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REPORT

FINAL TECHNICAL REPORT

The Second Access, Participation, Eligibility, and Certification Study (APEC II)

Estimating and Validating Statistical Models for Updating Estimates of Improper Payments in the NSLP and SBP

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April Yanyuan Wu

Quinn Moore

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Office of Policy Support

3101 Park Center Drive

Alexandria, CA 22302

Project Officer: Chan Chanhatasilpa

Contract Number: AG-3198-C-12-0001/AG-3198-D-12-0010

Submitted by:

Mathematica Policy Research

P.O. Box 2393

Princeton, NJ 08543-2393

Telephone: (609) 799-3535

Facsimile: (609) 799-0005

Project Director: Eric Zeidman

Reference Number: 40030.163

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EXECUTIVE SUMMARY

Objective

The Food and Nutrition Service (FNS) of the U.S. Department of Agriculture (USDA) funded the first and second Access, Participation, Eligibility, and Certification (APEC-I and APEC-II) studies to obtain national estimates of improper payment rates for the National School Lunch Program (NSLP) and the School Breakfast Program (SBP) for the school year (SY) 2005–2006 and SY 2012–2013 (see U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, 2015). These studies generate national estimates of both certification and non-certification error and the improper payments that result from such errors.

Certification errors occur when schools claim reimbursements for school meals at incorrect rates. Certification errors for schools not using the Community Eligibility Provision (CEP) occur when school districts claim reimbursement at the free or reduced-price rate for meals served to students who are not eligible for these benefits, or when school districts fail to claim reimbursement at the free or reduced-price rate for students who applied but were mistakenly denied benefits for which they were eligible. For schools using CEP, certification error occurs if the CEP group to which the school belongs uses free or paid meal reimbursement claiming percentages that are incorrect.[1]

Non-certification error occurs in the stages between certifying students' eligibility status (in non-CEP schools), establishing the identified student percentage (ISP) and free and paid meal reimbursement claiming rates (in CEP schools), and reporting meal counts to the State agency for reimbursement. The APEC-II study examined meal claiming error and three types of aggregation error. Meal claiming error occurs when cafeteria staff members make errors in assessing and recording whether a specific meal selection meets the criteria for a reimbursable meal under the NSLP or SBP. Aggregation error is the general term for errors made by schools and school food authorities (SFAs) in the process of counting the number of meals served and reporting these meal counts to State agencies for reimbursement.

As a part of the APEC-I study, Mathematica developed statistical models designed to estimate national improper payments due to certification error on an annual basis using district-level data available from Verification Collection Report (VCR; also known as the FNS-742). This enabled FNS to update its estimates of national improper payment rates for the NSLP and SBP in future years without having to conduct full rounds of primary data collection.

In the APEC-II study, we expanded on the modeling in APEC-I in several important ways. First, we refined the existing estimation models used by FNS staff for updating annual national estimates of overpayments, underpayments, and overall improper payments due to certification error in the NSLP and SBP. Second, for APEC-II we developed an approach for modeling

[1] The CEP can be elected by an individual school, by a set of schools within a local education agency (LEA), or by the entire LEA. The characteristics (number of enrolled students, number of directly certified students, and number of students who are certified eligible for free meals without having to submit an application) of the schools that elect CEP determine their free and paid meal reimbursement claiming percentages. Hereafter, we refer to an individual school/set of schools/LEA that elected CEP as the "CEP group."

improper payments in schools participating in the CEP, which was introduced in SY 2011–2012, available in six States plus the District of Columbia for SY 2012–2013 (when APEC-II took place), and available nationwide for SY 2013–2014. Finally, in addition to modeling certification error, APEC-II models improper payments due to meal claiming error.

Approach

Figure ES.1 provides an overview of the main steps in our process for developing statistical models of improper payments due to certification error in non-CEP schools, certification error in CEP schools, and meal claiming error in both non-CEP and CEP schools. These models will allow FNS to generate annual improper payment estimates in future years.

Gathering relevant data. We used APEC-II study data to estimate district-level improper payment rates for each district in the APEC-II sample. We then gathered data from several national data sources of information that might be associated with improper payment rates. Key data sources included the VCR, the Common Core of Data the Private School Survey, Census Small Area Income and Poverty Estimates, and Local Area Unemployment Statistics. These data contain rich information on district characteristics, school meal program policies, and local economic conditions.

Determining types of models to estimate. We considered models with a number of different specifications of improper payment rates. For example, for certification error in non-CEP schools, we considered models of improper payment rates that include only two improper payment rates per meal program—overpayments and underpayments (separately for the NSLP and SBP). We also considered models with more disaggregated improper payment rates—such as one that includes five types of overpayment rates and three types of underpayment rates, separately for the NSLP and SBP. Testing a variety of different model systems with a variety of estimation techniques allows us to identify the model that most closely matches the observed APEC-II improper payment rate estimates.[2]

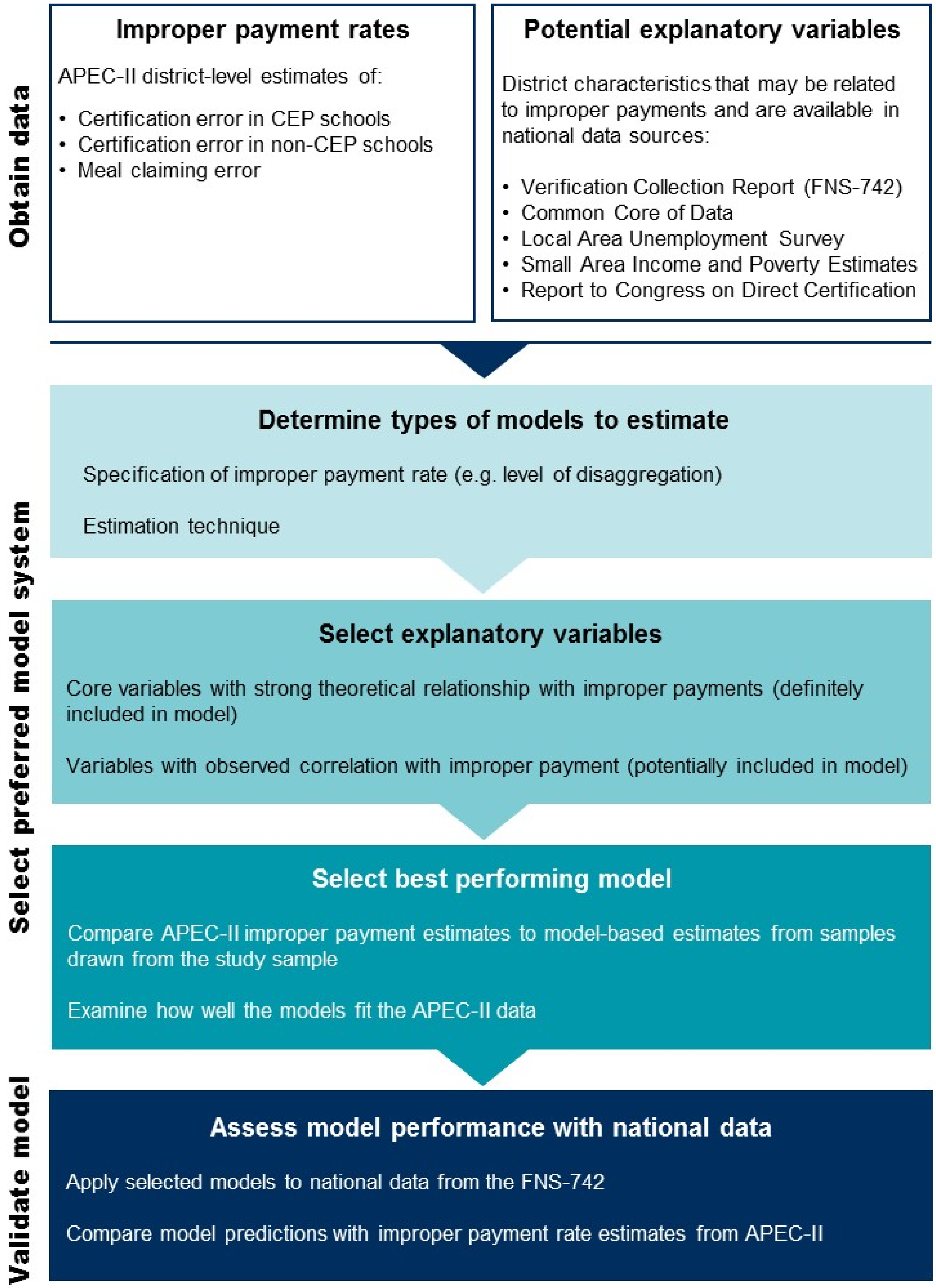
Selecting explanatory variables to include in the models. An important feature of effective models is the use of explanatory variables that are highly predictive of error rates, but also responsive to changes in district policy or characteristics; models will not perform well in future years if they include only relatively static demographic characteristics that are unlikely to change from year to year.

An important practical consideration in developing these models is that explanatory variables must be drawn from data sources that will be timely, available for all districts nationwide, and straightforward for FNS to merge with other included data sources. If these conditions are not met, FNS will not be able to use the models to estimate improper payments in future years in a timely manner. This consideration led us to use the VCR data set as a starting point for the APEC-II model development. We also explored including explanatory variables from the following data sources: Common Core of Data, Private School Survey, Census Small

[2] We considered the model system that minimizes the cross-validation difference between the predicted model system's improper payment rate and estimates of the observed APEC-II improper payment rates. Our final selection of model systems was based on this measure of performance and on goodness-of-fit measures for the regression equations included in the system.

Area Income and Poverty Estimates, and Local Area Unemployment Statistics. In addition to these data sources, we also considered including State direct certification performance measures available through the annual Reports to Congress on Direct Certification Implementation.

Figure ES.1. Process for developing and validating improper payment estimation model



In selecting the explanatory variables for each model, we sought factors with a strong theoretical relationship with certification error rates, ones that are likely to be responsive to changes in policy or implementation characteristics. For some model specifications, we also used explanatory variables selected based on the strength of the relationship with improper payments measured in the APEC-II sample.

Selecting the best performing model specification. After estimating a wide range of model types, each with different sets of explanatory variables, we used a within-sample cross-validation method for selecting the preferred model system specification. This technique offers an assessment of how well the model results will generalize to a data source other than the one on which it was estimated and how accurately a predictive model will perform in practice. It also reduces the chance of selecting a model that reflects relationships particular to the study sample rather than relationships applicable to a broader sample; such “over-fitted” models do not perform well when applied to external samples. We based the final model selection on cross-validation performance estimates and on estimates of how well the models fit the APEC-II data in the regression equations.

Validating the model. After selecting the preferred model for each type of error, we applied the models to national data for SY 2012–2013 to get national improper payment rate estimates. These estimates, which are derived in the same way that estimates would be derived by FNS in future years, allow us to assess how well the APEC-II model performs when applied to data other than the APEC-II data with which the model was estimated and selected; that is, they offer an external validation of the model’s performance. The process for generating the national estimates used for validation (and to be used in future years) is described next.

Applying the models to national data

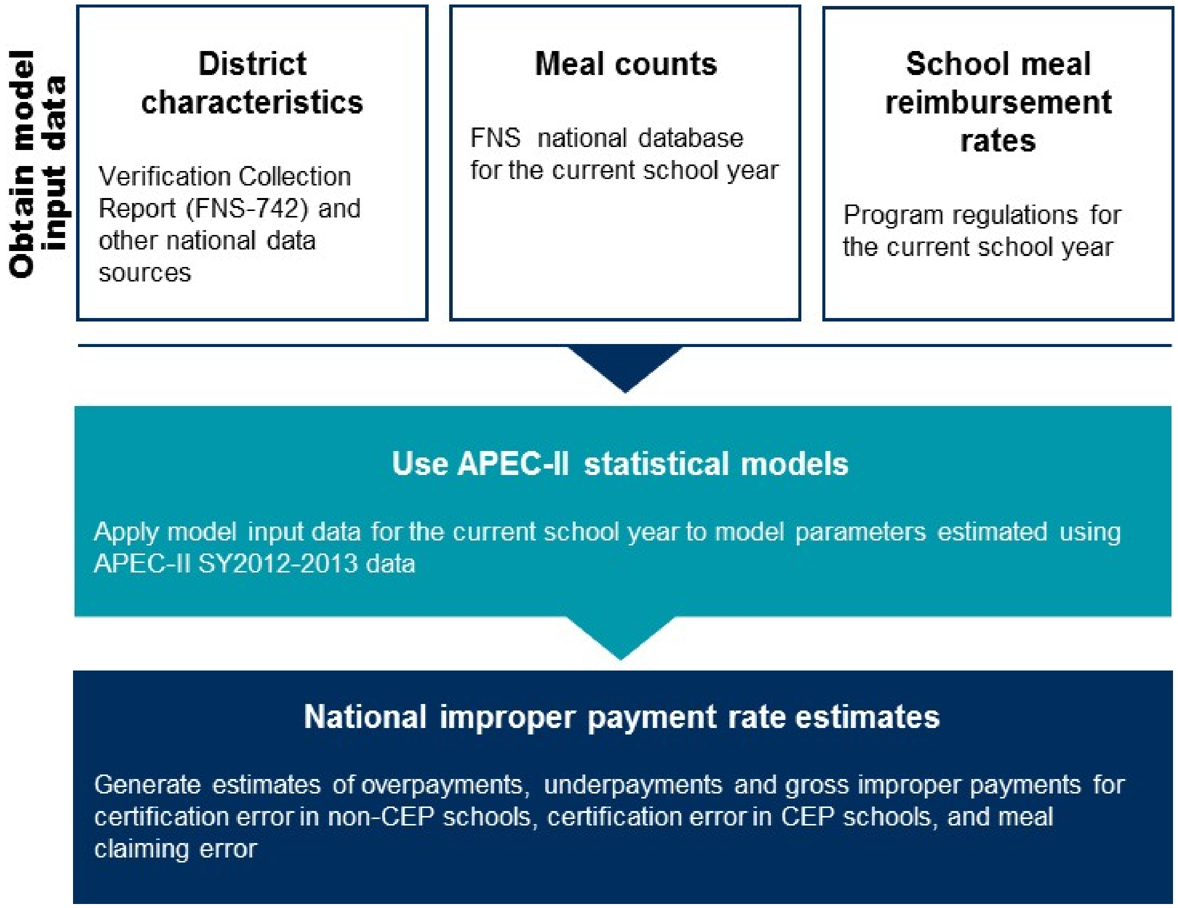
Figure ES.2 summarizes the process for using the APEC-II improper payment models to update estimates of improper payments due to certification and meal claiming error. The steps are described briefly below.

Gather model input data. The first step in using the APEC-II models is to gather the data upon which it relies. These data include national, district-level data on all of the explanatory variables included in the model. Updated improper payment estimates in future years also require current information on the number of school meals served and school meal reimbursement rates.

Use APEC-II statistical models. The statistical models estimate the relationship between the explanatory variables and improper payment rates. By combining these estimated relationships with updated data on the explanatory variables, the model is able generate updated estimates of improper payment rates for all districts.

Estimate national improper payment rates. The model allows us to sum district-level improper payment estimates to generate national improper payment rate estimates. In this way, the APEC-II models generate estimates of improper payments due to certification error in non-CEP schools, certification error in CEP schools, certification error in all schools, and meal claiming error.

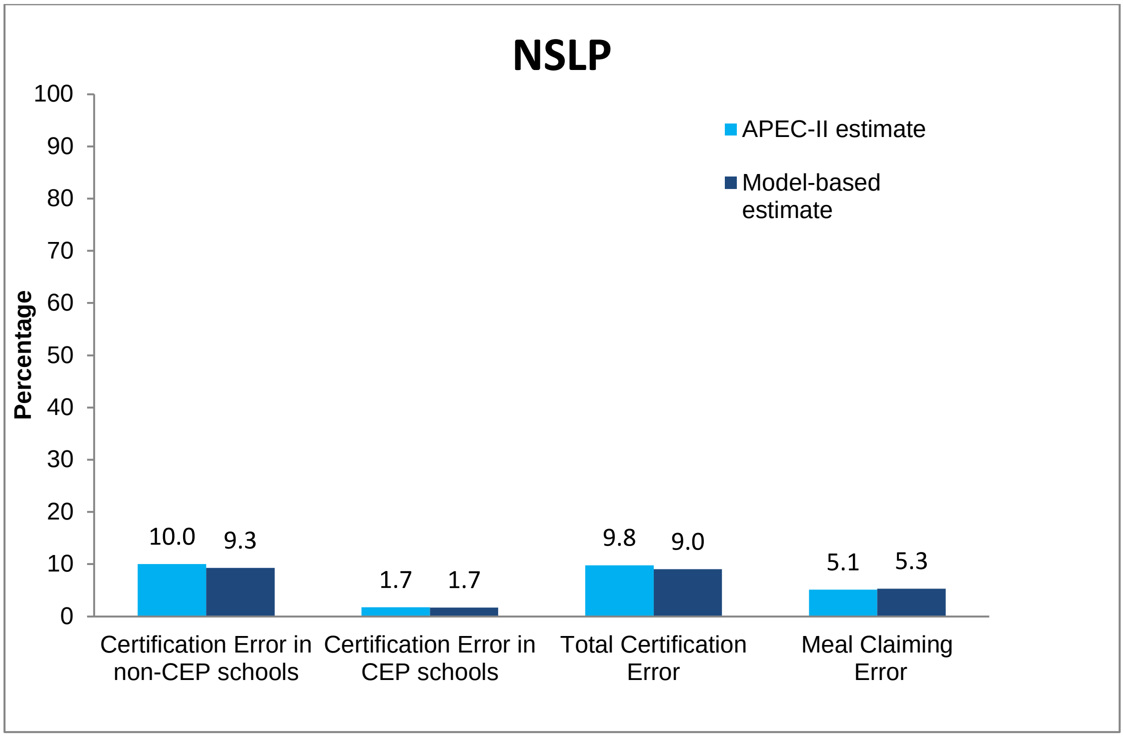
Figure ES.2. Process for using the model to estimate national improper payments

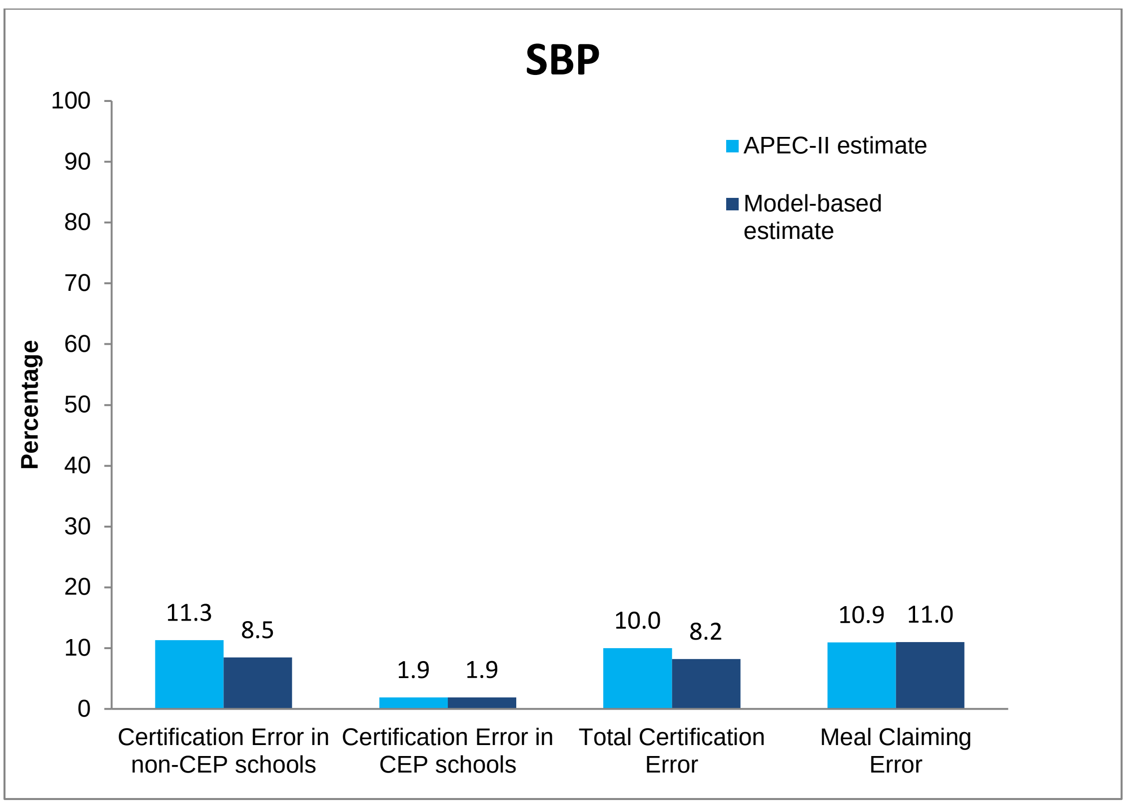


Results of the model validation

Figure ES.3 presents national model-based estimates of improper payments along with the main findings from the APEC-II study for SY 2012–2013. These results are discussed below.

Figure ES.3. National improper payment estimates based on the APEC-II statistical models, SY 2012–2013





Certification error in non-CEP schools. For both the NSLP and the SBP, the model system predictions for overpayment, underpayment, and total improper payments are slightly less than those from the APEC-II study. These differences are relatively small for the NSLP estimates and somewhat larger for the SBP estimates. For the NSLP, model-based estimates of gross improper payments due to non-CEP certification error were $1,028 million (9.27 percent of total reimbursements), compared to $1,153 million (10.01 percent of total reimbursements) in the APEC-II study. For the SBP, model-based estimates of gross improper payments from non-CEP certification error were $279 million (8.45 percent of total reimbursements), compared to $364 million (11.30 percent of total reimbursements) in the APEC-II study. All of the model-based estimates fall within the 95 percent confidence interval of the APEC-II estimates. Conversely, all of the APEC-II estimates fall within the 95 percent confidence interval of the model-based estimates, although the model-based confidence intervals are large.

Certification error in CEP schools. For both the NSLP and the SBP, the model system predictions of total improper payments are somewhat smaller than those from the APEC-II study. For the NSLP, model-based estimates of gross improper payments due to CEP certification error were 1.71 percent of total reimbursements, compared to 1.73 percent of total reimbursements in the APEC-II study. For the SBP, model-based estimates of gross improper payments related to CEP certification error were 1.87 percent of total reimbursements, compared to 1.88 percent of total reimbursements in the APEC-II study. All of the model-based estimates fall within the 95 percent confidence interval of the APEC-II estimates. Conversely, all of the APEC-II estimates fall within the 95 percent confidence interval of the model-based estimates, although, as with non-CEP certification error, the model-based confidence intervals are large relative to the point estimates.

Meal claiming error. For both the NSLP and the SBP, the model system predictions for overpayment, underpayment, and total improper payments are slightly greater than those from the APEC-II study. For the NSLP, model-based estimates of gross improper payments related to meal claiming error were $614 million (5.33 percent of total reimbursements), compared to $607 million (5.14 percent of total reimbursements) in the APEC-II study. For the SBP, model-based estimates of gross improper payments related to meal claiming error were $377 million (10.97 percent of total reimbursements), compared to $365 million (10.94 percent of total reimbursements) in the APEC-II study. All of the model-based estimates fall within the 95 percent confidence interval of the APEC-II estimates. Conversely, all of the APEC-II estimates fall within the 95 percent confidence interval of the model-based estimates, although, as with the previously discussed model system, the model-based confidence intervals are large.

Limitations of the models

Despite improvements to the model development process, important limitations of the modeling approach remain.

Substantial unexplained variation. The goodness of fit for most model equations is moderate. This means that a substantial amount of variation in improper payment rates remains unexplained by the models. In other words, there are unobserved factors that cause certification error rates to be higher in some districts than in others. To the extent that changes in these unobserved factors also lead to changes in improper payments in future years, the model will not capture these changes.

Assumption of stable relationships between error rates and district characteristics. Using a statistical model based on estimated relationships between district characteristics and certification and non-certification error rates in SY 2012–2013 to predict improper payments in the future implicitly assumes that these relationships remain constant over time. Although this implicit assumption is necessary and unavoidable, it may not be valid if there are important, systematic, year-to-year changes in both the school meal programs and the factors related to improper payments. The nationwide rollout of CEP might represent such a change, so predicted rates for future years should be interpreted cautiously. The further out in the future the SY 2012–2013 statistical model's results are used to predict improper payments, the less reasonable this assumption becomes.

CEP model limitations. We encountered some important challenges in developing the CEP certification error models. The CEP modeling is hampered by limited availability of national data related to CEP, such as CEP reimbursements, implementation features, and meal claiming rates. Many of these data limitations are the result of the fact that CEP is a new program; in future years, higher quality CEP data are likely to become available. For the time being, though, the CEP models had to be developed with few explanatory variables directly related to CEP implementation and had to be validated using data that relied heavily on imputation. These limitations may have important implications for the reliability of the model-based estimates in future years.

The reliability of the CEP certification error estimates may be further compromised by the fact that the CEP models were estimated using districts in States that had implemented CEP in SY 2012–2013. CEP became available nationwide starting in SY 2014–2015. Districts within the States that elected to use CEP in SY 2012–2013 may differ from typical districts nationally. As a result, the relationships estimated in the CEP models are likely to change, making the model-based improper payment estimates less accurate.

For these reasons, model-based estimates of improper payments due to certification error in CEP schools should be interpreted very cautiously in the future. That said, FNS is still required to provide estimates of improper payments for future years, and the CEP model provides the best estimates possible given the constraints in its estimation.

Model validation limitation. Our external validation approach focuses on comparing sample-based and model-based estimates of error rates of the current study period (SY 2012–2013), but there are no data to validate the models in different periods or future years. Therefore, this validation approach does not give information on out-of-sample predictions for future years.

The implication of these limitations is that in any future year, the predicted amounts and rates of improper payments will not be as accurate or credible as new estimates of these values from a large-scale, nationally representative study like the APEC-I and APEC-II studies.

Conclusions

The econometric model described in this report will provide predicted amounts and rates of improper payments that are reasonably accurate estimates of their actual values. Moreover, the predicted values will allow FNS to effectively track the direction and general magnitude of changes in improper payments in the future, at minimal cost and in a timely manner.

Summary

- This report presents statistical models designed to estimate national improper payments on an annual basis by using district-level data available from the Verification Collection Report.
- We developed statistical models for three types of improper payments in the NSLP and the SBP: (1) improper payments due to certification error for non-CEP schools, (2) improper payments due to certification error for CEP schools, and (3) improper payments meal claiming error and aggregation improper payment error. These models were based on APEC-II data for SY 2012–2013.
- Model development included the following steps: (1) gathering data; (2) constructing models with different specifications of improper payment rates; (3) selecting a preferred model system for each type of improper payment using cross-validation model performance analysis; and (4) applying estimated coefficients to national data to generate national estimates of improper payment rates and amounts.

I INTRODUCTION

The Food and Nutrition Service (FNS), U.S. Department of Agriculture (USDA), funded the Access, Participation, Eligibility, and Certification study (APEC-I) to obtain national estimates of improper payments rates for the National School Lunch Program (NSLP) and the School Breakfast Program (SBP) for school year (SY) 2005-2006. It was the first study to generate national estimates of both certification and non-certification error and the improper payments that result from such errors. As a part of the APEC-I study, Mathematica developed statistical models designed to estimate national improper payments on an annual basis using district-level data available from the Verification Collection Report (VCR; also known as the FNS-742). This enabled the FNS to update its national improper payments rate estimates for the NSLP and SBP in future years without having to conduct full rounds of primary data collection. FNS staff have used these models to update annual estimates of overpayments, underpayments, and overall improper payments in the NSLP and SBP.

In response to the APEC-I study's findings, FNS initiated several new measures to improve Federal and State oversight and technical assistance to identify, recover, and reduce improper payments in the school meal programs. It is possible that the relationship between improper payment rates and explanatory variables in the APEC-I model may have changed in response to these initiatives, or for other reasons. Therefore, models developed using data from APEC-I may no longer be appropriate for projecting future improper payment rates. Also, the national model developed by APEC-I focused on projecting certification error and did not include non-certification error.

