



Reducing SNAP Error Rates: Initial Observations from Modeling Public QC Data

JANUARY 30, 2026

In a typical month, more than 40 million individuals benefit from the Supplement Nutrition Assistance Program (SNAP), formerly called food stamps. About [1 in 2 children](#) will receive SNAP benefits at some point in their childhood and [1 in 4 children](#) are receiving benefits. Access to SNAP generates large benefits in terms of improving education, prosperity, and public safety.

The One Big Beautiful Bill (OBBB) passed in July, 2025 dramatically altered how SNAP is implemented by states. The Congressional Research Service [estimates](#) that the bill will lead to a \$187 billion reduction in the SNAP program over the next decade and another estimate indicates that 5.3 million people will lose more than \$25 monthly in SNAP food aid ([Urban 2025](#)).

HRI requires states to pay large [penalties](#) based on their SNAP payment error rate (PER). PER is measured using Quality Control (QC) data that states collect and that the federal government audits. Previously, states made policy decisions that often prioritized reducing food insecurity such that low-income individuals eligible for food aid were able to receive support. With the changes in OBBB, states are now required to focus exclusively on reducing payment errors as small as \$58 regardless of how changes intended to minimize payments errors also lead to exclusion of eligible households without errors. Currently, states incur no penalties for improperly denying or terminating SNAP benefits for eligible households (something a [proposed change](#) in rules would have addressed).

Based on existing error rates, 43 states will face penalties. Two thirds of states are facing severe penalties of over \$100 million a year, even as they receive significantly less funding in administrative support from the federal government.

Therefore, to support states to lower their PER, while still mitigating disruption of food aid to eligible households, we sought to use publicly-available data on error rates to help states as they grapple with changes from the OBBB. In the analysis below, we use predictive analytics to describe the primary reasons that SNAP cases are flagged as having a payment error. The analysis uses SNAP Quality Control (QC) data from 2017 to 2023 across all states. One caveat for understanding the [public QC data](#) is that it only includes payment errors for those individuals that were still deemed eligible. It does not include errors where the household was ineligible for SNAP completely.

The goal of these analyses is to begin to understand best practices for using these data to assess where errors come from and to inform a discussion of how they can change their application and processing practices in a way that would minimize errors. At the same time, an equally important goal is to mitigate the increase in hunger that is likely to occur as changes reduce SNAP access, which can be served by avoiding imprecise or incorrect targeting of these efforts.

A summary of our initial observations:

- For states that are modeling error rate predictors, adding a variable to reflect benefit amount as a share of max allotment improves model accuracy significantly. Households that have a lower level of SNAP benefits tend to have uncounted, not counted errors. Households close to or at the benefit max tend to have higher rates of counted errors (Figures 1 and 2).
- Some variables are effective because they proxy for missing data (such as a household member or a source of income), use variables that help capture the possibility of key unreported data, such as the ratio of shelter expenses divided by gross income (Figure 1).
- Self-employment may be less of a problem for generating payment errors than is typically understood: small errors are quite common, but over-threshold errors are less common than with traditional employment (Figure 3). We are seeking to confirm this with states that have access to their full QC data.
- Decision trees provide one way of quickly exploring the data for very targeted criteria that reduce the risks of burdening households that are unlikely to have errors (Figure 4).
- Importantly, the QC data offer opportunities to assess possible prioritization rules, such as a threshold for earned income combined with shelter expenses relative to gross income, for bias before putting them into production systems (Figure 5).

Figure 1: Top Ten Variables for Predicting Above-Threshold Overpayment Errors (SNAP QC PER Data, 2017–2023)

