Estimating Poverty in the Child Support Program

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Orange County Department of Child Support Services
Research Team

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EXECUTIVE SUMMARY

The motivating question for this project was: *What is the poverty rate in Orange County's child support caseload?* Understanding poverty within the realms of child support is important for:

- Examining whether child support reduces poverty
- Informing policies such as Disregard/Excess
- Understanding the impact of enforcement on poverty levels
- Setting appropriate orders
- Customizing service offerings for both parents
- Understanding barriers to payments

The Child Support Program in the United States is in a unique position to play an important role in reducing poverty. Why is poverty a concern to the Child Support Program? Children in poverty experience diminished mental, emotional, and behavioral health (Yoshikawa et al, 2012). When they grow up, poor children are more likely to be low-income adults compared with children whose parents have high incomes (Mitnik and Grusky, 2015). For adults, income is associated with life expectancy. The poor have shorter lifespans than those who are not impoverished (Chetty et al., 2016). Additionally, financial insecurity is often transmitted from generation to generation creating a cycle of poverty within a family (Wagmiller and Adelman, 2009).

For families in poverty, child support represents 40% of their income when they receive it (Sorensen, 2010). Moreover, the Child Support Program has a relationship with a large percentage of families in this country; and for a long duration of a child's formative years. In 2016, 15.6 million – or one in five – children were served by the Child Support Program, according to the U.S. Office on Child Support Enforcement (OCSE). Compared to other federal programs in the human services field, the Child Support Program ranks third behind Medicaid (35.8 million) and the Supplemental Nutrition Assistance Program (19.9 million) in terms of the number of children it serves. To put these numbers in perspective, the Temporary Assistance for Needy Families (TANF) serves 2.1 million children.

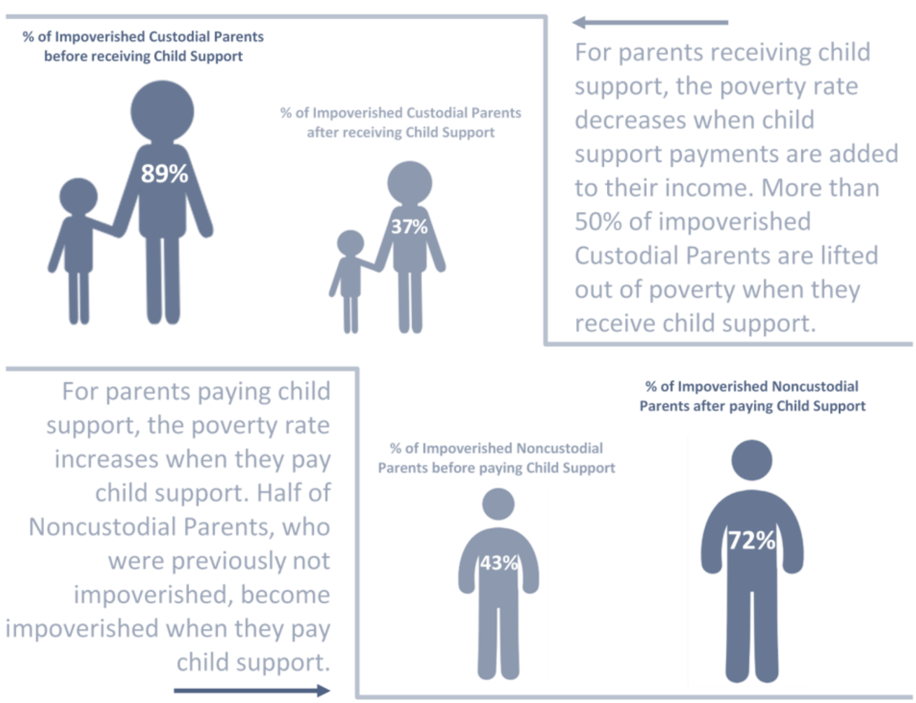
The first step in reducing poverty is for the Child Support Program to identify which families are in poverty. Doing so could serve two primary purposes:

1. Operationally, poor families in the caseload could be offered tailored case management, community services, and benefits assistance resources.

2. In terms of policy, the Child Support Program could gain a better understanding of how the poverty rate in the caseload changes over time, in varying socioeconomic conditions, and in reaction to different child support strategies (i.e., customer service initiatives, order enforcement tools, new rules and regulations).

To these ends, the Orange County Child Support Services Research Team developed a model to identify a parent's (and everyone in the household) poverty status because the nationally recognized poverty measures all require data elements that are not available in child support case files. In summary we:

1. Attempted to apply six nationally recognized poverty measures to the child support caseload to determine poverty levels, but found none feasible for use.
2. Developed our own poverty predication model specifically for child support cases.
3. Using this model, we found that parents in Deep Poverty and/or In/Near Poverty made up 91% of the Orange County child support caseload as a whole.
    a. However, each individual parental role – custodial parent (CP) and non-custodial parent (NCP) – is affected differently by child support. When child support is added to the CP's income, their poverty rate decreases from 89% to 37%. When child support is deducted from the NCP's income, their poverty rate increases from 43% to 72%.



This paper's intent is to describe how Orange County Child Support Services went about identifying impoverished parents in its caseload through the development of a poverty prediction model.

PROBLEM STATEMENT

It is not possible to apply existing poverty measures to child support caseloads because they require data not captured in child support case files; and they do not always consider geographic differences. Currently, there is not a national, standardized method for accurately assessing the poverty rates in child support caseloads. While we can observe that many families are low/very low income, we cannot assign poverty rates nor track them over time using existing poverty measures. There are six nationally recognized poverty measures, which are described below in depth. When these measures were applied to the Orange County child support caseload, the results were disparate; and upon case validation there was a high rate of inaccuracy for identifying child support caseload poverty levels.

The most commonly used poverty measure in the United States, the Official Poverty Measure (OPM), does not consider geographic differences in the cost of living. The OPM publishes one set of income thresholds that are applied to everyone regardless of where they live in the United States. During the 1990s, the federal government created the Supplemental Poverty Measure (SPM), which is an improvement over the OPM as it takes into account geographic differences in the cost of living. The California Poverty Measure (CPM) goes a step further by creating different thresholds for California counties, accounting for geographic differences in the cost of living as well as availability of benefits assistance resources such as housing subsidies.

How do these measures define poverty? If household or family income falls below an income ("resource") threshold, then they are in poverty. The thresholds in the OPM are not meant to be a complete description of what

It is important to note that the Orange County poverty prediction model process could be applied to child support caseloads in other geographic areas.

It is our hope the model can be used widely so more jurisdictions can better understand the poverty levels of the parents they serve.

people and families need to live (Fontenot et al, 2018). Rather, they are a “statistical yardstick” to compare poverty rates from year to year. The SPM provides a view of poverty at a large geographic level such as national or state. The thresholds in the SPM represent the dollar amount needed for a basic set of goods that consists of food, clothing, shelter, and utilities (FCSU) plus an additional amount for other basic needs such as household supplies, personal care, and nonwork-related transportation (Bridges and Gesumaria, 2015). Similar to the SPM, the thresholds in the CPM represent monetary resources required to maintain a basic standard of living (Bohn and Danielson et al., 2013).

Compared to fifty years ago, there is a smaller percentage of the population in poverty but the poor represent almost the same number of people. In 1959, 39.5 million people (or 22.4% of the population) were poor compared to 39.7 million (or 12.3%) in 2017. Childhood poverty has decreased but still remains large. In 1959, 17.6 million children (or 27.3%) were poor compared to 12.8 million (or 17.5%) in 2017. A much smaller percentage of the elderly are in poverty; in 1959, 5.5 million (or 35.2% of people aged 65 and older) were poor compared to 4.7 million (or 9.2%) in 2017. The age group that experienced an increase in the number of people in poverty is “working age” people; in 1959, 16.5 million (or 17% of people aged 18 to 64) were poor compared to 22.2 million (or 11.2%) in 2017.

