalFresh are getting those benefits. The equation to estimate PRI is shown below:

$$PRI = \frac{CalFresh\ Recipients\ -\ Disaster\ CalFresh\ Program\ Participants}{(pop < 130\%FPL) - (SSI * p) - \left((0.94\ Child\ Only\ Households) * 1.77 * \left(1 + \left(\frac{124}{177}\right)\right)\right)}$$

Equation 1: Program Reach Index formula where p: County proportion of SSI recipients below 130% FPL; .94: The proportion of child-only households that are child-only due to the immigration status of their parents; 1.77: The number of undocumented adults in a child-only CalFresh household; 1.24: The number of undocumented adults in a non-child-only CalFresh household. Source: California Department of Social Services, 2015.

PRI was created in 2015 by the CDSS as another method to measure CalFresh access at the county level other than Program Access Index (PAI), a metric used at the federal level by the U.S. Department of Agriculture's Food and Nutrition Service to measure how well states implement SNAP. The CDSS argues that PRI is a better metric than PAI for multiple reasons including: "PRI more correctly estimates access by removing undocumented persons from the denominator –ones who are eligible by poverty threshold but are not by CalFresh eligibility criteria, PRI provides better county level (Supplemental Security Income) estimates, [and] Allows a year-over-year comparison for 40 of the 58 largest counties" (CDSS Measure to Estimate Program Access, 2015). On top of the advantages PRI provides for California compared to PAI, the CDSS had PRI values estimated for the 58 counties that were published in the CalFresh Data Dashboard making it an easy metric to collect data on.

Given the dataset with many different variables tracked over long periods of time, I needed to narrow down which variables over what time frame to look at. PRI estimates were available for 2014 to 2018, so these five years were the ones I chose to hone in on for the purpose of answering the research question at hand. Next, using the guidance of the topic literature, I compiled the columns of the dataset that contained variables which could have had a logical link to PRI.

I then duplicated the dataset to begin the model selection routine to ultimately end up at a Ordinary Least Squares multiple linear regression model which uses multiple Independent Variables (IV) such as the number of people eligible for CalFresh in a county and a county's population to predict an outcome for the Dependent Variable (DV), namely Program Reach Index.

I then ran a Box-Cox transformation on one of the datasets, to see if order-preserving transformations were necessary to account for skewed variables in the data. Three different types of transformations were suggested, while the process suggested no transformation was necessary for PRI. These transformations included square-root-, cube-root-, and logarithmically-transforming two, three, and four different variables, respectively, and are outlined in more detail below in Table 1. If a variable is not included below, it did not require a transformation (or its suggested transformation was best rounded to 1, i.e. no transformation needed).

BoxCox Power Transformations alr3::powerTransform() in R		
Variable	**Transformation**	**Included in Model?**
Average Days to Approve	Logarithmic	No
Total County Population	Logarithmic	Yes
Gross Domestic Product	Logarithmic	No
Violent Crimes	Logarithmic	Yes
CalFresh Eligible	Square Root	Yes
Medi-Cal Eligible	Square Root	Yes
English as Second Language CalFresh Enrollees	Cube Root	No
Child Only Households	Cube Root	No
Active Error Rate	Cube Root	No

Table 1: BoxCox Transformation Suggestions

Now, there were two datasets to deal with, one with non-transformed data and one with transformed variables. The next step was applying an exhaustive search method to look at every combination of variables from a one- to 16-predictor OLS model to see which combination of variables provided the highest R-squared for each X-predictor model for X from 1-16. For example, the fifth output from this exhaustive search would be the best combination of five variables in terms of maximized R-squared.

With 16 model options to choose from, I then used two model selection criteria Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for guidance on which models were optimal. In general, a model that explains more variation in the DV and has less IV is best. Thus, AIC and BIC[1] are both good ways to choose among different candidate models by calculating a score based on model performance and model complexity (i.e. a "penalty" for adding a predictor to the model. Figure 1 shows there is a steep drop-off from two to three predictors in the model for both AIC and BIC. After this, the decrease continues for AIC until about nine or ten predictors and for BIC until about 7 predictors, after which the values begin to increase in both.

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[1] The specific formula for AIC and BIC can be found at: https://machinelearningmastery.com/probabilistic-model-selection-measures/
For the purposes of this paper, this process (from the exhaustive search to AIC/BIC calculations) was automated using the 'regsubsets' package in R.

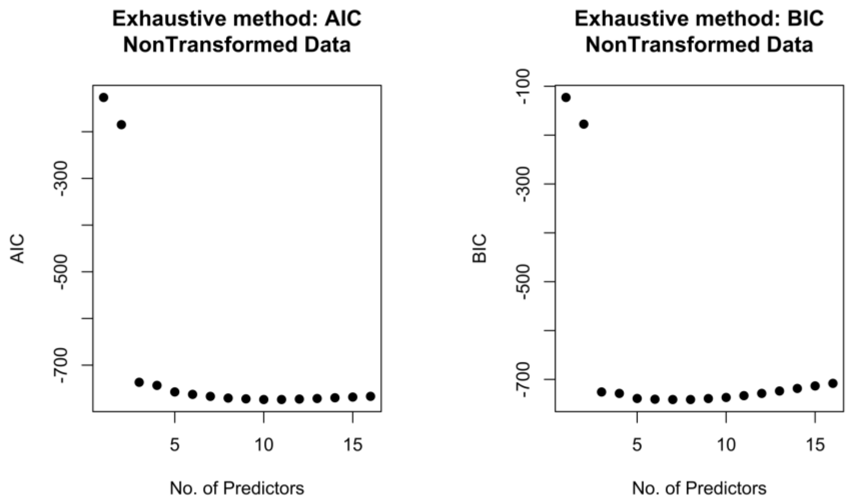

Figure 1: Akaike Information Criterion and Bayesian Information Criterion values for each best combination of one- to sixteen-predictor models as decided by an exhaustive search of each combination of variables at each level from one to sixteen.

Thus, the three-predictor model is likely the happiest medium in terms of far lower AIC/BIC values and minimizing the number of predictors in the model to prevent overfitting. Nonetheless, I decided that it would not hurt to investigate the data further and see if the findings hold up at this second threshold of the information criteria. Figure 2 is the same graph as Figure 1, with the first and second data points of both AIC/BIC graphs omitted. This "zooms in" on the rest of the data points and shows the claim above to be true.

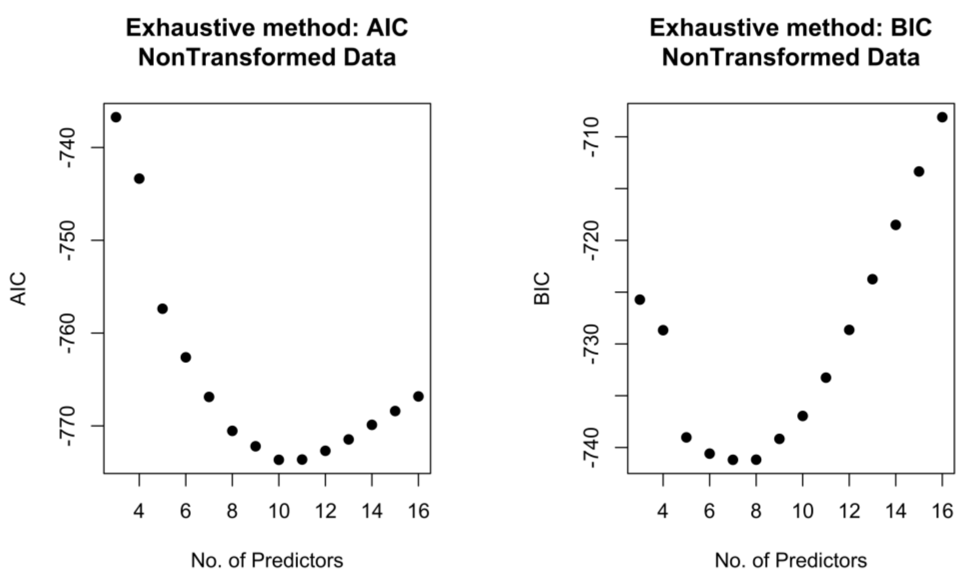

Figure 2: Akaike Information Criterion and Bayesian Information Criterion values for each best combination of three- to sixteen-predictor models as decided by an exhaustive search of each combination of variables at each level from three to sixteen.