FNS funded the APEC-II study to obtain estimates of the prevalence of various types of program error in the NSLP and SBP for SY 2012-2013 (see U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, 2015). APEC-II includes updating the statistical model developed in APEC-I. In the APEC-II study, we expanded on the modeling in APEC-I in several important ways. First, we refined the existing estimation models used by FNS staff for updating annual national estimates of overpayments, underpayments, and overall improper payments due to certification error in the NSLP and SBP. Second, for APEC-II we developed an approach for modeling improper payments in schools participating in the Community Eligibility Provision (CEP), which was introduced in SY 2011–2012, available in six States plus the District of Columbia for SY 2012–2013 (when APEC-II took place), and available nationwide for SY 2013–2014. Thus, it is important for FNS to have models for projecting certification error of CEP schools as CEP expands. Finally, in addition to modeling certification error, APEC-II models errors in meal claiming.

In this technical report, we describe the approach to modeling improper payments due to certification error in non-CEP schools, certification error in CEP schools, and non-certification error; discuss the process for using the model to predict future improper payment amounts and rates; and assess the model's performance relative to the main APEC-II study findings for SY 2012-2013. The report is intended to solicit technical feedback from FNS and the modeling task expert review panel. The report is not intended to present modeling findings to a broader audience of layreaders.

A. Improper payments in the NSLP and the SBP—SY 2012–2013

The APEC-II study generated national estimates of improper payments in the NSLP and the SBP for SY 2012–2013. These estimates included improper payments due to certification error for non-CEP schools, improper payment due to certification error for CEP schools, improper payment meal claiming error and aggregation improper payment error. This section includes a brief overview of the APEC-II study design and findings; more detail is available in the APEC-II final report (see U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, 2015).

1. Sample design and data sources

A multistage-clustered sample design was used to create the sample on which we based our estimates of improper payments. We selected representative samples of school districts and schools (public and private); free and reduced-price meal applicants; and directly certified students participating in the NSLP and SBP in the contiguous United States. The APEC-II study included samples of school districts and schools that operate under the CEP and those that do not. These samples include the following:

- For the non-CEP sample: 130 SFAs that administer the meal programs, 392 schools (387 public and 5 private), 3,761 students certified for free and reduced-price meals (including directly certified students) and 611 denied applicants
- For the CEP sample: 45 SFAs, 135 CEP schools, and 3,240 students (from each school, 24 students were sampled—10 from the list of identified students, 8 from the list of students certified by application, and 6 from the list of students not certified for school meal benefits)

APEC-II collected data on these samples from several sources, including surveys of households and School Food Authority (SFA) directors; administrative data from schools, districts, and States; and observational data collected during visits to sampled schools. The data sources provided information that enabled us to measure certification and non-certification error. Each of the errors was calculated independently and then summed, taking into account interactions among the errors to estimate total net improper payments for both the NSLP and SBP.

2. Estimation methods and results

a. Estimation methods and results for certification errors for non-CEP schools

Certification errors for non-CEP schools occur when school districts claim reimbursement at the free or reduced-price rate for meals served to students who are not eligible for these benefits, or when school districts fail to claim reimbursement at the free or reduced-price rate for students who applied but were mistakenly denied benefits for which they were eligible. Certification error was determined by comparing sampled students' certification status as recorded by the district with their actual eligibility status for either free or reduced-price meals. We determined students' certification status using data from school districts' master benefit lists. We determined students' eligibility status based on school documentation of direct certification status and information collected during the in-person household survey.

Overpayments are defined as reimbursements made by the USDA to school districts for free or reduced-price meals served to students whose household circumstances indicated they received a higher level of benefits than they were eligible for. Underpayments are reimbursements the USDA did not provide to districts for meals served to students who were certified for reduced-price benefits although they were eligible for free meals, or who applied for meal benefits but were not approved despite being from households whose circumstances indicated they were eligible for either free or reduced-price meal benefits. The total improper payments measure is simply the gross sum of overpayments and underpayments.

To calculate the improper payment rate due to certification error for the NSLP in non-CEP schools, we first calculated the sum of overpayments and underpayments nationally for students who applied for meal benefits and then divided this sum by the total reimbursement paid to districts for all meals served (inclusive of the value of commodities). We calculated the overpayment and underpayment amounts based on the number of meals consumed by students who were overcertified or undercertified and on the dollar amount of the error associated with each meal consumed. We then used similar procedures to calculate the rate of improper payments for the SBP.

In APEC-II, we found that during SY 2012–2013, gross improper payments due to certification error in non-CEP schools in the NSLP equaled $1.15 billion, or 10 percent of the roughly $11.5 billion in total cash and commodity reimbursements provided to school districts in the 48 contiguous States and the District of Columbia. Gross improper payments due to certification error in non-CEP schools in the SBP equaled $364 million, corresponding to 11 percent of total SBP reimbursements. For both NSLP and SBP, about seven-tenths of gross improper payments were overpayments and about three-tenths were underpayments.

b. Estimation methods and results for certification errors for CEP schools

The Healthy, Hunger-Free Kids Act of 2010 added the CEP as an alternative to household applications for free and reduced-price meals in high-poverty districts and schools. Under this provision, participating schools offer free program meals to all students and do not have to use standard procedures to establish certification status for all students. Program meals meeting regulatory standards are reimbursed at either the free or paid rate, with the "claiming percentage" for free meals equal to the percentage of enrolled students who are "identified students" (those not subject to verification, who are directly certified or approved for free meals without an application because they participate in means-tested programs or programs serving homeless, migrant, and runaway children, as of April 1 of the previous school year) times a multiplier (currently 1.6). All students in CEP schools receive free meals regardless of the claiming percentages.

For schools using CEP, certification error occurs if the CEP group's claiming percentage for free or paid meals is incorrect. Therefore, the key determinant of improper payments in CEP groups is the difference between the identified student percentage (ISP) used by the group (the observed ISP) and the ISP if all students had been given the proper identification status (the estimated actual ISP). An important distinction between improper payments due to certification error in CEP schools and those in non-CEP schools is that a CEP group cannot have both overpayments and underpayments. This is because under CEP, overidentification and underidentification can perfectly offset one another. In other words, error in the identification process will not lead to improper payments if the number of students identified is correct, even if individual students are not all correctly identified.

The estimated actual ISP is based on estimates of the number of students in each CEP group who were correctly identified and the number of students who should have been identified but were not. We estimated this based on three samples of students drawn from each CEP school for their reference year: (1) identified students, (2) students who were not identified but who were certified for school meal benefits based on an application, and (3) students who were not identified or certified for school meal benefits. After calculating the estimated actual ISP, we derived the estimated actual free and paid claiming percentages and used them and information on the number of reimbursable meals to derive estimates of improper payments for the NSLP and SBP for each CEP school.

APEC-II found that schools using the CEP had low rates of improper payments due to certification error. For CEP schools, which accounted for an estimated 2 percent of total NSLP reimbursements nationally for SY 2012–2013 and 4 percent of total SBP reimbursements, the gross improper payment rate due to certification error was less than 2 percent for both the NSLP and SBP. Note that these findings were based on a sample of schools from five States (of the 6 States and District of Columbia) that were participating in the CEP at the time of the APEC-II study.

c. Estimation methods and results for non-certification errors

Non-certification error occurs in the stages between certifying students' eligibility status (in non-CEP schools), establishing the identified student percentage (ISP) and free and paid claiming rates (in CEP schools), and reporting meal counts to the State agency for reimbursement. The APEC-II study examined meal claiming error and three types of aggregation error.

Meal claiming error occurs when cafeteria staff members make errors in assessing and recording whether a specific meal selection meets the criteria for a reimbursable meal under the NSLP or SBP. This includes claimed meals that do not include the food components required by the program, either because students did not select a complete reimburseable meal, or because the school did not provide a meal that met program standards. APEC-II found that gross improper payments due to meal claiming error were $607 million in the NSLP and represented 5 percent of total NSLP reimbursements in SY 2012–2013. Gross improper payments due to meal claiming error in the SBP equaled $365 million, or 11 percent of total SBP reimbursements. Most meal claiming error was due to schools incorrectly recording trays as being reimbursable, leading to overpayments. Overpayments accounted for more than 86 and 97 percent of gross improper payments in the NSLP and SBP, respectively.

Aggregation error is the general term for three kinds of possible errors made by schools and SFAs in the process of counting the number of meals served and reporting these to State agencies for reimbursement. *Point-of-sale aggregation error* occurs when the daily meal count totals from the points of sale are summed incorrectly. *School-to-SFA aggregation error* occurs when school totals are improperly recorded by the SFA. *SFA-to-State-agency aggregation error* occurs when school totals are improperly communicated from the SFA to the State agency. Findings from the APEC-II studies indicate that improper payments due to aggregation error are a very small portion of total reimbursements. Gross error rates for the three types of aggregation error examined in the APEC-II study were all less than one percent for NSLP and SBP, and several of these rates were very close to zero. Thus, there is not enough variation in aggregation error to support effective modeling. In particular, there are so few districts with appreciable aggregation error that it would be very difficult to identify characteristics that reliably predict aggregation error, making model-based estimates of improper payments in future years unreliable. For these reasons, aggregation error is not included in the APEC-II modeling work.

B. Overview of approach for updating estimates of improper payments in the NSLP and the SBP

1. Overall approach

The estimates of the dollar amounts and rates of improper payments for SY 2012–2013 (described in the previous section) are based on nationally representative primary data collected in the APEC-II study. Because improper payments made in the NSLP and the SBP during SY 2012–2013 are significant as defined by the Improper Payments Elimination and Recovery Act (significant improper payments are defined as those in any program that exceed both 2.5 percent of program payments and $10 million annually, or $100 million in improper payments regardless of the improper payment percentage), FNS will need to report annually on the amount of estimated improper payments in the NSLP and the SBP.

We developed statistical models of improper payments due to certification error in non-CEP schools, certification error in CEP schools, and meal claiming error; these models will allow FNS to generate annual improper payment estimates in future years. Developing these models involved several steps. We first disaggregated overall findings on the SY 2012–2013 improper payment rates into a set of district-level improper payment rates. We then estimated a series of regression models capturing the relationship between the characteristics of these districts and their estimated improper payment rates. In future years, estimated coefficients from these models can be used in conjunction with updated values of district characteristics to predict certification error in these years in any district for which data on the district characteristics are available. These improper payment rates can then be translated into amounts and rates of improper payments in each district. By doing this for a national set of districts and then aggregating the district-level estimates, national measures of predicted improper payments can be calculated for future years.

We considered models with different specifications of improper payment rates. For example, for certification error in non-CEP schools, we considered models of improper payment rates that were decomposed into two categories, overpayments and underpayments, as well as models in which improper payment rates were disaggregated by student certification and eligibility status (for example, the percentage of free school lunches served to students eligible for reduced-price meals). Throughout the report, we refer to a set of regression equations that allow for estimating gross improper payments as a model system. For example, the aggregated improper payment rate system for certification error in non-CEP schools consists of regression models of overpayments and underpayments. Model systems of more disaggregated specifications of improper payment rates would include more regression equations.

We selected a preferred model system for each type of improper payment using cross-validation model performance analysis, a technique used to assess how the results of a statistical analysis will generalize to an independent data set where the goal is prediction, and one wants to assess external validity and estimate how accurately a predictive model will perform in practice (Geisser 1993; Kohavi 1995). This method reduces the chance of selecting a model that reflects relationships that are particular to the study sample rather than more broadly applicable relationships; such "over-fitted" models do not perform well when applied to external samples.

The cross-validation model performance measure we developed is intended to summarize how well the model system as a whole (as opposed to individual equations within the system) yields predictions that align with the improper payment rates we estimated based on the APEC-II sample. Broadly speaking, this is accomplished by applying the model system regression equations that were estimated using a random sample of study districts (or estimation sample) to a "testing (or set aside)" sample of districts to generate predicted error rates. These predicted error rates then were translated into district-level estimates of gross improper payments. We repeated this procedure many times to generate district-level average predicted improper payments. We summed up all predicted improper payments across all "testing (or set aside)" samples to generate a total predicted improper payment amount and then divided this estimated total by the sum of the total reimbursements across all "testing" samples to get the predicted error rates of reimbursement for each model system. We also calculated overpayments and underpayments in error if applicable. The final step was to compare predicted rates to error rates of reimbursement estimated in the APEC-II study based on primary data for SY 2012–2013. In selecting a preferred model system, we only considered models the difference between the predicted model system's improper payment rate and the observed APEC-II improper payment rate estimates. Final selection of model systems was based on this measure of performance as well as goodness of fit measures for the regression equations included in the system.

After selecting a model system, we applied the model system to the national data for SY 2012–2013 to get national improper payment rate estimates. These estimates, which are derived in the same way in which estimates would be derived in future years, allow us to assess how well the model estimated using APEC-II performs when applied to data other than the APEC-II data with which the model was estimated and selected; they offer an external validation of model performance.

The final step to model improper payments rate is to compute standard errors and confidence intervals for estimated improper payments rate using bootstrapping methods. We considered two types of sampling and estimation errors: (1) the sampling error associated with the sample used to estimate the model system, and (2) the sampling error associated with the sample to which the model system is applied. Standard errors and confidence intervals reflect the combination of both types of sampling error.

2. Challenges with modeling certification error in CEP schools

There are several significant challenges for modeling certification error in CEP schools. Chief among these is the limited availability of national data pertaining to CEP that could be used in modeling and validation. Because CEP is relatively new, FNS's national data system does not include information on reimbursements to CEP schools or on CEP implementation characteristics (such as claiming rates and ISPs). If these data were available, implementation characteristics would be incorporated into the model system as explanatory variables, and reimbursement information would be used to yield a more accurate application of the models to national data.

The VCR was revised in SY 2013–2014 to collect information from all districts nationally on the number of schools using CEP and the number of students in those schools. However, the revised VCR was released the year after the school year during which APEC-II took place. As a result, variables from the revised VCR are not directly available to be included in the model. To take advantage of the fact that this information will be available in the future, we relied on information collected in the APEC-II SFA director survey to construct close analogs to variables from the revised VCR. However, there are significant missing data and data inconsistency issues with variables created using the SFA director survey and this substantially limited the effectiveness of the modeling.

Although we were able to generate analogs to the revised VCR CEP information for the APEC-II sample for model estimation, we do not have analogous information for the national SY 2012–2013 VCR sample for external model validation. As a result, we had to impute relevant variables based on the SY 2013–2014 VCR to generate model-based national estimates of improper payments of certification error in CEP schools for SY 2012–2013. This imputation implicitly assumes that CEP participation did not change between SY 2012–2013 and SY 2013–2014 in the States that offered CEP in SY 2012–2013; this assumption is unlikely to be accurate but no other national data for SY 2012–2013 are available. These imputed values were used to identify which districts were using CEP, estimate CEP reimbursements, and as inputs when applying the model systems. These imputed values are also used in certification error modeling for non-CEP schools to adjust numbers of meals served in CEP schools for districts that operate both CEP and non-CEP schools.

Finally, the fact that CEP was still a new program available in a limited number of States in SY 2012–2013 presents important limitations on models of CEP improper payments based on APEC-II data. In SY 2012–2013, CEP only operated in six States plus the District of Columbia; the APEC-II CEP sample includes schools from five of these States. Districts within States that elected to use CEP may differ from typical districts nationally. As a result, APEC-II models of the relationship between district characteristics and CEP improper payments may not reflect the relationship that will exist for a broader, national set of districts. This point is compounded by the fact that CEP is still new, and improper payment rates are likely to change as districts and schools become more familiar with the program. As a result, there may be serious limitations on the ability of models based on the APEC-II sample to generate accurate estimates of improper payments in CEP schools in future years. However, FNS is required to provide estimates of improper payments for future years. These models provide the best estimates possible given the constraints in their estimation.

C. Organization of the report

The remainder of the report is organized as follows. In Chapter II, we compare improper payment estimates for SY 2012–2013 based on the APEC-I statistical model to improper payment estimates from the APEC-II study. In Chapter III, we describe the data used in the analysis, both for the measures of certification error for non-CEP and CEP schools and the measures of meal claiming error used as dependent variables in the econometric models, and for the district characteristics that serve as explanatory variables in these models. Chapter IV describes the statistical models we used to estimate the relationship between explanatory variables and of error rates and the results of the estimation of these models. Chapter V presents the performance of the preferred improper payment model systems when applied to national VCR data for SY 2012–2013. We compare these model-based estimates to the sample-based estimates from the APEC-II study. In the final chapter (Chapter VI), we discuss the strengths and limitations of the model.

Summary

- We applied the APEC-I improper payment models to national VCR data for SY 2012–2013 to generate model-based estimates of improper payments related to certification error for that school year.
- Improper payment estimates for SY 2012–2013 based on the statistical models developed from the APEC-I modeling work were compared to improper payment estimates from the APEC-II study.
- For both the NSLP and SBP, the APEC-I model predicts an overpayment rate that is close to the APEC-II estimate of the overpayment rate but, the APEC-I model did not perform as well in estimating underpayment rates.

II UPDATED PERFORMANCE ESTIMATES FOR THE APEC-I MODEL

As a part of the APEC-I study, Mathematica developed statistical models designed to use district data available from the VCR to estimate national improper payments due to certification error on an annual basis. FNS staff have used the models to update annual estimates of overpayments, underpayments, and overall improper payments in the NSLP and SBP since SY 2005–2006.

A central concern associated with model-based estimation is that model performance will deteriorate over time if the relationship between improper payments and the characteristics included in the model change. Given the dynamic school meal policy environment and FNS' broad efforts to reduce improper payments, such changes may occur with the improper payment model.

In this chapter, we compare improper payment estimates for SY 2012–2013 based on the statistical model developed from the APEC-I modeling work to improper payment estimates from the APEC-II study. This analysis helps us understand how model performance has evolved over time and enables us to identify aspects of the modeling approach that should be refined. The APEC-I model performed well in estimating overpayments and total improper payments for SY 2005–2006, but the predicted underpayment rates were somewhat lower than those in the APEC-I study (Moore, Gleason, and Ponza 2008). The model-based NSLP total improper payment rate estimate was 9.10 versus 9.42 percent in the APEC-I study; the NSLP overpayment rates were 7.21 and 7.11 percent for the model- and sample-based estimates respectively, and the underpayment rates were 1.89 and 2.31 percent. The model-based SBP total improper payment rate was 8.39 percent versus 9.15 percent in the APEC-I study; the SBP overpayment rates were 7.13 and 7.07 percent, and those for the underpayment rates were 2.08 and 1.26 percent.

We applied the APEC-I improper payment imputation model to national VCR data for SY 2012–2013 to generate model-based improper payment estimates for that school year. The APEC-I modeling report (Moore, Gleason, and Ponza 2008) describes the process for generating the estimates, which is analogous to the process described in Chapter V.[3]

In Table II.1, we show model-based improper payment estimates for SY 2012–2013 alongside the sample-based improper payment estimates from the APEC-II study. For both the NSLP and SBP, the APEC-I model predicts an overpayment rate that is close to the APEC-II overpayment rate estimate (7.16 versus 6.98 percent for the NSLP and 7.08 versus 7.69 percent for the SBP). It is worth noting, though, that the APEC sample-based overpayment rate estimates changed little from SY 2005–2006 to SY 2012–2013.

The APEC-I model did not perform as well in estimating underpayment rates. The APEC-I model predicts an underpayment rate of 1.31 percent for the NSLP and 0.80 percent for the SBP, while the APEC-II sample-based underpayment estimates are 2.83 percent for the NSLP and 3.27 percent for the SBP. The model-based underpayment rate estimates for SY 2012–2013 fall outside the 95-percent confidence interval for the APEC-II study estimate for both the NSLP and SBP. Comparing the sample-based estimates of SY 2012–2013 based on the APEC-II study to those based on APEC-I study for SY 2005–2006, we found that underpayment rate was somewhat higher in SY 2012–2013 (2.83 versus 2.31 percent for the NSLP and 3.27 versus 2.08 percent for the SBP; see U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, 2007). However, the APEC-I model predicted a decrease in underpayment rates. It is possible that this incorrect prediction is the result of changes in the relationship between improper payments and the factors included in the model. Model performance for underpayment rates may be less stable over time because some of the decomposed underpayment rates included as dependent variables in the model are quite low and more challenging to model effectively.

Because the APEC-I model underpayment estimates were too low, the total improper payment rate estimates are low relative to the APEC-II sample-based estimates (8.47 versus 9.81 percent for the NSLP and 7.88 versus 10.97 percent for the SBP). The model-based estimates fall within the 95 percent confidence intervals for the APEC-II study estimates, although the difference in the model-based estimate and the sample-based estimate is larger for SY 2012–2013 than for SY 2005–2006, particularly for the SBP.

Given that the APEC-I model performed poorly in estimating underpayments due to certification error, we considered models with alternate specifications for underpayments in the APEC-II modeling work. These alternative specifications may improve the models' performance over time. However, findings related to estimates of the APEC-I model-based underpayment rate underscore the an important consideration: interpretations of model-based estimates in future years need to account for deterioration of the performance of the models over time in response to changes in the factors related to improper payments.

[3] We did not adjust for CEP schools when applying the APEC-I improper payment imputation model to national VCR data for SY 2012–2013, because the coefficients were estimated when CEP did not exist. Therefore, the adjustment is not appropriate. Furthermore, the CEP reimbursements for SY 2012–2013 were small, accounting for about two percent of reimbursements.

Table II.1. National improper payment estimates due to certification error for SY 2012-2013 based on the APEC-I imputation model and APEC-II study sample

	APEC-II sample-based estimation		APEC-I model-based estimation	
	NSLP	SBP	NSLP	SBP
Improper payments (in millions of dollars)				
Overpayments	824 (121) [588, 1060]	257 (46) [167, 347]	826	247
Underpayments	334 (59) [219, 449]	109 (26) [58, 160]	151	28
Total improper payments	1,158 (140) [884, 1,432]	366 (57) [255, 477]	977	274
Percentage of all reimbursements in error				
Overpayments	6.98 (1.01) [5.01, 8.95]	7.69 (1.35) [5.06, 10.32]	7.16	7.08
Underpayments	2.83 (0.51) [1.84, 3.82]	3.27 (0.75) [1.81, 4.73]	1.31	0.80
Total improper payments	9.81 (1.18) [7.51, 12.11]	10.97 (1.68) [7.69, 14.25]	8.47	7.88

Source: FNS-742 Verification Collection Reports and APEC-II study.

Note: Standard errors in parentheses; 95 percent confidence interval in brackets. APEC-II study sample certification error estimates include improper payments in CEP schools

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III DATA AND MEASURES

Summary

- Statistical models consist of district-level improper payment rates—the dependent variables in the models—and district characteristics—the explanatory variables in the models.
- A model system is a set of models that can be used to estimate total national improper payments of a particular type.
- For each type of error, we considered several different model systems, each of which used different specifications of the improper payment rates (dependent variables). We did this in order to test which model systems perform best.
- In building the models, we considered explanatory variables that included indicators of the administrative features of the NSLP and the SBP in the district, other characteristics of the district, demographic characteristics of students and families in the district, and other policy variables that are likely to be relevant to the types of error being modeled. These variables are drawn from the VCR and several other different sources.

The data required for the statistical model include the model's dependent variables: (1) district-level measures of certification error rates for non-CEP schools, (2) CEP-group level measures of certification error rates for CEP schools, and (3) district-level measures of error rates in meal claiming. The data also include independent variables, which are a set of district characteristics potentially relevant to (and therefore predictive of) these error rates. Finally, the models require information on meal counts by certification type for the construction of estimates of amounts of reimbursement.

The error rate measures used as dependent variables in the statistical models are based on primary data collected in the APEC-II study. APEC-II collected data on a nationally representative sample of school districts and schools (public and private), and on free and reduced-price meal applicants and directly certified students participating in the NSLP and SBP in the contiguous United States. The study includes samples of school districts and schools that operate under the CEP and those that do not. APEC-II collected data on these samples from several sources, and these data enabled us to measure both (1) certification error and improper payments among individual students and (2) non-certification error in the processes schools and districts use to claim reimbursements from State agencies.

The independent variables we considered for the model included indicators of the administrative features of the NSLP and the SBP in the district, other characteristics of the district, demographic characteristics of students and families in the district, and other policy variables that are likely to be relevant to the types of error being modeled. For certification errors in non-CEP schools, the district's verification outcomes were included as key explanatory variables, since they have been found to be predictive of error rates in the district in APEC-I modeling work.[4] For certification errors in CEP schools, we constructed variables to mimic the information that will be available on CEP schools in the district starting in SY 2013–2014 in the revised VCR. For meal claiming errors, we also included the district features most likely to be relevant to meal claiming. For the statistical model, we needed data on all these measures for only the districts included in the APEC-II sample, but in order to use the model to predict future improper payments at the national level, the data used to create the model's independent variables also had to be available for all districts nationally in the sample year and in future years.

The independent variables we considered were based on data from several sources: (1) district-level administrative data on district characteristics and verification outcomes from the School Food Authorities (SFA) Verification Collection Reports (Form FNS- 742), (2) public school district–level data from the Common Core of Data (CCD) and the decennial census, (3) private school data from the Private School Survey (PSS), (4) county-level data on unemployment rates from the U.S. Department of Labor's Local Area Unemployment Statistics (LAUS), (5) information on states' direct certification performance rates from the annual Report to Congress on Direct Certification Implementation, and (6) APEC-II study data on direct certification methods and other SFA characteristics. To translate estimated error rates into district-level estimates of improper payments, we also needed State meal counts information from the FNS national database.

We next describe each of these data sources and the relevant data items we used from each in more detail.

A. Dependent variables for certification error modeling for non-CEP schools

We first created the district-level error rates that serve as dependent variables in the models. We developed corresponding error rates for each model system we tested. To create these measures, we aggregated meal-level estimates of certification error across all meals served to sampled students in each of the districts in the APEC-II study sample.

1. Definitions of certification error measures for non-CEP schools

We tested four model systems for certification errors for non-CEP schools; each system had different specifications of certification error rates. These specifications differed primarily in the degree of aggregation in the certification error rates included in the model.[5] For example, the most aggregated certification error rates (used in model system 1) are the percentage of NSLP

[4] APEC-I modeling work found that districts that have higher percentages of verified applications in which benefits are reduced or terminated based on documentation provided by responding households tend to have higher %CF-PE-L and %CF-PE-B error rates. In particular, a 10-point increase in the percentage of certified free applications changed to reduced-price or paid status during verification is associated with a 1.40 percentage point increase in the predicted value of %CF-PE-L; this relationship is statistically significant at the .05 level.1 Similarly, a 10 percentage point increase in this same variable is associated with a 1.29 percentage point increase in the predicted value of %CF-PE-B; this relationship is also statistically significant at the .05 level.

[5] Improper payments related to Provision 2 and 3 schools are included into the non-CEP improper payment rates.

reimbursements that are overpayments and the percentage of NSLP reimbursements that are underpayments. The most disaggregated certification error rates (used in model system 3) include measures such as the percentage of free lunches served to students who were certified for free school lunches based on categorical eligibility (by direct certification or application), but who actually were eligible for reduced-price school lunches.

Non-CEP certification error model systems

Model system 1

- Improper payment rates were decomposed into two rates each for NSLP and SBP: overpayments and underpayments

Model system 2

- Improper payment rates were decomposed into six rates each for NSLP and SBP: three for overpayments and three for underpayments

Model system 3

- Improper payment rates were decomposed into eight rates each for NSLP and SBP: five for overpayments and three for underpayments

Model system 4

- Improper payment rates were decomposed into four rates each for NSLP and SBP: three for overpayments and one for underpayments

These different specifications allow us to assess whether model performance improves as error rates are more finely defined. This would be the case if the relationship with explanatory variables differs for different types of error rates. However, more finely defined district-level error rates are less precisely estimated in the APEC-II data which may lead to weaker models or models that reflect relationships specific to the APEC-II sample rather than more general relationships (that is, over-fitted models).

In model system 1, certification error rates were modeled in the most aggregate manner. We decomposed error rates into two separate categories for both the NSLP and SBP, underpayment rate and overpayment rate (Table III.1).