Figure 1

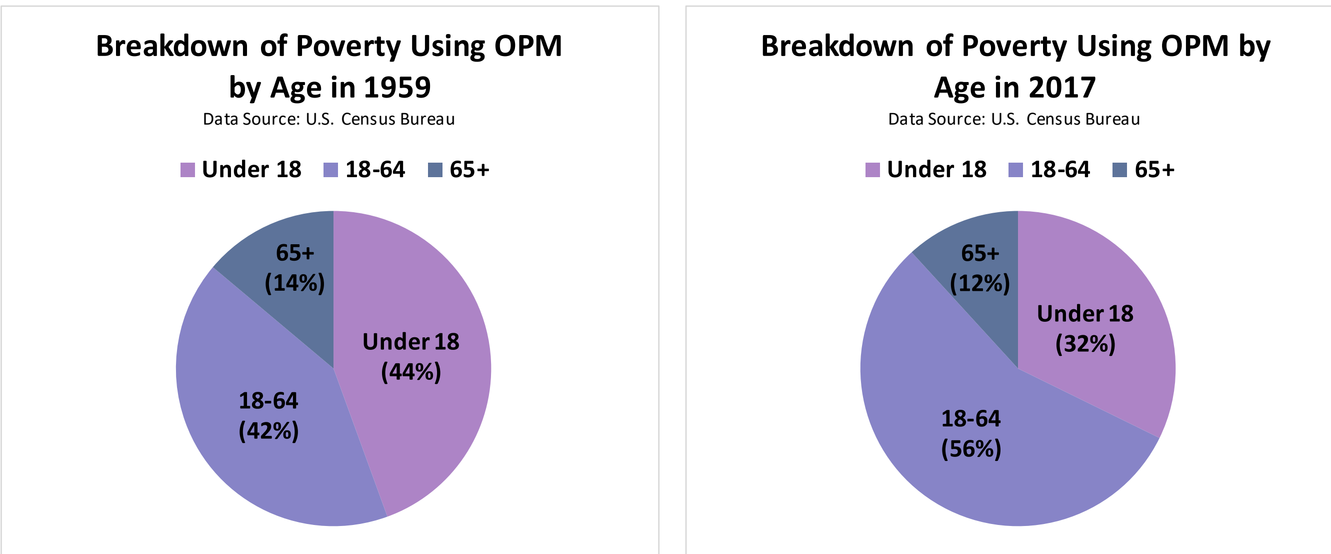
Poverty Rates Using OPM by Age
(Number of People in Poverty in Millions)
1959 vs. 2017

	1959	2017
Poverty rate in population	**22.4%** (=39.5/176.6)	**12.3%** (=39.7/322.5)
Childhood poverty rate (under 18)	**27.3%** (=17.6/64.3)	**17.5%** (=12.8/73.4)
Working age poverty rate (18-64)	**17.0%** (=16.5/96.7)	**11.2%** (=22.2/198.1)
65 and older poverty rate	**35.2%** (=5.5/15.6)	**9.2%** (=4.7/51.1)

NOTE: In parentheses, formulas are number of people in poverty divided by the population for each age segment

Being poor in this country looks different today compared to fifty years ago (DeSilver, 2014). The demographics of poverty have shifted to increasingly overlap with the demographics of child support customers – working age adults and single-parent families typically headed by a female. Focusing on age, working age people make up the largest share of the poor at 56% in 2017 compared to 42% in 1959. Furthermore, poor families are structured differently. Single-parent families headed by a female make up a much larger share of poor families today. Among poor families, 25% (or 1.9 million) in 1959 were single-parent families headed by a female compared to 51% (or 4 million) in 2017. Approximately, 10% of poor families are single-parent families headed by a male in 2017. Data is not available for single-parent families headed by a male for 1959.

Figure 2



Poverty is a function of geographic differences in the cost of living and available benefits assistance resources. For example, when we examine what poverty looks like for families in the Orange County caseload, one indicator is the cost of housing. Orange County has a very high cost of housing in comparison to the national and Statewide average. Thus, a person who is in poverty in Orange County might not be considered impoverished in other counties in California.

Figure 3

2017 Cost-of-Living Comparison
(Data source: U.S. Census Bureau)

	United States	California	Orange County, California
Median gross-rent-as-a-percentage-of-household-income	**29.8%**	**32.7%**	**33.6%**
Median gross rent for 2 bedrooms	**$991**	**$1,480**	**$1,813**

What is the income of someone who is impoverished? Figure 4 below describes how income is defined across different measures. Income is described as a "resource." According to the CPM, a single parent with one child living in Orange County, California, with $24,356 in annual *net* resources or below, is impoverished. The poverty threshold for Orange County is much higher than the thresholds for California and the United States.

Figure 4

2017 Poverty Thresholds for a One-Adult-One-Child Family
Comparison of OPM, SPM, and CPM

(Shown in the table below are OPM and SPM thresholds for United States and CPM threshold for Orange County, California)

	OPM	SPM*	CPM for Orange County‡
DESCRIPTION OF RESOURCE (INCOME, BENEFITS, ETC) MEASURE	Gross before-tax cash annual income	Annual cash income, plus noncash benefits that can be used to meet food, clothing, shelter, and utilities (FCSU) needs, minus taxes (or plus tax credits), work expenses, medical expenses, and child support paid to another household	Annual net resources (resources minus expenses) Resources include cash income, in-kind government programs, and net taxes/tax credits. Expenses include out-of-pocket expenses for commuting and other work expenses, medical costs, and childcare.
	RESOURCE AMOUNT (INCOME, BENEFITS, ETC)		
POVERTY THRESHOLD	**$17,385**	**$18,886**	**$24,356**
Deep Poverty (50% of Threshold)	**< $8,692**	**< $9,443**	**< $12,178**
In and/or Near Poverty (50%-150% of Threshold)	**$8,692 - $26,077**	**$9,443 - $28,330**	**$12,178 - $36,534**
Not in or Near Poverty (150% of Threshold)	**≥ $26,077**	**≥ $28,330**	**≥ $36,534**
California			
	OPM	**SPM**	**CPM**
	2016	**3-Year Average (2014-2016)**	**2016**
Poverty Rate	**14.3%**	**20.4%**	**19.4%**

*Threshold for renters
‡2013 CPM threshold for renters ($33,025) was adjusted for inflation.

THE PROJECT – DEVELOPING A POVERTY PREDICTION MODEL

METHODOLOGY

Data Sources

Most of the data was collected from the case management database, Child Support Enforcement (CSE), which is managed by the State of California Department of Child Support Services (DCSS). CSE contains data used to administer child support cases throughout California. The income data for this project was obtained from a specific page in CSE called the Guideline Support Calculation (GLC) Detail page which is used to determine the monthly child support order amount. Information recorded in GLCs, such as income, taxes, and expenses, are generally evaluated and validated under a uniform business process that is intended to limit errors in the data. Thus, GLCs are considered to be reliable as a data source.

Other data sources include the U.S. Census Bureau. The Consumer Price Index from the U.S. Bureau of Labor Statistics was used to adjust all monetary amounts for inflation. Other publicly available data was used to impute medical out-of-pocket (MOOP) expenses and SNAP benefits, and are discussed in the Appendices. Finally, financial data for child support cases was obtained from child support collections and distributions reports (CS 1257) published by DCSS.

Sample

Restrictions

The sample contained 34,883 records (19,657 CPs and 15,226 NCPs). To create the sample, the data was restricted to case participants with the following characteristics:

1) Had a case in Orange County that was open after October 1, 2012
2) Had an order established for their child support amount after October 1, 2012
3) Not a foster care case (98% of the cases in the Orange County caseload are not a foster care case)
4) Youngest child was active on the case (Youngest child is active on 74% of cases in the Orange County caseload)
5) Parents lived in California (76% of both parents live in California in the Orange County caseload)
6) Had a GLC in CSE
7) Parents who had wages imputed as minimum wage on the GLC were excluded because the income amounts could be presumed[1].

[1] California Code, Family Code - FAM § 17404.1. "*If the respondent's income or income history is unknown to the local child support agency, the local child support agency may serve a form of proposed judgment with the petition and other documents on the respondent that shall inform the respondent that income shall be presumed to be the amount of the state minimum*

Characteristics

The median age of CPs in the sample is thirty-three years old, and the median age of NCPs is thirty-five years old. When the oldest child on their case was born, the average CP age was 23 and the average NCP age was 25. Of those with reported income in CSE, CPs have less than half the median monthly income ($870) of NCPs ($2,010). A significantly smaller percentage of CPs have a criminal history (3.5%) compared with NCPs (19.2%). In addition, a significantly smaller percentage of CPs are male (6%) compared with NCPs (92%). Most CPs and NCPs use English as their primary language (78% and 69% respectively). Lastly, most CPs and NCPs identify as Hispanic (58% for both).

Figure 5

Sample Characteristics (n=34,883 cases)		
Variable	CP	NCP
Sample Size	19,657	15,226
Median Age	33	35
Median Age of Parent When Oldest Child on Case Was Born	23	25
Median Monthly Income on GLC	$870	$2,010
Criminal History	3.5%	19.2%
Male	6%	92%
Primary Language is English	78%	69%
Hispanic	58%	58%

Training Dataset

A training dataset is required for the predictive modeling process. It allows a model to identify which variables are strong predictors of poverty. Models are fitted to data in a training dataset containing values for the target variable. In this case, the target variable ("Poverty Level") is what is being predicted and is unknown in the child support caseload. Based on our review of the various poverty measures available we elected to use the CPM to determine the poverty status of each parent in the sample because it measures poverty of those living in California and takes into consideration geographic differences at the county level in cost-of-living.

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wage, at 40 hours per week, unless information concerning the respondent's income is provided to the court." https://leginfo.legislature.ca.gov/faces/codes_displayText.xhtml?lawCode=FAM&division=17.&title=&part=&chapter=2.&article=1.

PROJECT PHASES

In addition to explaining the results generated by the predictive model, and its purpose and applicability to child support, this paper describes the process involved in creating that model. These process elements are included for two primary reasons:

- To seek peer review on the viability of the model
- To save other researchers the time and expense of attempting to predict poverty in the child support program using existing measures, and instead focus efforts on testing and refining the model for use across the country

The most commonly used poverty measures in the United States – Official Poverty Measure (OPM), Federal Poverty Guidelines, Minimum Basic Standard of Adequate Care (MBSAC), Housing and Urban Development (HUD), Supplemental Poverty Measure (SPM), and California Poverty Measure (CPM) – require data elements that the Child Support Program does not have in a readily usable format. These measures incorporate household income, housing situation, family size, age of householder, and family composition; all data we do not have available at the local level. In light of this challenge the initial inquiry ultimately evolved into a multi-phase endeavor. We describe below the path that led to the development of our own model.