Overall, I decided to go with a three-predictor model as the minimalist model, a ten-predictor model (AIC) for the maximalist model, and a seven-predictor model for the middle-sized model (BIC). This created the three models for the non-transformed dataset.

This bimodal shape in the AIC/BIC graphs was evident in the transformed dataset as well, suggesting the three-predictor model was best as well to optimize performance and complexity. However, given this, I was interested in investigating more of the variables that underwent order-preserving transformations to see if how model performance was impacted in comparison to the larger Models 2 and 3. Both AIC and BIC suggested an eight-predictor model at the second dip. Note, the variables in Models 3 and 4 appeared in Model 2, the biggest model, as well.

Once given the number of predictors in each model, I went back to the exhaustive search of variables to find the best three-, ten-, seven-, and eight-predictor models for the data in terms of model performance. Note, the exhaustive search was conducted on both the non-transformed and transformed datasets, so the “eighth” result is not the same in each output.

In the results section, I will interpret the findings from the OLS multiple linear regression modeling for Model 2, as well as the importance of the first drop-off in AIC and BIC and what it means that a large amount of the variation can be explained by only three variables.

Results

Models				
Variable/Model	**Model 1**	**Model 2**	**Model 3**	**Model 4**
	Non-Transformed	Non-Transformed	Non-Transformed	Transformed
Intercept‡	0.07660***	-0.0029917	.01593	.128**
	(0.0530945, 0.1000984)	*(-0.045220, 0.039236)*	*(-0.01163, 0.04870)*	*(0.037342, 0.219100)*
Calendar Year 2015		0.0010046		-0.005317
		(-0.014816, 0.016826)		*(-0.019029, 0.008395)*
Calendar Year 2016		0.0085563		-0.00155
		(-0.001669, 0.036791)		*(-0.016331, 0.013213)*
Calendar Year 2017		0.0175608		0.004821
		(0.008162, 0.050098)		*(-0.010206, 0.019847)*
Calendar Year 2018		0.0291302		0.014743.
		(0.00074, 0.03782)		*(-0.000416, 0.029903)*
30-Day Churn Rate		-0.5305433***	-0.63264***	-.588605***
		(-0.837143, -0.223944)	*(-0.98074, -0.40973)*	(-0.850368, -0.326842)
90-Day Churn Rate		0.4643019**	0.57364***	.514756***
		(0.181058, 0.747546)	*(0.36113, 0.87182)*	(0.279804, 0.749708)
Total Populationº		0.0003708*	.0004287*	.003678**
		(0.000008, 0.000733)	(0.000077, 0.000780)	(0.001115, 0.006241)
CalFresh Eligibles†	-3.66068***	-3.5452782***	-3.50977***	-2.930783***
	(-3.8395243, -3.4818405)	*(-3.73482, -3.35573)*	*(-3.69072, -3.33905)*	*(-3.067888, -2.793677)*
Violent Crimes†		3.3024387*	4.15947**	0.014914*
		(0.084182, 6.520695)	*(1.33520, 7.51715)*	*(0.002848, 0.026980)*
Food Insecurity Rate		0.2766092.		

		(-0.003185, 0.556404)		
Child Only Households		2.8011437*		
		(0.591193, 5.011095)		
Dual-Enrolled Medi-Cal and CalFresh†	1.92477***	1.9177651***	1.91767***	1.971802***
	(1.8320872, 2.0174554)	*(1.821601, 2.013929)*	*(1.80349, 1.99001)*	*(1.885932, 2.057672)*
Medi-Cal Eligibles†	1.80431***	1.6183570***	1.69994***	1.996784***
	(1.7217214, 1.8869038)	*(1.502814, 1.733900)*	*(1.62226, 1.80416)*	*(1.893061, 2.100508)*
R-Squared	.9242	.9366	.9337	.9482
Adjusted R-Squared	.9234	.9336	.932	.9462
No. of Observations	289	288	288	288
No. of Independent Variables	3	10	7	8

Table 2: Multiple Linear Regression results for four different models.

95% confidence intervals are reported in parentheses
., *, **, *** indicates significance at the 90%, 95%, 99%, and 99.9% level, respectively
† indicates the value for a given county is (Variable Count / County Population)
‡ Calendar Year 2014 is the omitted variable, and the coefficients for each successive Calendar Year 201X is the average difference in PRI between 2014 and 201X.
ºTotal Population is in units of hundreds of thousands
Results (Writing)

Intro

Four different models are presented in this section. Among these are one model for which some of the variables underwent order-preserving transformations to decrease sensitivity to outlying values (Model 4) and three models for which no data underwent order-preserving transformations (Models 1, 2, and 3). Model 4 trades interpretability of estimates (one must "un-do" the order-preserving transformations to get the estimates in units that can be easily interpreted) for model validity. The inclusion of Models 1, 2, and 3, instead of just one transformed- and one non-transformed-data model is two-fold.

For one, AIC and BIC both suggest that there is a steep drop in both criteria values (lower values are better) when going from a two- to three-predictor model and then does not decrease as much for higher-numbered-predictor models. This suggests that the models bigger than the ideal model that contains three IV have minimal returns in terms of how much R-squared is increased versus the tradeoff of potential overfitting and reduced interpretability that comes with adding more predictors to an OLS model.

However, if the drop-off in AIC and BIC were to be ignored from two to three predictors, there is a second local minimum in both criteria that is visible (albeit less steep than from two to three predictors) located around nine/ten predictors for AIC and seven predictors for BIC after which AIC and BIC begin stagnating or increasing. For this reason, I investigated Models 2, 3, and 4 at this second threshold to get further insight into what variables help explain more variation in the DV.

However, it should be noted that the gains beyond the minimalist model are modest. The R-Squared value for the minimalist model is about .92, meaning that 92% of the variation in the DV is explained by the IV. In models 2 and 3, this value increases to a little over 93%. Adding 4-6 IV to the model to only get 1% more of the variation in the DV explained by the model is small. Including a larger model can serve as a robustness check if the size and direction of the estimates for each IV remains about the same while also helping to explain more about the DV statistically (higher R-squared is good, even if the gains are not as large as those seen from increasing from one-to-two and two-to-three IV in the model).

In terms of this above noted "robustness check," the findings hold up well. Among the different models, the number of IV in each varies. Even still, the sign (i.e. positivity or negativity) of the coefficients of the IV and statistical significance (in terms of p-values being below a significance level of either .10 or .05) remains the same across models. This suggests the relationship between a given IV and PRI is not sensitive to the specific model selection criteria.

In interpreting the results, I will refer to Model 2 to interpret the relationships between the independent variables and PRI. This decision is being made because the IV in Models 2-4 all appear in Model 2, and the lack of transformations on these variables makes interpretation most understandable. Note, choosing one model over the other to interpret in the Results section does not matter in terms of substance of the argument of this research as a whole given that the size and sign of the estimates hold up throughout the models.

After interpreting the results, there is an overview of the difference between the relationship of the churn rates (and why this research suggests that the churn rates' effect on PRI is minimal compared to what the topic literature might have argued) and enrollment/eligibility rates for CalFresh Eligibles, Medi-Cal Eligibles, and Dual Enrollees in Medi-Cal and CalFresh.

Before continuing with interpreting the variables, it might be first helpful to give a correlation matrix as shown below. By the metric of Pearson Correlation Coefficients, values closer to -1 or 1 indicate a stronger relationship between those two variables. Thus, the heatmap in Figure 3 shows which IV have stronger and weaker relationships with PRI.