Table III.1. Rates of improper payment due to certification error included in model system 1

Certification error rate	Description
% Over-L	Percentage of NSLP reimbursements that were overpayments
% Under-L	Percentage of NSLP reimbursements that were underpayments
% Over-B	Percentage of SBP reimbursements that were overpayments
% Under-B	Percentage of SBP reimbursements that were underpayments

In model system 2, we disaggregated the overall error rate into a set of district-level measures that describe the proportion of meals in a particular meal-price category that had a particular type of certification error. This modeling approach is identical to the APEC-I modeling approach. Specifically, we created the following 12 district-level error rate measures for the NSLP and the SBP:

Table III.2. Rates of improper payment due to certification error included in model system 2

Certification error rate	Description
%CF-RPE-L	Percentage of free school lunches served to students who were eligible for reduced-price lunches
%CF-PE-L	Percentage of free school lunches served to students who were not eligible for free or reduced-price lunches
%CRP-PE-L	Percentage of reduced-price school lunches served to students who were not eligible for free or reduced-price lunches
%CRP-FE-L	Percentage of reduced-price school lunches served to students who were eligible for free lunches
%NC-FE-L	Percentage of paid school lunches served to students who were eligible for free lunches
%NC-RPE-L	Percentage of paid school lunches served to students who were eligible for reduced-price lunches
%CF-RPE-B	Percentage of all free school breakfasts served to students who were eligible for reduced-price breakfasts
%CF-PE-B	Percentage of all free school breakfasts served to students who were not eligible for free or reduced-price breakfasts
%CRP-PE-B	Percentage of all reduced-price school breakfasts served to students who were not eligible for free or reduced-price breakfasts
%CRP-FE-B	Percentage of reduced-price school breakfasts served to students who were eligible for free breakfasts
%NC-FE-B	Percentage of paid school breakfasts served to students who were eligible for free breakfasts
%NC-RPE-B	Percentage of paid school breakfasts served to students who were eligible for reduced-price breakfasts

The third modeling approach system (model system 3) further disaggregated the error rates for free meals based on whether the error was related to students certified for free meals based on categorical eligibility (by direct certification or application) or those who were certified based on income. This approach takes advantage of the large difference in error rates between students who were categorically eligible and those who were not. Specifically, we created the following 16 district-level error rate measures for the NSLP and the SBP:

Table III.3. Rates of improper payment due to certification error included in model system 3

Certification error rate	Description
%CF-RPE-C-L	Percentage of free school lunches served to students who were certified for free school lunches based on categorical eligibility (by direct certification or application) but who were actually eligible for reduced-price school lunches
%CF-PE-C-L	Percentage of free school lunches served to students who were certified for free school lunches based on categorical eligibility (by direct certification or application) but who were actually not eligible for free or reduced-price school lunches
%CF-RPE-I-L	Percentage of free school lunches served to students who were certified for free school lunches based on income, but who were actually eligible for reduced-price school lunches
%CF-PE-I-L	Percentage of free school lunches served to students who were certified for free school lunches based on income, but who were actually not eligible for free or reduced-price school lunches
%CRP-PE-L	Percentage of reduced-price school lunches served to students who were certified for reduced-price school lunches, but who were actually not eligible for free or reduced-price school lunches
%CRP-FE-L	Percentage of reduced-price school lunches served to students who were certified for reduced-price school lunches, but who were actually eligible for free school lunches
%NC-FE-L	Percentage of paid school lunches served to students who were not certified for reduced-price or free school lunches, but who were actually eligible for free school lunches
%NC-RPE-L	Percentage of paid school lunches served to students who were not certified for reduced-price or free school lunches, but who were actually eligible for reduced-price school lunches
%CF-RPE-C-B	Percentage of free school breakfasts served to students who were certified for free school breakfasts based on categorical eligibility (by direct certification or application), but who were actually eligible for reduced-price school breakfasts
%CF-PE-C-B	Percentage of free school breakfasts served to students who were certified for free school breakfasts based on categorical eligibility (by direct certification or application), but who were actually not eligible for free or reduced-price school breakfasts
%CF-RPE-I-B	Percentage of free school breakfasts served to students who were certified for free school breakfasts based on income, but who were actually eligible for reduced-price school breakfasts
%CF-PE-I-B	Percentage of free school breakfasts served to students who were certified for free school breakfasts based on income, but who were actually not eligible for free or reduced-price school breakfasts
%CRP-PE-B	Percentage of reduced-price school breakfasts served to students who were certified for reduced-price school breakfasts, but who were actually not eligible for free or reduced-price school breakfasts
%CRP-FE-B	Percentage of reduced-price school breakfasts served to students who were certified for reduced-price school breakfasts, but who were actually eligible for free school breakfasts
%NC-FE-B	Percentage of paid school breakfasts served to students who were not certified for reduced-price or free school breakfasts, but who were actually eligible for free school breakfasts
%NC-RPE-B	Percentage of paid school breakfasts served to students who were not certified for reduced-price or free school breakfasts, but who were actually eligible for reduced-price school breakfasts

Model system 4 is a hybrid of model system 1 and model system 2. Underpayments were considerably smaller than overpayments were in both the NSLP and SBP programs. Moreover, some of the decomposed underpayment rates, especially the error rates of paid meals served to students who were eligible for free or reduced-price meals, are quite low and propose a challenge to modeling. Thus, in model system 4 we took a hybrid approach by separating overpayment errors into particular types of certification error, but aggregating the error due to underpayments into one measure. We created the following eight district-level error rate measures for the NSLP and the SBP:

Table III.4. Rates of improper payment due to certification error included in model system 4

Certification error rate	Description
%CF-RPE-L	Percentage of all free school lunches served to students who were eligible for reduced-price lunches
%CF-PE-L	Percentage of all free school lunches served to students who were not eligible for free or reduced-price lunches
%CRP-PE-L	Percentage of all reduced-price school lunches served to students who were not eligible for free or reduced-price lunches
% Under-L	Percentage of underpayments for lunches
%CF-RPE-B	Percentage of all free school breakfasts served to students who were eligible for reduced-price breakfasts
%CF-PE-B	Percentage of all free school breakfasts served to students who were not eligible for free or reduced-price breakfasts
%CRP-PE-B	Percentage of all reduced-price school breakfasts served to students who were not eligible for free or reduced-price breakfasts
% Under-B	Percentage of underpayments for breakfasts

2. Methods used to construct error rate measures

The approach used to estimate the certification error rate variables is methodologically consistent with analogous certification error rates estimated for SY 2005–2006 under APEC-I. Certification error is determined by comparing a student's certification status, as recorded by his or her SFA, and the student's free or reduced-price meal eligibility status, as determined by his or her household circumstances.

As in the APEC-I study, in APEC-II we measured students' certification status using data from the master benefit lists maintained by the school districts. We based our estimates on a sample that is representative of all students nationally who became certified during SY 2012–2013. We determined students' eligibility status for free or reduced-price meals based on information that we collected during the in-person household survey.

With some exceptions, the sample of certified students is representative of all students in the contiguous United States who were certified at any time during SY 2012–2013.[6] The sample of denied applicants includes students who applied but were denied benefits.

We determined students' certification status using data from school districts' master benefit lists. We determined students' eligibility status primarily based on school documentation of direct certification status and information collected during the in-person household survey. The household survey collected information on students' household income, household size, and receipt of other benefits, such as the Supplemental Nutrition Assistance Program (SNAP) or Temporary Assistance for Needy Families (TANF). This information reflected students' household circumstances at about the time the households submitted applications for free or reduced-price meals. For students who became certified without submitting an application (directly certified students), the information collected in the household survey reflected household circumstances at the beginning of the school year. Students for whom the school had documentation of direct certification were classified as eligible for free meals regardless of the information in the household survey. Students were classified as eligible for free meals at the time their application was certified (or the beginning of the school year if they became certified without an application) if they met any of the following conditions:

- The school provided documentation of direct certification for free meals.[7]
- The household survey indicated participation in SNAP, TANF, the Food Distribution Program on Indian Reservations (FDPIR), or other programs that confer categorical eligibility.
- The household survey indicated household income less than or equal to 130 percent of the Federal poverty level.

Students were classified as eligible for reduced-price meals if they were not eligible for free meals, but the household survey indicated household income less than or equal to 185 percent of the Federal poverty level. An additional eligibility requirement for either free or reduced-price meals was that for students certified by application, the district had to be able to locate the application in their files. If the district did not have an application on file, the student was classified as not eligible for free or reduced-price meals, as specified in FNS rules. Incomplete applications did not affect the eligibility determination.

The determination of students' eligibility status accounted for carryover cases when applicable. Carryover cases occur when a student certified for free or reduced-price meals during the previous school year (and not directly certified before the beginning of the new school year) continues to receive meals at the previous benefit level regardless of household circumstances until his or her new status is established, or for a period of up to 30 days. When the carryover period ends, the student's certification status from the previous school year ends.

[6] Estimates are not representative of students in Alaska, Hawaii, the U.S. territories, schools operated by the Department of Defense (DOD), and residential child care institutions.

[7] In addition to directly certified students, this group also includes other categories of students certified for free meals without having to submit an application, such as homeless or runaway children, children of migrant workers, and students extended free eligibility based on the participation of a household member in SNAP, TANF, or FDPIR.

Table III.5 summarizes the possible combinations of certification and eligibility status among students who have been approved for free or reduced-price meals. In the table, columns indicate students' certification status, and each row indicates the level of benefits for which the students are eligible. Cells in this table have been color-coded to indicate correct certification (blue), over-certification (red), or under-certification (green). For example, the students in Cell B are certified for reduced-price meals, but eligible for free meals; they are therefore under-certified.

Table III.5. Combinations of students' certification and eligibility status

	Certification status		
Eligibility status	Free	Reduced-price	Denied
Free	A	B	C
Reduced-price	D	E	F
Paid	G	H	I

Note: Cells in this table have been color-coded to indicate correct certification (blue), over-certification (red), or under-certification (green).

Certification error can come from household reporting error, district administrative error, or a combination of both types of error. Students in cells along the diagonal (A, E, and I) were certified accurately or were appropriately denied benefits. Students in cells below the diagonal (D, G, and H) were over-certified, and students in cells above the diagonal (B, C, and F) were under-certified. Once we determined whether a student was certified in error or was inappropriately denied benefits, we were able to construct the district-level error rate measures.

a. Constructing error rate measures for model system 1

In model system 1, the total improper payment is decomposed into two categories: overpayments and underpayments. This decomposition is done first for the NSLP and then for the SBP. For example, the underpayment rate for the NSLP is equal to the ratio of the gross dollar amount of NSLP underpayments to the total amount of reimbursements for all NSLP meals. Specifically, we calculated the number of school lunches provided to students who were undercertified and in cells above the diagonal (B, C, and F). We estimated the error rate by dividing the gross dollar amount of payments made in error to these students to the total amount of reimbursements for all NSLP meals. We estimated this error rate by dividing the gross dollar amount of payments made in error to students who were overcertified and in cells above the diagonal (D, G, and H) to the total amount of reimbursements for all NSLP meals. The dependent variables for the SBP are constructed in a similar manner.

b. Constructing error rate measures for model system 2

To construct the first four of six error rate measures of model system 2 for the NSLP and the SBP, we first restricted the sample to those students enrolled in a sampled district in the appropriate certification category. For example, we based the first dependent variable, *% CF-RPE-L*, on only the sample members certified for free meals.

Within each district, we then aggregated the number of school meals provided to all students in that certification category, as well as the number of meals provided to students in that category with a particular type of certification error.[8] For *% CF-RPE-L*, for example, we calculated the number of school lunches provided to students certified for free meals who were eligible for reduced-price meals (Cell D). We estimated the error rate by dividing this number by the total number of lunches provided to students in the free certified category (lunches provided to students in cells A, D, and G).

Calculating the final two dependent variables in each meal program required an additional step, since the denominator in each of these rates includes school meals provided to all non-certified students in the district, but the APEC-II sample included only non-certified students who had applied for, but were denied, free or reduced-price meal benefits (that is, denied applicants). Thus, we initially calculated the proportion of meals served to denied applicants that were in a particular error category, then we adjusted this figure by multiplying it by the ratio of the number of paid meals provided to denied applicants to the number of paid meals provided to all non-certified students in the district. We obtained information on the numerator (the number of meals served to denied applicants) by using information on meals consumed by the denied applicants in our sample. Information on the denominator (the number of meals served to all non-certified students) came from the SFA Director Survey. This approach is identical to the approach we used in APEC-I modeling.

c. Constructing error rate measures for the model system 3

To construct error rate measures of model system 3 for the NSLP and the SBP, we further disaggregated the error rates pertaining to free meals (the first two of six error rate measures) based on whether the error was related to students who were certified for free meals based on categorical eligibility (by direct certification or application) or who were certified based on income. Specifically, we based the first dependent variable, *% CF-RPE-C-L*, on only the sample members certified for free meals based on categorical eligibility (by direct certification or application). We calculated the number of school lunches provided to students who were certified for free meals based on categorical eligibility (by direct certification or application), but who were eligible for reduced-price meals. We estimated the error rate by dividing this number by the total number of free lunches provided to students certified for free meals based on categorical eligibility (by direct certification or application). For *% CF-RPE-I-L*, we calculated the number of school lunches provided to students who were certified for free meals based on income eligibility, but who were eligible for reduced-price meals. We estimated the error rate by dividing the number of free lunches with that particular error by the total number of lunches provided to students certified for free meals based on income eligibility.

d. Constructed error rate measures for the model system 4

There are eight error rate measures for the model system 4—there are three overpayment error rates and one underpayment error rate for the NSLP and similarly for the SBP. In each case, three types of overpayment error rate measures for model system 4 are identical to those in

[8] In aggregating meals provided to a particular group of sample members in a district, we used the appropriate sample weights so that the weighted sum reflected the estimated number of meals provided to all enrolled students in that particular group within the district.

model system 2 and the underpayment error measure was constructed the same manner as that in model system 1.

B. Dependent variables for certification error modeling for CEP schools

Improper payments under CEP are determined at the level of the CEP group rather than at the student level. An important distinction between improper payments due to certification error in CEP schools and those in non-CEP schools is that a CEP group cannot simultaneously have both overpayments and underpayments. With this feature of improper payments under CEP in mind, the error rate was modeled as the net percentage of CEP reimbursements in error. Because 40 of the 45 APEC-II sample districts have sample schools that are all in the same CEP group within district, the modeling analysis treats CEP-group-level improper payment rates as district-level improper payment rates, as described in greater detail below.

Table III.6. Model system certification error rate specification, CEP Schools

Certification error rate	Description
% Net-L	Net percentage of CEP reimbursements in error for NSLP
% Net-B	Net percentage of CEP reimbursements in error for SBP

This rate can take either positive or negative values, depending on whether the district had overpayments or underpayments (that is, depending on whether their free claiming percentage is too high or too low). The gross improper payment rate is the absolute value of the net improper payment rate.

The key determinants of reimbursements for schools participating in CEP are the number of meals served to all students and the percentage of students in their CEP group identified as having been approved for free meals with a method that does not require verification during a reference year. CEP groups do not claim reimbursements based on the certification of individual students. Instead, CEP groups claim reimbursements during the four-year CEP cycle using two claiming percentages that are applied to total reimbursable meals separately for the NSLP and the SBP: (1) a free claiming percentage (FCP) and (2) a paid claiming percentage (PCP). The FCP and PCP are calculated from the percentage of enrolled students in the CEP group who were directly certified (or certified by methods other than by application) as of April in an earlier reference year. This rate of direct certification is called the identified student percentage (ISP) (after subtracting the FCP from 100 percent). The FCP is equal to 1.6 times the ISP, and the PCP is equal to the residual percentage. The FCP cannot exceed 100 percent. Reimbursements are calculated based on the FCP, PCP, total meals served, and the reimbursement amount for free/paid meals (please see Chapter VI, Volume I of the APEC-II main report for a more complete description of how reimbursement in CEP schools are calculated).

The large differences in how reimbursements are calculated in CEP and non-CEP schools mean that improper payments must be conceptualized differently for CEP schools. The improper payment analysis for schools not using CEP was driven by the accuracy of the certification status of individual students. However, for schools using CEP, reimbursements are based on the claiming percentages of the CEP group as a whole (and all students receive free meals regardless of the claiming percentages). Therefore, improper payments occur only if a CEP group's claiming percentage for free or paid meals (FCP or PCP) is incorrect.

The approach to estimating certification error in CEP schools has two steps: (1) assessing the accuracy of the ISP and the resulting FCP and PCP and (2) comparing observed reimbursements (based on the ISP used by the CEP school) with corrected reimbursements (based on the estimated actual ISP calculated by the analysis team). To do so, we collected student-level data pertaining to the CEP reference year for randomly selected CEP schools in the five States included in the analysis. We also collected program data from State agencies and districts. After calculating net error rates for CEP schools, we aggregated the error rates to the CEP group level, applying the appropriate weights.

Although improper payments under CEP are determined at the level of the CEP group, there is no national data source that contains information at the CEP group level. Therefore, it would not be possible to develop CEP-group level models that FNS could use to generate national estimates of improper payments in future years. As a result, our models of CEP improper payments must be estimated at the district level. The APEC-II sample includes 5 districts with more than one CEP group, with three districts having two CEP groups, one district having three CEP groups, and one district having six CEP groups. The same district characteristics are used for constructing and estimating the model for the CEP groups in the same district.

C. Dependent variables for error modeling in meal claiming

Meal claiming error occurs when cafeteria staff members make errors in assessing and recording whether a specific meal selection meets the criteria for a reimbursable meal under the NSLP or SBP. This includes meals that do not include the food components required by the program, either because students did not select a complete reimbursable meal, or because the school did not provide a meal that met program standards.

1. Definitions of error measures

The meal claiming error is estimated at the district level. We decomposed meal claiming error into two separate categories, overpayment and underpayment, for both the NSLP and SBP:

Table III.7. Model system meal claiming error rate specification

Certification error rate	Description
% Over-L	Percentage of overpayments for NSLP
% Under-L	Percentage of underpayments for NSLP
% Over-B	Percentage of overpayments for SBP
% Under-B	Percentage of underpayments for SBP

Further disaggregation of meal claiming error rates is not possible. The APEC-II study was not able to separate improper payment rates based on the certification status of the student receiving the meals, because it would cause issues with student data confidentiality.

2. Methods used to construct error rate measures

The methodology used to estimate meal claiming error was the same as in APEC-I and had three stages. First, field staff collected data on random samples of more than 48,000 breakfast and lunch transactions from a nationally representative sample of more than 400 schools. Second, research staff analyzed the collected data, using the final rule entitled “Nutrition Standards in the National School Lunch and School Breakfast Programs” (2012), the accompanying “Questions and Answers for Program Operators” (2013), and the USDA’s “A Menu Planner for Healthy School Meals” (USDA 2008), to determine whether each tray was reimbursable. Third, Mathematica used the aforementioned determination as the true reimbursable status of the tray and compared this with the reimbursable meal status recorded by the school. Trays were counted as having a meal claiming error whenever the school’s determination differed from Mathematica’s independent assessment. These comparisons were then used to estimate national rates and amounts of improper payments due to meal claiming error.

Once we determined whether each tray at a school was reimbursable and identified meal claiming errors, two error rates corresponding to overcounting and undercounting of reimbursable meals were calculated: (1) the fraction of meals that schools recorded as reimbursable, but that Mathematica determined to be non-reimbursable, and (2) the fraction of meals that schools recorded as being non-reimbursable, but that Mathematica determined to be reimbursable. Ideally, we would have been able to calculate the improper payment for a tray based on the certification status of the student, but student confidentiality issues prevented us from following this approach. To estimate improper payments at the school, we instead assumed that meal claiming error affected the reimbursements for each meal type proportionately. We multiplied the error rates by the total reimbursements for each meal type at the school and summed these dollar amounts of error. We used this process to calculate overpayments and underpayments at the school. Then we took the weighted sum of the dollar amounts of errors over schools to the district level. We calculated the improper payment rate by dividing the estimate of improper payments in the district (in dollars) by the district’s total reimbursements. We repeated this process separately for the NSLP and SBP.

D. Potential measurement concerns related to dependent variables

Information from the study’s household survey is the basis for determining the student’s “true” eligibility for school meal benefits. Whether intentionally or not, respondents may inaccurately report family size and income on the household survey. Inaccurate information about households affects our ability to measure true eligibility status and determine certification error and erroneous payments. We took the following steps to ensure the most accurate reporting: (1) households were sent a letter from USDA establishing the legitimacy and importance of the study; (2) study correspondence stipulated to respondents that their responses would be kept strictly confidential and would not affect the benefits they receive, and field staff were trained to reiterate these points; (3) the reference period for the survey was the month covered by the application; (4) most households were interviewed within three months of their certification or application date; and (5) an iterative computer-assisted personal interviewing (CAPI) procedure streamlined reporting on income, reconciled differences between reported and documented amounts, and enabled respondents to review and identify missing or inaccurate income sources and/or amounts. Although it is clear that some misreporting occurred, the extent to which this happened is unknown. Unfortunately, the study did not have the resources, nor was it feasible, to link APEC-II household survey data to Social Security Records or other administrative data sources to directly examine the extent of measurement error in our sample.

However, to get some sense of the effects that measurement error might have on results, we did, in the APEC-II main study, examine the extent to which alternative definitions and assumptions affected our base estimates of the rates of erroneous payments. These sensitivity checks test not only the effect of changing the criteria for inclusion in the economic unit but also the assumptions about the eligibility of students who had missing or incomplete applications or direct-certification documentation, or who reapplied later in the school year. For example, we found that considering as ineligible students for whom incomplete applications were submitted resulted in gross erroneous payment rates of 9.7 percent for the NSLP and 10.6 percent for the SBP. We also found that assuming that students who reapplied later in the school year were certified without error yielded gross erroneous payment rates of 9.2 percent for the NSLP and 10.2 percent for the SBP. In short, these alternative definitions resulted in gross erroneous payment estimates that differed just slightly from the NSLP and SBP base estimates presented in the main text of the report, which were 9.6 percent and 10.6 percent, respectively.

Furthermore, the main estimates of improper payments in the APEC-II study are based on actual meals received. Therefore, these estimates do not adjust for the fact that undercertified students would receive more meals with the correct certification status, and overcertified students would receive fewer meals with correct certification status. In the APEC-II study, we generated alternative improper payment estimates in which the actual number of meals received by students with an incorrect certification status was replaced with an imputed meal count based on the correct certification status. These alternative estimates resulted in estimates of overpayment rates that were identical to rates in which the base measure of meal imputation was used. Underpayment rates increased just slightly—by less than one percentage point—for both the NSLP and the SBP, resulting in slightly higher gross erroneous payments.

Ultimately, there is not much we can do about measurement error in our household survey reports of income sources and amounts other than to acknowledge that the potential for error exists, since the best we can do with the modeling effort is to replicate the APEC-II study estimates, which are themselves subject to measurement error. For more details on the methodology we used to estimate the improper payments, readers should refer to the main report as well as Appendix F in that report for the sensitivity checks we conducted.

E. Explanatory variables

Explanatory variables should be highly predictive of error rates, but also responsive to changes in district policy or characteristics; models will not perform well in future years if they include only relatively static demographic characteristics that are unlikely to change from year to year.

An important practical consideration in developing these models is that explanatory variables must be drawn from data sources that will be timely, available for all districts nationwide, and straightforward for FNS to merge with other included data sources. If these conditions are not met, FNS will not be able to use the models to estimate improper payments in future years in a timely manner. For this reason, the APEC-I model only used explanatory variables drawn from the VCR. APEC-I explored the value of including additional data sources, but FNS and Mathematica concluded that the additional explanatory power provided by data sources other than the VCR did not justify the complications to producing annual improper payment estimates that incorporating these data sources would introduce. Specifically, including additional data sources would require that FNS wait until all relevant data sources are available, merge those data sources with VCR data, and create the necessary variables from those additional data sources.

The APEC-II modeling analysis followed APEC-I procedures in using the VCR as the base data source and evaluating whether the contribution of the additional data sources are sufficiently valuable to justify the complication of including them. APEC-II included variables from the following data sources as candidates for inclusion in the error rate models: the CCD, the PSS, the census Small Area Income and Poverty Estimates (SAIPE), and LAUS. In addition to these data sources, we also explored including State direct certification characteristics available through the Direct Certification Improvement Study and the annual Reports to Congress on Direct Certification Implementation. In the remainder of this section, we describe the explanatory variables we constructed using these data sources.

1. Measures constructed from SFA verification collection reports (Form FNS-742)

The VCR data on SFA characteristics, certification outcomes, and verification outcomes for the APEC-II study's SFA sample were used to develop the statistical models. In addition, these data were used to form the national source of district data needed to predict improper payments nationally (and to be used in future years to predict improper payments). There were 18,673 SFAs in the SY 2012–13 VCR data file. The number of students enrolled in these SFAs equaled 50,593,453. We eliminated districts that did not fall within our study population of all public and private SFAs in the contiguous 48 states and the District of Columbia. Therefore, we removed (1) districts in Alaska, Hawaii, and U.S. territories; (2) schools operated by the Department of Defense, and (3) residential childcare institutions. This resulted in a final edited data file of 18,529 SFAs.

a. Constructed variables for estimating improper payment models

The data from the VCR were used to create the following variables:

- Type of SFA (public or private)
- Number of schools operating the NSLP and/or the SBP
- Number of Provision 2 or 3 (P23) non–base-year schools
- Number of enrolled students with access to the NSLP and/or the SBP
- Number of students in P23 non–base-year schools
- Average school size
- Percentage of students certified for free meals, by certification method:
  - Percentage certified for free meals, not subject to verification
  - Percentage certified for free meals based on income/household size information submitted on applications
  - Percentage certified for free meals based on categorical eligibility from information on their applications

    - Percentage of students certified as eligible for free meals in P23 non–base year schools
- Percentage of students certified for reduced-price meals
    - Percentage of students certified for reduced-price meals
    - Percentage of students certified as eligible for reduced-price meals in P23 non–base-year schools
- Number of applications selected for verification
- Percentage of total applications selected for verification
- Verification sampling method
- Percentage of applications verified by certification category (free-categorically approved, free-income approved, and reduced-price–income approved)
- Verification results for each certification category:
    - Percentage of verified applications in which household responded, no change
    - Percentage of verified applications in which household responded, benefits changed
    - Percentage of verified applications in which household responded, benefits reduced or terminated
    - Percentage of verified applications in which household responded, benefits increased
    - Percentage of verified applications in which household did not respond, benefits terminated

b. Constructed variables for estimating certification error in CEP schools

As discussed in the previous chapter, the CEP modeling tasks were significantly challenged by the lack of available data. We had to impute CEP-relevant variables based on the combination of the information from the SY 2013–2014 VCR and the information collected in the SFA Director Survey. The modeling tasks were also challenged by the lack of available explanatory variables. It would be useful to have more detailed information on CEP implementation, but the relevant variables are not available. Given the information we had, using the combination of the revised VCR and SFA Director Survey, we constructed the following variables:

- Percentage of students in schools operating CEP
- Percentage of schools operating CEP

For APEC-II districts used in estimating the model, these variables were derived from information collected in the SFA Director Survey. For the national set of districts in the SY 2012–2013 VCR, these data were filled in with values from the SY 2013–2014 VCR. As noted earlier, this imputation implicitly assumes that CEP participation did not change between SY 2012–2013 and SY 2013–2014 in the States that offered CEP in SY 2012–2013; this assumption is unlikely to be accurate, but no other national data for SY 2012–2013 are available.

c. Data edits and imputations

We first examined the raw variables in the VCR data file for missing data and recording errors (inappropriate codes, extreme values) and assessed the need to impute values when data were missing on key items. We repeated the process for constructed variables, examining missing and unusually low or high values.

FNS' improved data reporting and cleaning procedures resulted in an SY 2012–2013 VCR had little missing data, unlike the SY 2005–2006 VCR used for the APEC-I study. Therefore, no imputation was necessary for data construction. Our data cleaning efforts focused mainly on data reasonableness checks and edits. For instance, we checked districts with low numbers or percentages of students certified for free or reduced-price meals; these typically included small private schools whose student body contained few students in low-income families, and were not altered. We also checked values of interrelated variables in which a variable corresponding to a total should align with the sum of the components of the total. We edited the extreme outliers (for example, percentages exceeding 100 percent); these outliers were either set equal to 100 percent or assigned mean value replacement as judged appropriate. When constructing ratios, if the denominators were zero, we created a missing indicator and set the value of the variable as zero.