Figure 6

SUMMARY OF PROJECT PHASES	
Phase	**Findings**
1	Using existing poverty measures to estimate poverty is difficult because CSS does not have the required data elements in a readily usable format. To estimate poverty, the Child Support Program needs a method that uses data that is collected during the child support process.
2	Developing a prediction model to identify a parent's poverty level is possible using information from Income & Expense (I&E) Declarations but results could be inaccurate due to the relatively small sample size, existence of sample selection bias, and the self-reported nature of I&E data.
3	Data from Guideline Calculations (GLC[2]) generally improves the accuracy of most prediction models. The models could serve different purposes – policy or operational – depending on the target variable and the model's misclassification rate.

Phase 1

In Phase 1, the goal was to gain a broad understanding of the poverty literature, develop an inventory of existing poverty measures, and determine poverty rates of parents using a variety of these existing and commonly used poverty measures.

The inventory of recognized poverty measures in California and the United States revealed a shortcoming. (See the Appendix for the inventory.) They all required data elements that Child Support Services agencies (CSS) do not have in a readily usable format. These include household income, housing situation, family size, age of householder, and family composition. Imputing all of the data elements would be challenging, and more importantly, would lead to less precise and potentially inaccurate conclusions.

Nevertheless, we attempted to use the six poverty measures from the inventory and a newly created CSS Adjusted Measure – which adjusted the OPM based on the cost-of-living in Orange County – to estimate poverty in Orange

[2] A statewide "calculator" that estimates the amount of child support on a case

County's child support caseload. We did this by imputing the required data elements for each measure that are not captured in child support case files[3]. Depending on the measure, poverty rates ranged from 19% to 87% as noted below.

Figure 7

Poverty Measure	Minimum Basic Standard of Adequate Care	Official Poverty Measure	Federal Poverty Guidelines	Supplemental Poverty Measure	California Poverty Measure	HUD eligibility for assisted housing programs
% of Caseload in Poverty	19%	34%	35%	53%	59%	87%

We concluded that, to understand poverty in the Child Support Program, we needed to estimate poverty using data that is collected during the child support process because each measure requires data that is not captured in child support case files and imputation methods might not be precise enough to obtain accurate results. We also considered that imputing data might not be feasible for many child support agencies across the country which could be a barrier for measuring poverty in child support caseloads nationwide

Phase 2

In Phase 2, it was determined that a prediction model would be developed to estimate a person's poverty level using data that the Child Support Program typically collects. To complete this phase, a partnership was forged with the Public Policy Institute of California (PPIC) who provided technical assistance and research guidance. PPIC is based in San Francisco and is a nonprofit think tank dedicated to improving public policy in California through independent, objective, and nonpartisan research. PPIC and its partner, Stanford University, developed the CPM.

The CPM was selected as the foundation of our prediction model because it is the most reliable and well-tested method for determining poverty for those living in California. This poverty measure is an improvement on the OPM which uses only one set of thresholds for the entire country. In contrast, the CPM considers geographic

[3] The imputed data elements included: household income, family size, age of householder, family composition, and housing situation (rent vs. own).

differences in California in regards to socioeconomic conditions such as cost-of-living and available benefits assistance resources at the county level. See Appendix C for a description of the CPM's history and design.

The purpose of Phase 2 was to compare the accuracy of three prediction model types that we developed: (1) Five-Level Categorical Model, (2) Three-Level Categorical Model, and (3) Binary Model. Each had a different target variable shown in the following table.

Figure 8

<table>
<tr><th>Model Type 1

Five-Level Categorical Variable of Poverty</th><th>Model Type 2

Three-Level Categorical Variable of Poverty</th><th>Model Type 3

Binary Variable of Poverty</th></tr>
<tr><td>Under 50% of CPM Threshold</td><td>Under 50% of CPM Threshold</td><td rowspan="2">In Poverty</td></tr>
<tr><td>50%-99% of CPM Threshold</td><td>50%-99% of CPM Threshold</td></tr>
<tr><td>100%-149% of CPM Threshold</td><td rowspan="3">100% or Above the CPM Threshold</td><td rowspan="3">Not in Poverty</td></tr>
<tr><td>150%-199% of CPM Threshold</td></tr>
<tr><td>200% or Above the CPM Threshold</td></tr>
</table>

The Binary Models performed the best. The Binary Model that used the statistical approach, gradient boosting, had a 31% misclassification rate. That is, the model predicted a person's poverty status incorrectly 31% of the time. This model used imputed values for all key data elements: household income, housing situation, family size, and family composition. Forty-five variables were used to develop the prediction model. The final model ended up being fairly complex with twenty-two variables being significant enough to enter the model.

We also ran models on data obtained from Income & Expense (I&E) Declarations which are filled out by parents with information about their income and expenses. Using I&E data allowed us to reduce the number of elements that needed to be imputed. During this run, the modified decision tree had the lowest misclassification rate of 20%. The increase in accuracy suggests that I&E data improved the predictive power of the model. The other models – which also used I&E data – did not perform as well as the Binary Models. The Five-Level Categorical Model had a misclassification rate of 44% and the Three-Level Categorical Model, 65%. Detailed misclassification information is located in Appendix A.

In Phase 2, we concluded that a prediction model could be developed to estimate poverty with a high level of accuracy using I&E data and a binary target variable. However, I&E data has its shortcomings.

First, I&E data has sample selection bias: parents who complete I&Es are notably different than parents throughout the caseload. In an attempt to address this bias, 900 records were chosen for the sample using a stratified random sampling method based on case participant role (CP or NCP), race, and court order type. Another shortcoming is that I&E data is self-reported and could contain misrepresentations of the parent's actual income and expenses. See Appendix E to view a sample I&E form.

Phase 3

In this phase, we developed methods for imputing SNAP benefits and MOOP expenses. SNAP benefits comprise part of the "Resources" calculation for the CPM. Resources is defined as pre-tax income including cash income, in-kind government programs, and net taxes/tax credits. MOOP expense is part of the expenses calculation for the CPM.

In light of their relevance to the CPM, and because SNAP benefits and MOOP expense information are not readily available, it was important to develop imputation methods for these elements. SNAP benefits comprise a substantial portion of a family's budget and is widely used among low-income families. Similarly, MOOP expenses represent a large percentage of spending for most families. One element for which we did not develop an imputation method was housing subsidies, due to the complexity involved. Imputing who receives a subsidy would be difficult because few eligible families actually receive a housing subsidy. A more detailed description of our imputation methods is in Appendix D.

Phase 3 resulted in six prediction models that have different design features: (1) degree of poverty represented by the target variable, (2) case participant role, and (3) gross income adjustment (GIA[4]). The following table contains a description of the different target variables for the two-level and three-level model designs.

[4] GIA is defined as either paying or receiving child support.

Figure 9

MODEL DESIGNS

Two-Level Poverty Target	
Impoverished	Household income is less than 100% of the California Poverty Measure (CPM) threshold
Not Impoverished	Household income is at or above 100% of the CPM threshold
Three-Level Poverty Target	
Deep Poverty	Household income is less than 50% of the CPM threshold
In or Near Poverty	Household income is between 50% and 150% of the CPM threshold
Not in Poverty	Household income is at or above 150% of the CPM threshold

As noted, the models were also designed specifically in consideration of participant role: CP and NCP. We hypothesized that different factors are correlated with ability to meet basic needs depending on case participant role. The results confirm our hypothesis; the prediction models for CPs have different poverty indicators from the prediction models for NCPs.

Gross Income Adjustment (GIA) refers to either paying or receiving child support. For example, if you are the parent receiving child support, your income increases.

Last, the models differ according to their income. Some models used GIA which accounts for child support payments in a person's income. For CPs, the monthly child support amount paid was added to their monthly income. For NCPs, the monthly child support amount paid was deducted from their monthly income. Accounting for child support in a person's income yields a more realistic picture of their financial situation.

Figure 10

Gross Income Adjustment (GIA)	
With GIA	• For CPs, the monthly child support amount was added to their monthly income • For NCPs, the monthly child support amount paid was deducted from their monthly income
Without GIA	• For CPs and NCPs, child support amount paid is <u>not</u> accounted for in the calculation of monthly income

Finally, due to the differing strength of results, the Research Team suggests using the models for different purposes. The two-level models are better suited for policy discussions and the three-level models should only be used for operational purposes. The two-level models have a relatively low misclassification rate (19-26%) making them accurate enough for high-level policy discussions. Using the two-level poverty target variable, four prediction models were developed by examining a different case participant (CP or NCP) and GIA (with and without child support as part of the income calculation). However, the two-level models are less helpful for operational use because they give only a black-and-white view of poverty that does not accurately depict the more fluid day-to-day realities of parents. In fact, segments of parents can fall in and out of poverty on a frequent basis.