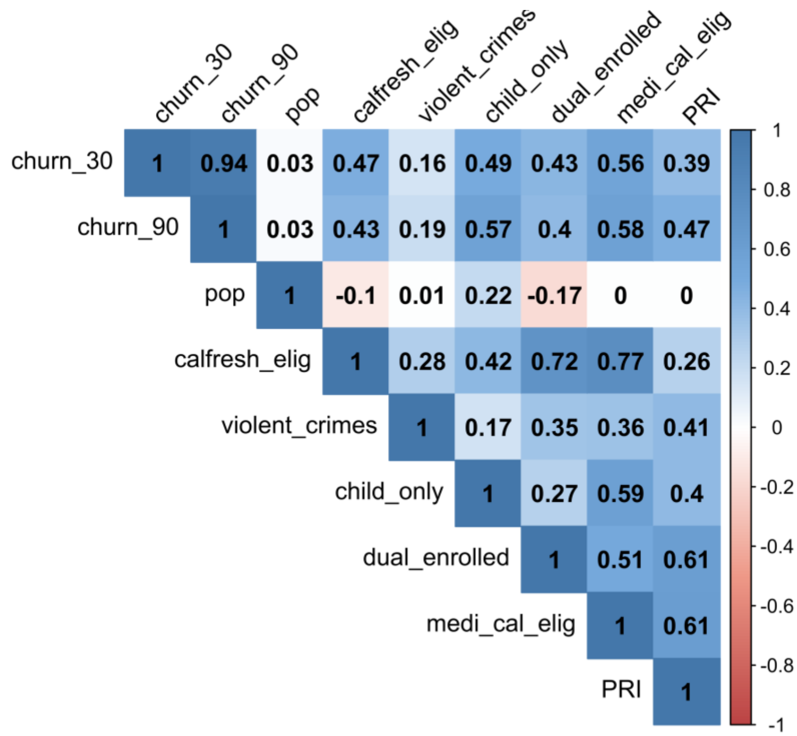

Figure 3: Correlation matrix between variables as measured by Pearson Correlation Coefficient.

A. Calendar Year

The IV Calendar Year 2018 is significant at the .05 level, indicating average PRI for 2018 is statistically significantly different from average PRI in 2014. This can be illustrated in Figure 4, which graphs the relationship of Statewide PRI over time. While PRI in 2018 appears to be less than the previous three years (perhaps suggesting that the preceding three years should also be significant), the relationship between Calendar Year and PRI (and all IV and PRI in Multiple Linear Regression) is calculated after accounting for all other variables in the model. Thus, after all the IV's were accounted for, a significant amount of the remaining variation in PRI can be explained by the year 2018. More specifically, holding all other IV at a constant value, we would expect that PRI in 2018 would be about 2% higher than PRI in 2014. The year fixed effects show an upward trend in Program Reach, suggesting that holding all else constant, bureaucratic capacity has improved in the years studied through a progressive learning process in program assignment, which is to be expected.

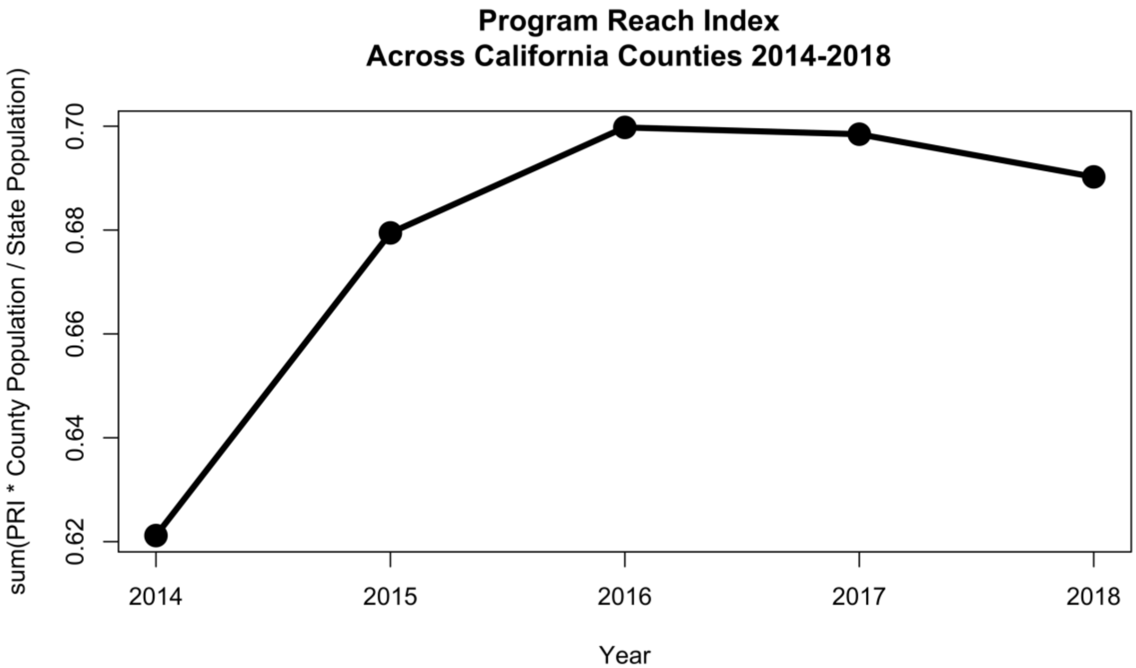

Figure 4: To look at the effect statewide over time, PRI values must be weighted by a county's population as a measure of the whole state population for that given year. Graphed above is the population-weighted county mean value for each year.

B. Churn Rate

On churn rate, the variables should be analyzed together due to their strong correlation as shown in Figures 3 and 5. This is important to note because given that as one churn rate increases, the other churn rate tends to increase at about the same exact rate, the opposite signs of their coefficients are telling about the average net effect of churn on PRI. That is, it appears that for the most part when the churn rate in a county increases, the 30-Day Churn rate has a negative relationship with PRI (as 30DC increases, we would expect PRI to decrease) while 90-Day Churn rate has a positive relationship with PRI (as 90DC increases, we would expect PRI to increase). Thus, the signs and magnitude of these two variables effectively cancel each other out in terms of their overall effect on PRI.

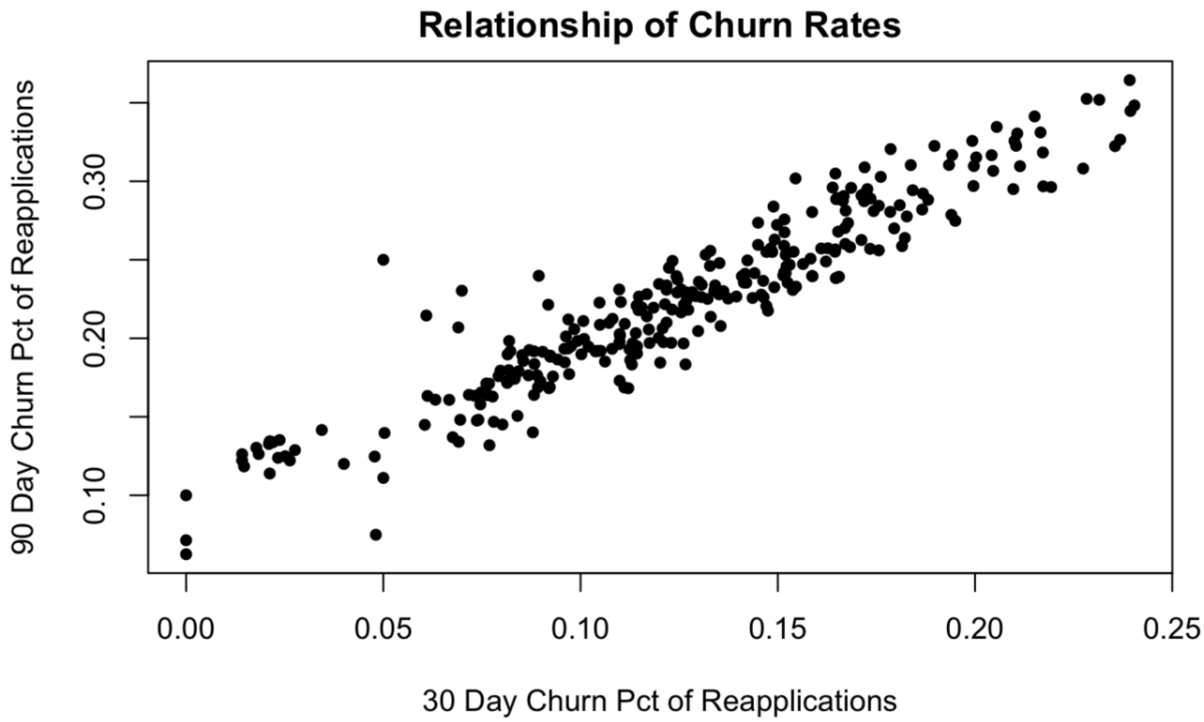

Figure 5: 30- and 90 -Day Churn Rate variables have a Pearson correlation coefficient of 0.942.