2. Measures constructed from the CCD

The CCD is the U.S. Department of Education's primary statistical database on public elementary and secondary schools and districts. Updated annually through surveys sent to state education agencies, this data set contains demographic and administrative information on all public schools and districts in the United States, and is designed to be comparable across all states. Information from the merged CCD files (Local Education Agency Universe Survey, Local Education Agency Finance Survey, and Public School Universe Survey) was used to construct the following variables, which were considered as independent variables:

- Grade span by district
- Enrollment by race/ethnicity/gender/grade
- Location of district (for example, large city, mid-size city, large town, small town)
- Number of SFA administrators and support staff overall and per student
- Number of teachers, school administrators, and support services staff overall and per student
- Spending on food services, food service salaries, and administrative support services overall and per student

We examined the variables constructed from the data file for missing data and recording errors (for example, inappropriate codes or extreme values) and imputed values when data on key items were missing. There are schools that have records in the CCD Universe Survey or in the CCD Finances survey, but not in both. Since the values of many variables we constructed do not vary much over time, in most cases, missing values were replaced with the values from the closest year of data. Specifically, for the schools that have records only in the Universe Survey but not in the Finances survey, we checked the next closest year of the Finances data to see if data on these schools were available, and did the same for the schools with data in Finances but not in Universe. When an appropriate replacement could not be found, missing values were assigned with mean value replacement.

Because the CCD is collected only for public schools and districts, private SFAs originally had missing values for all CCD-based measures. When data on variables such as grade span and race/gender composition were available, these missing values were filled in based on information from the PSS, described next.

3. Measures constructed from the PSS

The PSS, collected by the National Center for Education Statistics, is a national data set on private schools. It includes information on the school's religious orientation, the grade levels it serves, total enrollment, and enrollment by gender. We used the PSS as a source of information about private schools that participate in the NSLP or the SBP. We also linked each participating private school to the public school district in which it is located to obtain relevant public school district–level information (such as district-level income and poverty data from the census, discussed in the next section). There are variables can be constructed using CCD data but are not available in the PSS data, such as spending on food services, food service salaries, and administrative support services. For these variables, we set the value as zero for schools and districts from PSS data, but created an interaction between these spending variables and type of SFA (public or private).

4. Measures constructed from SAIPE data

Both a district's median income and its poverty rate (overall poverty rate and school-age poverty rate) may be important predictors of improper payments. To measure income and poverty rates, we used annual estimates of county-level income and poverty rates from the SAIPE. The SAIPE uses both Current Population Survey (CPS) and decennial census data to estimate district-level income and poverty rates in non-census years. As noted, private SFAs were linked to the public school districts in which they are located. Because we were able to match all sample SFAs to the Census County and SAIPE data, no missing value imputations were necessary.

5. Measures constructed from LAUS data

Improper payment rates in a district may also be correlated with its unemployment rate, because local economic conditions are related to the income and poverty status of the families in the area, and thus may relate to the number of families who apply for benefits. The LAUS data provide monthly estimates of unemployment rates at the county level, and these can be linked to public school districts. The Bureau of Labor Statistics produces the estimates in conjunction with state employment security agencies. The estimates for counties are based on a variety of data sources, including the CPS, Current Employment Statistics, the decennial census, and state unemployment insurance systems, and are updated each month.

6. Measures drawn from the annual Reports to Congress on Direct Certification Implementation

The success that States have in directly certifying eligible students may be related to improper payment rates, particularly given the relatively low rates of improper payments associated with directly certified students in non-CEP schools and the importance of accurate direct certification in reducing certification error in CEP schools. As such, we used State information from the annual Reports to Congress on Direct Certification Implementation to find the State's percentage of school-age children in families that participate in SNAP who were directly certified for free school meals. Because these reports are produced annually, the data will be available for use in future years.

7. Additional data items that could be used if collected by FNS

In addition to the data items already discussed, other administrative data, not currently collected by FNS, could potentially enhance estimates of improper payments in future years. For example, Performance Standard Violations information from Coordinated Review Effort (CRE) are likely highly correlated with meal claiming and administrative certification error and responsive to changes in district policy or characteristics. However, the CRE has been replaced with the administrative review process, and national district-level data pertaining to these processes are not available. Similarly, using offer versus serve (OVS) status and meal planning approach status for SBP were shown to have associations with meal claiming error(U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, 2015); however, these variables are not available on the national level.

The variables listed here were constructed using data from the APEC-II study SFA director survey:

- Type of direct certification approach used (no match, district-level match, state-level match, other method)
- Whether district uses a food management company to run its meal programs
- OVS status and meal planning approach status for SBP[9]

[9] We also tested including additional data items that are not currently collected by FNS. For instance, including OVS status for meal claiming error modeling and direct certification approach for certification error modeling for non-CEP schools. We found that in general including these variables improve R-square of the regression equation, suggesting these variables might be useful to collect for enhancing estimates of improper payments in future years.

IV DEVELOPMENT OF THE APEC-II IMPROPER PAYMENT MODEL

Summary

- An important practical consideration in developing these models is that explanatory variables must be drawn from data sources that will be timely, available for all districts nationwide, and straightforward for FNS to merge with other data sources. This led us to use the VCR data set as a starting point for the APEC-II model development.
- In selecting the explanatory variables for each model, we sought a core set of factors that have a strong theoretical relationship with improper payment rates and that are likely to be responsive to changes in policy or implementation characteristics. Such variables expand the model's capacity to perform well on samples other than the one used to estimate the model.
- In addition to specifications based only on these core explanatory variables, we considered specifications that include core explanatory variables plus a small number of additional variables selected according to their observed correlation with improper payment rates. These additional variables were selected with an automated procedure.
- After identifying the variables to include in each model system equation, we selected the model most likely to perform well in practice. We made this selection using a within-sample cross-validation method, taking into account the model's goodness of fit.

In this chapter, we describe the statistical models we used to estimate the relationship between district characteristics and three types of error rates: certification error rates for non-CEP schools, certification error rates for CEP schools, and meal claiming error rates. This description includes the process for selecting explanatory variables to include in the model systems and the within-sample validation methods used to select the preferred model system for each type of error.

A. Statistical models for certification error in non-CEP schools

We estimated four model systems corresponding to different specifications of certification error rates in non-CEP schools, as described in chapter IV. Each model system was composed of different numbers of regression equations. The basic form of all four model systems is:

(1) $CE_{kj} = X_{kj}\beta_k + u_{kj}$, where k varies for different model system

with CE_{kj}= rate of certification error type k in district j

X_{kj}= characteristic of district j included in equation k

β_k = relationship between characteristic X_{kj} and error rate CE_{kj}

u_{kj} = term representing unobserved effects on the error rate CE_{kj}

We estimated these equations using ordinary least squares (OLS).

While the dependent variables used for each equation were described in chapter III, an additional aspect of the dependent variables is worth noting. As discussed in the previous chapter, each dependent variable is an estimate, based on samples of students within the APEC-II study districts. Thus, each dependent variable is subject to measurement error (resulting from the sampling error of these estimates). Further, since the size of the APEC-II study samples varies somewhat from district to district for a given certification category, the underlying variability in this measurement error will differ from district to district. In other words, the variance of the disturbance term in equation (1) will vary from observation to observation, a condition known as heteroskedasticity. Following the approach of APEC-I modeling, we adjusted for this heteroskedasticity by estimating robust standard errors of the coefficients in the regression equations.

1. Approach used to select independent variables

In selecting the independent variables for each model, we sought factors with a strong theoretical relationship with certification error rates that are likely to be responsive to changes in policy or implementation characteristics. We designated such factors as core variables to be included in the improper payment models. Selecting variables based on their theoretical relationships, rather than their observed correlation with error within the sample, reduces the chance of selecting a model that reflects relationships particular to the study sample rather than relationships applicable to a broader sample; such “over-fitted” models do not perform well when applied to external samples. We also consider specifications in which the core variables are supplemented by a small number of variables selected based on their observed correlation with improper payment rates, as discussed in greater detail in the next section.

As discussed in the main APEC-II report, certification error can arise in two ways. First, a household can report incorrect information on its application for meal benefits, resulting in a certification status for which it may not be eligible. This type of error is called reporting error. Reporting error may be influenced both by administrative features of the programs (such as the type of verification procedures used) and by the demographic characteristics of students and families in the district. Second, school districts can make mistakes processing applications or direct certification documents, determining eligibility, recording certification status information on the application, or transmitting status from the application or direct certification documents onto the master benefit list. This second type of error is called administrative error. Administrative error is likely to be most heavily influenced by administrative features of the school meal program in the district and by other administrative characteristics of the district. Therefore, the explanatory variables we considered included indicators of the administrative features of the NSLP and the SBP in the district, other characteristics of the district, and demographic characteristics of students and families in the district.

We also included variables representing verification results in the model, as we believed that they would likely be highly predictive of districts’ certification error rates, based on theory and findings in the APEC-I modeling analysis.

Aside from including in the model independent variables that theory suggests should be predictive of certification error rates, three additional considerations influenced our strategy for selecting a specification for the econometric model: (1) the limited number of degrees of freedom in the model, (2) the need to focus on policy-sensitive variables, and (3) the practical need to end up with a model that will be easy for FNS to use to predict future improper payments. We next describe each of these considerations.

The degrees of freedom for each of the equations to be estimated as part of the econometric model are limited by the fact that the APEC-II sample included 130 non-CEP districts. With a limited number of degrees of freedom, the number of independent variables whose relationship with certification error rates can be estimated with a reasonable degree of precision is also limited. Thus, we needed to be economical in selecting independent variables for the model.

Second, this need to be economical in defining the specification of each equation led us to focus especially on variables representing factors that could potentially proxy for or be influenced by the districts' efforts to improve the integrity of the NSLP or the SBP. If, for example, districts were making policy changes resulting in more accurate certification, we wanted independent variables whose values would change from year to year to reflect the underlying policy changes. These policy-sensitive variables would be more valuable in our model than variables such as student demographic characteristics that might be correlated with districts' error rates, but would be unlikely to change much from year to year in response to changing meal program policies.

Finally, our strategy for selecting the model's independent variables was influenced by the fact that the results of the model are designed to be used in future years to predict improper payments. This future effort will involve assembling a data set that includes values of each independent variable over all districts across the nation that offer the NSLP or the SBP. Thus, we had to select independent variables that would be available in future years and could be incorporated into a single data file with relative ease and at modest cost.

This consideration led us to use the VCR data set as a starting point. Three features of this data set were particularly important for the modeling effort. First, aside from a relatively small set of districts that failed to provide data, the VCR file contains information on the full population of public and private districts across the nation that participate in the meal programs. Second, the data will be collected in future years and available to the FNS relatively quickly at the conclusion of each school year. Third, the key independent variables in the model—verification procedures and results—are available in the VCR data set. In addition to the variables available from VCR data, we also considered variables constructed from the other data sources listed in chapter IV. D. Although most of these data sources will be available in future years, they must be merged with the VCR data to be used in the modeling effort. Because the system for identifying districts in the VCR data set differs from that used by these other data sets, this data merge is not straightforward. Thus, any improvements in the model's predictive power arising from the inclusion of independent variables from these other data sources must be weighed against the future costs of creating a merged data file that can be used to predict improper payments if such variables are included.

2. Variable selection

Our strategy for selecting a set of variables and specifications for each modeling system for certification error in non-CEP schools consisted of the following elements:

- We first came up with a list of variables as candidates to be explanatory variables in the model. This list included variables from the VCR as well as variables from the other data sources we acquired.
- Based on theoretical relevance and data availability, we selected from the VCR data a set of independent variables we defined as core variables that would definitely be included in the model.
- We used an automated procedure for selecting an additional set of variables to be included in the equation as independent variables; VCR data were used to construct the independent variables. In the automated procedure, the variables that explained the greatest proportion of the variation of the residual after controlling for the core variables were included in the model as additional independent variables. We then repeated this process, including as candidate variables from all available data sets.
- We allowed each equation of each model system to have a unique set of independent variables. In other words, each equation includes the independent variables that best predict that equation's dependent variable.
- We used a split-sample cross-validation method to identify cross-validation model performance, and selected the specification with the strongest predictive performance, which is measured by both minimizing the differences between predicted rates of improper payments and observed rates in the APEC-II study sample, and by measures of goodness of fit.

The candidate variables we considered, along with their data sources, are listed in Table IV.1. In addition to the basic version of these variables, we also considered squared terms of some of the key variables, and interactions between selected variables. From among these candidate variables, the core variables represent verification procedures and results, the proportion of students in the district in various certification categories, and district enrollment.

Table IV.1. Independent variables considered for inclusion in the certification error model for non-CEP schools, by data source

Data source	Variables considered for inclusion in the certification error model for non-CEP schools
VCR	Type of SFA (public or private) Number of schools operating the NSLP and/or the SBP Number of P23 non–base-year schools Number of enrolled students with access to the NSLP and/or the SBP Number of students in P23 non–base-year schools Average school size Percentage of students certified for free meals, by certification method Number of applications selected for verification Percentage of total applications selected for verification Verification sampling method Percentage of applications verified by certification category (free-categorical approved, free-income approved, and reduced-price–income approved) Verification results for each certification category
CCD	Grade span: elementary schools, middle schools, high schools Race All spending on food services per student School admin/support staff per student Urbanicity
PSS	Grade span: elementary schools, middle schools, high schools Race Urbanicity
LAUS and SAIPE	Median household income Unemployment rate

VCR= Verification Collection Report; CCD = Common Core of Data; PSS = Private School Survey; LAUS = Local Area Unemployment Statistics; SAIPE = Small Area Income and Poverty Estimates

Each equation of each model system has a unique set of independent variables. For example, in equations in which the dependent variable represents an error rate among meals served to students certified for free meals, the core independent variables show verification results among the free meal applications that were verified. In equations in which the dependent variable is a reduced-price meal error rate, the core independent variables show verification results among the reduced-price applications that were verified.

After selecting the core variables, an automated process was used to select additional variables for the model. These additional variables were selected in a stepwise fashion based on correlations of all variables in the set being considered with each dependent variable, controlling for the core variables (that is, with the residual from the regression of each dependent variable on the core variables). The variables that explained the greatest proportion of the variation of this residual were included as additional independent variables in the model. Using this process, we developed five specifications for each of the four model systems:

- Core variables only
- Core variables plus one additional variable from the VCR
- Core variables plus three additional variables from the VCR

- Core variables plus one additional variable from any data set
- Core variables plus three additional variables from any data set[10]

3. Cross-validation model performance

After identifying the variables to include in each model system equation, we selected the model with the strongest within-sample cross-validation model performance.[11] Cross-validation is a model validation technique for assessing how the results of a statistical analysis will generalize to an independent data set where the goal is prediction, and the researcher wants to assess external validity and estimate how accurately a predictive model will perform in practice. Implementing the cross-validation analysis includes four main steps:

- We randomly split the sample into 10 groups of equal size. Data on one group (the testing sample) were excluded and each equation of the model system was fitted to the data in the other 9 groups (the estimation sample).
- We used the 9 groups to estimate the equations in the model system specification, then applied the coefficients estimated from these equations using the 9 groups to the reserved group to obtain the predicted dependent variable.
- We used the predicted dependent variable with district-level meal counts and reimbursement rates to obtain dollar amounts of improper payments of a certain type for each district.
- We summed the predicted improper payments from each equation within the model system for each meal program to get predicted underpayment, overpayment, and gross certification error payment amounts for lunch program and breakfast program separately for each district.

We repeated this procedure using each of the other randomly selected groups as the reserved sample. Each of the 10 groups from that the sample was split into at the beginning of the procedure had taken a turn as the reserved testing sample. We repeated this procedure 20 times, generating 20 replications of tenfold cross-validation. The final step was to average predicted improper payments across the 200 rounds for each meal program for each district.

We summed these predicted district-level improper payments and calculated district-level reimbursements for all 20 randomly drawn testing samples to generate total improper payments and total reimbursements for each meal program separately for all test samples. The total predicted improper payment for each meal program then was divided by the total reimbursement of that meal program to generate predicted implied underpayment, overpayment, and overall error rates of lunch and breakfast program separately of all testing samples. The final step was to

[10] Most of the variables included in the model are core variables, which were selected on the basis of their theoretical relationship to improper payment, not according to their observed correlation with improper payment rates. Models based purely on observed correlation are likely to be overspecified to the estimation sample and are unlikely to perform well when applied to other samples. However, for informational purposes, we tested a model based purely on the observed correlation with improper payment rates, and the model's performance was no better than what we have.

[11] An alternative model specification selection strategy would be to base the selection on model performance when applied to the VCR data. The concern is that such an approach would lead to a model that is overfitted to the SY 2012-2013 data, and therefore less accurate for future years.

compare these predicted rates to the error rates estimated based on the APEC-II study. We compared the relative differences—the ratios as well as the absolute differences between the corresponding rates. We also took into consideration the goodness of fit of the model.

4. Model system selection

Table IV. 2 summarizes the results from cross-validation for the NSLP. Specifically, for each specification of each model system, it shows the percentage of NSLP reimbursements in error (overall, overpayments, and underpayments) averaged across the cross-validation testing samples, the percentage of NSLP reimbursements in error as estimated in the APEC-II study, and the difference in these rates.

The cross-validation analysis indicated that, in comparing our cross-validation model performance to the APEC-II sample-based estimation, model system 1 performed better in estimating underpayment error rates across all specifications, but model system 2 performed better in estimating overpayment error rates. These findings suggest that modeling overpayments is more effective when the overpayment rate is disaggregated at a finer level, whereas modeling underpayments is more effective with a more aggregated error rate. Given this finding, we estimated a hybrid of model systems 1 and 2; this was model system 4, which uses disaggregated overpayment rates and aggregated underpayment rates.

Based this cross-validation analysis, we selected the specification of model system 4 that includes the core explanatory variables plus one additional variable as our preferred one. This specification is the only one to consistently minimize the relative differences between cross-validation predicted certification error rates, including overall, underpayment, and overpayment error rates, and those of the APEC-II sample estimated error rates: predicted certification overall certification error rate is within 6 percent (0.6 percentage points) of the APEC-II sample's estimated error rates, and the predicted overpayment rate is nearly the same as the sample-based estimate. The difference for underpayment is relative large, but still among the smallest across all specifications. Table IV.3 lists the explanatory variables included in the selected model system.

Table IV. 4 summarizes the results for the SBP non-CEP certification error cross-validation analysis. Patterns in these findings are similar to those for NSLP. After evaluating differences between predicted rates and the error rates estimated based on the APEC-II study, the goodness of fit measure, as well as weighing the improvement of model performance against the cost of using a model that includes multiple data sources in future years, we selected the specification of model system 4 that includes the core explanatory variables plus one additional variable from the VCR as our preferred specification. The preferred model system and specification not only predicts an overall error rate that is among the closet ones to that based on APEC-II study, but predicts each component of the overall error rate well. The explanatory variables included in the selected model system are listed in Table IV.5.

Table IV.2. Cross-validation results for model systems of certification error in non-CEP schools, NSLP

Model system 1	Cross-validation testing sample predicted improper payment rates			APEC-II estimated improper payment rates			Comparison		
Model specification	**IPR**	**OPR**	**UPR**	**IPR**	**OPR**	**UPR**	**Difference in IPR**	**Difference in OPR**	**Difference in UPR**
Model system 1									
Core	0.134	0.088	0.045	0.100	0.072	0.027	1.335	1.234	1.691
Core + 1 from VCR	0.119	0.083	0.035	0.100	0.072	0.027	1.187	1.164	1.321
Core + 3 from VCR	0.128	0.090	0.038	0.100	0.072	0.027	1.279	1.262	1.405
Core + 1 from any source	0.124	0.088	0.036	0.100	0.072	0.027	1.240	1.232	1.340
Core + 3 from any source	0.124	0.090	0.035	0.100	0.072	0.027	1.242	1.253	1.291
Model system 2									
Core	0.087	0.074	0.013	0.100	0.072	0.027	0.869	1.037	0.474
Core + 1 from VCR	0.083	0.071	0.013	0.100	0.072	0.027	0.833	0.985	0.479
Core + 3 from VCR	0.094	0.081	0.013	0.100	0.072	0.027	0.943	1.130	0.503
Core + 1 from any source	0.087	0.074	0.012	0.100	0.072	0.027	0.868	1.039	0.463
Core + 3 from any source	0.089	0.076	0.013	0.100	0.072	0.027	0.889	1.064	0.479
Model system 3									
Core	0.068	0.056	0.013	0.100	0.072	0.027	0.682	0.775	0.474
Core + 1 from VCR	0.067	0.054	0.013	0.100	0.072	0.027	0.671	0.759	0.479
Core + 3 from VCR	0.072	0.058	0.013	0.100	0.072	0.027	0.714	0.811	0.503
Core + 1 from any source	0.067	0.054	0.012	0.100	0.072	0.027	0.668	0.760	0.463
Core + 3 from any source	0.073	0.061	0.013	0.100	0.072	0.027	0.734	0.846	0.479
Model system 4									
Core	0.120	0.075	0.045	0.100	0.072	0.027	1.199	1.043	1.691
Core + 1 from VCR	0.106	0.071	0.035	0.100	0.072	0.027	1.058	0.985	1.321
Core + 3 from VCR	0.120	0.082	0.038	0.100	0.072	0.027	1.195	1.144	1.405
Core + 1 from any source	0.110	0.074	0.036	0.100	0.072	0.027	1.100	1.037	1.340
Core + 3 from any source	0.112	0.077	0.035	0.100	0.072	0.027	1.115	1.076	1.291

Source: FNS-742 Verification Collection Reports and APEC-II study.

IPR = Percentage of total reimbursements in error; OPR = Percentage of overpayment in error; UPR = Percentage of underpayment in error

Highlighted row represents final model system specification selected for analysis.

Table IV.3. Explanatory variables included in models of NSLP certification error for non-CEP schools

		Overpayment			Underpayment
		%CF-RPE-L	%CF-PE-L	%CRP-PE-L	%Under-L
Verification variables (core)					
(1)	Used alternate random verification sample	X	X	X	X
(2)	Percentage of verified free applications that had benefits reduced or terminated in verification	X	X		
(3)	Interaction of (1) and (2)	X	X		
(4)	Percentage of verified reduced-price applications that had benefits increase in verification			X	X
(5)	Interaction of (1) and (4)			X	X
(6)	Percentage of verified free applications that did not respond in verification	X	X		
(7)	Interaction of (1) and (6)	X	X		
(8)	Percentage of verified reduced-price applications that had benefits terminated in verification			X	
(9)	Interaction of (1) and (8)			X	
(10)	Percentage of all verified applications that had benefits changed in verification				X
(11)	Interaction of (1) and (10)				X
(12)	Percentage of verified reduced-price applications that did not respond in verification			X	
(13)	Interaction of (1) and (12)			X	
(14)	Percentage of verified reduced-price applications that had benefits increased in verification				X
(15)	Interaction between (1) and (14)				X
(16)	Percentage of verified all applications that did not respond in verification				X
(17)	Interaction of (1) and (16)				X
Certification variables (core)					
(18)	Percentage of students certified without an application	X	X	X	X

Table IV.3 *(continued)*

		Overpayment			Underpayment
		%CF-RPE-L	%CF-PE-L	%CRP-PE-L	%Under-L
(19)	Percentage of students certified categorically	X	X	X	X
District characteristics (core)					
(20)	Enrollment	X	X	X	X
(21)	Percentage of students certified for free meals	X	X	X	X
(22)	Percentage of students certified for reduced-price meals	X	X	X	X
(23)	Privately operated	X	X	X	X
Policy variables (core)					
(24)	State direct certification performance rate	X	X	X	X
Additional variables from the VCR (selected based on correlation with the dependent variable)					
(25)	Number of schools operating special provision	X			
(26)	Number of application certified categorically eligible		X		X
(27)	Percentage of students certified without an application			X	

%CF-RPE-L= Percentage of free school lunches served to students who were eligible for reduced-price lunches

%CF-PE-L= Percentage of free school lunches served to students who were not eligible for free or reduced-price lunches

%CRP-PE-L=Percentage of reduced-price school lunches served to students who were not eligible for free or reduced-price lunches

%Under-L=Percentage of underpayment for the NSLP

Table IV.4. Cross-validation results for model systems of certification error in non-CEP schools, SBP

Model system 1	Cross-validation testing sample predicted error rates			APEC-II sample-based estimated error rates			Comparison		
Model specification	IPR	OPR	UPR	IPR	OPR	UPR	Difference in IPR	Difference in OPR	Difference in UPR
Model system 1									
Core	0.103	0.067	0.035	0.113	0.080	0.033	0.909	0.844	1.066
Core + 1 from VCR	0.100	0.069	0.031	0.113	0.080	0.033	0.887	0.865	0.944
Core + 3 from VCR	0.100	0.073	0.026	0.113	0.080	0.033	0.884	0.922	0.796
Core + 1 from any source	0.100	0.069	0.031	0.113	0.080	0.033	0.881	0.862	0.930
Core + 3 from any source	0.095	0.069	0.025	0.113	0.080	0.033	0.838	0.872	0.759
Model system 2									
Core	0.086	0.071	0.014	0.113	0.080	0.033	0.758	0.894	0.433
Core + 1 from VCR	0.086	0.072	0.014	0.113	0.080	0.033	0.762	0.899	0.436
Core + 3 from VCR	0.091	0.077	0.015	0.113	0.080	0.033	0.807	0.960	0.443
Core + 1 from any source	0.086	0.072	0.014	0.113	0.080	0.033	0.760	0.902	0.420
Core + 3 from any source	0.086	0.072	0.014	0.113	0.080	0.033	0.765	0.907	0.426
Model system 3									
Core	0.066	0.052	0.014	0.113	0.080	0.033	0.588	0.653	0.433
Core + 1 from VCR	0.067	0.053	0.014	0.113	0.080	0.033	0.593	0.660	0.436
Core + 3 from VCR	0.071	0.057	0.015	0.113	0.080	0.033	0.631	0.711	0.443
Core + 1 from any source	0.069	0.055	0.014	0.113	0.080	0.033	0.608	0.687	0.420
Core + 3 from any source	0.069	0.055	0.014	0.113	0.080	0.033	0.610	0.688	0.426
Model system 4									
Core	0.107	0.072	0.035	0.113	0.080	0.033	0.949	0.902	1.066
Core + 1 from VCR	0.102	0.070	0.031	0.113	0.080	0.033	0.901	0.884	0.944
Core + 3 from VCR	0.104	0.078	0.026	0.113	0.080	0.033	0.924	0.979	0.796
Core + 1 from any source	0.102	0.071	0.031	0.113	0.080	0.033	0.904	0.894	0.930
Core + 3 from any source	0.098	0.073	0.025	0.113	0.080	0.033	0.867	0.913	0.759

Source: FNS-742 Verification Collection Reports and APEC-II study.

IPR = Percentage of total reimbursements in error; OPR = Percentage of overpayment in error; UPR = Percentage of underpayment in error.

Highlighted row represents model selected for analysis.