The three-level models however were developed for operational use. These models provide a more precise view of the financial insecurity that parents face. In addition, these models recognize that impoverished parents are not all the same. Some are closer to the poverty line than others. However, these models should not be used to inform overarching policy discussions because of their misclassification rates (32% and 38%) . More importantly, these models overestimate poverty which is not problematic for operational use (i.e., some parents might be offered services that they might not need) but could be misleading in policy discussions.

There are some additional limitations on how the prediction models can be used. Specifically, the models are intended to be applied only to parents meeting the following characteristics:

1) Has an open case in Orange County
2) Is not a foster care case
3) Youngest child is active on the case (not an arrears-only case[5])

[5] Accumulating arrears is caused by child support not being paid by the NCP. Some cases may be paid in full on the current monthly amount due, but still carry a past-due balance also known as "arrears".

4) Lives in California

Two case types were restricted from the sample due to data availability and parent behavior: (1) foster care and (2) arrears-only cases. Foster care cases are cases in which the dependent child has been placed with foster care parents and the CP's right to child support has been suspended. Arrears-only cases have a complicated disbursement process depending on whether the CP has ever received public assistance. Most likely, these case types have different factors that are correlated with their poverty level compared to the rest of the caseload. To understand the poverty rate of foster care or arrears-only parents, separate and specific models should be developed in future research.

The results of Phase 3 are presented in the following section.

PREDICTIVE MODELING RESULTS

RESULTS: POVERTY IN ORANGE COUNTY'S CASELOAD USING TWO-LEVEL MODELS

Orange County's April 2018 caseload was first scored using the two-level prediction models. For this project, scoring equates to applying a previously fitted statistical model to a data set in order to predict a parent's poverty level. Model A (CP without GIA) indicates that the poverty rate for CPs is 89%. Model B (CP with GIA) indicates a poverty rate of 37%. Therefore, the results suggest that child support lifts 50% of CPs out of poverty each year. Model C (NCP without GIA) indicates that the poverty rate for NCPs is 43%. Model D (NCP with GIA) indicates a poverty rate of 72%. The results suggest that the collection of child support pushes approximately a quarter of NCPs into poverty each year. When we examine all case participants (CPs and NCPs combined), the models suggest that child support reduces poverty from 68% to 53%. Note that all models performed fairly well with misclassification rates between 19% and 26%.

Figure 11

Poverty in the Orange County Caseload (April 2018) Using Two-Level Poverty Models (n=73,359)						
	WITHOUT GIA			**WITH GIA**		
DEGREE OF POVERTY	**CP**	**NCP**	**All Case Participants**	**CP**	**NCP**	**All Case Participants**
	Model A	Model C	Total	Model B	Model D	Total
Impoverished	**89%** (35,308)	**43%** (14,582)	**68%** (49,890)	**37%** (14,672)	**72%** (24,050)	**53%** (38,722)
Not Impoverished	**11%** (4,478)	**57%** (18,991)	**32%** (23,469)	**63%** (25,114)	**28%** (9,523)	**47%** (34,637)

RESEARCH FINDING: For CPs, the poverty rate decreases when child support payments are added to their income. More than half of impoverished CPs are lifted out of poverty. On the other hand, for NCPs, the poverty rate increases when child support payments are deducted from their income. Half of NCPs – who were previously classified as Not Impoverished – become Impoverished. The net impact, considering both populations is a positive impact on poverty reduction, lifting in excess 15% of individuals out of poverty.

RESULTS: POVERTY IN ORANGE COUNTY'S CASELOAD USING THREE-LEVEL MODELS

Orange County's April 2018 caseload was also scored using the three-level prediction models. All models use income that accounts for child support payments which provides a more realistic picture of a person's financial situation. Model E (CP with GIA) indicates that 31% of CPs are in Deep Poverty, 64% are In or Near Poverty, and 6% are Not in Poverty. Model F (NCP with GIA) indicates that 26% of NCPs are in Deep Poverty, 61% are In or Near Poverty, and 13% are Not in Poverty. When the data on CPs and NCPs are combined, the models indicate that 29% of parents are in Deep Poverty, 62% are In or Near Poverty, and 9% are Not in Poverty. The results confirm that most parents (91%) are in or near poverty, or worse, in deep poverty. Note that the models performed fairly well, but not as well as the two-level models, with misclassification rates of 38% and 32%.

Figure 12

Poverty in the Orange County Caseload (April 2018) Using Three-Level Poverty Models (n=73,359)				
	WITH GIA			
DEGREE OF POVERTY	**CP**	**NCP**	**All Case Participants**	**Median Monthly Income**
	Model E	Model F	Total	
Deep Poverty (Income is less than 50% of CPM Threshold)	**31%** (12,226)	**26%** (8,714)	**29%** (20,940)	**$1,180**
In or Near Poverty (Income is between 50% and 150% of CPM Threshold)	**64%** (25,331)	**61%** (20,387)	**62%** (45,718)	**$1,660**
Not in Poverty (Income is at or above 150% of CPM Threshold)	**6%** (2,229)	**13%** (4,472)	**9%** (6,701)	**$5,560**

RESEARCH FINDING: Parents in Deep Poverty or In or Near Poverty made up **91%** of the CSS caseload. Thus, there is a clear imperative for providing families with tailored case management, additional services, and/or community resources to help them meet their basic needs.

CHARACTERISTICS OF PARENTS IN POVERTY

Impoverished parents cannot afford to pay their child support due to their low income, resulting in a lower rate of child support payments and a higher arrears balance. Noteworthy is the arrears balance of parents who are In or Near Poverty using the three-level prediction model. They have the highest arrears balance compared to the other two groups: Deep Poverty and Not in Poverty. The factors contributing to the accrual of arrears in the In or Near Poverty group needs further exploration.

USING THE TWO-LEVEL PREDICTION MODEL

The following is a summary Orange County parents by poverty using the two-level prediction model:

- Impoverished parents have lower monthly child support obligations ordered than Not Impoverished parents
- Impoverished parents have less monthly income than Not Impoverished parents
- Impoverished parents have higher arrears balances than Not Impoverished parents
- Impoverished parents pay less child support (42%) than Not Impoverished parents (97%)

Figure 13

Characteristics of Parents by Poverty Level
Orange County's Caseload (April 2018)
Using Two-Level Poverty Models – All Case Participants with GIA (n=73,359)

	Impoverished (n=38,722)	**Not Impoverished** (n=34,637)
Average Child Support Order Amount	$298	$456
Median Child Support Order Amount	$250	$340
Average Monthly Income	$1,651	$4,084
Median Monthly Income	$1,190	$3,170
Average Arrears Balance	$12,036	$8,369
Median Arrears Balance	$1,100	$0
Total Arrears (in millions)	$466.0	$289.7
Records Owing Arrears	23,815	14,946
Median % of Child Support Paid	42%	97%
% Never Received Public Aid	26%	49%

More than half of the Not Impoverished parents have a child support case with zero arrears. The large number of zero-arrears cases in the Not Impoverished group is probably due to the design restrictions on the sample used to develop the models as well as restrictions on cases that were scored. As noted, we excluded cases with emancipated children which tend to be arrears-only cases.

USING THE THREE-LEVEL PREDICTION MODEL

The following is a summary of characteristics of Orange County parents using the three-level prediction model:

- Parents who are in Deep Poverty have lower order amounts than those who are In or Near Poverty or Not in Poverty
- Parents who are in Deep Poverty have the lowest monthly income
- Parents who are in Deep Poverty have the lowest average arrears balances
- Parents who are In or Near Poverty have the highest average arrears balances
- The median arrears for those who are in Deep Poverty and those Not in Poverty is $0
- Parents who are in Deep Poverty paid less child support than the other two poverty groups

For the Deep Poverty group, the median child support order amount is $0. Ninety percent of those in Deep Poverty have a zero-dollar order.[6] The large number of zero-dollar orders is probably due to the parents' limited income which plays a major role in the child support order amount formula. Other factors that might be contributing to their zero-dollar orders include incarceration, disability, and unemployment – all of which needs to be further explored. Moreover, the median arrears balance for the Deep Poverty group is $0, which makes sense as most of these cases cannot accrue arrears because there is no child support due each month.

For the Not in Poverty group, the median arrears balance is also $0. In fact, 58% of those who are Not in Poverty have zero arrears. This is possibly due to their higher income which allows NCPs to pay the full amount of their child support each month with less impact to their basic needs.