This effect is shown in Figure 6. If we were to vary 30DC and 90DC from 30DC's minimum to 90DC's maximum while holding all other IV at their respective means, the predicted PRI values would be expected to be ever so slightly negative, because the negativity of 30DC's effect and positivity of 90DC's effect would cancel each other out for the most part (which is illustrated by the dashed red line which has an almost flat slope in Figure 6). However, it should be noted that the red line should not be taken mathematically at face value, because of the fact that while the correlation between 30DC and 90DC is very strong (R = .94), the relationship is not 1-to-1. Rather, Figure 6 shows the general relationship between 30DC and 90DC to illustrate the overall effect of churn on PRI is minimal – and slightly negative, if anything, because the magnitude of 30DC's effect is greater than that of 90DC's.

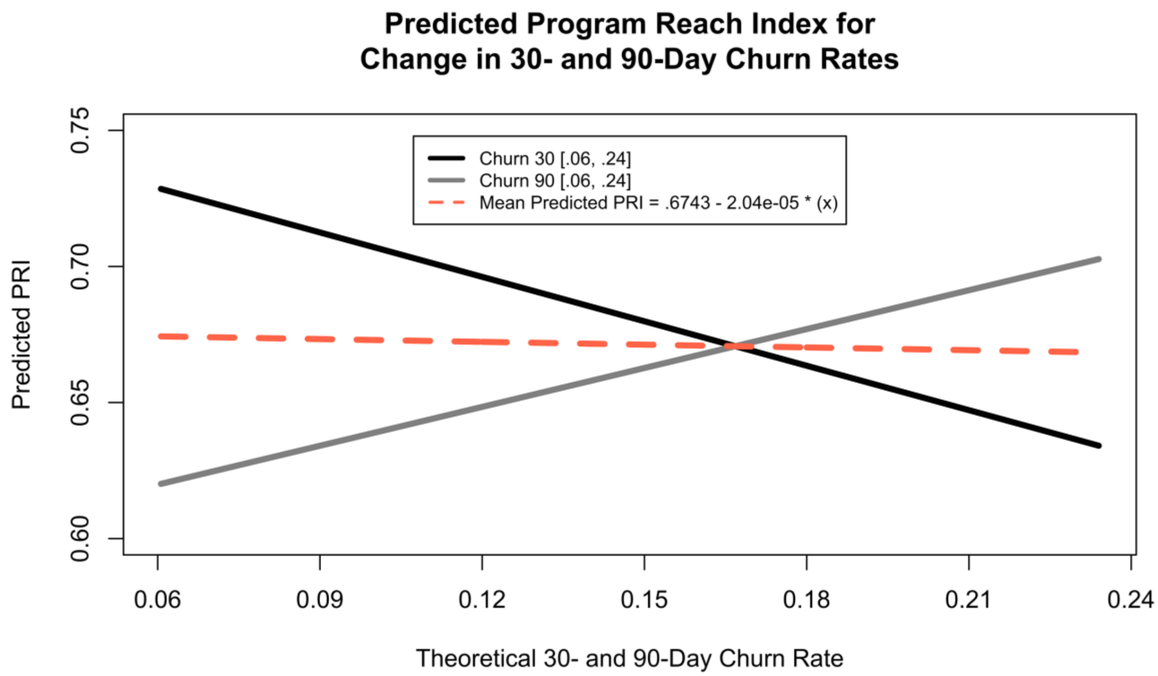

Figure 6: Predicted values for Model 2 holding all X-variables constant at their respective means and varying 30- and 90-Day Churn from the minimum observed value for 30-Day Churn to the maximum observed value for 90-Day Churn.

C. Total Population per County (in hundreds of thousands)

Total Population in each county is calculated in hundreds of thousands, and contains one of the weaker relationships with PRI compared to the other variables selected. Nonetheless, the IV has a significant, (slightly) positive relationship at the α = .10 significance level in Model 2 and at the α = .05 significance level in Model 2. In Model 2, the estimate for Total Population suggests that if a county increased in population by 100,000 people, we would expect PRI to increase about .03%. One might argue that there is little practical significance given that such a population shift is unlikely to happen over a short period of time.

However, there could be countervailing effects at play. For one, it's possible that county bureaucracies in larger populations could have a harder time enrolling eligible participants because there are more people and more applications to address typically. Consider to the alternative, though, that large counties are also probably better financed and benefit from economies of scale, on average as well. Thus, on balance the positive effects seem to prevail once one accounts for attributes of the population, bureaucratic strategies and efficiency as have been done in the model. Nonetheless, these countervailing effects could explain why the effect for total population is small.

It should also be noted that once Total Population per County was transformed logarithmically – a typical tool to address the right-skewness of population data – it was dropped from the models suggested by the model selection routine altogether. This implies that the significance of the variable in Model 2 was likely driven primarily by a small number of outlying cases with very large populations. Moreover, it casts doubt on the practical significance of the variable for real-world applications given that the variable was not included in the more statistically sound model (Model 4) which accounts for the outlyingness of this variable.

D. CalFresh Eligibles

The IV CalFresh Eligbles, which is the proportion of people eligible for CalFresh in a given county of that county's population, has a negative relationship with PRI after controlling for all other IV in the model. This means counties with more people eligible for CalFresh in a county are expected to have lower PRI values, on average, in comparison to counties with less people eligible for CalFresh. More specifically, if CalFresh Eligibles increased by 100%, we would expect PRI to decrease about 350% holding all other IV constant. Of course, as will be the theme with these variables, this extrapolation of the data should be avoided as no county is going to go from 0% of their population to 100% of their population being eligible for CalFresh. Thus, it might be prudent to scale down these values and analyze from a different unit of scale. For example, an alternative description of this variable (and future ones in a similar proportion-based unit) is that if CalFresh Eligibles increased by 10% we would expect PRI to decrease about 35% holding all other IV constant. Overall, this relationship makes sense because a higher number of CalFresh Eligibles likely means that a county has to process more applications to reach the same PRI value as a smaller county. If that county is not able to handle the capacity of these higher numbers of application, their PRI could suffer.

E. Dual-Enrolled Medi-Cal and CalFresh

The proportion of people dual-enrolled in both Medi-Cal and CalFresh in a given county (of that county's population) has a positive relationship with PRI. This suggests that as this proportion increases, we would expect PRI to increase as well holding all other IV constant. Staying wary of extrapolation, the coefficient for this variable can be interpreted as if proportion of DEMC increased 100%, we would expect PRI to increase almost 200%. Resizing these estimates again as above, we might interpret this variable as meaning that holding all other IV constant, a 10% increase in the proportion of DEMC would be expected to be associated with a 20% increase in PRI. Figure 7 below shows how we might expect PRI to change for higher levels of DEMC should a county go from the minimum observed value to the maximum observed value in DEMC holding all other variables at their means.

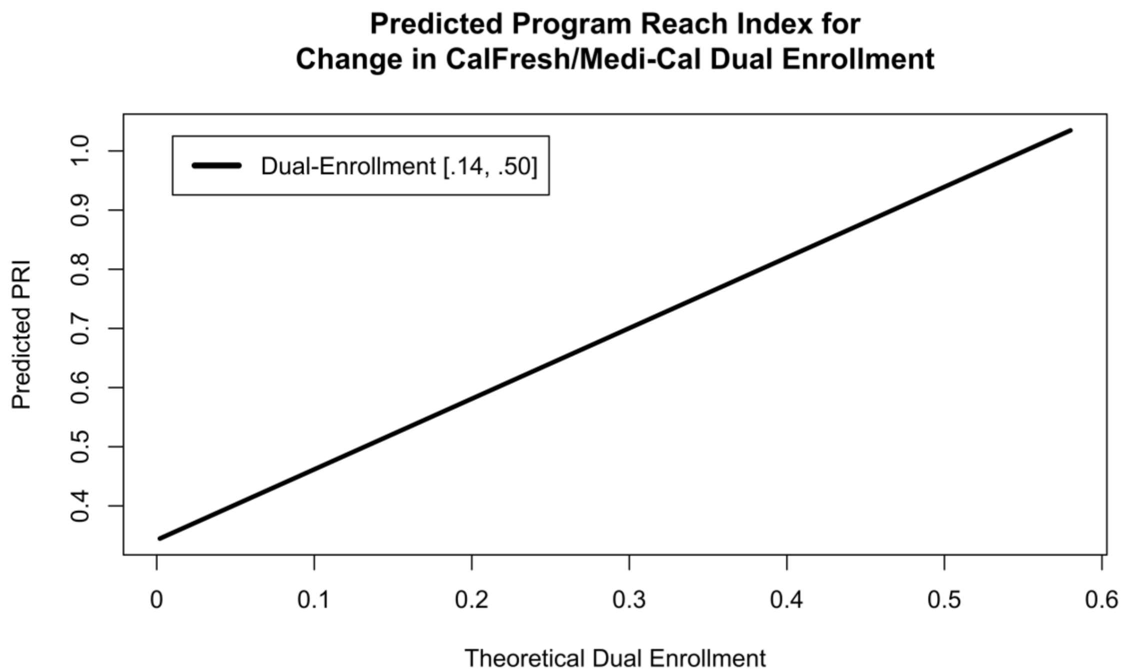

Figure 7: Predicted values for Model 2 holding all X-variables constant at their respective means and varying Dual-Enrollment from its minimum to its maximum.