Table IV.5. Explanatory variables included in models of SBP certification error for non-CEP schools

		Overpayment			Underpayment
		%CF-RPE-B	%CF-PE-B	% RPF-PE-B	%under-B
Verification variables (core)					
(1)	Used alternate random verification sample	X	X	X	X
(2)	Percentage of verified free applications that had benefits reduced or terminated in verification	X	X		
(3)	Interaction of (1) and (2)	X	X		
(4)	Percentage of verified reduced-price applications that had benefits increase in verification			X	X
(5)	Interaction of (1) and (4)			X	X
(6)	Percentage of verified free applications that did not respond in verification	X	X		
(7)	Interaction of (1) and (6)	X	X		
(8)	Percentage of verified reduced-price applications that had benefits terminated in verification			X	
(9)	Interaction of (1) and (8)			X	
(10)	Percentage of all verified applications that had benefits changed in verification				X
(11)	Interaction of (1) and (10)				X
(12)	Percentage of verified reduced-price applications that did not respond in verification			X	
(13)	Interaction of (1) and (12)			X	
(14)	Percentage of verified reduced-price applications that had benefits increased in verification				X
(15)	Interaction between (1) and (14)				X
(16)	Percentage of verified all applications that did not respond in verification				X
(17)	Interaction of (1) and (16)				X
Certification variables (Core)					
(18)	Percentage of students certified without an application	X	X	X	X
(19)	Percentage of students certified categorically	X	X	X	X

Table IV.5 *(continued)*

		Overpayment			Underpayment
		%CF-RPE-B	%CF-PE-B	% RPF-PE-B	%under-B
District characteristics (core)					
(20)	Enrollment	X	X	X	X
(21)	Percentage of students certified for free meals	X	X	X	X
(22)	Percentage of students certified for reduced-price meals	X	X	X	X
(23)	Privately operated	X	X	X	X
Policy variables (core)					
(24)	State direct certification performance rate	X	X	X	X
Additional variable from the VCR (selected based on correlation with the dependent variable)					
(25)	Total number of certified applications (in thousands)	X			
(26)	Number of application certified categorically eligible		X		X
(27)	Percentage of students certified without an application			X	

%CF-RPE-B= Percentage of free school lunches served to students who were eligible for reduced-price breakfasts

%CF-PE-B= Percentage of free school lunches served to students who were not eligible for free or reduced-price breakfasts

%CRP-PE-B=Percentage of reduced-price school lunches served to students who were not eligible for free or reduced-price breakfasts

%under-B=Percentage of underpayment for the SBP

5. Regression results for certification error model system for non-CEP schools

In Tables IV.6 and IV.7, we summarize the regression results for the NSLP and SBP, respectively. The R-squared values for regression equations in the preferred model systems are moderately low in the %CF-PE models (0.1 for the NSLP and 0.07 for the SBP) but higher in the remaining equations, ranging from 0.12 to 0.56 for the NSLP and 0.18 to 0.52 for the SBP. Most of the model coefficients are not statistically significant. Higher district enrollment and percentages of students certified for free meals based on categorical eligibility are associated with significantly lower NSLP underpayment rates; more applications certified based on categorical eligibility are associated with lower NSLP underpayment rates. Higher State direct certification performance rates are associated with significantly lower percentages of free lunches served to reduced-price-eligible students; higher percentages of students certified for reduced-price meals are associated with significantly lower percentages of free lunches served to ineligible students. Patterns are similar for the SBP model system, although we also found that districts using random verification samples have significantly higher percentages of free meals served to reduced-price–eligible students, as do private districts.

We also experimented using weighted regressions for our large pool of model systems/specifications for each type of error, where district-level reimbursement total is used as the weights. The results do not suggest that weighted regressions improve the model performance. The findings on factors significantly correlated with the improper payments rate based on weighted regressions and unweighted regressions are consistent. Therefore, we only included the results from unweighted regressions in this report.

Table IV.6. Coefficient estimates from estimated regression equations, certification error for non-CEP schools, NSLP

Variables		% UnderPayment_L	% CF_RPE_L	% CF_PE_L	% CRP_PE_L
Verification variables (core)					
(1)	Used alternate random verification sample	1.352 (2.698)	0.626 (4.225)	-8.425 (7.695)	4.448 (21.90)
(2)	Percentage of verified reduced-price applications that had benefits changed in verification	0.0385 (0.0367)	- -	- -	- -
(3)	Interaction of (1) and (2)	-0.000985 (0.0826)	- -	- -	- -
(4)	Percentage of all verified applications that had benefits changed in verification	-0.0622 (0.0453)	- -	- -	- -
(5)	Interaction of (1) and (4)	-0.0679 (-0.114)	- -	- -	- -
(6)	Percentage of verified reduced-price applications that did not respond in verification	0.0403 (0.0268)	- -	- -	0.156 (0.135)
(7)	Interaction of (1) and (6)	-0.129 (0.0833)	- -	- -	0.0182 (0.331)
(8)	Percentage of verified all applications that did not respond in verification	-0.0493 (0.0378)	- -	- -	- -
(9)	Interaction of (1) and (8)	0.0951 (0.102)	- -	- -	- -
(10)	Percentage of verified free applications that had benefits reduced or terminated in verification	- -	-0.0425 (0.0418)	-0.0486 (0.0759)	- -
(11)	Interaction of (1) and (10)	- -	-0.00670 (0.106)	0.249 (0.191)	- -
(12)	Percentage of verified free applications that did not respond in verification	- -	0.0301 (0.0377)	-0.0437 (0.0685)	- -
(13)	Interaction of (1) and (12)	- -	0.0106 (0.0765)	0.195 (0.139)	- -
(14)	Percentage of verified reduced-price applications that had benefits reduced or terminated in verification	- -	- -	- -	0.0236 (0.193)
(15)	Interaction of (1) and (14)	- -	- -	- -	0.214 (0.395)
(16)	Percentage of verified reduced-price applications that had benefits increased in verification	- -	- -	- -	-0.319 (0.500)

Table IV.6 *(continued)*

Variables		% UnderPayment_L	% CF_RPE_L	% CF_PE_L	% CRP_PE_L
(17)	Interaction of (1) and (16)	-	-	-	0.0157
		-	-	-	(1.022)
Certification variables (core)					
(18)	Percentage of students certified without an application	-0.0246	-0.0474	-0.140	-
		(0.0489)	(0.0840)	(0.154)	-
(19)	Percentage of students certified categorically	-0.394**	-0.0269	-0.00297	-
		(0.157)	(0.265)	(0.496)	-
District characteristics (core)					
(20)	Enrollment (by 10K)	-0.0913**	0.0377	0.169	-0.228
		(0.0454)	(0.0960)	(0.144)	(0.304)
(21)	Percentage of students certified for free meals	-0.0107	-0.0661	0.122	-0.199
		(0.0388)	(0.0668)	(0.123)	(0.268)
(22)	Percentage of students certified for reduced-price meals	0.205	0.407	-0.941**	-0.852
		(0.148)	(0.261)	(0.458)	(1.081)
(23)	Publicly operated	1.755	7.197	7.941	22.48
		(3.798)	(6.723)	(12.23)	(32.57)
Policy variables (core)					
(24)	State direct certification performance rate	0.00227	-0.287***	0.0548	0.443
		(0.0406)	(0.0716)	(0.129)	(0.346)
Additional variables					
(25)	Percentage of students certified without an application	-	-	-	0.547
					(0.385)
(26)	Number of application certified categorically eligible	0.00131***	-	-0.000464	-
		(0.000134)		(0.000426)	
(27)	Any special provision	-	-0.0587	-	-
			(0.0418)		
Constant					
Constant		1.704	26.30***	0.854	-43.40
		(5.549)	(9.471)	(17.22)	(47.02)
Number of districts		123	123	123	123
R-squared		0.556	0.239	0.097	0.115

Standard errors are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

%CF-RPE-L= Percentage of free school lunches served to students who were eligible for reduced-price lunches

%CF-PE-L= Percentage of free school lunches served to students who were not eligible for free or reduced-price lunches

%CRP-PE-B=Percentage of reduced-price school lunches served to students who were not eligible for free or reduced-price lunches

%Underpayment-L=Percentage of underpayment for the NSLP

Table IV.7. Coefficient estimates from estimated regression equations, certification error for non-CEP schools, SBP

Variables		% UnderPayment_B	% CF_RPE_B	% CF_PE_B	% CRP_PE_B
Verification variables (core)					
(1)	Used alternate random verification sample	1.386 (2.141)	12.65** (4,897)	0.150 (7.315)	5.815 (19.47)
(2)	Percentage of verified reduced-price applications that had benefits changed in verification	0.0206 (0.0336)	- -	- -	- -
(3)	Interaction of (1) and (2)	-0.0113 (0.0759)	- -	- -	- -
(4)	Percentage of all verified applications that had benefits changed in verification	-0.0307 (0.0410)	- -	- -	- -
(5)	Interaction of (1) and (4)	-0.0190 (0.103)	- -	- -	- -
(6)	Percentage of verified reduced-price applications that did not respond in verification	0.0405* (0.0243)	- -	- -	0.0867 (0.133)
(7)	Interaction of (1) and (6)	-0.123* (0.0728)	- -	- -	0.319 (0.307)
(8)	Percentage of verified all applications that did not respond in verification	-0.0251 (0.0343)	- -	- -	- -
(9)	Interaction of (1) and (8)	0.0704 (0.0870)	- -	- -	- -
(10)	Percentage of verified free applications that had benefits reduced or terminated in verification	- -	0.00451 (0.0523)	-0.0128 (0.0779)	- -
(11)	Interaction of (1) and (10)	- -	-0.295** (0.130)	0.190 (0.192)	- -
(12)	Percentage of verified free applications that did not respond in verification	- -	0.029 (0.0478)	0.00779 (0.0714)	- -
(13)	Interaction of (1) and (12)	- -	-0.0825 (0.0925)	-0.0580 (0.137)	- -
(14)	Percentage of verified reduced-price applications that had benefits increased in verification	- -	- -	- -	-0.441 (0.509)
(15)	Interaction of (1) and (14)	- -	- -	- -	0.544 (0.973)
(16)	Percentage of verified RP applications that had benefits reduced or terminated in verification	- -	- -	- -	0.00875 (0.190)

Table IV.7 *(continued)*

Variables		% UnderPayment_B	% CF_RPE_B	% CF_PE_B	% CRP_PE_B
(17)	Interaction of (1) and (16)	-	-	-	-0.110
		-	-	-	(0.379)
Certification variables (core)					
(18)	Percentage of students certified without an application	-0.0191	-0.0592	-0.245	-
		(0.0443)	(0.114)	(0.164)	-
(19)	Percentage of students certified categorically	-0.187	0.172	0.424	-
		(0.142)	(0.341)	(0.527)	-
District characteristics (core)					
(20)	Enrollment (by 10K)	-0.0885**	-0.163	0.152	-0.395
		(0.0416)	(0.140	(0.155)	(0.308)
(21)	Percentage of students certified for free meals	-0.0326	-0.045	0.140	-0.352
		(0.0354)	(0.0919)	(0.132)	(0.271)
(22)	Percentage of students certified for reduced-price meals	0.188	0.365	-0.886*	-0.141
		(0.135)	(0.334)	(0.489)	(1.093)
(23)	Publicly operated	0.0304	-13.41**	5.241	2.223
		(2.212)	(5.498)	(8.211)	(21.24)
Policy variables (core)					
(24)	State direct certification performance rate	0.0248	-0.180**	0.166	0.505
		(0.0359)	(0.0897)	(0.134)	(0.341)
Additional variables					
(25)	Percentage of students certified without an application	-	-	-	0.850**
		-	-	-	(0.386)
(26)	Number of application certified categorically eligible	0.00113***	-	-0.000641	-
		(0.000123)	-	(0.000459)	
(27)	Total number of certified applications (in thousands)	-	-0.111	-	-
		-	(0.112)	-	-
Constant		0.156	34.00***	-9.360	-33.81
		(4.006)	(19.95)	(14.85)	(37.83)
Observations		127	127	127	127
R-squared		0.519	0.244	0.073	0.181

Source: FNS-742 Verification Collection Reports and APEC-II study.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

%CF-RPE-B= Percentage of free school lunches served to students who were eligible for reduced-price breakfasts

%CF-PE-B= Percentage of free school lunches served to students who were not eligible for free or reduced-price breakfasts

%CRP-PE-B=Percentage of reduced-price school lunches served to students who were not eligible for free or reduced-price breakfasts

%Under-B=Percentage of underpayment for the SBP

B. Statistical model for certification error for CEP schools

Improper payments under CEP are determined at the level of the CEP group rather than at the district level. Since a CEP group cannot have both overpayments and underpayments, the error rate is modeled as the net percentage of CEP reimbursements in error. The overall statistical model for certification error for CEP schools consists of one equation each for NSLP and SBP, estimated using CEP group error rates as dependent variables and district-level data for explanatory variables.

The basic form of the model is similar to that for certification error in non-CEP schools:

(2) $$CEPE_{kj} = X_{kj}\beta_k + u_{kj}$$

with $CEPE_{kj}$ = rate of certification error type k (lunch vs. breakfast) in CEP group j

X_{kj} = characteristic of district j where CEP group j locates included in equation k

β_k = relationship between characteristic X_{kj} and error rate $CEPE_{kj}$

u_{kj} = term representing unobserved effects on the error rate $CEPE_{kj}$

Since the certification error rates for CEP schools include negative values, zeros, and positive values, we used OLS estimation techniques to estimate these equations. As in certification error modeling for non-CEP schools, each dependent variable is an estimate, based on samples of students within the APEC-II study districts. Thus, each dependent variable is subject to measurement error. Further, for CEP modeling, the error rates are at the CEP group level, but the explanatory variables are at the district level. Therefore, the model is not able to explain the difference in error rates for CEP groups in the same district.

1. Independent variable selection

Factors that are likely to be highly correlated with certification error in CEP schools include (1) certification variables, (2) administrative characteristics of the district, (3) demographic and economic characteristics of students and families in the district, and (4) other variables that are likely to be relevant to certification error in CEP schools, such as State direct certification procedures. However, the CEP modeling is significantly challenged by the lack of availability of relevant CEP data at the national level. We were further restricted by small sample size. Because we only have 55 observations in our sample, with a limited number of degrees of freedom, the number of independent variables whose relationship with certification error rates can be estimated with a reasonable degree of precision is also limited.

Our strategy for selecting a set of variables and specifications for certification error for CEP schools was similar to the one we used for certification error for non-CEP schools:

- We first came up with a list of candidate variables to consider as potential independent variables in the model.
- Based on theoretical relevance and data availability, we selected variables from a set of independent variables that we defined as core variables in the model.
- We used an automated procedure for selecting an additional set of variables to be included in the equation as independent variables, with those independent variables constructed using

VCR data included in the set of candidate variables. We then repeated this process, including as candidate variables independent variables from all available data sets.

- We allowed equations of SBP and NSLP to have a unique set of independent variables.
- After identifying the variables that will be included in each equation, we then estimated and tested a series of regression equations within the model system and selected the specification with the strongest cross-validation model performance.

The candidate variables we considered, along with their data sources, are listed in Table IV.8. The core variables we selected for certification error for non-CEP schools include:

- **CEP implementation characteristics.** The core variables include the only nationally available variables related to CEP implementation, which are the percentage of students in schools operating CEP and the percentage of schools operating CEP.
- **Characteristics related to direct certification.** CEP claiming rates are based primarily on the percentage of students directly certified for school meal benefits. As such, the core variables include variables likely to be related to the accuracy of direct certification. We include the State direct certification performance rate calculated annually in the Report to Congress on direct certification implementation (U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support. November 2013). We also include whether the district was privately operated, because private districts are less likely to have sophisticated direct certification systems.
- **Local economic conditions.** Schools in communities with higher poverty rates are likely to have higher free meal claiming rates under CEP. Therefore, the core variables include the school-age poverty rate at the county level.

Table IV.8. Independent variables considered for inclusion in the certification error model for CEP schools, by data source

Data source	Variables considered for inclusion in the certification error model for CEP schools
VCR	Percent of students in schools operating CEP Percent of schools operating CEP Privately operated Proportion of students certified for free meals Proportion of students certified without an application Proportion of students certified categorically Average school size (enrollment/number of school) Total number of applications certified
CCD	Grade span: elementary schools, middle schools, high schools Race All spending on food services per students School admin/support staff per student Urbanicity
PSS	Grade span: elementary schools, middle schools, high schools Race Urbanicity
BLS and SAIPE	Median household income Unemployment rate School age poverty

VCR= Verification Collection Reports; CCD = Common Core of Data; PSS = Private School Survey; BLS = Bureau of Labor Statistics; SAIPE = Small Area Income and Poverty Estimates

The three specifications we developed and tested for certification error in CEP schools are:

- Core variables only
- Core variables plus one additional variable from the VCR
- Core variables plus one additional variable from any data set, including VCR, CCD/PSS, LAUS and SAIPE

2. Model specification selection

The cross-validation procedure we conducted for certification error in CEP schools is methodologically identical to the one we used for certification error for non-CEP schools. We carried out tenfold cross-validation with 20 replications. The cross-validation model performance measures were the mean of the 200 values. Ultimately, we compared these implied error rates from the three specifications described above to error rates based on the APEC-II CEP school study sample to determine a preferred specification. We also took into consideration the goodness of fit of the model.

Table IV. 9 summarizes the results from cross-validation for NSLP. The cross-validation analysis indicates that all model specifications have similar predicted improper payment rates, and the absolute differences between predicted rates from each specification and the rates estimated based on APEC-II sample are all within one percent. Taking into consideration the goodness of fit, a limited number of degrees of freedom due to small sample size, and the costs of using multiple data sources, we selected the specification that included only core variables as our final specification for NSLP certification error in CEP schools. The specific variables included in this specification are listed in Table IV.10.

Table IV.9. Cross-validation results for certification error for CEP schools, NSLP

Model system 1	Cross-validation testing sample predicted error rates			APEC-II sample-based estimated error rates			Comparison		
Model specification	IPR	OPR	UPR	IPR	OPR	UPR	Difference in IPR	Difference in OPR	Difference in UPR
Model system 1									
Core	0.009	0.0005	0.0086	0.017	0.0003	0.0171	0.535	1.567	0.504
Core + 1 from VCR	0.011	0.0002	0.0106	0.017	0.0003	0.0171	0.640	0.788	0.622
Core + 1 from any source	0.008	0.0005	0.0075	0.017	0.0003	0.0171	0.468	1.595	0.438

Source: FNS-742 Verification Collection Reports and APEC-II study

Highlighted row represents model selected for analysis.

Table IV.10. Independent variables included in models used in estimating net certification error for CEP schools, NSLP and SBP

	% Net-L	% Net-B
Percentage of students in schools operating CEP	X	X
Percentage of schools operating CEP	X	X
Privately operated	X	X
State direct certification performance rate	X	X
School age poverty rate at county level	X	X

Note: All variables included in this model are core variables.

The cross-validation results for the SBP are summarized in Table IV.11. These results are quite similar to those for the NSLP. The external validation check shows that all predicted improper payment rates are quite close to each other, and the absolute differences between predicted rates from each specification and the rates estimated based on APEC-II sample are all within 1 percent. We selected the specification that included only core variables as our final specification for SBP certification error in CEP schools. The specific variables included are the same ones listed in Table IV.10.

Table IV.11. Cross-validation results for certification error for CEP schools, SBP

Model system 1	Cross-validation testing sample predicted error rates			APEC-II sample-based estimated error rates			Comparison		
Model specification	IPR	OPR	UPR	IPR	OPR	UPR	Difference in IPR	Difference in OPR	Difference in UPR
Model system 1									
Core	0.010	0.0004	0.0099	0.019	0.0004	0.0184	0.544	1.070	0.539
Core + 1 from VCR	0.012	0.0002	0.0116	0.019	0.0004	0.0184	0.621	0.549	0.629
Core + 1 from any source	0.009	0.0005	0.0087	0.019	0.0004	0.0184	0.484	1.146	0.475

Source: FNS-742 Verification Collection Reports and APEC-II study.

Highlighted row represents model selected for analysis.

3. Regression results for certification error model system for CEP schools

In Table IV.12, we summarize the regression results for the CEP certification error model systems for both the NSLP and the SBP. The R-squared values for the regression equations are moderately low (0.09 for the NSLP and 0.08 for the SBP). None of the coefficients included in the model is statistically significant. The findings are consistent with concerns about the availability of strong predictors for certification errors in CEP schools.

Table IV.12. Coefficient estimates from estimated regression equations, certification error for CEP schools, NSLP and SBP

	% Net error rate - NSLP	% Net error rate - SBP
Variable name (core)	**Coefficients**	**Coefficients**
Percentage CEP students	-0.059	-0.057
	(.071)	(.071)
Percentage CEP schools	0.097	0.096
	(.084)	(.084)
Publicly operated	-0.315	-0.302
	(1.905)	(2.002)
Percentage SNAP recipients directly certified for free meals	-0.096	-0.101
	(.079)	(.081)
Percentage 5-17 year olds living in poverty	-0.092	-0.099
	(.140)	(.146)
Observations	55	55
R-squared	0.086	0.084

Source: FNS-742 Verification Collection Reports and APEC-II study.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

C. Statistical models for meal claiming error

Meal claiming error occurs when cafeteria staff make errors in assessing and recording whether a specific meal selection meets the criteria for a reimbursable meal under the NSLP or SBP. This includes meals claimed which do not include the food components required by the program (overpayments), either because students did not select a complete reimbursable meal, or because the school did not provide a meal that met program standards; it also includes claiming reimbursements for meals served to non-students. Meals meeting program requirements and served to students that should have been claimed for reimbursement but were not are also meal claiming errors (underpayments).

We estimated two model systems representing meal claiming error. In model system 1, we modeled overpayments and underpayments using a simple, single-equation approach. In model system 2, we used a two-stage approach for overpayments in which we accounted for the fact that meal-claiming overpayments are skewed to the right, that is, meal-claiming overpayments were concentrated in a minority of districts with relatively high meal-claiming error rates rather than distributed evenly across districts.

In the first stage of the two-stage approach, we used a logic model to predict whether a district's overpayment error rate is above the median overpayment rate. We then estimated separate models of overpayment rates depending on whether the district was above or below the median. In applying the model to external data, districts with a first-stage predicted probability below 50 percent were assigned a predicted overpayment rate based on the "below the median" second-stage equation, whereas districts with a first-stage predicted probability of at least 50 percent were assigned a predicted overpayment rate based on the "above the median" second-stage equation.

1. Independent variable selection

In selecting explanatory variables to consider for the meal claiming model systems, we used the VCR as the starting point, as was done in the certification error analysis. These data contain a variety of information on district characteristics. However, whereas the VCR verification outcome variables provide a strong theoretical foundation for the certification error models, these outcomes are unlikely to be strongly associated with cashier error. In fact, no district-level national data sets contain information on a process that is analogous to measuring meal claiming error in the way that the verification process is roughly analogous to measuring certification error.

Our strategy for selecting a set of variables and a specification for meal claiming error was similar to the one we used for certification error modeling:

- We first came up with a list of candidate variables to consider as potential independent variables in the model.
- Based on theoretical relevance and data availability, we selected from a set of independent variables we defined as core variables in the model.
- We used an automated procedure for selecting an additional set of variables to be included in the equation as independent variables, with independent variables constructed using VCR data included in the set of candidate variables. We then repeated this process, including as candidate variables independent variables from all available data sets.
- We allowed each equation of each model system of SBP and NSLP to have a unique set of independent variables.
- After identifying the variables to be included in each model system equation, we estimated and tested a series of regression equations within each model system and selected the model system with the strongest cross-validation model performance.
- We used a split-sample cross-validation method to assess model performance, and selected the model system and specification with the strongest predictive performance, which is measured by both minimizing the differences between predicted improper payment rates and observed rates in APEC-II study sample, and by measures of goodness of fit.

The candidate variables we considered, along with their data sources, are listed in Table IV.13. The core variables we selected for meal claiming error include:

- **Student certification characteristics.** Schools with higher percentages of students eligible for school meal benefits might have more efficient meal claiming systems. For this reason, the core variables include the percentage of students certified for free meals, and the percentage certified for free meals not subject to verification (primarily through direct certification).
- **District verification results.** It is possible that district meal claiming error is associated with certification error. Specifically, the verification process might proxy for the extent to

which the district's administration of the meal programs is designed to promote program integrity. For this reason, the core variables include the percentage of applications with benefits changed in verification.

- **District characteristics.** These core variables include total enrollment, average school size, and whether the district is publicly operated.

Table IV.13. Independent variables considered for inclusion in meal claiming error model, by data source

Data source	Variables considered for inclusion in the meal claiming error model
VCR	Type of SFA (public or private) Number of schools operating the NSLP and/or the SBP Number of P23 non–base-year schools Number of enrolled students with access to the NSLP and/or the SBP Number of students in P23 non–base-year schools Average school size Percentage of students certified for free meals, by certification method Number of applications selected for verification Percentage of total applications selected for verification Percentage of applications verified by certification category (free-categorical approved, free-income approved, and reduced-price–income approved)
CCD	Grade span: elementary schools, middle schools, high schools Race All spending on food services per student School admin/support staff per student Urbanicity
PSS	Grade span: elementary schools, middle schools, high schools Race Urbanicity
BLS and SAIPE	Median household income Unemployment rate

VCR=Verification Collection Report; CCD = Common Core of Data; PSS = Private School Survey; BLS = Bureau of Labor Statistics; SAIPE = Small Area Income and Poverty Estimates

For both model system 1 and model system 2, we developed and tested five specifications for the NSLP and SBP in which the covariates included in the system vary.

- Core variables only
- Core variables plus one additional variable from the VCR
- Core variables plus three additional variables from the VCR (only one additional variable for the underpayment equation)
- Core variables plus one additional variable from any data set, including VCR, CCD/PSS, LAUS and SAIPE
- Core variables plus three additional variables from any data set, including VCR, CCD/PSS, LAUS and SAIPE (only one additional variable for underpayment equation)

2. Model specification selection

We conducted split-sample cross-validation to assess the performance of the models. We carried out tenfold cross-validation with 20 replications. The cross-validation model performance measures were the mean of the 200 values. We compared these implied error rates from two model systems and five specifications described above to error rates based on the APEC-II study sample-based estimates to determine a preferred specification. We also took into consideration the goodness of fit of the regression equations that made up the model systems.

Table IV.14 summarizes the results from cross-validation for NSLP meal claiming error. There are a couple of model system specifications that predicts small differences between predicted error rates and the APEC-II sample-based estimates, but all except one rely on data sources other than the VCR. We selected the remaining specification, which is the specification of model system 1 that includes only the core explanatory variables. The explanatory variables included in the selected model system are listed in Table IV.15.

Table IV.16 summarizes the results from the cross-validation for SBP meal claiming error. After evaluating differences between predicted rates and the error rates estimated based on the APEC-II study, the goodness of fit, the costs of using multiple data sources, and the ability of the model to predict error rates skewed towards the right-hand side of the improper payment rate distribution, we again selected the model system 1 specification that includes only core variables.[12] The specific variables included in this specification are listed in Table IV.17.

3. Regression results for meal claiming error model system

In Tables IV.18 and IV.19, we summarize the regression results for the NSLP and SBP meal claiming error models, respectively. The R-squared values for the NSLP model system equations are moderately low at 0.10 for overpayments and at 0.13 for underpayments. The fit of the SBP underpayment model was also moderately low at 0.12 while the overpayment model R-squared was 0.03. It is important to note that goodness-of-fit for other specifications of SBP overpayments were equally poor, indicating that available national data are unable to explain much of the variation in SBP meal claiming overpayments.

Two factors were significantly associated with NSLP overpayments. Districts with higher percentages of students certified for free meals without being subject to verification (primarily directly certified students) had significantly lower overpayment rates, as did private districts. No modeled factors were significantly associated with NSLP underpayments. Similarly, only two explanatory variable in SBP meal claiming error model equations had a statistically significant coefficient. Districts with higher percentages of applications that changed during verification had higher underpayment rates. This finding suggests that the verification process is associated with meal claiming error, perhaps because it proxies for the extent to which the district's administration of the meal programs is designed to promote program integrity of the district,

[12] When evaluating the national models of meal claiming error for SBP, we identified two models with similar validation results: a single-equation model with core variable only and a two-stage hybrid model with core variable only. After examining State-level results, we believe that the single-equation model with core variable only will produce more reliable results. Therefore, we decided to select single-equation model with core variable only as the final model specification for our analysis.

which highly correlates with meal claiming error. As in NSLP, privately operated districts had lower overpayment rates for SBP compared to publicly operated districts.