Figure 14

Characteristics of Parents by Poverty Level
April 2018 Caseload in Orange County
Using Three-Level Poverty Models – All Case Participants with GIA
(n=73,359)

	Deep Poverty (n=20,940)	In or Near Poverty (n=45,718)	Not in Poverty (n=6,701)
Average Child Support Order Amount	$35	$465	$800
Median Child Support Order Amount	$0	$350	$610
Average Monthly Income	$2,200	$2,260	$7,140
Median Monthly Income	$1,180	$1,660	$5,560
Average Arrears Balance	$7,990	$11,640	$8,400
Median Arrears Balance	$0	$890	$0
Total Arrears (in millions)	$167.3	$532.3	$56.2
Records Owing Arrears	6,371 (30%)	29,552 (65%)	2,838 (42%)
Median % of Child Support Paid	0%	82%	99%
% Never Received Public Aid	15%	41%	77%

[6] Zero-Dollar orders are when the verified NCP does not have ability to pay any child support. Instances that would warrant a zero child support order include but are not limited to:

- Obligor's only source of income is from a needs based program such as:
  - Supplemental Security Income - Title XVI (SSI/SSP)
  - Temporary Assistance for Needy Families (TANF/CalWORKs)
  - Cash Assistance Program for Immigrants (CAPI)
  - General Relief (GR)
- Obligor currently incarcerated and no source of income
- Obligor currently institutionalized in a psychiatric facility and no source of income
- Obligor has a medically verified permanent disability and no source of income

CONCLUSION

The Child Support Program is often described as a poverty reduction program[7]. This project identifies poverty in Orange County's caseload to shed light on how child support affects the family as a whole. In a multi-phase endeavor, we developed six prediction models to identify a person's poverty level using GLC data. This study did not attempt to measure the impact of enforcement actions on poverty; however studying enforcement actions through the lens of poverty is recommended.

Our analysis showed that the two-level models are accurate enough to inform macro-level policy discussions on the Child Support Program's impact on poverty. For example, these models could be used to determine changes in the poverty rate within Orange County's caseload over time and in varying political and economic conditions. The three-level models however, provide a more nuanced view of poverty. These models could be used at the micro level for segmenting the caseload according to poverty level so that parents in Deep Poverty or In or Near Poverty could be offered tailored case management, services, and resources.

Multiple opportunities exist for building upon this initial research effort. As discussed in the prior section, future research could develop prediction models that incorporate different data elements to improve the accuracy of the prediction models and that focus on different segments of the caseload. The results would add both operational value, as the research would be relevant to a greater portion of parents, and policy value, because it would inform legislative and regulatory discussions such as those considering the effectiveness of child support as a recoupment tool for public assistance, for example.

CONSIDERATIONS FOR FUTURE RESEARCH

Child support cases often have a complex set of circumstances. Thus, we could not consider all of the many different case scenarios in this one study. However, future research could examine the following topics and research questions:

- **Arrears Payments**: Should the amount that NCPs pay in past due child support should be deducted from their income? By doing so, we would represent NCPs financial situation more realistically. Moreover, this amount could be added to CP's income when appropriate. Including arrears payments in CP's income is difficult

[7] Federal Register / Vol. 81, No. 244 / Tuesday, December 20, 2016 / Rules and Regulations, DEPARTMENT OF HEALTH AND HUMAN SERVICES Centers for Medicare & Medicaid Services, 42 CFR Part 433 [CMS–2343–F] RIN 0938–AR92. Administration for Children and Families, 45 CFR Parts 301, 302, 303, 304, 305,307, 308, and 309. https://www.gpo.gov/fdsys/pkg/FR-2016-12-20/pdf/2016-29598.pdf

because disbursement of arrears depends on the whether the CP had ever received public assistance. In almost two-thirds of the Orange County caseload, NCPs owe arrears. Additionally, accounting for interest on child support that is owed would further refine the economic status of NCPs.

- **Crossfiles**: Should child support payments for all crossfiles in California should be taken into consideration[8]? Payments for all crossfiles could be deducted from NCP's income and child support received from all crossfiles would be added to CP's income. Because we have access to statewide data, including child support payments from all crossfiles would not be difficult. In the OC caseload, 16% of NCPs have a crossfile – in which they are the NCP – currently open in California. It is also possible for NCPs to be a CP in a crossfile. If we account for both parental roles in crossfiles, then the percent of NCP crossfiles would increase. In addition, calculating income would become more difficult.

- **Disregard and Excess Amounts**: In California, CPs receive the first fifty dollars (disregard) of a child support payment when the CP is a welfare recipient. The rest of the child support payment is used to reimburse the State's welfare program; hence, anything above fifty dollars that the NCP pays goes to the State, not the CP. When an NCP pays more than the CP's public assistance amount, the extra money is referred to as excess and is paid to the CP when specific case conditions exist; however, this rarely occurs. What is the effect of disregard and excess dollars on CP's level of poverty? In OC's caseload, approximately 17% of cases are currently receiving public assistance and 48% of cases formerly received public assistance. In future research, accounting for disregard and excess amounts would be challenging due to the variety of scenarios that would need to be considered. However, pursuing this policy question would be a valuable contribution to the child support field. It could provide insight into whether recouping public assistance dollars through child support aligns with the program goal of reducing poverty.

[8] A crossfile is a companion case involving a non-custodial parent or custodial party. These cases usually consist of other children by either parent with a different mother or father.

APPENDIX A: MODEL COMPARISONS

Using SAS Enterprise Miner software, various models were run on the training dataset. The software program fits a model to the data and provides diagnostic statistics on the accuracy of the model as well as a list of significant predictor variables. The sample was partitioned using a 50/50 ratio. Fifty percent of the sample was used as the training dataset and 50% of the sample was used as the validation dataset. Running the prediction models on the validation dataset provides information on how well the models generalize to the child support caseload.

The statistic that was used to assess the performance and fit of the models was the misclassification rate on the validation dataset. The misclassification rate indicates the percent of time that the model inaccurately predicts the target variable. If the misclassification rate is low for the training dataset but high for the validation dataset, then the model might be overfitted. That is, it performs well on the training dataset but it does not generalize to the child support caseload. In this project, none of the models were overfitted.

We used two different versions of the target variable: (1) two-level poverty (Impoverished / Not Impoverished) and (2) three-level poverty (Deep Poverty / In or Near Poverty / Not In Poverty). A set of five statistical models were run on the data for each version of the target variable. Three of the models were different versions of a decision tree. The following table shows how the trees differed in minimum leaf size, surrogate rules (which are used when SAS Enterprise Miner comes across missing data), significance level for the splitting rule, and whether inputs are used only once. The other models were gradient boosting and regression. All of these other models were run on the data with default settings.

Figure 15

MODEL DESCRIPTION	Minimum Leaf Size	Surrogate Rules	Splitting Rule Significance Level	Use Input Once
1) Decision Tree	100	0	0.05	Yes
2) Decision Tree #2	100	0	0.50	Yes
3) HP Tree	5	0	0.20	No

The decision tree was selected as the best approach to predicting poverty because of the low misclassification rate and ease of interpreting the results. The following table contains misclassification rates for all statistical models.

Figure 16

	Two-Level Model Misclassification				Three-Level Model Misclassification	
	Model A	Model B	Model C	Model D	Model E	Model F
	CP Without GIA	**CP With GIA**	**NCP Without GIA**	**NCP With GIA**	**CP With GIA**	**NCP With GIA**
Gradient Boosting	18.12%	20.14%	22.26%	23.84%	26.70%	23.01%
Decision Tree	19.29%	22.38%	24.69%	26.16%	27.77%	24.42%
Decision Tree #2	19.29%	22.38%	24.69%	26.16%	27.77%	24.42%
HP Tree	19.40%	22.33%	24.40%	25.58%	27.66%	23.62%
Regression	19.77%	25.26%	31.13%	23.72%	39.09%	30.87%

VARIABLES IN THE MODELS

A total of thirty-six variables were used to develop the prediction models. The variables in the models are a mixture of participant and case variables. Variables that predicted poverty are indicated below with a checkmark.

Figure 17

PARTICIPANT VARIABLES						
	Two-Level Poverty Models (Impoverished / Not Impoverished)				Three-Level Poverty Models (Deep Poverty / In or Near Poverty / Not in Poverty)	
	Model A	Model B	Model C	Model D	Model E	Model F
	CP Without GIA	**CP With GIA**	**NCP Without GIA**	**NCP With GIA**	**CP With GIA**	**NCP With GIA**
Reported Monthly Income	✓	✓	✓	✓	✓	✓
Percent of Those With HS Degree in Census Tract Where Parent Lives						✓
Primary Language						✓
Ratio of Order to NCP's Wage						✓

Other variables that were considered but were not significant predictors of poverty include:

1. Age of Parent
2. Age of Parent When Oldest Child on Case Was Born
3. Criminal History (Yes/No)
4. Employed at Time of GLC (Yes/No)
5. Ever Had a License (Yes/No)
6. Ever Had an SSN (Yes/No)
7. Ever in the Military (Yes/No)
8. Gender
9. Has Address in CSE (Yes/No)
10. Has Email in CSE (Yes/No)
11. Has Phone in CSE (Yes/No)
12. Median Rent-as-a-Percent-of-Household-Income in Census Tract Where Parent Lives
13. Number of Crossfiles in OC
14. Number of Health and Social Assistance Establishments in Zip Code Where Parent Lives
15. Number of Violent Crimes Per 100,000 Inhabitants Where Parent Lives
16. Participant Identification Number
17. Percent of Those With College Degree in Census Tract Where Parent Lives
18. Race

Figure 18

CASE VARIABLES						
	Two-Level Poverty Models (Impoverished / Not Impoverished)				Three-Level Poverty Models (Deep Poverty / In or Near Poverty / Not in Poverty)	
	Model A	Model B	Model C	Model D	Model E	Model F
	CP Without GIA	**CP With GIA**	**NCP Without GIA**	**NCP With GIA**	**CP With GIA**	**NCP With GIA**
Child Support Order Amount			✓		✓	✓
Percent of Child Support Paid Over One Year		✓	✓		✓	
Public Aid Status	✓	✓			✓	
Order Type for the First Court Order					✓	
Count of Dependents on Case						✓

Other variables that were considered but were not significant predictors of poverty include:

1. Arrears Balance at Start of 12 Months
2. Case Age (Years)
3. Case Function
4. Number of Times Case Was Closed
5. Number of Times Case Was Opened
6. Oldest Dependent's Age (Years)
7. Youngest Dependent's Age (Years)
8. Youngest Dependent's Parentage Status
9. Youngest Dependent's Status on Case

MISCLASSIFICATION OF TWO-LEVEL MODELS

All two-level models performed fairly well with misclassification rates between 19% and 26%. Misclassification rates are produced by SAS Enterprise Miner as part of the diagnostic statistics. There is no industry standard for an acceptable maximum for misclassification rates. For this project, we defined an acceptable maximum as 40%. Any model that had a misclassification rate below 40% was considered acceptable for our research purposes.