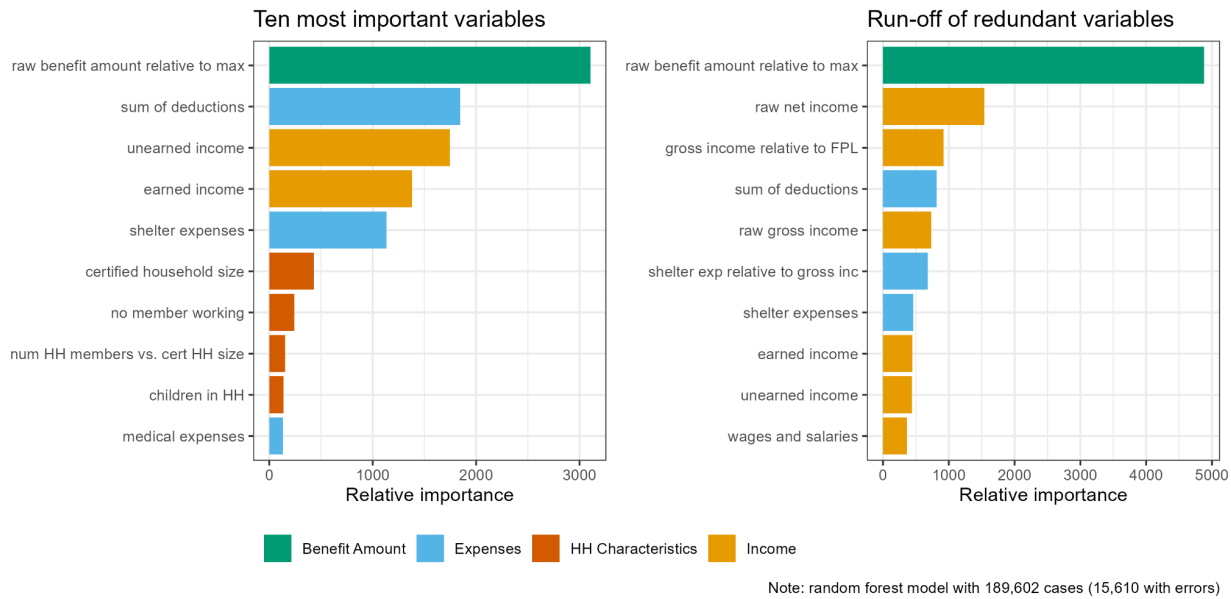
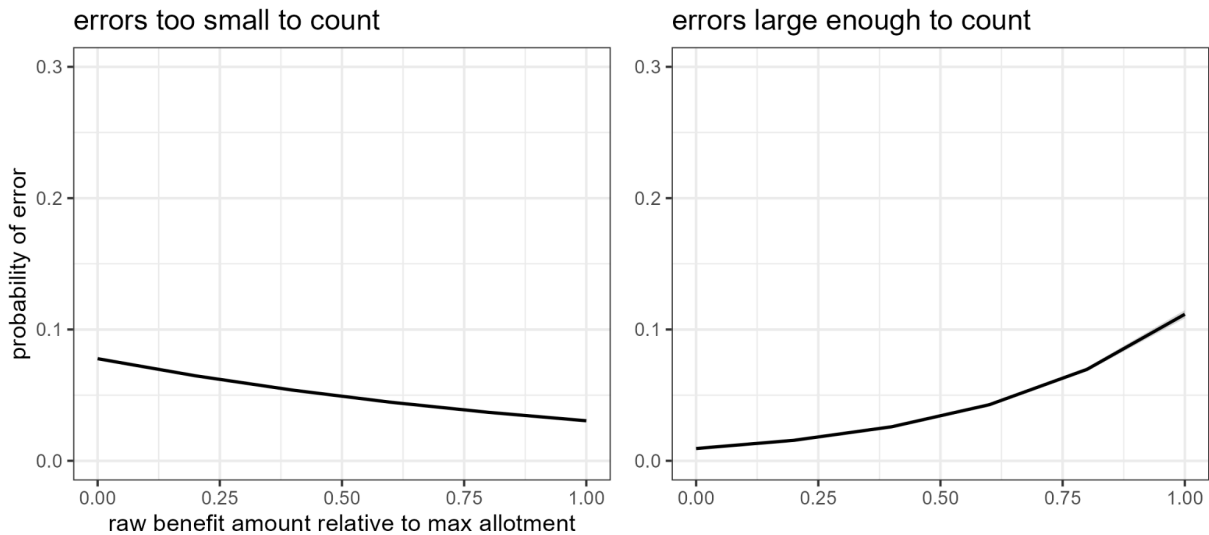
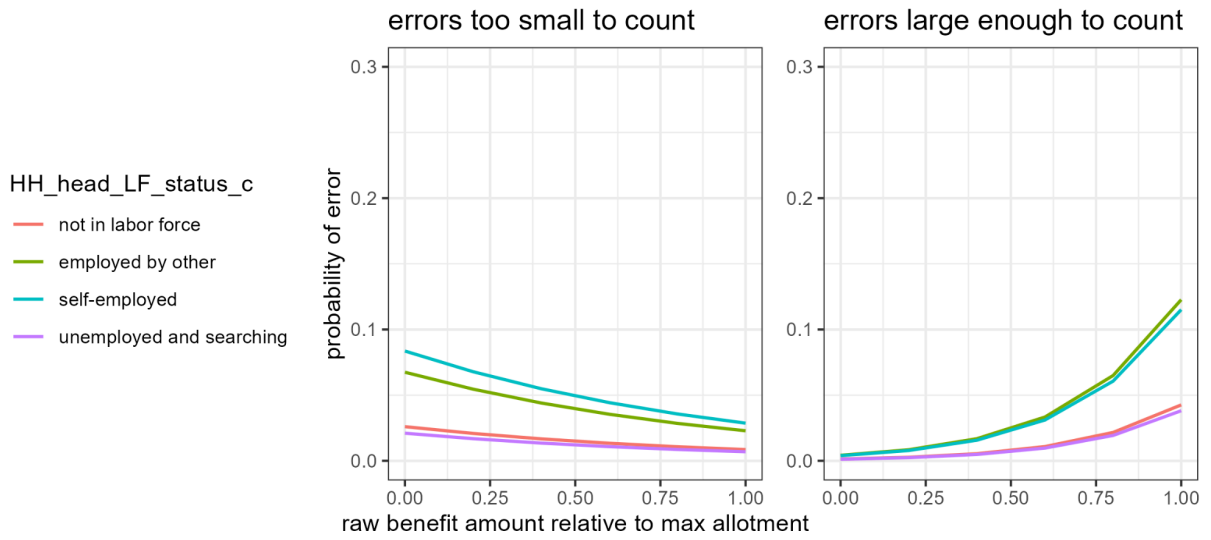