It makes sense that higher rates of dual-enrollment in Medi-Cal and CalFresh would be correlated with higher CalFresh enrollment rates. This is because when DEMC is higher, it inherently means that people are enrolled in CalFresh at a higher rate than counties with lower DEMC. But, beyond this, this finding also mirrors discussions in topic literature as well. Counties that are able to enroll people in both Medi-Cal and CalFresh are likely better in some way at borrowing administrative capacities. If counties are able to enroll people who should be eligible for both programs (typically) in both of said programs, then it is plausible that those counties have figured out a way to capitalize on the similarity in eligibility for Medi-Cal and CalFresh. At the very least, this finding suggests that further investigating ways to enroll people in both Medi-Cal and CalFresh given that they are already eligible and enrolled in one could be a way to increase PRI across the state.

F. Medi-Cal Eligibles

As is the theme with the other variables of its type, as the proportion of people who are eligible for Medi-Cal in a county increases, we would expect that the PRI values will increase as well, on average. Should this proportion increase 10%, we would expect that PRI would increase by about 16.6% holding all other IV constant. This clashes with the finding in part D about CalFresh eligible given that the eligibility criteria for Medi-Cal and CalFresh are similar. However, it could be that the overlap between Medi-Cal Eligibles and CalFresh Eligibles are “noisy” enough (or not strongly correlated with each other enough) such that an entirely different phenomenon could explain why Medi-Cal Eligibles has a positive relationship with higher PRI values. One plausible hypothesis for this difference could be that Medi-Cal Eligibles, who don't need inherently need to be processed for CalFresh benefits, could be an indicator of poverty and subsequently higher food insecurity rates. If poverty and food insecurity rates are higher in a county, CalFresh could be more of a necessity in these counties driving up the demand and participation rates for CalFresh without being as drastic of an overload of the system that it bogs down PRI (i.e. when CalFresh Eligibles are high, this could mean that a county has a lot more cases to process that it simply can't handle).

G. Food Insecurity

An estimate of .276 for the variable Food Insecurity would hint that for a 10% increase in food insecurity rate in a given county, it would be expected that PRI would increase about 2.8% holding all other IV constant. One reason that this could be the case is that higher levels of food insecurity in a county could mean that people are more likely to seek assistance to buy groceries. It could be the case that when the demand for food is higher (or the supply of it being less accessible) but all other variables (socioeconomic, economic, etc.) are held constant, people are more motivated to seek out CalFresh benefits due to a more dire need for food, leading to higher enrollment rates.

H. Child Only Households

Child Only Households (COH) measures the proportion of CalFresh households where only a child in the house is enrolled in the program (i.e. their parent is not enrolled) of a county's population. The large estimate for COH, in Model 2 seems to be misleading at face value. While alone, it might be interpreted to suggest than a 100% increase in the proportion of COH would be expected to be associated with a 180% increase in PRI holding all other IV constant (or a 10% increase in proportion of COH would be expected to be associated with an 18% increase in PRI holding all other IV constant).

However, consider when the model selection routine contains the process of mathematical transforming variables (with COH undergoing a cube-root transformation) before using AIC and BIC to suggest an MLR model. In this scenario (i.e. Model 4), COH is not included. This is important because mathematically transforming variables is a statistical technique that is typically used to shift data that is not evenly transformed. In turn, one might consider the process of transformation as an added step which increases the legitimacy of the model-making process. Thus, when a model is no longer suggested to be added after having its uneven distribution accounted for, it could suggest that that variable should not have been added to the model in the first place.

For this reason, while the model selection process – without the added robustness check of transforming the data – might suggest to add COH to Model 2, the practical significance is minimal. A variable whose significance is dependent on not transforming the data likely cannot be trusted to give insight into the complexities of the CalFresh problem at hand. At the very least, the more robust model selection process in Model 4 suggests that there are other IV that can better explain change in PRI than COH.

I. Violent Crimes

The relationship between the number of violent crimes as a proportion of a county's population is the most complicated of the relationships shown in Table 2 given that the estimates change drastically from Model 2 to Model 4, after Violent Crimes undergoes an order-preserving transformation. At face value, the effect of the Violent Crimes variable in Model 2 might suggest that counties with more violent crimes as a proportion of that county's population have higher PRI values than counties with less. More specifically, Model 2's estimate for Violent Crimes suggests that a 100% increase in the proportion of Violent Crimes in a county as a proportion of that county's population would be expected to be associated with a 423% increase in PRI holding all other IV constant.

However, there are multiple things to note. First, the extrapolation note is especially important here as it is highly unlikely that there would be the same number of violent crimes as number of people in a county (which is what a value of 1.0 or 100% for the variable of Violent Crimes would indicate).

Secondly, the large estimate for this variable needs to be taken in context with the right-skewed nature of this IV as illustrated in Figure 8. Notice that before the log transformation, the uneven distribution of the Violent Crimes variable is apparent in bottom left histogram of Figure 8 and the relationship between VC and PRI in the scatterplot of the two variables in the top right of Figure 8. After transforming the variables, both graphs on the right are visually more evenly distributed. Even beyond visuals though, the Multiple Linear Regression model will be fit better if a variable that should be transformed is transformed.

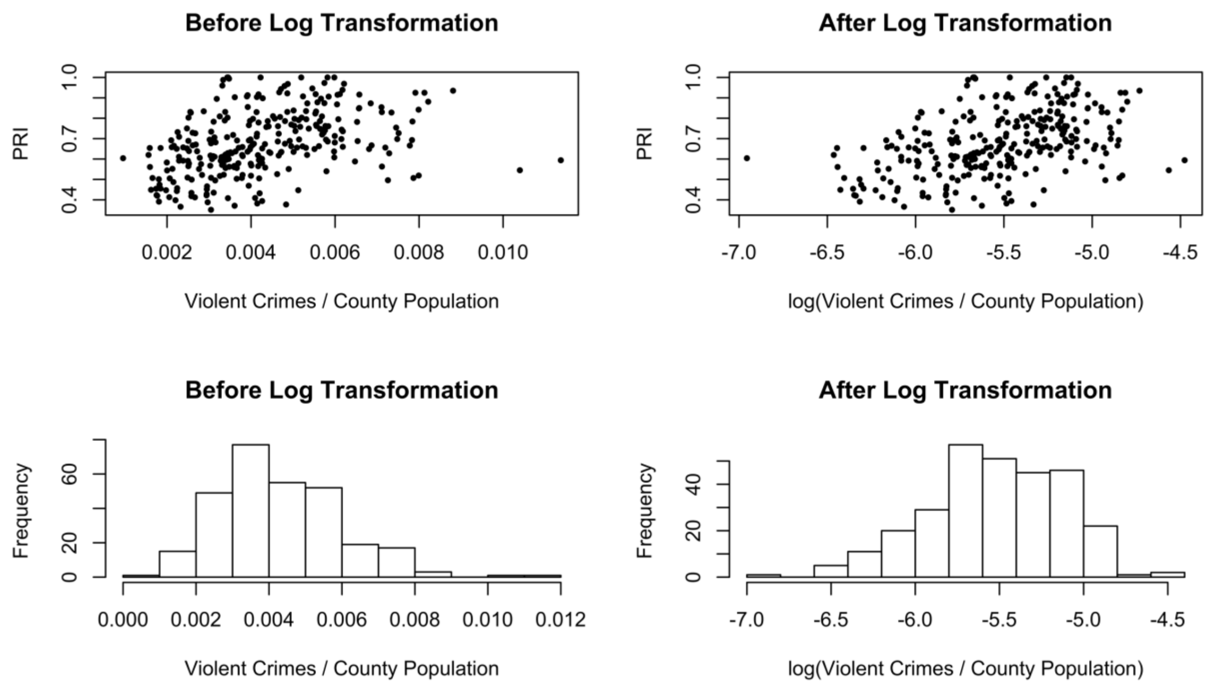

Figure 8: A scatterplot of Violent Crimes / County Population against PRI and histogram of Violent Crimes / County Population are given before (Left) and after (Right) the logarithmic transformation was applied to the variable.