For the two-level models, Model A (CP without GIA) has a misclassification rate of 19%. That is, the model incorrectly identifies the poverty status of case participants 19% of the time. Model B (CP with GIA) has a misclassification rate of 23%. Model C (NCP without GIA) has a misclassification rate of 25%. Lastly, Model D (NCP with GIA) has a misclassification rate of 26%.

Misclassification rates were also produced by manually validating the models. This was done by comparing a parent's income to CPM thresholds. First, the April 2018 caseload in Orange County was scored. Then, a random sample was selected. Then, record by record, the data in the sample was verified against information in CSE which is considered the official record of child support cases. This step served two purposes: (1) ensure that the data was extracted and cleaned correctly; and (2) confirm that poverty predictions made sense in regards to various case characteristics. Finally, for each parent, their income was measured against the CPM thresholds to obtain a poverty status. This poverty status was then compared to the predicted poverty status to calculate a "manual validation" misclassification rate.

The CP models (with and without GIA) had slightly higher misclassification rates when validated manually. Model A (CP without GIA) has a manual validation misclassification rate of 23% compared to the SAS Enterprise Miner misclassification rate of 19%. Model B (CP with GIA) has a manual validation misclassification rate of 29% compared to the SAS Enterprise Miner misclassification rate of 23%.

On the other hand, the NCP models (with and without GIA) performed better when validated manually. Model C (NCP without GIA) has a manual validation misclassification rate of 8% compared to the SAS Enterprise Miner misclassification rate of 25%. Model D (NCP with GIA) has a manual validation misclassification rate of 22% compared to the SAS Enterprise Miner misclassification rate of 26%.

One reason that the models performed differently in the two validation processes is that the data sources are different. The data used in SAS Enterprise Miner to validate the models was extracted from a case participant's GLC. The data used to manually validate the models was extracted from information in CSE. Income on the GLC is self-reported and verified with paycheck stubs and/or tax returns. Income in CSE is self-reported and/or obtained from various national databases such as the National Directory of New Hires. The different income data sources could explain the different validation results.

In addition, we considered the type of error the prediction models made. For the two-level models, false negatives indicate how much the models underestimate poverty. These errors occur when, in this project, a person is estimated to be Not Impoverished when they actually are Impoverished. False positives indicate how much the models overestimate poverty. These errors occur when a person is estimated to be Impoverished when they actually are Not Impoverished.

When validated manually, some two-level models performed well in regard to false negatives. Both Model B (CP with GIA) and Model C (NCP without GIA) captured almost everyone who was Impoverished (98% and 99% respectively). These models have very little false negatives. However, the rest of the models underestimate poverty at much higher rates. Models A and D captured fewer people who were Impoverished (71% and 81% respectively). These models have a considerable amount of false negatives.

Regarding false positives, all of the models overestimate poverty. Models A and C incorrectly identified people as Impoverished when they actually are Not Impoverished about 13% of the time. The other models (Models B and D) misidentified the poverty status at much higher rates (40% and 25% respectively). We are not concerned about false positives when informing policy because even those who are not classified as impoverished are often low income and may also benefit from program enhancements that are primarily intended to benefit those in poverty.

Figure 19

Two-Level Models (Impoverished / Not Impoverished)					
		SAS Enterprise Miner Validation	**Manual Validation**		
MODEL		**Misclassification Rate**	**Misclassification Rate**	**Correctly Identified as Impoverished**	**Incorrectly Identified as Impoverished**
CP Without GIA	**Model A**	19%	23%	71%	13%
CP With GIA	**Model B**	23%	29%	98%	40%
NCP Without GIA	**Model C**	25%	8%	99%	13%
NCP With GIA	**Model D**	26%	22%	81%	25%

MISCLASSIFICATION OF THREE-LEVEL MODELS

According to SAS Enterprise Miner, all three-level models performed fairly well. Model E (CP with GIA) has a misclassification rate 38%. This model performed better when validated manually with a misclassification rate of 31%. According to SAS Enterprise Miner, Model F (NCP with GIA) has a misclassification rate of 32%. This model performed worse when validated manually with a misclassification rate of 40%. As discussed above, a reason that the models perform differently when validated manually could be due to the different income data used in the validation processes.

In addition, we considered the type of error the prediction models made. For the three-level models, a false positive was not considered detrimental because the cost of identifying a person as being in Deep Poverty when they actually are Not in Poverty is providing that person with too much customer service. False negatives are costlier because this type of error would cause the child support program to overlook the needs of an impoverished person.

When validated manually, both models performed well in regards to false negatives. Both Model E (CP with GIA) and Model F (NCP With GIA) captured almost everyone who was in Deep Poverty or In or Near Poverty and put them in one of these two categories. These models have very little false negatives. Model E (CP with GIA) incorrectly identified 2% of people as Not in Poverty when they were either in Deep Poverty or In or Near Poverty. Model F (NCP with GIA) incorrectly identified 5%. False positives are ignored in this analysis because the consequence of misidentifying a person who is Not in Poverty as either in Deep Poverty or In or Near Poverty is minor.

Figure 20

Three-Level Models (Deep Poverty / In or Near Poverty / Not in Poverty)				
		SAS Enterprise Miner Validation	**Manual Validation**	
MODEL		**Misclassification Rate**	**Misclassification Rate**	**Incorrectly Identified as Not in Poverty**
CP With GIA	**Model E**	38%	31%	2%
NCP With GIA	**Model F**	32%	40%	5%

APPENDIX B: OVERVIEW OF POVERTY MEASURES

Figure 21

Measure	Organization	Concept/Origin	Reference Unit	Income Definition	Income Before or After Taxes	Non Cash Benefits Used in Calculation	Geographic Identifier	Poverty Thresholds Adjusted Geographically	Data Source
Official Poverty Measure	U.S. Census Bureau	Orshansky's original work was a research project suggesting the insufficiency of family funds for the rearing of children relating minimal food costs to family income. Later she was asked to develop research into poverty thresholds.	Family size of persons related to the householder	Earnings, unemployment, workers' compensation, Social Security, Supplemental Security Income, public assistance, veterans' payments, survivor benefits, pension or retirement, interest, dividends, rents, royalties, estates, trusts, alimony, child support, and other miscellaneous sources	Before Taxes	No	United States	No	Consumer Price Index (CPI-U)
Federal Poverty Guidelines	U.S. Dept. of Health and Human Services	Orshansky's original work was repurposed for use by policy makers. The new purpose was to make budgetary decisions for programs providing services but with a slightly rounded dollar presentation.	Family size of persons related to the householder	Uses the same income as the Official Poverty Measure	Before Taxes	No	48 contiguous states, Alaska, Hawaii	Yes	Consumer Price Index (CPI-U)
MBSAC Minimum Basic Standard of Adequate Care (Section 11452)	California Department of Finance	Created for California County enforcement of six kinds of minimum care	Number of eligible needy persons in the same family	Salaries, wages, tips, professional fees, and other dollars received from physical/ mental work	Not Applicable	Yes	California Counties Separated into regions I & II	Yes	California Necessities Index (Department of Finance)

Measure	Organization	Concept/Origin	Reference Unit	Income Definition	Income Before or After Taxes	Non Cash Benefits Used in Calculation	Geographic Identifier	Poverty Thresholds Adjusted Geographically	Data Source
Housing and Urban Development	U.S. Dept. of Housing and Urban Development	HUD is required by law to set income limits that determine eligibility of applicants for assisted housing programs. Statutory basis for HUD's income limit policies is Section 3 of the U.S. Housing Act of 1937, as amended (42 U.S.C. 1437b).	Four person family	Earnings, unemployment, workers' compensation, Social Security, Supplemental Security Income, public assistance, veterans' payments, survivor benefits, pension or retirement, interest, dividends, rents, royalties, estates, trusts, alimony, child support, and other miscellaneous sources	Before Taxes	Yes	48 contiguous states, DC, Alaska and Hawaii (Metropolitan Statistical Areas)	Yes	American Community Survey (ACS), Consumer Price Index (CPI)
SPM Supplemental Poverty Measure	U.S. Census Bureau and Office of Management and Budget	The SPM extends information provided by the official poverty measure. The 1995 assessment by National Academy of Science (NAS) recommended measures that better reflected contemporary social and economic realities and government policy. SPM was the result of the recommendations.	All related individuals who live at the same address, including any co-resident, unrelated children who are cared for by the family (foster children) and any cohabiters and their relatives	Cash income (all sources), in-kind benefits (nutrition assistance, subsidized housing, etc.)	After Taxes	Yes	United States, 298 Metropolitan Statistical Areas (MSAs)	Yes	American Community Survey (ACS), Consumer Expenditure Survey (CE)