Table IV.14. Cross-validation results for meal claiming error, NSLP

Model specification	Cross-validation testing sample predicted error rates: IPR	OPR	UPR	APEC-II sample-based estimated error rates: IPR	OPR	UPR	Comparison: Difference in IPR	Difference in OPR	Difference in UPR
Model system 1									
Single stage: Core	0.054	0.046	0.008	0.051	0.045	0.007	1.053	1.042	1.121
Single stage: Core + 1 from VCR	0.055	0.046	0.009	0.051	0.045	0.007	1.073	1.029	1.355
Single stage: Core + 3 from VCR	0.054	0.045	0.009	0.051	0.045	0.007	1.057	1.009	1.363
Single stage: Core + 1 from any source	0.055	0.047	0.007	0.051	0.045	0.007	1.060	1.063	1.045
Single stage: Core + 3 from any source	0.056	0.046	0.010	0.051	0.045	0.007	1.087	1.041	1.388
Model system 2									
Hybrid (overpayment low group:Tobit): Core	0.063	0.056	0.008	0.051	0.045	0.007	1.234	1.251	1.152
Hybrid (overpayment low group:Tobit): Core + 1 from VCR	0.060	0.051	0.009	0.051	0.045	0.007	1.164	1.142	1.324
Hybrid (overpayment low group:Tobit): Core + 3 from VCR	0.059	0.050	0.010	0.051	0.045	0.007	1.154	1.121	1.390
Hybrid (overpayment low group:Tobit): Core + 1 from any source	0.057	0.050	0.007	0.051	0.045	0.007	1.106	1.116	1.057
Hybrid (overpayment low group:Tobit): Core + 3 from any source	0.058	0.049	0.009	0.051	0.045	0.007	1.127	1.091	1.366
Hybrid (overpayment low group:OLS): Core	0.063	0.055	0.008	0.051	0.045	0.007	1.221	1.238	1.125
Hybrid (overpayment low group:OLS): Core + 1 from VCR	0.059	0.050	0.009	0.051	0.045	0.007	1.149	1.124	1.330
Hybrid (overpayment low group:OLS): Core + 3 from VCR	0.059	0.049	0.010	0.051	0.045	0.007	1.140	1.105	1.384
Hybrid (overpayment low group:OLS): Core + 1 from any source	0.057	0.050	0.007	0.051	0.045	0.007	1.103	1.113	1.058
Hybrid (overpayment low group:OLS): Core + 3 from any source	0.057	0.048	0.010	0.051	0.045	0.007	1.113	1.073	1.391

Source: FNS-742 Verification Collection Reports and APEC-II study.

Highlighted row represents model selected for analysis.

IPR = Percentage of total reimbursements in error; OPR = Percentage of overpayment in error; UPR = Percentage of underpayment in error.

Table IV.15. Independent variables included in models used in estimating meal claiming error, NSLP

	% Underpayment-L	% Overpayment-L
Enrollment (by 10k)	X	X
Average size (enrollment/number of school)	X	X
Percentage of students certified for free meals	X	X
Interaction term: percentage of students certified for free meals interacts with the dummy variable of > 50% (first create a dummy variable set equal to 1 if percentage of students certified for free meals > 50%; zero otherwise)	X	X
Percentage of certified as free not subject to verification	X	X
Percentage of application with benefits changed in verification	X	X
Publicly operated	X	X

Note: All variables included in this model are core variables.

Table IV.16. Cross-validation results for meal claiming error, SBP

Model system 1	Cross-validation testing sample predicted error rates			APEC-II sample-based estimated error rates			Comparison		
Model specification	IPR	OPR	UPR	IPR	OPR	UPR	Difference in IPR	Difference in OPR	Difference in UPR
Model system 1									
Single stage: Core	0.116	0.114	0.002	0.109	0.107	0.002	1.061	1.062	1.024
Single stage: Core + 1 from VCR	0.116	0.113	0.002	0.109	0.107	0.002	1.058	1.058	1.055
Single stage: Core + 3 from VCR	0.114	0.111	0.003	0.109	0.107	0.002	1.040	1.036	1.208
Single stage: Core + 1 from any source	0.116	0.114	0.002	0.109	0.107	0.002	1.059	1.062	0.925
Single stage: Core + 3 from any source	0.112	0.110	0.002	0.109	0.107	0.002	1.024	1.024	1.034
Model system 2									
Hybrid (overpayment low group:Tobit): Core	0.108	0.106	0.002	0.109	0.107	0.002	0.989	0.988	1.021
Hybrid (overpayment low group:Tobit): Core + 1 from VCR	0.094	0.092	0.002	0.109	0.107	0.002	0.859	0.855	1.060
Hybrid (overpayment low group:Tobit): Core + 3 from VCR	0.091	0.088	0.003	0.109	0.107	0.002	0.831	0.822	1.224
Hybrid (overpayment low group:Tobit): Core + 1 from any source	0.111	0.109	0.002	0.109	0.107	0.002	1.016	1.018	0.931
Hybrid (overpayment low group:Tobit): Core + 3 from any source	0.110	0.107	0.002	0.109	0.107	0.002	1.002	1.002	1.036
Hybrid (overpayment low group:OLS): Core	0.111	0.109	0.002	0.109	0.107	0.002	1.018	1.018	1.012
Hybrid (overpayment low group:OLS): Core + 1 from VCR	0.094	0.092	0.002	0.109	0.107	0.002	0.860	0.856	1.056
Hybrid (overpayment low group:Tobit): Core + 3 from VCR	0.090	0.087	0.003	0.109	0.107	0.002	0.819	0.811	1.220
Hybrid (overpayment low group:OLS): Core + 1 from any source	0.112	0.110	0.002	0.109	0.107	0.002	1.022	1.024	0.940
Hybrid (overpayment low group:Tobit): Core + 3 from any source	0.113	0.111	0.002	0.109	0.107	0.002	1.037	1.037	1.040

Source: FNS-742 Verification Collection Reports and APEC-II study.

Highlighted row represents model selected for analysis.

IPR = Percentage of total reimbursements in error; OPR = Percentage of overpayment in error; UPR = Percentage of underpayment in error

Table IV.17. Independent variables included in models used in estimating meal claiming error, SBP

	% Underpayment-L single equation	% Overpayment-L (Two-stage three equations)
Enrollment (by 10k)	X	X
Average size (enrollment/number of school)	X	X
Percentage of students certified for free meals	X	X
Interaction term: percentage of students certified for free meals interacts with the dummy variable of > 50% (first create a dummy variable set equal to 1 if percentage of students certified for free meals > 50%; zero otherwise)	X	X
Percentage of certified as free not subject to verification	X	X
Percentage of application with benefits changed in verification (excluding those who did not respond to the verification)	X	X

Note: All variables included in this model are core variables. In the two-stage three equations approach, at the first stage, we predicted whether a district's overpayment error rate is above the median. In the second stage, we estimated the relationship between explanatory variables and the error rates separately for those above the median and below the median. The variables included in these three equations are identical.

Table IV.18. Coefficient estimates from estimated regression equations, meal claiming error, NSLP

	% Overpayment	% Underpayment
Variable Name (core)	**Coefficients**	**Coefficients**
Enrollment (by 10k)	0.0121 (0.0168)	-0.002 (0.006)
Average school size	0.001 (0.002)	0.000 (0.001)
Percentage of students certified for free meals	-0.0178 (0.0652)	-0.0250 (0.0424)
Interaction term: percentage of students certified for free meals interacts with the dummy variable of > 50%	0.0132 (0.0345)	0.003 (0.0221)
Percentage of certified as free not subject to verification	-0.101*** (0.0270)	0.002 (0.0103)
Percentage of applications with benefits changed in verification (excluding those who did not respond to the verification)	-0.0537* (0.0313)	0.006 (0.0105)
Publicly operated	5.772*** (1.952)	-4.979 (4.732)
Constant	3.212 (1.970)	6.305 (5.666)
Observations	143	143
R-squared	0.104	0.134

Source: FNS-742 Verification Collection Reports and APEC-II study.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IV.19. Coefficient estimates from estimated regression equations, meal claiming error, SBP

Variable name	% Overpayment	% Underpayment
Enrollment (by 10k)	-0.0815 (0.0838)	-0.00177 (0.00151)
Average school size	0.00753 (0.00776)	-0.00009 (0.000129)
Percentage of students certified for free meals	0.171 (0.201)	-0.00325 (0.00676)
Interaction term: percentage of students certified for free meals interacts with the dummy variable of > 50%	-0.130 (0.124)	-0.00216 (0.00382)
Percentage of certified as free not subject to verification	0.081 (0.180)	-0.00010 (0.00147)
Percentage of applications with benefits changed in verification (excluding those who did not respond to the verification)	-0.038 (0.074)	0.00522* (0.00285)
Publicly operated	10.27** (5.122)	0.160 (0.175)
Constant	-9.194 (10.80)	0.206 (0.257)
Observations	141	141
R-squared	0.027	0.121

Source: FNS-742 Verification Collection Reports and APEC-II study.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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V APPLYING APEC-II IMPROPER PAYMENT MODELS TO NATIONAL DATA

Summary

- After selecting the preferred model for each type of error, we applied the models to national data for SY 2012–2013 to get national improper payment rate estimates. By applying the estimated coefficients from regression models to the data on the explanatory variables, the model is able to generate the estimates of improper payment rates for all districts across the nation. This process is the same as the one that will be used to generate model-based improper payment rates in future years.
- We can assess model performance by comparing model-based estimates for SY 2012–2013 to sample sample-based estimates from APEC-II for the same year.
- In addition to generating estimates of improper payments, we are able to estimate the precision of those estimates by bootstrapping standard errors and confidence intervals.

In this chapter, we describe the performance of the preferred improper payment model systems when applied to national VCR data for SY 2012–2013. In this analysis, we use the same process to generate model-based improper payment estimates that FNS will use to generate improper payment estimates in future years. By comparing model-based improper payment estimates for SY 2012–2013 to sample-based estimates from the APEC-II study, we are able to validate whether the models accurately predict improper payments when applied to national data.

A. National model-based improper payment estimates due to certification error in non-CEP schools

After we selected the preferred model system, we estimated the regression equations that make up the model system using data from the full set of APEC-II study sample districts. The estimated parameters from this model could be used to generate national estimates of overpayments, underpayments, and overall improper payments in future years.

An important step after generating these error rate estimates is to translate them into district-level estimates of improper payments that can then be summed to generate national estimates of improper payments. This step requires using each district’s observed characteristics along with the estimated relationship between error rates. It also requires district-level counts of free, reduced-price, and paid meals. The VCR does not include information on the number of reimbursable meals in each district. In APEC-I, district-level meal counts were imputed based on information in the VCR on the number of enrolled students in each certification category and State meal counts drawn from the FNS national data base. In APEC-II modeling, we followed the same approach as APEC-I because no other data source containing this information is available at the national level.

1. Procedure for generating model-based improper payment estimates

The procedure for predicting future improper payment includes the following steps:

Step 1: Obtain the data. The first step is to collect data for all districts across the nation on all of the district characteristics represented by the variables in the vector of explanatory variables for each of the 8 equations in model system 4. In the preferred specification of the model, all variables except one (state direct certification performance rate) come from the VCR data set, so collecting the data to be used in the model means collecting and cleaning the VCR data. We treat the VCR data as if there were an observation for every district in the nation that offers the NSLP and/or the SBP. The model's improper payment estimates are based on the assumption that rates of improper payments in these districts are similar to rates in districts that are represented in the data.

Step 2: Generate predicted NSLP and SBP meal error rates in each district across the nation. The next step involves multiplying the values of explanatory variables by the values of the associated coefficients from the statistical model to generate a predicted value of each type of NSLP and SBP meal error rate for each district in the VCR data. In particular, in our selected model, model system 4, there are eight predicted error rates for each of these districts for the NSLP and SBP. Each will represent the predicted percentage of a particular type of meal (free, reduced-price, or paid) served in the district that has a particular type of error (for example, a free meal that should have been reimbursed at the paid rate). Specifically, these predicted rates are: $\%\widehat{\mathrm{CF}-\mathrm{RPE}}-\mathrm{L}$, $\%\widehat{\mathrm{CF}-\mathrm{FE}}-\mathrm{L}$, , $\%\widehat{\mathrm{CRP}-\mathrm{FE}}-\mathrm{L}$, $\%\widehat{\mathrm{underpayment}}-\mathrm{L}$, , $\%\widehat{\mathrm{CF}-\mathrm{RPE}}-\mathrm{B}$, $\%\widehat{\mathrm{CF}-\mathrm{FE}}-\mathrm{B}$, $\%\widehat{\mathrm{CRP}-\mathrm{PE}}-\mathrm{B}$, $\%\widehat{\mathrm{underpayment}}-\mathrm{B}$.

Step 3: Impute the number of each category of meals served (free, reduced-price, or paid) in each district. In this step, we impute the number of each category of meals served (free, reduced-price, or paid) in each district. The VCR data set does not contain information on the number of free, reduced-price, or paid meals served in each district. In APEC-I, district-level meal counts were imputed based on information in the VCR on the number of enrolled students in each certification category and State meal counts drawn from the FNS national data base. The assumption here is that the district served the same percentage of the total meals served in the state, by eligibility category, as its percentage of the total number of students enrolled in the state, by eligibility category. We followed the same approach in APEC-II modeling.

To impute the number of each category of lunches served (free, reduced-price, or paid) in each district, we first divided the number of students certified for free meals in each district by the sum of students certified for free meals in all districts present in the VCR data of the State in which the district is located. This fraction represents the proportion of the State's students certified for free meals in a certain district. Then we multiply this proportion by the total number of free lunches served in the state. The total number of free lunches served by State is obtained from the FNS national data file. The resulting product represents the imputed number of free lunches served in each district.

The process for imputing the number of school breakfasts served in each district in each category is analogous, but includes one additional step. For the breakfast program, it is necessary to estimate the number of free and reduced-price breakfasts served in severe-needs schools, since the federal reimbursement level for these meals is different from that for free and reduced-price meals served in non–severe-needs schools. Since the VCR database does not include information on severe-needs status, we assumed that the district served the same percentage of the total breakfasts served in severe needs schools in the state, by eligibility category, as its percentage of the total number of students enrolled in the state, by eligibility category.

Based on the procedure described above, we created eight categories of meals served in each district:

1. #CF-L_j: Number of free lunches served in all schools in district j
2. #CR-L_j: Number of reduced-price lunches served in all schools in district j
3. #NC-L_j: Number of paid lunches served in all schools in district j
4. #CF-B_j: Number of free breakfasts served in all schools in district j
5. #CF-SNB_j: Number of free breakfasts served in severe-needs schools in district j
6. # CR-B_j: Number of reduced-price breakfasts served in all schools in district j
7. # CR-SNB_j: Number of reduced-price breakfasts served in severe-needs schools in district j
8. #NC-B_j: Number of paid breakfasts served in all schools in district j

For districts that also operate both CEP and non-CEP schools, we need to adjust to account for meals served in CEP schools. Because CEP schools do not serve reduced-price meals, the adjustments only need to be made to free or paid meals. In order to make this adjustment, we would need the number of CEP schools operating in each district in SY 2012–2013. However, there is no national data source that contains this information. Instead, we imputed CEP participation in SY 2012–2013 using national data for SY 2013–2014. Because CEP participation increases between these two school years, the imputation overstates the number of CEP schools. Therefore, we overstate CEP reimbursements and understate non-CEP reimbursements (although CEP imputed reimbursements are a small proportion of overall reimbursements for SY 2012–2013). In future years, imputation of CEP reimbursements will be more accurate because current national data on CEP participation will be available. Imputation of CEP reimbursements is discussed in more detail in Section B below.

For districts that operate CEP schools, we created two ratios for each district:

Non-CEP-free-ratio = Free students in non-CEP schools /

(Free student equivalents in CEP schools + Free students in non-CEP schools)

Non-CEP-paid-ratio = Paid students in non-CEP schools / (total enrollment –

(Free student equivalents in CEP schools + Free students in non-CEP schools) -

total reduced-price eligible students)

The free/paid student equivalents were estimated based on the predicted fraction of students certified for free meals in CEP schools. We estimated an imputation model in which the dependent variable is the identified student percentage (ISP) in the CEP group. The detailed description of how we created free/paid student equivalents in CEP schools can be found in the section B where we discuss the statistical model for certification error for CEP schools. For districts operating CEP, we multiplied each category of estimated meal counts for free or paid meals by these two ratios to get meals served at non-CEP schools in the district.

Step 4: Calculate the total number of meals in each error category for each district. In this step, we calculate the total number of meals in each error category for each district. This calculation involves multiplying the district's error rate in each error category by its imputed number of free, reduced-price, or paid meals, as appropriate. For the NSLP, three calculations are needed for the decomposition of overpayments:

- Number of free lunches erroneously served to reduced-price-eligible students in district j = (Number of free lunches served in j) * (predicated % of free lunches served to reduced-price–eligible students)

  Or $\#CF\text{-}RPE\text{-}L_j = \#CF\text{-}L_j * \%\widehat{CF-RPE}-L_j$

- Number of free lunches erroneously served to paid eligible students in district j = (Number of free lunches served in j) * (predicted % of free lunches served to paid-eligible students)

  Or $\#CF\text{-}PE\text{-}L_j = \#CF\text{-}L_j * \%\widehat{CF-PE}-L_j$

- Number of reduced-price lunches erroneously served to paid eligible students in district j = (Number of reduced-price lunches served in j) * (predicted % of reduced-price lunches served to free-eligible students)

  Or $\#CRP\text{-}PE\text{-}L_j = \#CR\text{-}L_j * \%\widehat{CRP-PE}-L_j$

The calculation of estimated underpayments is different and will be discussed in step 5.

The calculations for the SBP involve an extra step. We must also calculate estimates of meals erroneously served in severe needs schools, because the dollar amount associated with some error types is different in severe needs schools than in other schools. Following the approach of APEC-I, we assumed that the error rates at severe-needs schools versus other schools in a given district are the same. We also need to distinguish between erroneously served paid meals in severe-needs schools and those in other schools, since the amount of the improper payment will depend on whether the school is a severe-needs school. To do this, we again followed the APEC-I's approach, multiplying the number of paid breakfasts served in the district by the fraction of free (or reduced-price) meals served to students in severe-needs schools in the district. For the SBP, the calculations for overpayments are:

- Number of free breakfasts erroneously served to reduced-price–eligible students in all schools in district j = (Number of free breakfasts served in district j) * (predicted % of free breakfasts served to reduced-price–eligible students)

  Or $\#CF\text{-}RPE\text{-}B_j = \#\ CF\text{-}B_j * \%\ \widehat{CF-RPE}-B_j$

- Number of free breakfasts erroneously served to paid–eligible students in all schools in district j = (Number of free breakfasts served in district j) * (predicted % of free breakfasts served to paid–eligible students)

  Or $\#CF\text{-}PE\text{-}B_j = \#\, CF\text{-}B_j * \%\, \widehat{CF-PE} - B_j$

- Number of reduced-price breakfasts erroneously served to paid eligible students in district j = (Number of reduced-price breakfasts served in j) * (predicted % of reduced-price breakfasts served to paid-eligible students)

  Or $\#CRP\text{-}PE\text{-}B_j = \#CR\text{-}B_j * \%\, \widehat{CRP-PE} - B_j$

- Number of free breakfasts erroneously served to paid-eligible students in severe needs schools in district j = (Number of free breakfasts served in severe-needs schools in j) * (predicted % of free breakfasts served to paid-eligible students)

  Or $\#CF\text{-}PE\text{-}SNB_j = \#\, CF\text{-}SNB_j * \%\, \widehat{CF-PE} - B_j$

- Number of reduced-price breakfasts erroneously served to paid eligible students in severe needs schools in district j = (Number of reduced-price breakfasts served in severe needs schools in district j) * (predicted % of reduced-price breakfasts served to paid-eligible students)

  Or $\#CRP\text{-}PE\text{-}SNB_j = \#\, CR\text{-}SNB_j * \%\, \widehat{CRP-PE} - B_j$

The calculation of underpayment is different and will be discussed in next step.

Step 5: Calculate the total dollars erroneously reimbursed in each meal category, as well as the total dollars reimbursed overall for lunch and breakfast for each district. To calculate dollars erroneously reimbursed, we multiplied the total number of meals in each error category by the dollar value of improper payments per meal in that category. Per-meal improper payments and total payments for each category for the NSLP and the SBP are shown in Tables V.1 and V.2.

Table V.1. Per meal underpayments and overpayments due to certification error in the NSLP, SY 2012–2013

Student's certification status	Student's eligibility status	Total payments	Underpayments	Overpayments
Fewer than 60 percent of lunches are free or reduced-price				
Free	Free	3.0875	0.00	0.00
Free	Reduced-price	3.0875	0.00	0.40
Free	Paid	3.0875	0.00	2.59
Reduced-price	Free	2.6875	0.40	0.00
Reduced-price	Reduced-price	2.6875	0.00	0.00
Reduced-price	Paid	2.6875	0.00	2.19
Denied	Free	0.4975	2.59	0.00
Denied	Reduced-price	0.4975	2.19	0.00
Denied	Paid	0.4975	0.00	0.00
60 percent or more of lunches are free or reduced-price				
Free	Free	3.1075	0.00	0.00
Free	Reduced-price	3.1075	0.00	0.40
Free	Paid	3.1075	0.00	2.59
Reduced-price	Free	2.7075	0.40	0.00
Reduced-price	Reduced-price	2.7075	0.00	0.00
Reduced-price	Paid	2.7075	0.00	2.19
Denied	Free	0.5175	2.59	0.00
Denied	Reduced-price	0.5175	2.19	0.00
Denied	Paid	0.5175	0.00	0.00

Source: FNS program data.

Note: Schools in School Food Authorities that served 60 percent or more free and reduced-price lunches in SY 2010–2011 received an additional $0.02 per lunch.

FNS = Food and Nutrition Service; NSLP = National School Lunch Program; SY = school year.

Table V.2. Per meal underpayments and overpayments due to certification error in the SBP, SY 2012–2013

Student's certification status	Student's eligibility status	Total payments	Underpayments	Overpayments
SBP, non-severe need schools				
Free	Free	1.55	0.00	0.00
Free	Reduced-price	1.55	0.00	0.30
Free	Paid	1.55	0.00	1.28
Reduced-price	Free	1.25	0.30	0.00
Reduced-price	Reduced-price	1.25	0.00	0.00
Reduced-price	Paid	1.25	0.00	0.98
Denied	Free	0.27	1.28	0.00
Denied	Reduced-price	0.27	0.98	0.00
Denied	Paid	0.27	0.00	0.00
SBP, severe need schools				
Free	Free	1.85	0.00	0.00
Free	Reduced-price	1.85	0.00	0.30
Free	Paid	1.85	0.00	1.58
Reduced-price	Free	1.55	0.30	0.00
Reduced-price	Reduced-price	1.55	0.00	0.00
Reduced-price	Paid	1.55	0.00	1.28
Denied	Free	0.27	1.58	0.00
Denied	Reduced-price	0.27	1.28	0.00
Denied	Paid	0.27	0.00	0.00

Sources: FNS program data.

Note: Schools are considered to be in severe need for SY 2012–2013 if they served 40 percent or more free and reduced-price lunches in SY 2010–2011. Severe need schools receive an additional $0.30 per free and reduced-price breakfast.

FNS = Food and Nutrition Service; SBP = School Breakfast Program; SY = school year.

As noted in Table V.1, districts in which more than 60 percent of lunches are reimbursed at the free or reduced-price rates receive an extra reimbursement of $0.02 for each lunch served. This additional reimbursement does not affect our calculations of improper payments (since it applies to all meal types), but it does affect the calculation of total reimbursements. As in the APEC-I study, to account for these "60 percent districts," we created a binary indicator ($FRP60\text{-}L_j$) showing whether at least 60 percent of the district's lunches are reimbursed at the free or reduced-price level. We used this variable and other previously constructed variables to calculate improper payments and total reimbursements for the NSLP as follows:

Total dollars of improper payments for free lunches served to reduced-price–eligible students in district j = (Number of free lunches erroneously served to reduced-price-eligible students in district j) * (per meal improper payment for free lunches served to reduced-price–eligible students)

Or $\$CF\text{-}RPE\text{-}L_j = \#CF\text{-}RPE\text{-}L_j * \$0.40$

$\$CF\text{-}PE\text{-}L = \#CF\text{-}PE\text{-}L * \$2.59$

$\$CRP\text{-}PE\text{-}L_j = \#CRP\text{-}PE\text{-}L_j * \$2.19$

Total dollars of NSLP reimbursements in a district are based on the number of lunches of each type served in the district:

$$FRP60\text{-}L_j = 1 \text{ if } (\#CF\text{-}L_j + \#CRP\text{-}L_j) / (\#CF\text{-}L_j + \#CRP\text{-}L_j + \#NC\text{-}L_j) > 0.60$$

$$= 0 \text{ otherwise}$$

$$\$TR\text{-}L_j = (\#CF\text{-}L_j * \$3.0875) + (\#CRP\text{-}L_j * \$2.6875) + (\#NC\text{-}L_j * \$0.4975) + FRP60\text{-}L_j *(\#CF\text{-}L_j + \#CRP\text{-}L_j + \#NC\text{-}L_j)*\$0.02$$

Since the overpayment rate is equal to the ratio of the gross dollar amount of overpayment to the total amount of reimbursements for all meals, the calculation of underpayments is:

$$\$\ Underpayment\text{-}Lj = \$\ Under\text{-}L_j = \%\ \widehat{\text{Under}} - L_j * \$TR\text{-}L_j$$

For SBP, the amount of improper payments for a given meal depends in part on whether the meal is served in a severe-needs school. Each type of improper payment and total payment differs according to whether the meals are served at severe-needs schools:

$\$CF\text{-}RPE\text{-}B_j = \#CF\text{-}RPE\text{-}B_j * \$0.30$

$\$CF\text{-}PE\text{-}B_j = \#CF\text{-}PE\text{-}B_j * \$1.28 + \#CF\text{-}PE\text{-}SNB_j * \$0.30$

$\$CRP\text{-}PE\text{-}B_j = \#CRP\text{-}PE\text{-}B_j * \$0.98 + \#CRP\text{-}PE\text{-}SNB_j * \$0.30$

Total dollars of SBP reimbursements in a district are based on the number of breakfasts of each type served in the district, as well as the number of these breakfasts served in severe-needs schools:

$$\$TR\text{-}B_j = (\#CF\text{-}B_j * \$1.55 + \#CF\text{-}SNB_j * 0.30) + (\#CRP\text{-}B_j * \$1.25 + \#CRP\text{-}SNB_j * \$\,0.30) + (\#NC\text{-}B_j * \$0.27)$$

$$\$\ Underpayment\text{-}Bj = \$\ Under\text{-}B_j = \%\widehat{\text{Under}} - B_j * \$TR\text{-}B_j$$

Step 6: Calculate the estimates of total reimbursements, as well as the total amounts and rates of overpayments, underpayments, and overall improper payments across all districts nationally. After we calculated total reimbursements as well as improper payments in each of the relevant error categories for each district nationally for certification error in non-CEP schools, we grouped the appropriate error categories into overpayments and summed these totals across districts. The estimates of improper payment rates are calculated by dividing the initial amount of improper payments by the total reimbursements.[13] For the NSLP, the relevant calculations are as follows:

$$\text{OP-L}_{\text{prelim}} = \sum_{j=1}^{J}(\$\text{CF} - \text{RPE} - \text{L}_j + \$\text{CF} - \text{PE} - \text{L}_j + \$\text{CRP} - \text{PE} - \text{L}_j)$$

$$\text{UP-L}_{\text{prelim}} = \sum_{j=1}^{J} \$\text{Underpayment} - \text{L}_j$$

$$\text{EP-L}_{\text{prelim}} = \text{OP-L}_{\text{prelim}} + \text{UP-L}_{\text{prelim}}$$

$$\text{TR-L}_{\text{prelim}} = \sum_{j=1}^{J} \text{TR} - \text{L}_j$$

$$\text{OPR-L}_{\text{prelim}} = \frac{\text{OP}-\text{L}_{\text{prelim}}}{\text{TR}-\text{L}_{\text{prelim}}} * 100$$

$$\text{UPR-L}_{\text{prelim}} = \frac{\text{UP}-\text{L}_{\text{prelim}}}{\text{TR}-\text{L}_{\text{prelim}}} * 100$$

$$\text{EPR-L}_{\text{prelim}} = \frac{\text{EP}-\text{L}_{\text{prelim}}}{\text{TR}-\text{L}_{\text{prelim}}} * 100$$

An analogous set of calculations can be made for the SBP:

$$\text{OP-B}_{\text{prelim}} = \sum_{j=1}^{J}(\$\text{CF} - \text{RPE} - \text{B}_j + \$\text{CF} - \text{PE} - \text{B}_j + \$\text{CRP} - \text{PE} - \text{B}_j)$$

$$\text{UP-B}_{\text{prelim}} = \sum_{j=1}^{J} \$\text{Underpayment} - \text{Lj}$$

$$\text{EP-B}_{\text{prelim}} = \text{OP-B}_{\text{prelim}} + \text{UP-B}_{\text{prelim}}$$

$$\text{TR-B}_{\text{prelim}} = \sum_{j=1}^{J} \text{TR} - \text{B}_j$$

$$\text{OPR-B}_{\text{prelim}} = \frac{\text{OP}-\text{B}_{\text{prelim}}}{\text{TR}-\text{B}_{\text{prelim}}} * 100$$

$$\text{UPR-B}_{\text{prelim}} = \frac{\text{UP}-\text{B}_{\text{prelim}}}{\text{TR}-\text{B}_{\text{prelim}}} * 100$$

$$\text{EPR-B}_{\text{prelim}} = \frac{\text{EP}-\text{B}_{\text{prelim}}}{\text{TR}-\text{B}_{\text{prelim}}} * 100$$

Step 7. Bootstrapping standard errors and confidence intervals. After generating estimates of improper payment amounts and rates for non-CEP schools, we computed standard errors and confidence intervals for predictions of improper payments using bootstrapping methods. We bootstrapped the whole model system, rather than each individual equation within the model. We considered two types of error: (1) error associated with estimating coefficients used for generating national estimates of improper payments from the APEC-II modeling, which is subject to sampling error; and (2) error associated with calculating national estimates of

[13] In APEC-I, the analogous estimates were further adjusted to account for improper payments in schools using Provisions 2 or 3. However, the APEC-II study did not oversample Provision 2 or Provision 3 schools, so the adjustment factors were not updated. Moreover, it is anticipated that use of Provisions 2 and 3 will decline rapidly with the expansion of CEP. For these reasons, making static adjustments for Provisions 2 and 3 is likely to introduce additional error in the national estimates.

improper payments from applying model-based estimates to national data, which is subject to sampling error from the VCR data.