Figure 2: Benefit Level Helps Distinguish Small vs. Large Errors at Certification (SNAP QC PER Data, 2017–2023)



Note: logistic regression models of 189,017 cases (15,257 had errors above the penalty threshold, 16,908 had errors below the threshold).

Figure 3: “Employed by Other” Associated with Income Errors at Certification



Note: logistic regression models of 189,017 cases (7,574 had income errors above the penalty threshold, 6,693 had income errors below).

Figure 4: Decision Tree for Available CA Data (2017–2023)

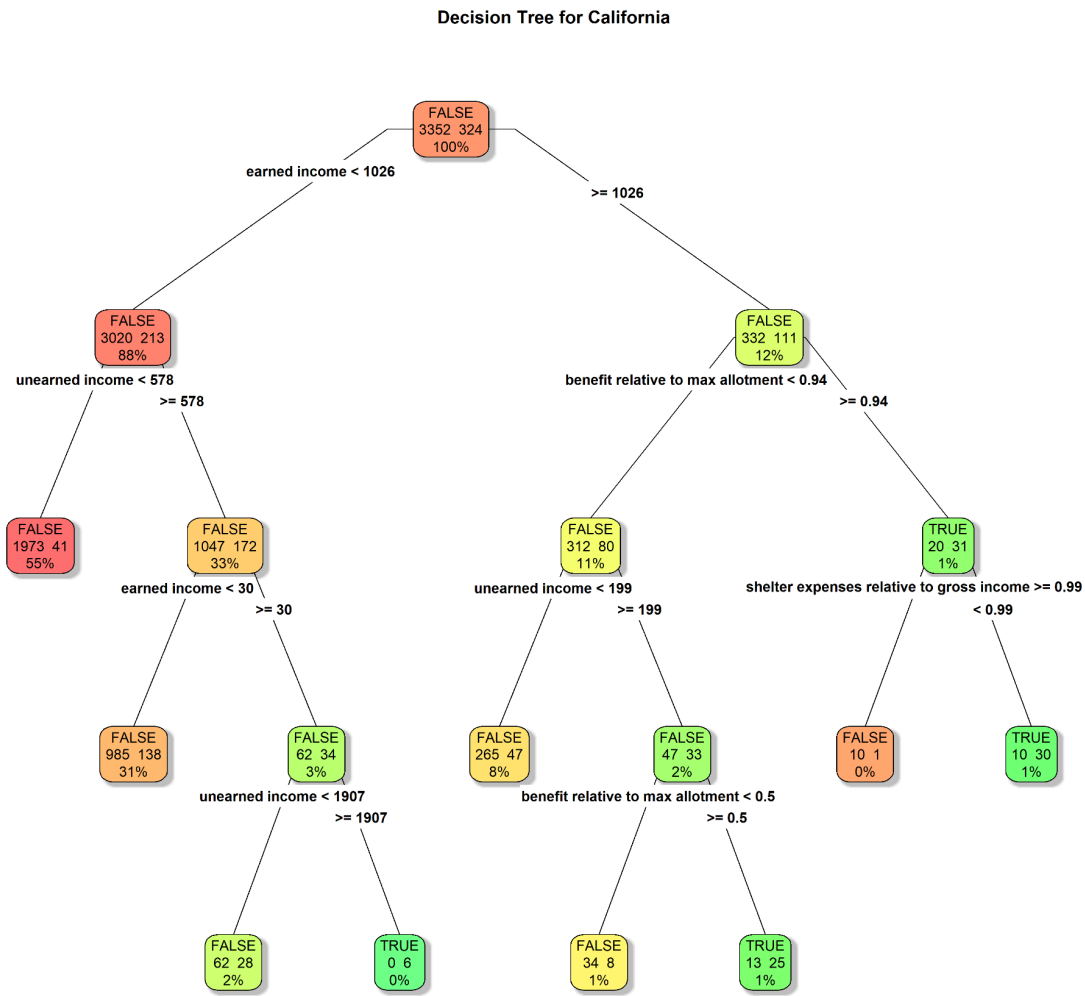
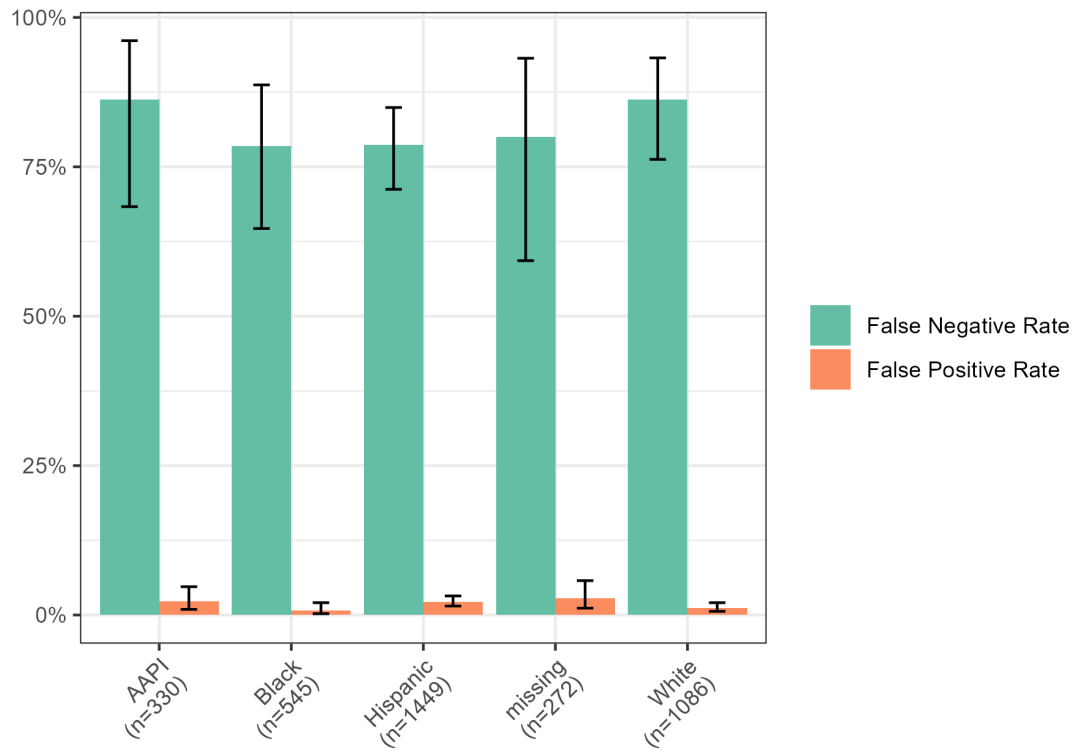


Figure 5: Assessing Hypothetical Rules based on Decision Tree Criteria for Bias (CA)



Note: hypothetical criteria based on decision tree.
N=3,682 cases, 328 with errors.