Measure	Organization	Concept/Origin	Reference Unit	Income Definition	Income Before or After Taxes	Non Cash Benefits Used in Calculation	Geographic Identifier	Poverty Thresholds Adjusted Geographically	Data Source
CPM California Poverty Measure	Public Policy Institute of California and Stanford University Center on Poverty and Inequality	Provides county-level estimates of poverty, for exploration of how current policy is affecting poverty rates, and examination of the potential impact of certain policy changes.	Head of household and his or her relations, unmarried partner, unmarried partner's children, foster children, and other unrelated children	Wage and salary income, self-employment, Social Security (including Disability), interest and dividends, and income from the Supplemental Security program (All earnings reported in ACS)	After Taxes	Yes	California County FIPS Code	Yes	American Community Survey (ACS), IPUMS version of the Current Population Survey Social and Economic Supplement (CPS)

APPENDIX C: THE CALIFORNIA POVERTY MEASURE

Public Policy Institute of California (PPIC) and Stanford University Center of Poverty and Inequality created the California Poverty Measure (CPM) in 2013 (Bohn et al., 2013). PPIC and Stanford created the CPM to help California policy makers and stakeholders determine whether programs aimed at reducing poverty reach those in need.

The federal government has measured poverty since the 1960s using the Official Poverty Measure (OPM; Fisher, 1997) which uses one set of thresholds for the entire nation. During the 1990s, the federal government created the Supplemental Poverty Measure (SPM) which improves on the OPM by taking into account geographic differences in cost-of-living.

PPIC adapted some of the SPM’s methodology for the CPM to create different thresholds for California counties. In addition, the CPM accounts for geographic differences in the availability of benefits assistance resources such as the Supplemental Nutrition Assistance Program (SNAP) and housing subsidies.

The CPM’s poverty thresholds represent the resources needed to meet a basic standard of living. Unlike the OPM which is based on just food spending, CPM thresholds are based on a wider set of considerations, including food, shelter, clothing, and utilities. Unlike the OPM, the CPM has a different set of thresholds depending on a family’s housing situation (i.e., renting, paying a mortgage, or living in a paid-off home).

The CPM compares a family’s net resources to a threshold to determine their poverty level. To calculate net resources, a family’s expenses are subtracted from its resources. A family’s resources include cash income, in-kind government programs, and net taxes/tax credits. A family’s expenses include out-of-pocket expenses for commuting and other work expenses, medical costs, and childcare.

Below is the list of CPM variables and how we used them in the Orange County prediction model:

Figure 22

Variables	Data Source	Notes
Housing Situation	Impute	Make assumption that all families are renters
Family Composition	GLC	Impute from tax status and exemptions Most GLC records have information about tax status and exemptions
RESOURCES		
Wage and Salary Income	GLC	All records have net income of $0 or more
Self-Employment Income	Exclude	Most GLC records have missing values
Social Security Income	Exclude	Most GLC records have missing values
Welfare and SSI Income	Exclude	Most GLC records have missing values
Interest and Dividend Income	Exclude	Most GLC records have missing values
Pension Income	Exclude	Most GLC records have missing values
Alimony	Exclude	Most GLC records have missing values
Veteran's Benefits	Exclude	Most GLC records have missing values
Child Support Received	CS 1257 Report	Line 24a for 12 months after the date of the guideline calculation
SNAP (Food Stamps)	Impute	Impute using eligibility requirements and grant amounts
Tax Credits (EITC, CTC) and Liabilities	Exclude	Most GLC records have missing values
School Meals	Impute	Impute using eligibility requirements and reimbursement amounts Data sources: Federal Register, Vol. 80, No. 61, March 31, 2015 and Vol. 80, No. 137, July 17, 2015 Assumption is that CPs used the program if they were eligible
Housing Subsidies	Exclude	A small number of people receive this benefit due to its lack of availability in Orange County
EXPENSES		
Medical Out-of-Pocket Expenses	Impute	Impute using estimates from The Kaiser Family Foundation and The Centers for Medicare and Medicaid Services
Child Care Out-of-Pocket Expense	Exclude	Most GLC records have missing values
Commuting and Other Non-Discretionary Work Expenses	Exclude	Most GLC records have missing values

APPENDIX D: IMPUTING MEDICAL OUT-OF-POCKET EXPENSES

The CPM takes expenses into consideration when determining whether a household is in poverty. Expenses include commuting and other work expenses, childcare, and medical costs. This section focuses on medical costs.

For this study, we use administrative data from the GLC, which calculates child support order amounts. The GLC has fields for some types of medical costs; however, information is typically not recorded in these fields. Thus, medical costs need to be imputed. Medical costs are divided into two parts: (1) insurance premiums and (2) other out-of-pocket expenses.

IMPUTING INSURANCE PREMIUMS

A SAS program was written to impute the amount of each family's health insurance premium. The following logic serves as the basis of the SAS program. All monetary amounts are adjusted for inflation to 2017 dollars using the U.S. Bureau of Labor Statistics' Consumer Price Index.

1. **IS THE FAMILY ELIGIBLE FOR MEDI-CAL?** A family is eligible if their income is at or below 138% of the Federal Poverty Level (FPL). We used a family's Federal Adjusted Gross Income in the GLC to determine eligibility.
    a. If YES, then their insurance premium is imputed to $0.
    b. If NO, then go to step #2.
2. **ARE THE CHILDREN ELIGIBLE FOR MEDI-CAL?** Children are eligible if a family's income is at or below 266% of FPL.
    a. If YES, then the children's health insurance premium is imputed to $0.
        i. **ARE THE PARENT(S) EMPLOYED?**
            1. If YES, then the health insurance premium for the parent(s) is imputed to the price of the Single or Plus-One Plan based on their marital status indicated by their tax filing status. If their tax filing status is either "Single" or "Head of Household" then their premium is imputed to the price of the Single Plan. Otherwise, their premium is imputed to the price of the Plus-One Plan.
            2. If NO, then the health insurance premium for the parent(s) is imputed to the price of the Individual Market Plan. Determine the number of family members who are not eligible for Medi-Cal and multiply that number by the price of the Individual Market Plan.

b. If NO, then go to step #3.

3. **ARE THE PARENT(S) EMPLOYED?**
    a. If YES, then the family's health insurance premium is imputed to the price of the Single, Plus-One, or Family Plan based on their tax filing status and tax exemptions.
    b. If NO, then their health insurance premium is imputed to the price of the Individual Market Plan. Multiply the number of family members by the price of the Individual Market Plan.

Table 2 contains premium estimates published by the Kaiser Family Foundation. This organization calculated average premiums by state. Its calculations are based on two data sources: (1) Medical Expenditure Panel Survey (MEPS) Insurance Component and (2) Health Coverage Portal™. MEPS is an annual survey that collects information about employer-based health insurance and the Health Coverage Portal™ contains information about the individual health insurance market.

Figure 23

Table 1 – Medi-Cal Annual Income Eligibility Limits (2017)

Family Size	All Family Members	Children Only
1	$16,643	
2	$22,411	$43,198
3	$28,180	$54,317
4	$33,948	$65,436
For each additional person	$5,768	$11,119

Figure 24

Table 2 – Average Annual Premium by Insurance Type in California

Description	Annual Amount
SINGLE PREMIUM (2016) per Enrolled Employee For Employer-Based Health Insurance	$1,146
EMPLOYEE-PLUS-ONE PREMIUM (2016) per Enrolled Employee For Employer-Based Health Insurance	$3,182
FAMILY PREMIUM (2016) per Enrolled Employee For Employer-Based Health Insurance	$4,829
PREMIUM PER PERSON (2013) In the Individual Market	$2,697

IMPUTING MEDICAL OUT-OF-POCKET EXPENSES

A SAS program was written to impute the amount of medical out-of-pocket expenses for each family. Basically, expenses are based on the age and gender of each person in the family. Table 3 contains annual medical out-of-pocket expenses published by the Centers for Medicare & Medicaid Services.

When age and gender are unknown, these characteristics are imputed. For example, children are assumed to be between 0 and 18 years of age. Because we do not know the children's gender, we use the average of the male and female amounts. Lastly, the number of children in a family is based on tax filing status and tax exemptions. Spouses are assumed to be the same age and opposite gender as the NCP or CP. Lastly, regardless of whether a family is eligible for Medi-Cal, medical out-of-pocket expenses are calculated the same for all families.