For this reason, Model 4's results are more valid when it comes to accurately estimating the effects of IV which are naturally skewed. The estimate in Model 4 can be interpreted (after "undoing" the mathematical transformation that was applied) as meaning that for every 1% increase in Violent Crimes as a proportion of a county's population, a .014914% increase in PRI.

J. Differentiating Between CalFresh/Medi-Cal/DEMC and Churn Rates Relationships

An interesting note here, is the relationship between the three variables CalFresh Eligibles, Medi-Cal Eligibles, and DEMC, and the distinction between this three-way relationship and that of churn rate discussed earlier in which highly-correlated, opposite-signed coefficients effectively cancelled each other out. As Figure 8 shows, there is a strong relationship between CalFresh Eligibles and DEMC and CalFresh Eligbles and Medi-Cal Eligibles, with Pearson Correlation Coefficient values of .72 and .77, respectively. DEMC and Medi-Cal Eligibles has a moderate positive relationship with Pearson's correlation coefficient of .51.

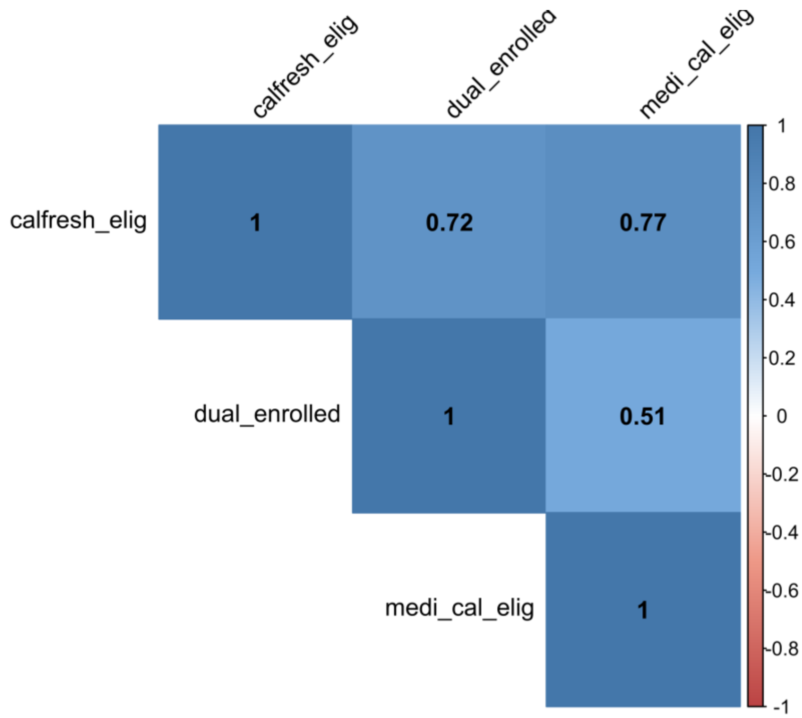

Figure 9: Correlation matrix between three variables as measured by Pearson Correlation Coefficient. Note: this is a subset of the correlation matrix shown in Figure 3.

The difference between this three-way relationship and the churn-rate relationship can be seen in two ways: magnitude of correlation with each other and magnitude of correlation with themselves and PRI.

Firstly, the magnitude of correlation between in the relationship between CalFresh Eligibles, DEMC, and Medi-Cal Eligibles are markedly lower than that of Churn Rate. In fact, the .94 R-value between 30DC and 90DC is the highest correlation value of any two variables (Figure 7) by .17 units (with the relationship between CalFresh Eligibles and Medi-Cal Eligibles coming in next-highest at .77). Given this, it is more difficult to make the claim that the differing signs of these slope estimates cancel each other out, because while the churn rates increase at almost a one-to-one relationship, this isn't as much the case in the relationship between CalFresh Eligibles, DEMC, and Medi-Cal Eligibles.

Consider the calculated predicted values for PRI if a given county transformed itself from the minimum observed to the maximum observed in both of the relationships in question. In other words, if county X had the minimum observed values for 30- and 90-Day Churn Rates and went to the maximum for both of these IV, what would the predicted PRI be holding all other IV constant? And, if county Y had the minimum observed values for CalFresh Eligibles, Medi-Cal Eligibles, and DEMC, and went to the maximum observed values for all three of these IV, what would the predicted PRI be holding all other IV constant? More importantly, how much does PRI change, if at all?

As shown below in Table 2, the respective relationships between the two groups and PRI are markedly different. Spanning from the minimum to the maximum for both churn rate would be associated with a net change of .011 (about 1%) for Predicted PRI. However, going from the observed minimum to the observed maximum for the three enrollments IV would be expected to be accompanied by a 46.8% change in Predicted PRI.

IV	Minimum	Maximum	Estimate from Model 2	Predicted PRI Change from Min to Max	Group Change
	m	M	B	B(M-m)	$\Sigma B(M-m)_{GROUP}$
CalFresh Eligibles	.0575	.304	-3.545	-.872	
DEMC	.141	.501	1.918	.690	+.468
Medi-Cal Eligibles	.151	.553	1.61	.650	
30-Day Churn	0.000	.240	-.531	-.128	+.012
90-Day Churn	.0625	.364	.464	.140	

Table 3: Expected Change in Predicted PRI after spanning IV from Minimum to Maximum for both groups (CalFresh/Medi-Cal/DEMC) and Churn Rates.

These findings are illustrated graphically in Figure 8 as well. Spanning the variables from the minimum observed to the maximum observed values of the enrollment variables have a drastically larger effect on Predicted PRI than is the case of the effect of changing the churn rates from their minimums to the maximums on Predicted PRI.

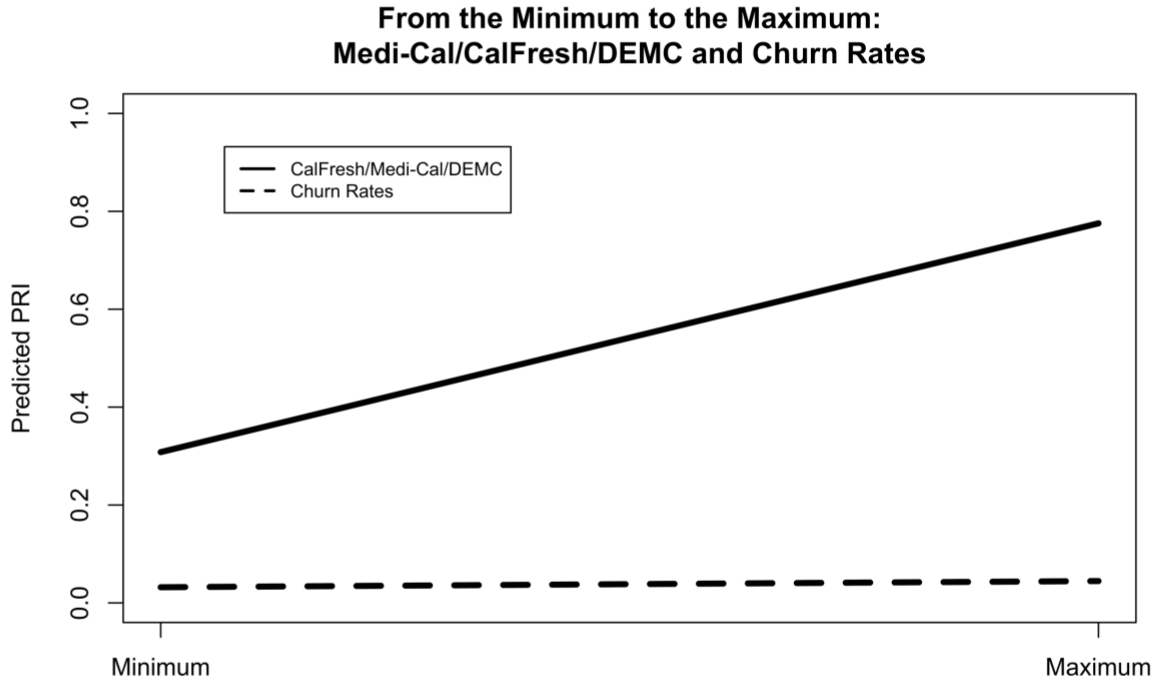

Figure 10: The above graph tracks Predicted PRI changes after spanning from the minimum observed value for CFE, MCE, and DEMC to the maximum observed value for each variable, and then spanning from the minimum observed value for 30- and 90-Day Churn Rates to the maximum observed value for both variables. Note, the intercept is added here to graph actual PRI values, whereas Table 3 only looks at change in Predicted PRI.