The first type of sampling error comes from using a finite/limited sample to estimate model coefficients. While the statistical model is estimated using a national representative sample selected for the APEC-II study, the concerns remain when applying the model-based estimates that are based on a finite sample to generate national estimates; this is particularly true if the sample size is limited. For this consideration, we simulated 100 replications of the APEC-II sample and estimated the selected model system using each of these replications, resulting in 100 sets of estimated coefficients. Then we applied these 100 sets of coefficients to the VCR data set to generate 100 sets of predicted error rates of each type. Following steps 1 to 6 described above, we translated these predicted error rates into district-level estimates of improper payments that can then be summed to generate national estimates of improper payments, resulting in 100 national measures of the predicted improper payments that were due to certification error in non-CEP schools. This procedure allowed us to compute the standard error and confidence interval of these predicted improper payments due to certification error.

While the VCR comes close to representing every public or private SFA in the country that offers one of the USDA school meal programs, the data set excludes districts that failed to comply with these reporting requirements. Therefore, national estimates of improper payments from applying model-based estimates to national data are subject to sampling error from the VCR. Assuming estimated coefficients using the APEC-II sample do not need any refinement, we used the VCR sample to simulate 100 replications with the same size as the VCR data set and applied the estimated coefficients to each of these simulated samples, as well as the original sample, to generate predicted error rates of each type. Then we translated these predicted error rates into district-level estimates of improper payments that can then be summed to generate national estimates of improper payments by following step 1 to 6 described above. Since we have 100 replications of the VCR data set, we generated 100 national measures of the predicted improper payments due to certification error. The corresponding standard error and confidence interval of the predicted number of improper payments caused by certification error can be generated.

Finally, we considered both types of sampling error simultaneously. We estimated the selected model using 100 replications of the APEC-II sample, and applied these 100 sets of coefficients from the model to 100 replications of the VCR data set to generate 10,000 national estimates of improper payments. The standard error and confidence interval were computed based on the distribution of these 10,000 predicted improper payments due to certification error.

The procedure described above allows us compute three sets of standard error and confidence interval based on each type of sampling error and the combination of both errors.

2. Model-based estimates of improper payments due to certification error in non-CEP schools

In Table V.3, we present national estimates of predicted improper payments resulting from certification error for non-CEP schools as derived from the model system, along with the main findings from the APEC-II study for SY 2012–2013. For both the NSLP and SBP, the model system predictions for overpayment, underpayment, and total improper payments are slightly less than those from the APEC-II study. The differences are relatively small for the NSLP estimates and somewhat larger for the SBP estimates. For the NSLP, model-based estimates of gross improper payments due to non-CEP certification error were $1,028 million (9.27 percent of total reimbursements) versus $1,153 million (10.01 percent of total reimbursements) in the APEC-II study. For the SBP, model-based estimates of gross improper payments from non-CEP certification error were $279 million (8.45 percent of total reimbursements) versus $364 million (11.30 percent of total reimbursements) in the APEC-II study. All the model-based estimates fall within the 95 percent confidence interval of the APEC-II estimates. Conversely, all the APEC-II estimates fall within the 95 percent confidence interval of the model-based estimates, although the model-based confidence intervals are large.

Table V.3. Comparison of national estimates of improper payments based on APEC-II study and on imputation model, certification error for non-CEP schools

	APEC-II study		Model-based estimation	
	NSLP	SBP	NSLP	SBP
Improper payments (in millions of dollars)				
Overpayments	824 (121) [587,1,061]	257 (46) [167,347]	744 (129) [492, 996]	213 (46) [123, 302]
Underpayments	329 (59) [213,445]	107 (26) [56,158]	284 (107) [74, 494]	66 (26) [16, 117]
Total improper payments	1,153 (140) [879,1,427]	364 (57) [252,476]	1,028 (172) [691, 1,365]	279 (54) [172, 386]
Percentage of all reimbursements in error				
Overpayments	7.16 (1.04) [5.12,9.20]	7.97 (1.40) [5.23,10.71]	6.71 (1.17) [4.41, 9.01]	6.44 (1.41) [3.68, 9.20]
Underpayments	2.86 (0.52) [1.84,3.88]	3.32 (0.78) [1.79.4.85]	2.56 (0.92) [0.76, 4.36]	2.01 (0.76) [0.53,3.50]
Total improper payments	10.01 (1.21) [7.64.12.38]	11.3 (1.74) [7.89,14.71]	9.27 (1.50) [6.32, 12.21]	8.45 (1.68) [5.17,11.74]

Source: FNS-742 Verification Collection Reports and APEC-II study.

Note: Standard errors in parentheses; 95 percent confidence interval in brackets. The difference between model based estimates and estimates from APEC-II sample may partly due to the fact that adjustments for CEP reimbursements were based on imputed data. As discussed in technical report, we overestimated the SFAs and schools operating CEP and the imputation of fraction of free certified students in CEP schools are subject to measurement error.

B. National model-based improper payment estimates due to certification error in CEP schools

As with the non-CEP modeling, after using the APEC-II sample to estimate the regression equations that make up the model, it is straightforward to use those equations to generate estimates for error rates for all districts nationally. The extra step involved in this procedure is to identify districts operating CEP in SY 2012–2013; then we used each CEP district's observed characteristics along with the estimated relationship between error rates.

1. Procedure for generating model-based improper payment estimates

To predict future improper payments due to certification error in CEP schools, we took the following steps:

Step 1: Obtain the data and generate predicted NSLP and SBP net error rates for each district operating the CEP. Unlike the non-CEP modeling, for which information on explanatory variables for the preferred specification is drawn from the VCR file, for the CEP modeling we collected the information for explanatory variables from multiple data sources, including the VCR for SY 2012–2013, the revised VCR for SY 2013–2014 (for imputation of CEP-related variables), and the annual Report to Congress on Direct Certification Implementation for State direct certification performance rates. We then multiplied the values of explanatory variables by the values of associated coefficients from the statistical model to generate predicted net error rates for NSLP and SBP separately for each district in the VCR data. Specifically, these predicted rates are $\%\widehat{\mathrm{NET}-}\mathrm{L}_\mathrm{J}$ and$\%\widehat{\mathrm{Net}-}\mathrm{B}_\mathrm{J}$.

Step 2: Identify CEP districts and impute data for free CEP student equivalent and paid CEP student equivalent. An important step after generating these error rate estimates is to translate them into district-level estimates of CEP improper payments which can then be summed to generate national estimates of CEP improper payments. This step requires district-level estimates of CEP reimbursements or district-level estimates of ISPs and meal counts (which can be combined to generate estimates of CEP reimbursements). The challenge is that we do not have any CEP information from SY2012-2013 VCR file. This step relies on a large number of assumptions. The results would be greatly improved in future application of the model if the imputed values for CEP reimbursements and claiming rates were replaced with data based on administrative records, if such data were to become available.

The first step in generating district-level estimates of CEP reimbursements or district-level estimates of ISPs and meal counts is to identify districts operating CEP in SY 2012–2013. The challenge is that we do not have any CEP information from the SY 2012–2013 VCR file. We have to impute this information using multiple sources:

- From the APEC-II sample, identify SFAs operating CEP in SY 2012–2013
- From the revised VCR file, identify SFAs operating CEP in SY 2013–2014, then use this information proxy for the CEP status in SY 2012–2013 but restrict it to states operating CEP in SY 2012–2013
- Combine the above two strategies to create an indicator for SFAs operating CEP in the SY 2012–2013 VCR file

After imputing the set of districts operating CEP in SY 2012–2013, we estimated CEP reimbursements for these districts. State meal counts were drawn from the FNS national database; however, these meal counts do not distinguish CEP meal counts from non-CEP meal counts. Therefore, we imputed the district-level CEP meal counts based on information on the number of enrolled CEP students in the free or paid meals category.

Although the revised VCR includes information on CEP enrollment and schools, it does not separate CEP students by their eligibility status. Thus, we need to impute the number of enrolled CEP students in the free or paid categories. To do so, we estimated an imputation model in which the dependent variable is the identified student percentage (ISP) in the CEP group; this information came from APEC-II study sample estimates from the CEP analysis. The explanatory variables in this imputation model are identical to core variables we used for certification error modeling in CEP schools, including the percent of students in schools operating CEP, the percent of schools operating CEP, whether the school was privately operated, the State direct certification performance rate, and the school-age poverty rate. We estimated the regression equation to obtain the coefficients. Then we multiplied the values of these five explanatory variables by the values of the associated coefficients from the statistical model to generate predicted ISP for each district identified as operating CEP in the VCR data. Then we multiplied $\widehat{\text{ISP}}$ by 1.6 to get $\widehat{\text{FCP}}$ (the free claiming percentage). Multiplying $\widehat{\text{FCP}}$ by the number of CEP students in the district, we then generated the estimate for the free CEP student equivalent in district operating CEP, and a paid CEP student equivalent estimated as (1-$\widehat{\text{FCP}}$) * # CEP students.

The estimated free CEP student equivalent and paid CEP student equivalent were used to calculate the ratio of CEP free/paid students to total free/paid students in the district:

CEP-free-ratio= Free student equivalents in CEP schools /

(Free student equivalents in CEP schools + free students in non-CEP schools)

CEP-paid-ratio = Paid student equivalents in CEP schools / (total enrollment –

(Free student equivalents in CEP schools + free students in non-CEP schools)

- total reduced-price students)

These reimbursement estimates rely on a great deal of imputation and, as a result, are likely subject to considerable error.

Step 3: Impute the number of meals served in each category (free or paid) in CEP schools in districts operating CEP. Following the same methodology used in APEC-I modeling and modeling for certification error for non-CEP schools, we first imputed the number of each category of meals served (free, reduced-price, or paid) in each district operating CEP based on information in the VCR on the number of enrolled students in each certification category and State meal counts drawn from the FNS national database. For NSLP, we divided the number of students certified for free meals in each district by the sum of students certified for free meals in all districts present in the VCR data of the State in which the district is located. Then we multiplied this proportion by the total number of free lunches served in the State. For SBP, we assumed that the district served the same percentage of the total breakfasts served severe needs schools in the state, by eligibility category, as its percentage of the total number of students enrolled in the state, by eligibility category. Then we estimated the number of free and reduced-price breakfasts served in severe-needs schools. We created eight categories of meals served in each district:

- #CF-L_j: Number of free lunches served in all schools in district j
- #CR-L_j: Number of reduced-price lunches served in all schools in district j
- #NC-L_j: Number of paid lunches served in all schools in district j
- #CF-B_j: Number of free breakfasts served in all schools in district j
- #CF-SNB_j: Number of free breakfasts served in severe-needs schools in district j
- #CR-B_j: Number of reduced-price breakfasts served in all schools in district j
- #CR-SNB_j: Number of reduced-price breakfasts served in severe-needs school in district j
- #NC-B_j: Number of paid breakfasts served in all schools in district j

We further adjusted these meal counts, taking into consideration two factors: (1) CEP schools do not serve reduced-price meals; and (2) the need to adjust district-level meal counts by CEP-free-ratio and CEP-paid-ratio. For the first consideration, we set reduced-price meal counts as zero for CEP schools. For the second consideration, we multiplied the free meal counts by CEP-free-ratio and the paid meal counts by CEP-paid-ratio. Therefore, for each district operating the CEP, we created the following five categories of meal counts:

- #CF-L-CEP_j (Number of free lunches served in CEP schools in district j) = #CF-L_j $* CEP - \widehat{free} - ratio_j$
- #NC-L-CEP_j (Number of paid lunches served in CEP schools in district j) = #NC-L_j $* CEP - \widehat{paid} - ratio_j$
- #CF-B-CEP_j (Number of free breakfasts served in CEP schools in district j) = #CF-B_j $* CEP - \widehat{free} - ratio_j$
- #CF-SNB-CEP_j (Number of free breakfasts served in severe-needs CEP schools in district j) = #CF-SNB_j $* CEP - \widehat{free} - ratio_j$
- #NC-B-CEP_j (Number of paid breakfasts served in CEP schools in district j) = # NC-B_j $* CEP - \widehat{free} - ratio_j$

Step 4: Calculate the total net dollars improperly reimbursed, as well as the total dollars reimbursed overall, for lunch and breakfast for each district. To calculate dollars improperly reimbursed, we multiplied the total number of meals in each meal category served in CEP schools by the dollar value of per-meal reimbursement in that category, then we multiplied this product by the absolute value of estimated net error rates.

$$\$ \text{Net-}L_j = |\%\widehat{\text{NET}} - L_j| * (\#\text{CF-L-CEP}_j * 3.0875 + \#\text{NC-L-CEP}_j * 0.4975)$$

$ Net-B_j = $|\%\widehat{\text{Net}} - B_j|$ * (#CF-B-CEP_j *1.55 + #NC-B-CEP_j * 0.27 + #CF-SNB-CEP_j * 0.23)

Total dollars of NSLP reimbursements in CEP schools in a district j

$TR- L-$CEP_j$ = (#CF-L-CEP_j *$3.0875) + (#NC-L-$CEP_j$ * $0.4975) +

FRP60-L_j * (#CF-L_j-CEP + #NC-L-CEP_j) * $0.02

$TR-B-$CEP_j$ = (#CF-B-CEP_j * $1.55 + #CF-SNB-$CEP_j$ * 0.23) + (#NC-B-CEP_j * $0.27)

Step 5: Calculate the estimates of total reimbursements, as well as the total amounts and rates of improper payments, across all districts nationally. After we calculated total reimbursements as well as improper payments for each district across the country operating CEP, we summed these totals across districts. The preliminary estimates of improper payment rates were calculated by dividing the initial amount of improper payments by total reimbursements. For the NSLP, the relevant calculations are as follows:

$$\text{NET-L}_{\text{prelim}} = \sum_{j=1}^{J} \$\text{Net} - \text{L}_j$$

$$\text{TR-L-CEP}_{\text{prelim}} = \sum_{j=1}^{J} \text{TR} - \text{L} - \text{CEP}_j$$

$$\text{EPR-L}_{\text{prelim}} = \frac{\text{NET}-\text{L}_{\text{prelim}}}{\text{TR}-\text{L}-\text{CEP}_{\text{prelim}}} * 100$$

$$\text{NET-B}_{\text{prelim}} = \sum_{j=1}^{J} \$\text{Net} - \text{B}_j$$

$$\text{TR-B-CEP}_{\text{prelim}} = \sum_{j=1}^{J} \text{TR} - \text{B} - \text{CEP}_j$$

$$\text{EPR-B}_{\text{prelim}} = \frac{\text{NET}-\text{B}_{\text{prelim}}}{\text{TR}-\text{B}-\text{CEP}_{\text{prelim}}} * 100$$

Step 6: Bootstrapping standard error and confidence interval. As described in the discussion of certification error modeling for non-CEP schools, in this final step, we computed standard errors and confidence intervals for predictions of improper payments using bootstrapping methods. We considered two types of sampling error: (1) the sampling error from the VCR file, and (2) the sampling error from the APEC-II sample used to develop the statistical model; we generated three sets of standard errors and confidence intervals based on each type of sampling error and the combination of both.

2. Model-based estimates of improper payments due to certification error in CEP schools

In Table V.4, we present national estimates of predicted improper payments resulting from certification error for CEP schools as derived from the model system, along with the main findings from the APEC-II study for SY 2012–2013. Given the need to impute district CEP participation based on SY 2013–2014 data (when CEP participation was higher than in SY 2012–2013), the model-based estimates overstate the number CEP schools and SFAs. With the imputation procedure, we identified 568 SFAs and 3,739 schools operating CEP in SY2012–2013. Yet, according to FNS's Community Eligibility Provision Evaluation Report, a total of 420

LEAs and 2,312 schools participated in CEP in SY 2012–2013 (see U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, 2014).

Table V.4. Comparison of national estimates of improper payments based on APEC-II study and on imputation model, certification error for CEP schools

	APEC-II study		Model-based estimation	
	NSLP	SBP	NSLP	SBP
Improper payments (millions of dollars)				
Overpayments	0.09 (0.05) [0,0.19]	0.04 (0.03) [-0.02,0.1]	0.10 (1.15) [-2.1,2.4]	0.03 (0.35) [-0.7,0.7]
Underpayments	4.88 (2.67) [-0.4,10.2]	2.17 (1.17) [-0.2,4.6]	7.34 (2.56) [2.3,12.4]	2.63 (0.89) [0.9, 4.4]
Total improper payments	4.96 (2.67) [-0.3,10.3]	2.22 (1.17) [-0.2,4.6]	7.44 (2.76) [2.03, 12.8]	2.66 (0.96) [0.8, 4.5]
Improper payment rates (percentages)				
Overpayments	0.03 (0.02) [-0.01,0.07]	0.04 (0.03) [-0.02,0.1]	0.02 (0.24) [-0.45, 0.50]	0.02 (0.23) [-0.43,0.48]
Underpayments	1.71 (0.98) [-0.26,3.66]	1.84 (1.02) [-0.16,3.76]	1.68 (0.59) [0.52,2.85]	1.85 (0.63) [0.62, 3.08]
Total improper payments	1.73 (0.98) [-0.19,3.65]	1.88 (1.03) [-0.14,3.90]	1.71 (0.63) [0.48, 2.94]	1.87 (0.67) [0.57, 3.18]

Source: FNS-742 Verification Collection Reports and APEC-II study.

Note: Standard errors in parentheses; 95 percent confidence interval in brackets

As a result of overestimating CEP schools and SFAs, we overestimate the number of meals served to CEP schools and CEP reimbursements. The imputed total reimbursements for CEP schools in SY2012–2013 are $436 million in the NSLP and $142 million in the SBP versus $286 million in the NSLP and $118 million in the SBP from the APEC-II study. For this reason, it is not useful to compare model-based and APEC-II improper payment amounts related to CEP certification error. Instead, we focus on improper payment rates, which are not affected by imputed reimbursements because the regression equations provide net improper payment rate estimates (see Steps 4 and 5 above for a description of how model-based error rates are combined with imputed reimbursements). In future years, imputed CEP reimbursements should be closer to actual CEP reimbursements because they will be based on current-year CEP participation (although CEP reimbursements used in the model will still be based on fairly substantial imputation and therefore subject to error).

For both the NSLP and SBP, the model system predictions error rates of total improper payments are similar to those from the APEC-II study. For the NSLP, model-based estimates of gross improper payments related to CEP certification error were 1.71 percent of total reimbursements compared to 1.73 percent of total reimbursements in the APEC-II study. For the SBP, model-based estimates of gross improper payments related to CEP certification error were 1.87 percent of total reimbursements compared to 1.88 percent of total reimbursements in the APEC-II study. All the model-based estimates fall within the 95 percent confidence interval of the APEC-II estimates. Conversely, all the APEC-II estimates fall within the 95 percent confidence interval of the model-based estimates.

C. National model-based improper payment estimates due to certification error in all schools

We generated national estimates of predicted improper payments resulting from certification error for in all schools by adding improper payment estimates due to certification error in non-CEP schools and CEP schools.

In Table V.5, we present these findings along with the main findings from the APEC-II study for SY 2012–2013. For both the NSLP and SBP, the model system predictions for overpayment, underpayment, and total improper payments are slightly less than those from the APEC-II study. The differences are relatively small for the NSLP estimates and larger for the SBP estimates. The pattern of all schools is quite similar to that of non-CEP schools, which is not surprising, because CEP schools only accounted for an estimated 2 percent of total NSLP reimbursements nationally for SY 2012–2013 and 4 percent of total SBP reimbursements. For the NSLP, model-based estimates of gross improper payments due to certification error for all schools were $1,035 million (9 percent of total reimbursements) versus $1,158 million (9.81 percent of total reimbursements) in the APEC-II study. For the SBP, model-based estimates of gross improper payments from certification error for all schools were $282 million (8.2 percent of total reimbursements) versus $366 million (10.97 percent of total reimbursements) in the APEC-II study. All the model-based estimates fall within the 95 percent confidence interval of the APEC-II estimates. Conversely, all the APEC-II estimates fall within the 95 percent confidence interval of the model-based estimates.

D. National model-based improper payment estimates due to meal claiming error

1. Procedure for generating model-based improper payment estimates

To predict future improper payments due to meal claiming error, we performed the following steps:

Step 1: Obtain the data and generate predicted NSLP and SBP underpayment and overpayment error rates for each district nationally. In the preferred specification of the model, all variables come from the VCR data set, so collecting the data to be used in the model means collecting and cleaning the VCR data. We then multiplied the values of explanatory variables by the values of associated coefficients from the statistical model to generate predicted under- and overpayment error rates for NSLP and SBP separately for each district in the VCR data. Specifically, these predicted rates are $\%\widehat{\text{Over}} - \text{L}_\text{J}$, $\%\widehat{\text{Under}} - \text{L}_\text{J}$, $\%\widehat{\text{Over}} - \text{B}_\text{J}$, and $\%\widehat{\text{Under}} - \text{B}_\text{J}$.

Table V.5. Comparison of national estimates of improper payments based on APEC-II study and on imputation model, certification error for all schools

	APEC-II study		Model-based estimation	
	NSLP	SBP	NSLP	SBP
Improper payments (in millions of dollars)				
Overpayments	824 (121) [588, 1060]	257 (46) [167, 347]	744 (128) [492,996]	213 (46) [123,303]
Underpayments	334 (59) [219, 449]	109 (26) [58, 160]	291 (108) [79,503]	69 (26) [19,119]
Total improper payments	1,158 (140) [884, 1,432]	366 (57) [255, 477]	1,035 (173) [697,1,374]	282 (55) [174, 390]
Percentage of all reimbursements in error				
Overpayments	6.98 (1.01) [5.01, 8.95]	7.69 (1.35) [5.06, 10.32]	6.46 (1.13) [4.24,8.67]	6.18 (1.37) [3.50, 8.85]
Underpayments	2.83 (0.51) [1.84, 3.82]	3.27 (0.75) [1.81, 4.73]	2.53 (0.89) [0.78,4.27]	2.00 (0.73) [0.58,3.44]
Total improper payments	9.81 (1.18) [7.51, 12.11]	10.97 (1.68) [7.69, 14.25]	8.98 (1.45) [6.13,11.83]	8.18 (1.62) [5.00,11.36]

Source: FNS-742 Verification Collection Reports, and APEC-II study.

Note: Standard errors in parentheses; 95 percent confidence interval in brackets. The numbers in this table are the weighted sum of the estimates of cert error in non-CEP schools (Table V.3) and in CEP schools (Table V.4).

Step 2: Impute the number of meals served in each category (free, reduced-price, or paid) in each district. Using the same methodology described in previous sections, we imputed the number of meals served in each category (free, reduced-price, or paid) in each district based on information in the VCR on the number of enrolled students in each certification category and State meal counts drawn from the FNS national database. For the NSLP, we divided the number of students certified for free meals in each district by the sum of students certified for free meals in all districts present in the VCR data of the State in which the district is located. Then we multiplied this proportion by the total number of free lunches served in the State. For the SBP, we assumed that the district served the same percentage of the total breakfasts served in severe needs schools in the State, by eligibility category, as its percentage of the total number of students enrolled in the State, by eligibility category. Then we estimated the number of free and reduced-price breakfasts served in severe-needs schools. We created eight categories of meals served in each district:

- #CF-L_j: Number of free lunches served in all schools in district j
- #CR-L_j: Number of reduced-price lunches served in all schools in district j
- #NC-L_j: Number of paid lunches served in all schools in district j

- #CF-B_j: Number of free breakfasts served in all schools in district j
- #CF-SNB_j: Number of free breakfasts served in severe-needs schools in district j
- #CR-B_j: Number of reduced-price breakfasts served in all schools in district j
- #CR-SNB_j: Number of reduced-price breakfasts served in severe-needs school in district j
- #NC-B_j: Number of paid breakfasts served in all schools in district j

Step 3: Calculate the total dollars improperly reimbursed, as well as the total dollars reimbursed overall, for lunch and breakfast for each district. We assumed that meal claiming error is equally distributed among each meal category. Therefore, to calculate dollars amounts of improperly reimbursed meals, we first calculated total dollars reimbursed overall by multiplying the total number of meals in each meal category served by the dollar value of per-meal reimbursement in that category. Then we multiplied the total reimbursement by estimated error rates to get overpayments and underpayments.

Total dollars of NSLP reimbursements in district j:

$$\$TR\text{-}L_j = (\#CF\text{-}L_j * \$3.0875) + (\#CRP\text{-}L_j * \$2.6875) + (\#NC\text{-}L_j * \$0.4975) +$$

$$FRP60\text{-}L_j * (\#CF\text{-}L_j + \#CRP\text{-}L_j + \#NC\text{-}L_j) * \$0.02$$

$$\$\ Over\text{-}L_j = \%\ \widehat{\text{Over}} - L_j * \$TR\text{-}L_j$$

$$\$\ Under\text{-}L_j = \%\ \widehat{\text{Under}} - L_j * \$TR\text{-}L_j$$

$$\$TR\text{-}Bj = (\#CF\text{-}B_j * \$1.55 + \#CF\text{-}SNB_j * 0.30) + (\#CRP\text{-}B_j * \$1.25 +$$

$$\#CRP\text{-}SNB_j * \$0.30) + (\#NC\text{-}B_j * \$0.27)$$

$$\$\ Over\text{-}B_j = \%\widehat{\text{Over}} - L_j * \$TR\text{-}B_j$$

$$\$\ Under\text{-}B_j = \%\widehat{\text{Under}} - L_j * \$TR\text{-}L_j$$

Step 4: Calculate the preliminary estimates of total reimbursements, as well as the total amounts and rates of overpayments, underpayments, and overall improper payments, across all districts nationally. After we calculated total reimbursements, as well as overpayments and underpayments, for each district across the nation, we summed these totals across districts. The preliminary estimates of improper payment rates are calculated by dividing the initial amount of improper payments by total reimbursements. For the NSLP, the relevant calculations are as follows:

$$\text{OP-L prelim} = \sum_{j=1}^{J} \text{Over} - \text{Lj}$$

$$\text{UP-L prelim} = \sum_{j=1}^{J} \text{Under} - \text{Lj}$$

$$\text{EP-L prelim} = \text{OP-L prelim} + \text{UP-L prelim}$$

$$\text{TR-L prelim} = \sum_{j=1}^{J} \text{TR} - \text{Lj}$$

OPR-L prelim $= \frac{\text{OP}-\text{L prelim}}{\text{TR}-\text{L prelim}} * 100$

UPR-L prelim $= \frac{\text{UP}-\text{L prelim}}{\text{TR}-\text{L prelim}} * 100$

EPR-L prelim $= \frac{\text{EP}-\text{L prelim}}{\text{TR}-\text{L prelim}} * 100$

An analogous set of calculations can be made for the SBP:

OP-B prelim = $\sum_{j=1}^{J} \text{E} - \text{Bj})$

UP-B prelim = $\sum_{j=1}^{J}(\$\text{CRE} - \text{FE} - \text{Bj} \ + \ \$\text{NC} - \text{PE} - \text{Bj} \ + \ \$\text{NC} - \text{RPE} - \text{Bj})$

EP-B prelim = OP-B prelim + UP-B prelim

TR-B prelim = $\sum_{j=1}^{J} \text{TR} - \text{Bj}$

OPR-B prelim = $\frac{\text{OP}-\text{Bprelim}}{\text{TR}-\text{B prelim}} * 100$

UPR-B prelim $= \frac{\text{UP}-\text{Bprelim}}{\text{TR}-\text{Bprelim}} * 100$

EPR-B prelim = $\frac{\text{EP}-\text{B prelim}}{\text{TR}-\text{B prelim}} * 100$

Step 5: Bootstrapping standard error and confidence interval. Taking the same approach, we computed three sets of standard errors and confidence intervals based on two types of sampling error—the sampling error from the VCR file and the sampling error from the APEC-II sample used to develop the statistical model—and the combination of both sampling errors.