Figure 25

Table 3 – Annual Medical Out-of-Pocket Per-Capita Spending by Gender and Age Group (2012)[9]

Description	0-18	19-44	45-64	65-84	85+
Males	$375	$430	$1,106	$2,481	$5,003
Females	$393	$698	$1,315	$2,563	$5,823
Average	$384	$842	$563	$1,213	$2,938

[9] This was the available data at the time of the development of the models. https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/Age-and-Gender.html

APPENDIX E: INCOME & EXPENSE DECLARATION

CSS collects I&E data from parent who are in the process of creating or modifying a child support order. I&E forms contain data elements the California Poverty Measure (CPM) uses to estimate poverty thresholds. The highlighted sections of the following I&E pages were used in phases I and II of the project.

Figure 26

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ATTORNEY OR PARTY WITHOUT ATTORNEY *(Name, State Bar number, and address)*:

TELEPHONE NO.:
E-MAIL ADDRESS *(Optional)*:
ATTORNEY FOR *(Name)*:

FOR COURT USE ONLY

SUPERIOR COURT OF CALIFORNIA, COUNTY OF
STREET ADDRESS:
MAILING ADDRESS:
CITY AND ZIP CODE:
BRANCH NAME:

PETITIONER/PLAINTIFF:
RESPONDENT/DEFENDANT:
OTHER PARENT/CLAIMANT:

INCOME AND EXPENSE DECLARATION

CASE NUMBER:

1. **Employment** *(Give information on your current job or, if you're unemployed, your most recent job.)*

Attach copies of your pay stubs for last two months (black out social security numbers).

a. Employer:
b. Employer's address:
c. Employer's phone number:
d. Occupation:
e. Date job started:
f. If unemployed, date job ended:
g. I work about hours per week.
h. I get paid $ gross (before taxes) ☐ per month ☐ per week ☐ per hour.

(If you have more than one job, attach an 8½-by-11-inch sheet of paper and list the same information as above for your other jobs. Write "Question 1—Other Jobs" at the top.)

2. **Age and education**
a. My age is *(specify)*:
b. I have completed high school or the equivalent: ☐ Yes ☐ No If no, highest grade completed *(specify)*:
c. Number of years of college completed *(specify)*: ☐ Degree(s) obtained *(specify)*:
d. Number of years of graduate school completed *(specify)*: ☐ Degree(s) obtained *(specify)*:
e. I have: ☐ professional/occupational license(s) *(specify)*:
☐ vocational training *(specify)*:

3. **Tax information**
a. ☐ I last filed taxes for tax year *(specify year)*:
b. My tax filing status is ☐ single ☐ head of household ☐ married, filing separately
☐ married, filing jointly with *(specify name)*:
c. I file state tax returns in ☐ California ☐ other *(specify state)*:
d. I claim the following number of exemptions (including myself) on my taxes *(specify)*:

4. **Other party's income.** I estimate the gross monthly income (before taxes) of the other party in this case at *(specify)*: $
This estimate is based on *(explain)*:

(If you need more space to answer any questions on this form, attach an 8½-by-11-inch sheet of paper and write the question number before your answer.) Number of pages attached: ______

I declare under penalty of perjury under the laws of the State of California that the information contained on all pages of this form and any attachments is true and correct.

Date:

(TYPE OR PRINT NAME) ▶ (SIGNATURE OF DECLARANT)

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Form Adopted for Mandatory Use
Judicial Council of California
FL-150 [Rev. January 1, 2007]

INCOME AND EXPENSE DECLARATION

Family Code, §§ 2030–2032, 2100–2113, 3552, 3620–3634, 4050–4076, 4300–4339
www.courtinfo.ca.gov

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PETITIONER/PLAINTIFF:	CASE NUMBER:
RESPONDENT/DEFENDANT:	
OTHER PARENT/CLAIMANT:	

Attach copies of your pay stubs for the last two months and proof of any other income. Take a copy of your latest federal tax return to the court hearing. *(Black out your social security number on the pay stub and tax return.)*

	Last month	Average monthly
5. **Income** *(For average monthly, add up all the income you received in each category in the last 12 months and divide the total by 12.)*		
a. Salary or wages (gross, before taxes)	$______	______
b. Overtime (gross, before taxes)	$______	______
c. Commissions or bonuses	$______	______
d. Public assistance (for example: TANF, SSI, GA/GR) ☐ currently receiving	$______	______
e. Spousal support ☐ from this marriage ☐ from a different marriage	$______	______
f. Partner support ☐ from this domestic partnership ☐ from a different domestic partnership	$______	______
g. Pension/retirement fund payments	$______	______
h. Social security retirement (not SSI)	$______	______
i. Disability: ☐ Social security (not SSI) ☐ State disability (SDI) ☐ Private insurance	$______	______
j. Unemployment compensation	$______	______
k. Workers' compensation	$______	______
l. Other (military BAQ, royalty payments, etc.) *(specify):*	$______	______
6. **Investment income** *(Attach a schedule showing gross receipts less cash expenses for each piece of property.)*		
a. Dividends/interest	$______	______
b. Rental property income	$______	______
c. Trust income	$______	______
d. Other *(specify):*	$______	______
7. **Income from self-employment, after business expenses for all businesses**	$______	______

I am the ☐ owner/sole proprietor ☐ business partner ☐ other *(specify):*

Number of years in this business *(specify):*

Name of business *(specify):*

Type of business *(specify):*

Attach a profit and loss statement for the last two years or a Schedule C from your last federal tax return. Black out your social security number. If you have more than one business, provide the information above for each of your businesses.

8. ☐ **Additional income.** I received one-time money (lottery winnings, inheritance, etc.) in the last 12 months *(specify source and amount):*

9. ☐ **Change in income.** My financial situation has changed significantly over the last 12 months because *(specify):*

10. **Deductions**	Last month
a. Required union dues	$______
b. Required retirement payments (not social security, FICA, 401(k), or IRA)	$______
c. Medical, hospital, dental, and other health insurance premiums *(total monthly amount)*	$______
d. Child support that I pay for children from other relationships	$______
e. Spousal support that I pay by court order from a different marriage	$______
f. Partner support that I pay by court order from a different domestic partnership	$______
g. Necessary job-related expenses not reimbursed by my employer *(attach explanation labeled "Question 10g")*	$______

11. **Assets**	Total
a. Cash and checking accounts, savings, credit union, money market, and other deposit accounts	$______
b. Stocks, bonds, and other assets I could easily sell	$______
c. All other property, ☐ real and ☐ personal *(estimate fair market value minus the debts you owe)*	$______

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PETITIONER/PLAINTIFF: RESPONDENT/DEFENDANT: OTHER PARENT/CLAIMANT:	CASE NUMBER:

12. The following people live with me:

Name	Age	How the person is related to me? *(ex: son)*	That person's gross monthly income	Pays some of the household expenses?
a.				☐ Yes ☐ No
b.				☐ Yes ☐ No
c.				☐ Yes ☐ No
d.				☐ Yes ☐ No
e.				☐ Yes ☐ No

13. Average monthly expenses ☐ Estimated expenses ☐ Actual expenses ☐ Proposed needs

a. Home:
   (1) ☐ Rent or ☐ mortgage . . . $ ________
   If mortgage:
      (a) average principal: $ ________
      (b) average interest: $ ________
   (2) Real property taxes . . . . $ ________
   (3) Homeowner's or renter's insurance (if not included above) . . . . $ ________
   (4) Maintenance and repair . . . . $ ________
b. Health-care costs not paid by insurance . . . $ ________
c. Child care . . . . $ ________
d. Groceries and household supplies . . . . $ ________
e. Eating out . . . . $ ________
f. Utilities (gas, electric, water, trash) . . . . . . $ ________
g. Telephone, cell phone, and e-mail . . . . $ ________
h. Laundry and cleaning . . . . $ ________
i. Clothes . . . . $ ________
j. Education . . . . $ ________
k. Entertainment, gifts, and vacation . . . . $ ________
l. Auto expenses and transportation (insurance, gas, repairs, bus, etc.) . . . . $ ________
m. Insurance (life, accident, etc.; do not include auto, home, or health insurance) . . . $ ________
n. Savings and investments . . . . $ ________
o. Charitable contributions . . . . $ ________
p. Monthly payments listed in item 14 *(itemize below in 14 and insert total here)* . . $ ________
q. Other *(specify)*: . . . . $ ________
r. **TOTAL EXPENSES** (a–q) *(do not add in the amounts in a(1)(a) and (b))* $ ________
s. **Amount of expenses paid by others** $ ________

14. Installment payments and debts not listed above

Paid to	For	Amount	Balance	Date of last payment
		$	$	
		$	$	
		$	$	
		$	$	
		$	$	
		$	$	

15. Attorney fees *(This is required if either party is requesting attorney fees.)*:

a. To date, I have paid my attorney this amount for fees and costs *(specify)*: $
b. The source of this money was *(specify)*:
c. I still owe the following fees and costs to my attorney *(specify total owed)*: $
d. My attorney's hourly rate is *(specify)*: $

I confirm this fee arrangement.

Date:

________________________________ ▶ ________________________________
(TYPE OR PRINT NAME OF ATTORNEY) (SIGNATURE OF ATTORNEY)

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