Moreover, the relationship between DEMC and PRI versus the relationship between any of the churn rates and PRI are markedly different highlighting the importance of DEMC and unimportance of the churn variables. Below, Figure 11 outlines a weak relationship that doesn't suggest churn predicts PRI even alone. However, Figure 12 illustrates a different picture. Without controlling for any other IV, the relationship drawn in Figure 12 shows that DEMC and PRI alone have at least a moderate to moderately strong relationship. In fact, the model selection routine suggests that the best one-predictor OLS model to predict PRI would be with DEMC as the IV. Model 4 reiterates the importance of including the enrollment rate variables, as the best three-predictor OLS model to predict PRI includes CalFresh Eligibles, Medi-Cal Eligibles, and DEMC, as its IV.

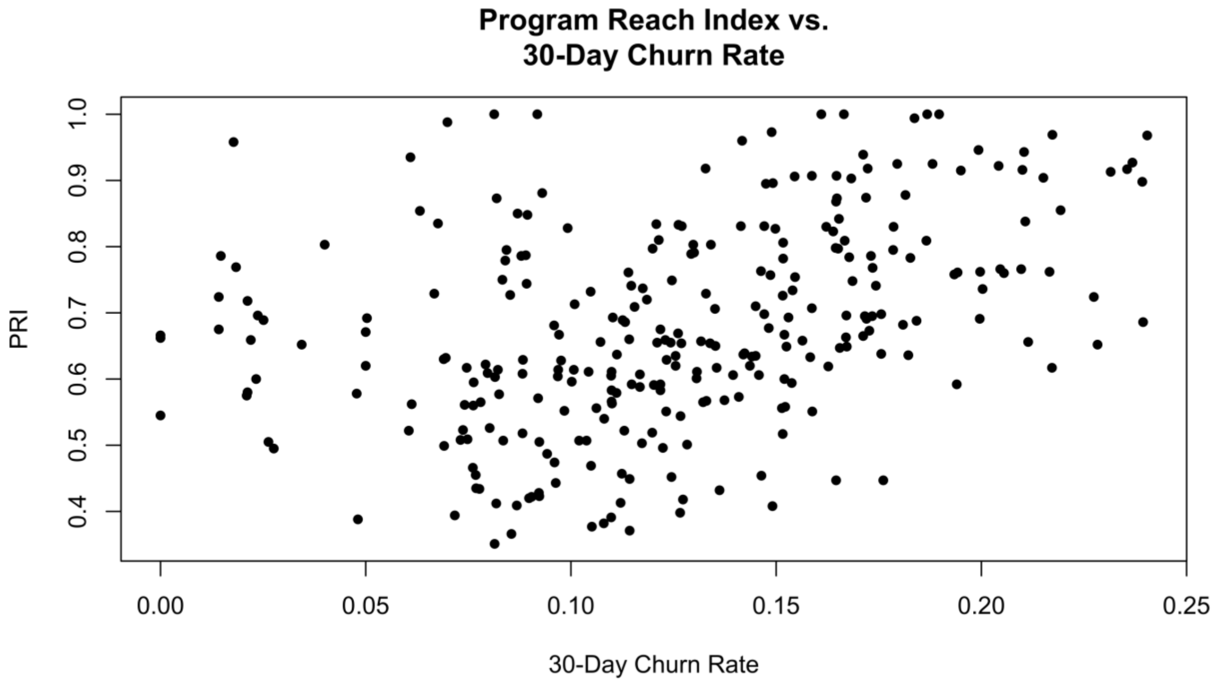

Figure 11: Scatterplot of Program Reach Index against 30-Day Churn Rate.

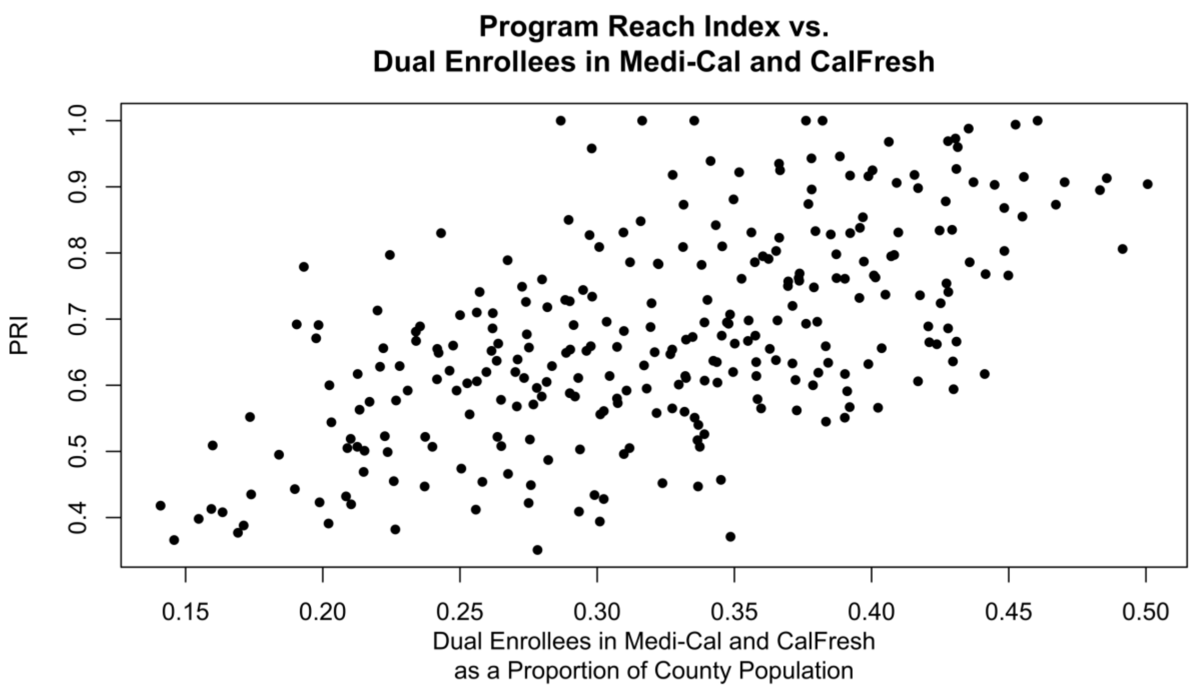

Figure 12: Scatterplot of Program Reach Index against Dual Enrollees in Medi-Cal and CalFresh (as a proportion of county population).

Discussion

In terms of finding associations between certain characteristics of counties and those counties' respective abilities to enroll people in the CalFresh program, this research is promising. Using publicly available data, this research is able to address two specific phenomena that the topic literature has often discussed as areas of concern for the CalFresh program moving forward, churn rates and the borrowing of administrative capacity between the agencies that administer CalFresh and Medi-Cal.

On churn rate, this research pushes back against some of the concerns about churn in the CalFresh program – at least as it pertains to Program Reach Index. Whereas much of the topic literature identifies churn as a problem that has existed for years (SF Marin Food Bank, 2017; TransformCalFresh.org, 2014), this research casts doubt on whether churn is actively hurting people's access to enrollment. While the SF Marin Food Bank (2017) reports that it can take ½ to 1/3 of the cost to process a recertification than a new application, the effect on PRI doesn't materialize in the data analysis side of things.

There could be a few explanations for this. For one, it should be noted that this quantitative finding does not necessarily disprove the fact that churn likely puts unnecessary stress on the applicant and the eligibility workers who have to process whole new applications, alike. In fact, given that churn is an issue across the state, it could be that the counties that are best able to handle these inefficiencies are better able to enroll larger amounts of their populations.

Alternatively, another plausible explanation is that because of the nature of churn applications being ones that have already been seen in the system and likely are still eligible for CalFresh (but lost benefits for administrative reasons) are not too difficult to process. Or, at the very least, they are not so difficult to process that the accumulation of all churned cases does not significantly hinder a county's ability to process the rest of their non-churn applications.

While churn may not actively affect PRI in the time frame looked at – in comparison to some of the other IV in the models – it is possible that its effects on the CalFresh program are outside of the scope of what PRI can capture. In terms of acute pains to CalFresh, churn may hurt applicants who lose benefits for the time period while they wait for their churned application to be processed and the counties who have to spend more money to process the new applications which take longer than simply recertifying the applicant. In the long term, churn may also hurt the county as these costs add up over time, perhaps hindering their ability to market CalFresh, hire more multilingual eligibility workers, or have enough capacity to process an influx of applications due to sudden economic downturn.

But, focusing on the other main finding of this paper may help policymakers increase PRI and decrease churn at the same time. Dual enrolling people in Medi-Cal and CalFresh at a high rate had an incredibly strong relationship with higher rates of PRI. At first glance, the fact that higher proportions of Medi-Cal Eligibles in a county is associated with higher PRI and higher proportions of CalFresh Eligibles in a county is associated with lower PRI could be confusing given that a high number of people who are eligible for CalFresh are also eligible for Medi-Cal. However, their strong correlation and opposing signs largely nullify their joint effect on PRI similar to why churn's effect was effectively nullified.

But this analysis is less sound for this three-way relationship than it was with churn rates due to a weaker relationship between the variables in terms of Pearson's correlation coefficient than was the case with the churn rate variables and the relationship between DEMC and PRI being alone quite strong.

DEMC's standalone strength in relationship with PRI paired with its relevance in previous topic literature suggests that calls for strengthening ties between the agencies that oversee CalFresh and Medi-Cal were correct. More specifically, it appears that legislation like Senate Bill 1002 introduced by then-State-Senator Kevin de León could be helpful in terms of setting up California for long-term PRI increases. The bill would have borrowed administrative capacity from the State Departments of Health Services and Social Services to determine or redetermine eligibility for CalFresh or Medi-Cal given that a person was already enrolled in one or the other. In 2014, then-Governor Jerry Brown vetoed the bill citing "Each department is working with the appropriate controlling federal agency to use existing program eligibility information to accomplish the goals of the bill" (Brown, 2014).

Nonetheless, PRI has stagnated in recent years across California. Given that DEMC has decreased over that same span (Figure 13), the data suggests that more must be done to increase dual enrollment to see continual gains in PRI. Though Brown decided SB 1002 was "not necessary" (2014) suggesting its goals might have been fulfilled regardless of the bill's passage, more should be investigated to see if this was indeed the case or what other steps can be taken to further simplify the process of dual enrollment.

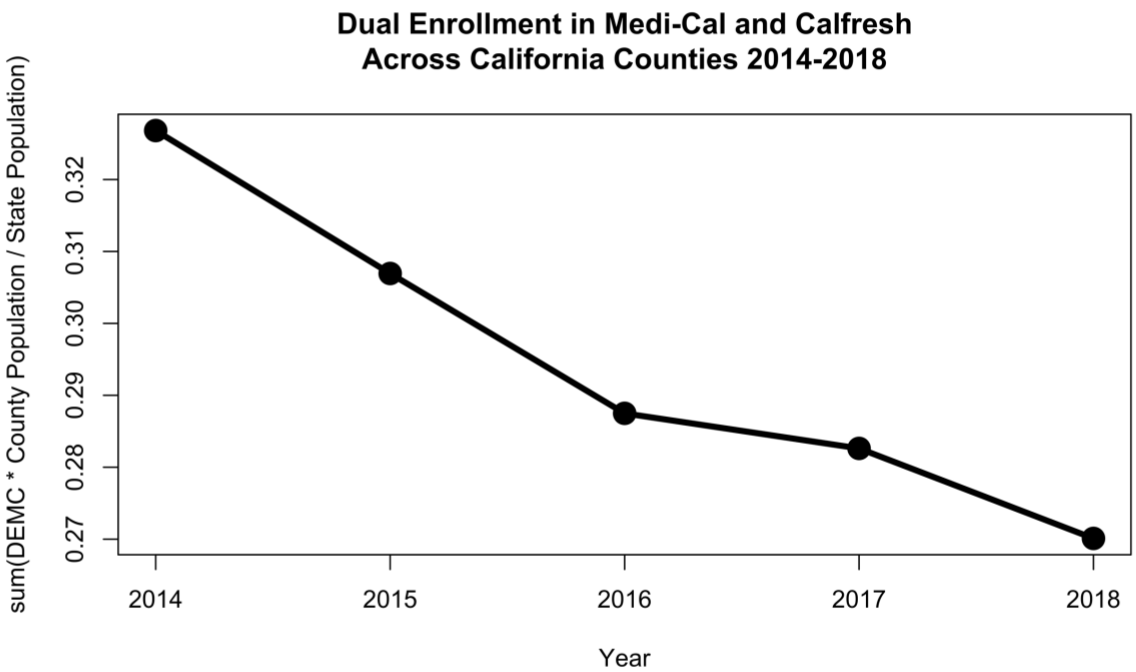

Figure 13: To look at the effect statewide over time, DEMC values must be weighted by a county's population as a measure of the whole state population for that given year. Graphed above is the population-weighted county mean for DEMC each year.

The progress in borrowing administrative capacity could double to help alleviate problems with churn in its own right. As the SF Marin Food Bank (2017) argued, "simplifying bureaucratic forms" and overall making the process of recertifying throughout the benefits year (p. 6) are significant ways to reduce churn. Thus, while churn itself might not be associated with drastic changes in PRI, focusing on increasing dual enrollment rates by reducing bureaucratic bloat that people have to navigate through to apply and maintain both CalFresh and Medi-Cal benefits could go far in increasing PRI and decreasing churn across California.

Conclusion

In answering the question of what aspects are commonly seen for counties that are particularly good or bad at implementing the CalFresh program, OLS modeling can be used to quantitatively answer this question. By analyzing PRI with OLS modeling, it is evident that higher proportions of people Dual Enrolled in Medi-Cal and CalFresh in a county are associated with higher PRI values on average. Contrary to popular belief in past topic literature, churn rates have little statistical significance when it comes to how well they explain variation in PRI across counties. In terms of policy decisions, these findings suggest that the California Department of Health Services and California Department of Social Services should borrow administrative capacity from each other to enroll eligible people in programs with similar eligibility requirements. If a person is enrolled in Medi-Cal and in the system with the DHS and are eligible for CalFresh, it would likely benefit CalFresh reach to use the credentials logged in the DHS' system to determine or redetermine eligibility for CalFresh, and vice versa.

While the data heavily suggests the findings above, it is important to note the nature of this research as an observational study. Because I looked specifically at 5 years of data and no experiment was run to determine if policies to increase DEMC would certainly cause an increase in PRI, these findings cannot necessarily be generalized to current affairs and a causal relationship between the IV and DV cannot be made. Nonetheless, this research can provide a helpful insight into what factors are common among counties that have successfully implemented CalFresh in the past. If an experiment were to be ran, this research could also be helpful in terms of providing possible treatments with logical and statistical arguments to support their inclusion.

Going forward, future research should investigate and accurately track the effect of certain treatments applied at the county level to see if meaningful, statistically significant differences are observed. Future research should continue to analyze data as it is published by the CDSS to see if these findings hold up over time. While a 5-year sample size is considerably large, it's possible that a change in policy or how CalFresh is implemented could have happened since 2018 that could be the reason for drastic PRI changes since then. By looking at the problems of CalFresh, Dual Enrollment in Medi-Cal and CalFresh, and others that could be plaguing California's battle to enroll eligible participants in the program, continuing to consider qualitative perspectives of those in county offices enrolling people and quantitative perspectives of published data should both work together to increase enrollment as a whole statewide.

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