2. Model-based estimates of improper payments due to meal claiming error

In Table V.6, we present national estimates of predicted improper payments resulting from meal claiming error for all schools as derived from the model system and the main findings from the APEC-II study for SY 2012–2013. For both the NSLP and SBP, the model system predictions for overpayment, underpayment, and total improper payments are greater than those from the APEC-II study. The differences are particularly small for the NSLP estimates and somewhat larger for the SBP estimates. For the NSLP, model-based estimates of gross improper payments related to meal claiming error were $614 million (5.33 percent of total reimbursements) compared to $607 million (5.14 percent of total reimbursements) in the APEC-II study. For the SBP, model-based estimates of gross improper payments related to meal claiming error were $378 million (10.97 percent of total reimbursements) compared to $365 million (10.94 percent of total reimbursements) in the APEC-II study. All the model-based estimates fall within the 95 percent confidence interval of the APEC-II estimates. Conversely, all the APEC-II estimates fall within the 95 percent confidence interval of the model-based estimates, although, as with the previously discussed model system, the model-based confidence intervals are large.

Table V.6. Comparison of national estimates of improper payments based on APEC-II study and on imputation model, meal claiming error

	APEC-II study		Model-based estimation	
	NSLP	SBP	NSLP	SBP
Improper Payments (in millions of dollars)				
Overpayments	525 (82) [364,280]	358 (40) [280,436]	532 (70) [395, 668]	372 (58) [259, 485]
Underpayments	81 (24) [34,28]	8 (3) [2,14]	82 (29) [25, 139]	6 (1) [3, 9]
Total improper payments	607 (86) [438,776]	365 (40) [287,443]	614 (77) [462, 765]	378 (58) [265, 491]
Percentage of all reimbursements in error				
Overpayments	4.45 (0.50) [3.47,5.43]	10.71 (1.13) [8.50,12.92]	4.61 (0.58) [3.48, 5.74]	10.8 (1.68) [7.51, 14.09]
Underpayments	0.69 (0.20) [0.30,1.08]	0.23 (0.08) [0.07,0.39]	0.71 (0.25) [0.22, 1.20]	0.17 (0.04) [0 .08, 0 .25]
Total improper payments	5.14 (0.60) [3.96,6.32]	10.94 (1.13) [8.73,13.15]	5.33 (0.64) [4.08, 6.58]	10.97 (1.68) [7.68, 14.26]

Source: FNS-742 Verification Collection Reports and APEC-II study.

Note: Standard errors in parentheses; 95 percent confidence interval in brackets.

Summary

- The APEC-II modeling work introduced the following important innovations: models to produce estimates of both certification and non-certification error, an approach for modeling improper payments due to certification error in schools participating in the CEP, a within-sample cross-validation method for selecting the preferred model system specification, and the use of bootstrapping techniques to compute standard errors and confidence intervals.
- Despite these improvements to the model development process, the modeling approach is limited in several ways. The key limitations include (1) the possibility that the models will not perform well in future years because the relationship between improper payments and district characteristics is not stable over time, (2) remaining variation in improper payments that is unexplained by the models, and (3) limited availability of national data related to CEP. Given the recent nationwide rollout of CEP and its rapid, widespread adoption by eligible districts, the concern about the unstable relationship between CEP improper payments and district characteristics may be particularly salient. Although the analysis of model validation suggests that the models perform reasonably well for SY 2012–2013, the limitations suggest that future estimates of improper payment rates should be interpreted cautiously.

VI STRENGTHS AND LIMITATIONS OF THE MODELING APPROACH

In this chapter, we discuss the strengths and limitations of the APEC-II modeling. As part of the APEC-I study, Mathematica developed statistical models designed to estimate national improper payments due to certification error on an annual basis, using district-level data available from VCR data. Since 2005–2006, FNS staff have used these models to update annual estimates of overpayments, underpayments, and overall improper payments in the NSLP and SBP. To assess how well the APEC-I model predicts improper payments in future school years, we applied the APEC-I models to national data for SY 2012–2013 and compared the resulting model-based improper payment estimates of certification error to the APEC-II study sample-based estimates of certification error for that school year. We found that the model predicted overpayment rates well, but predicted underpayment rates that were significantly too low. Based on these findings, when updating the model, we tested alternative model specifications of underpayments due to certification error in the hopes of identifying a model that better predicts underpayments. These findings also underscore the fact that when interpreting model-based estimates in future years, it is important to consider the potential for deterioration of the performance of the models over time in response to changes in the factors related to improper payments.

The APEC-II modeling work used APEC-I model development work as a starting point while introducing several important innovations:

- We developed models to produce estimates of both certification and non-certification error (APEC-I focused only on certification error).
- We developed an approach for modeling improper payments due to certification error in schools participating in the CEP.
- We implemented a within-sample cross-validation method for selecting the preferred model system specification. This technique offers an assessment of how well the model results will generalize to a data source other than the one on which it was estimated and how accurately a predictive model will perform in practice. We selected models based on cross-validation performance estimates as well as model goodness of fit, whereas APEC-I model specification selection was based on goodness of fit alone.
- We tested a broader set of certification error specifications, including hybrid specifications in which overpayment rates and underpayment rates were aggregated to different levels.
- We computed standard errors and confidence intervals for the APEC-II model-based improper payment estimates using bootstrapping techniques.

Despite these improvements to the model development process, important limitations of the modeling approach remain. These limitations include:

- **Substantial unexplained variation.** The goodness of fit for most model equations is moderate, thus a substantial amount of variation in improper payment rates remains unexplained by the models. In other words, there are unobserved factors that cause certification error rates to be higher in some districts than in others. To the extent that changes in these unobserved factors also lead to changes in error rates (and consequently improper payments) in future years, the model will not capture these changes.

  In order to further explore this concern, we estimated alternate specifications of models with particularly low R-square values in which all variables were selected based on correlation with the dependent variable; in other words, models that included no core variables, but tested all the possible data sources that could be used based on statistical correlation. In most cases, these purely over-fitted models had R-square values similar to those of the selected models. This finding suggests that available national data do not explain a substantial portion of the variance in some improper payment rates.
- **Assumption of stable relationships between error rates and district characteristics.** As with the APEC-I model, the strategy of using a statistical model based on estimated relationships between district characteristics and certification and non-certification error rates in 2012–2013 to predict improper payments in the future implicitly assumes that these relationships remain constant over time. Although this implicit assumption is necessary and unavoidable, it may not be valid if there are important, systematic, year-to-year changes in the school meal programs and in the factors related to improper payments. The nationwide rollout of the CEP might represent such a change, so predicted rates for future years should be interpreted cautiously.

  Related to this point, in comparing the coefficients of the same variables based on the APEC-II model to those based on the APEC-I model, we observed changes in relationships for some. For any methodology in which regression models from one period are used to forecast outcomes in future periods, the regression parameters may not be stable over time both because administrative features of the program change over time (for example, CEP and direct certification) and because the administrators are likely to react to the APEC findings (for example, to reduce errors, to attempt to increase the utilization of direct certification). Therefore, the further out in the future the SY 2012–2013 statistical model results are used to predict improper payments, the less reasonable this assumption becomes.

- **Additional modeling assumptions.** As with the APEC-I modeling, in the course of using the results of the statistical model to predict amounts and rates of improper payments, the procedures we implemented rest on various additional assumptions, including assuming (1) that meal claiming error affected the reimbursements for each meal type proportionately, (2) the proportion of a State's meals of a given meal price category (for example, free NSLP lunches) served in a given district is the same as the proportion of the State's students in that meal price category who are enrolled, and (3) that the distribution across districts of free and reduced-price breakfasts served in severe needs schools is the same as the distribution across districts of all free meals served in that State. These assumptions are likely to be accurate on average, but in any given district, the assumed value of a particular variable might differ substantially from its actual value.

- **Model validation limitation.** Our external validation approach focuses on comparing sample-based and model-based estimates of error rates of the current study period (SY 2012-2013). The data required to validate the models in different periods or future years are not available. Therefore, this validation approach does not give information on out-of-sample predictions for future years.

- **CEP model limitations.** We encountered some important challenges in developing the CEP certification error models. The CEP modeling is hampered by limited availability of national data related to CEP, such as CEP reimbursements, CEP implementation features, and meal claiming rates. Many of these data limitations are the result of the fact that CEP is a new program; in future years, higher quality CEP data are likely to become available. For the time being, though, the CEP models had to be developed with few explanatory variables directly related to CEP implementation, and had to be validated using data that relied heavily on imputation. These limitations may have important implications for the long-term reliability of the model-based estimates of improper payments due to certification error in CEP schools. Better information will allow more efficient modeling and more accurate estimation.

  The reliability of the CEP certification error estimates may be further compromised by the fact that the CEP models were estimated by using districts in States that had implemented CEP in SY 2012–2013. The CEP will be available nationwide starting in SY 2014–2015. Districts within the States that elected to use the CEP in SY 2012–2013 may differ from typical districts nationally. As a result, the relationships estimated by the CEP models are likely to change, making the estimates of model-based improper payments less accurate. Building the models in the post-CEP environment will be helpful, as it will improve the confidence in predicting error rates in future years.

  Furthermore, the limited availability of national data related to the CEP also affected our estimation of certification error for non-CEP schools indirectly because we need to adjust data to account for meals served in CEP schools for districts that also operate both CEP and non-CEP schools. We used national data for SY 2013–2014 to impute CEP participation in SY 2012–2013. This approach overstates CEP reimbursements and understates non-CEP reimbursements. In future years, the imputed CEP reimbursements will be more accurate because current national data on CEP participation will be available.

Despite the limitations of model estimates based on SY 2012–2013, FNS is required to provide estimates of improper payments for future years, and the current models provide the best estimates possible given the constraints.

In addition to these limitations, a key caveat is that the purpose of the statistical models is to predict improper payments in the future. It is not designed to measure causal relationships between improper payments and district characteristics, and the results of the model should not be used as a basis for developing policies aimed at reducing improper payments.

The implication of these limitations is that in any future year, the predicted amounts and rates of improper payments will not be as accurate or credible as new estimates of these values from a large-scale, nationally representative study similar to the APEC-I and APEC-II studies. However, conducting additional APEC-style studies in the near future would be costly and time-consuming. In addition, we believe that the econometric model described in this report will provide predicted amounts and rates of improper payments that are reasonable estimates of their actual values. Moreover, the predicted values will allow FNS to effectively track the direction and general magnitude of changes in improper payments in the future, at minimal cost and in a timely manner.

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APPENDIX A
SUMMARY OF COMMENTS FROM EXTERNAL REVIEWERS

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We submitted draft versions of the APEC-II technical reports on national and State statistical models of improper payments in the National School Lunch Program (NSLP) and School Breakfast Program (SBP) to three external experts for their review. The reviewers acknowledged the difficulty of the modeling objective and agreed that we used appropriate empirical methods for the modeling and that the modeling work was carefully done. The reviewers also suggested some potential revisions to the report in which we present our methodologies and findings. This appendix summarizes the major issues raised by the reviewers and how we addressed them in the final version of both the model and the report. The reviewers' comments are organized by subject: (1) data issues, (2) model estimation, (3) model validation, (4) interpretation, and (5) other issues.

A. Data issues

1. Potential for measurement error in the APEC-II study's household survey data

Reviewer 2 expressed concern about how different types of errors are measured and indicated that the report should include a discussion of this issue and its implications for our approach to updating the estimates of erroneous payments. Reviewer 3 also commented on the potential measurement error in calculating error rates for the NSLP and the SBP, focusing particularly on the possibility that the error rate calculations systematically undervalue underpayments in comparison with overpayments by not accounting for the effect of certification status (and price) on the number of meals received.

Mathematica's response

In the APEC-II study, we took the following steps to ensure the most accurate reporting: (1) households were sent a letter from USDA establishing the legitimacy and importance of the study; (2) study correspondence stipulated to respondents that their responses would be kept strictly confidential and would not affect the benefits they receive, and field staff were trained to reiterate these points; (3) the reference period for the survey was the month covered by the application; (4) most households were interviewed within three months of their certification or application date; and (5) an iterative CAPI procedure streamlined income reporting, reconciled differences between reported and documented amounts, and enabled respondents to review and identify missing or inaccurate income sources and/or amounts. We agree with the reviewers that this kind of measurement error in reported income sources and amounts can never be eliminated entirely. We took the suggestion from Reviewer 1 and added a brief discussion of this point to Chapter III in the national report. We also referred readers to the main report for more details on the methodology used to estimate the improper payments.

Reviewer 3 is correct that the main estimates of improper payments in the APEC-II report are based on actual meals received. Therefore, these estimates do not adjust for the fact that undercertified students would receive more meals with the correct certification status, and overcertified students would receive fewer meals with the correct certification status. In the APEC-II analysis, we generated alternative estimates of improper payments in which the actual number of meals received by students with an incorrect certification status is replaced with an imputed meal count based on the correct certification status. In Chapter III, when discussing the concerns about potential measurement error regarding dependent variables, we referred the readers to the description of this analysis in Appendix F of the main report for the sensitivity checks we conducted. These alternative improper payment estimates are similar to the estimates based on the main analysis. Therefore, this comment does not affect the modeling report.

B. Model estimation issues

1. Comparing the APEC-II model-based estimates to the APEC-I model-based estimates

Reviewer 1 noted that the difference between the overpayment estimates for SY 2012–2013 based on the statistical model developed for the APEC-I study and the APEC-II sample-based overpayment estimate is relatively smaller than the difference between model-based overpayment estimates based on the APEC-II model and the APEC-II sample-based overpayment estimate. Reviewer 1 suggested that we further decompose each component of the overpayment to help us understand the reasons for this difference.

Reviewer 3 also brought up this issue in discussing how the model's predictive power might evolve over time. The reviewer suggested that we add information about which variables explain the difference between the APEC-II and the APEC-I model, whether the coefficients have changed, or whether there are new variables in the model in APEC-II that do much of the estimation work.

Mathematica's response

Although the difference between point estimates of overpayment for SY 2012–2013 based on the APEC-I model and the APEC-II sample-based estimate of overpayment is somewhat smaller than the difference between point estimates based on the APEC-II model and the APEC-II sample-based estimate of overpayment, all the APEC-II sample-based estimates and estimates based on the APEC-I models fall within the 95 percent confidence interval of the APEC-II model-based estimates. Thus, these estimates are not statistically significantly different from each other.

In response to the reviewers' comments, we further explored the difference between the estimates of the APEC-II model and the APEC-I model. As shown in Table A.1, we compared the sample- and model-based estimates of improper payments due to each subcomponent of the overpayment rate.

Table A.1. Model- and sample-based estimates of NSLP and SBP overpayments, by type of overpayment

	APEC-I model model-based estimates	APEC-II model model-based estimates	APEC-II sample-based estimates
NSLP			
Dollar amount of improper overpayments	$825,715,735	$744,064,551	$763,352,592
Certified free, reduce-priced eligible	$68,099,305	$69,303,054	$69,836,656
Certified free, not eligible	$504,937,117	$511,028,394	$484,647,216
Certified reduced price, not eligible	$252,679,313	$163,733,103	$208,878,720
Improper overpayment rate	7.163%	6.709%	6.912%
Certified free, reduced-price eligible	0.591%	0.625%	0.632%

	APEC-I model model-based estimates	APEC-II model model-based estimates	APEC-II sample-based estimates
Certified free, not eligible	4.381%	4.608%	4.389%
Certified reduced price, not eligible	2.192%	1.476%	1.891%
SBP			
Dollar amount of improper overpayments	$ 201,328,212	$212,661,386	$202,100,674
Certified free, reduced-price eligible	$23,300,806	$29,239,042	$23,985,310
Certified free, not eligible	$155,072,332	$147,933,256	$129,728,696
Certified reduced-price, not eligible	$65,485,983	$35,389,088	$48,386,668
Improper overpayment rate	7.080%	6.425%	7.189%
Certified free, reduced-priced eligible	0.676%	0.883%	0.853%
Certified free, not eligible	4.502%	4.469%	4.615%
Certified reduced price, not eligible	1.901%	1.072%	1.721%

It should be noted that the APEC-II sample-based estimates of the total improper overpayment amount and rate reported here are slightly lower than those reported in Table V.3 of the main report. The reason for this difference is that the estimates reported here do not include schools that determined eligibility for free and reduced-priced meals on the basis of Provision 2 or 3 of the National School Lunch Act and schools were not in their base year during the APEC-II data collection period. We have only school-level data on over- and underpayments, so it was not possible to break down these error estimates by certification and eligibility status.

We found that for both the NSLP and the SBP, the component that differs most between APEC-I and APEC-II model-based estimates is the estimate for improper payments due to students certified for reduced-price meals but actually not eligible for school meal benefits. The APEC-II model tends to underestimate this component compared with the APEC-I model, and the estimates from the APEC-II model are also lower than those based on the APEC-II sample.

We also found that the estimates based on the APEC-I model for improper payment amount/rate due to the errors of certified free but reduced-price eligible, and certified free but not eligible are slightly lower than estimates based on the APEC-II model (except the estimate for certified free but not eligible, for improper payments in the SBP). One factor that might explain some of this difference is that APEC-I model-based estimates did not adjust for reimbursements for CEP schools, so the denominator is slightly higher than it should be. Because the coefficients of the APEC-I model were estimated when the CEP did not exist, the adjustment is inappropriate.

Further, we took Reviewer 3's suggestion to further explore the difference between estimated coefficients from the APEC-II model and those from the APEC-I model to explain the reasons for the difference in performance of the APEC-I relative to the APEC-II model. However, the comparison is not straightforward because the imputation models for the APEC-I and the APEC-II are different. For example, one of variables used for the APEC-I model—type of application (individual student, household, or both)—for certification error for non-CEP schools no longer exists in the VCR data because all applications are now household applications. Moreover, when developing the APEC-II model, we included in several of our equations the State direct certification characteristics available through the Direct Certification Improvement Study and the annual Reports to Congress on Direct Certification Implementation as explanatory variables. The success that States have in directly certifying eligible students may be related to improper payment rates, particularly given the relatively low rates of improper payments associated with directly certified students in non-CEP schools and the importance of accurate direct certification in reducing certification error in CEP schools. However, this variable is not available for the APEC-I model. Because the APEC-I and the APEC-II models do not include an identical set of explanatory variables, direct comparison is neither feasible nor meaningful. One strategy could be to compare these two models by grouping variables together based on whether they were present in both APEC-I and APEC-II models or appeared in only one set of models. However, the results of this analysis do not provide meaningful insight into the differences in the models. In particular, the constant terms of the regression equations are not directly comparable because the explanatory variables differ in the specifications that are compared. We present the results for completeness.

Table A.2a summarizes the findings comparing the predicted rate of certified free but reduced-price eligible from the APEC-I imputation model with that of the APEC-II imputation model. The rates presented in this table are not comparable to those in Table A.1. Table A.1 shows improper payments as a percentage of total national reimbursements of a certain type (for example, the percentage of total national reimbursements estimated to be improper payments due to students who are certified free but are reduced price eligible). Table A.2a shows the average district improper payments as a percentage of reimbursements of a certain type (for example, the percentage of district reimbursements for free meals estimated to be improper payments due to students certified free but reduced price eligible).

The second row of Table A.2a shows the predicted rate from the regression equation based on the APEC-I and the APEC-II models, respectively, as well as the difference between these two predicted rates. The second column decomposes this predicted rate from the APEC-I model into three subcomponents: (1) the subcomponent predicted by overlapped variables in the APEC-I and the APEC-II models, (2) the subcomponent predicted by variables used in the APEC-I model only, and (3) the constant of the regression equation. The third column provides analogous values for the APEC-II model. Column four shows the difference between the APEC-I predicted rate and the APEC-II predicted rate as well as the difference between each component of these rates. Column five shows the percentage of total difference in the APEC-I and APEC-II predicted rates explained by each subcomponent. In column five, the bottom four rows add up to be the first row of this column.

Our analysis suggests that most of the difference (375.84 percent) between the predicted rates based on the APEC-I and the APEC-II models is explained by the difference between the estimated constants from these two models. The difference between overlapped coefficients also explains a big proportion (-105.34 percent) of the difference in predicted rates; this suggests that the underlying relationship represented by these coefficients has changed over time. Furthermore, we found that the difference in modeling strategy—which is represented by the differences in variables included in the model, particular the new variables we included in the APEC-II model—also explains a considerable proportion (-170.68 percent) of the difference in predicted rates for certified free but reduced-price eligible.

We conducted the same analysis for each subcomponent of the overpayment rate. The results are summarized in Table A.2b through B.2f. For most equations, the predicted rates based on the APEC-I model and on the APEC-II model are consistent except for equations for certified reduced-price eligible but actually not eligible, where the difference between the predicted rates from two models is substantial (Table A.2c). Most of the difference is due to the difference in the estimated constant and in the difference in modeling strategy (the new variables we included in the APEC-II model).

Table A.2a. Decomposition: APEC-I imputation model vs. APEC-II imputation model, certified free, reduced-price eligible, NSLP

	APEC-I imputation model	APEC-II imputation model	Difference	% of total difference
Certified free, reduced-price eligible (%)	**7.66**	**4.87**	**2.79**	**100.00%**
Overlapped variables	-3.70	-0.76	-2.94	-105.34%
Variables in APEC-I model only	0.00	-	0.00	0.18%
Variables in APEC-II model only	-	4.77	-4.77	-170.68%
Constant	11.35	0.85	10.50	375.84%

Table A.2b. Decomposition: APEC-I imputation model vs. APEC-II imputation model, certified free, not eligible, NSLP

	APEC-I imputation model	APEC-II imputation model	Difference	% of total difference
Certified free, not eligible (%)	**5.25**	**6.03**	**-0.78**	**100.00%**
Overlapped variables	-3.93	-0.87	-3.07	393.17%
Variables only in APEC-I model	0.01	-	0.01	-0.86%
Variables only in APEC-II model	-	-19.40	19.40	-2488.73%
Constant	9.18	26.30	-17.12	2196.42%

Table A.2c. Decomposition: APEC-I imputation model vs. APEC-II imputation model, certified reduced- priced, not eligible, NSLP

	APEC-I imputation model	APEC-II imputation model	Difference	% of total difference
Certified reduced-price, not eligible (%)	**25.12**	**14.61**	**10.51**	**100.00%**
Overlapped variables	-4.80	6.97	-11.77	-111.99%
Variables in APEC-I model only	0.15	-	0.15	1.44%
Variables in APEC-II model only	-	51.04	-51.04	-485.61%
Constant	29.77	-43.40	73.17	696.15%

Table A.2d. Decomposition: APEC-I imputation model vs. APEC-II imputation model, certified free, reduced-price eligible, SBP

	APEC-I imputation model	APEC-II imputation model	Difference	% of total difference
Certified free, reduced-price eligible (%)	**4.82**	**5.91**	**-1.09**	**100.00%**
Overlapped variables	0.40	-3.53	3.94	-361.38%
Variables in APEC-I model only	0.01	-	0.01	-1.01%
Variables in APEC-II model only	-	18.80	-18.80	1724.81%
Constant	4.40	-9.36	13.76	-1262.41%

Table A.2e. Decomposition: APEC-I imputation model vs. APEC-II imputation model, certified free, not eligible, SBP

	APEC-I imputation model	APEC-II imputation model	Difference	% of total difference
Certified free, not eligible (%)	**5.37**	**10.93**	**-5.56**	**100.00%**
Overlapped variables	1.05	-7.17	8.22	-147.93%
Variables in APEC-I model only	0.02	-	0.02	-0.28%
Variables in APEC-II model only	-	-16.52	16.52	-297.18%
Constant	4.30	34.62	-30.32	545.39%

Table A.2f. Decomposition: APEC-I imputation model vs. APEC-II imputation model, certified reduced-price, not eligible, SBP

	APEC-I imputation model	APEC-II imputation model	Difference	% of total difference
Certified reduced-price, not eligible (%)	**21.90**	**19.10**	**2.80**	**100.00%**
Overlapped variables	-0.65	-12.10	11.44	408.16%
Variables in APEC-I model only	-0.13	-	-0.13	-4.75%
Variables in APEC-II model only	-	65.01	-65.01	-2318.83%
Constant	22.69	-33.81	56.50	2015.43%

2. Differences between the sample-based estimate of error and the model-based estimate of error

Reviewer 1 questioned why there would be a difference between the sample-based estimate of error and the model-based estimate of error. Reviewer 1 was also curious about whether the difference between the sample- and model- based estimates is due to differences in the average values of explanatory variables leading to differences in the average district errors in the sample and in the population or whether the difference is due to the correlation between the district weight (proportion of meals served) and the district estimate of error rate.

Mathematica's response

We estimated the model of improper payment rates by using one sample of districts (APEC-II sample) and applying the model's estimated coefficients to another sample of districts (data from VCR, also known as the FNS-742). Therefore, the difference between the sample-based estimate of improper payment rates and the model-based estimate of improper payment rates is expected.

Specifically, in the exercise of developing estimation models, we estimated our models by using the APEC-II sample and then selected the best specification based on a comparison of model-based estimates to APEC-II sample-based estimates. We used a within-sample cross-validation method for selecting the preferred model system specification. This technique offers an assessment of (1) how well the model results will generalize to a data source other than the one on which the model was estimated and (2) how accurately a predictive model will perform in practice. The technique also reduces the chances of selecting a model that reflects relationships particular to the study sample instead of relationships that can be applied to a broader population; such "over-fitted" models do not perform well when applied to external samples. We based the final model selection on cross-validation performance estimates and on estimates of how well the models fit the APEC-II data.

After selecting the preferred model for estimating each type of error, we applied the models to national data (the VCR) for SY 2012–2013 to get national estimates of improper payment rates. These estimates (when compared with the national estimates based on APEC-II sample data) allow us to assess how well the APEC-II model performs when applied to data other than the APEC-II data with which the model was estimated and selected; that is, the national estimates offer an external validation of the model's performance.

Furthermore, because a multistage, clustered sample design was used for the APEC-II study, there is sampling error from the APEC-II sample. (The design includes representative samples of school districts, schools (public and private), and applicants for free and reduced-price meals, as well as directly certified students participating in the NSLP and SBP in the contiguous United States.) There is also sampling error in the VCR data: although the VCR comes close to representing every public or private SFA in the country that offers one of the USDA school meal programs, the data set excludes districts that failed to comply with these reporting requirements. Therefore, national estimates of improper payments derived from applying model-based estimates to national data are subject to sampling error from the VCR. Therefore, there will be a difference between the sample-based estimate of error and the model-based estimate of error when estimated coefficients are applied to the VCR data. Our bootstrapping procedure estimates imprecision due to sampling error.

In response to Reviewer 1's second comment, we conducted an additional analysis to compare the APEC-II and VCR samples. We compared the average values of key characteristics in the APEC-II sample to the average values in the VCR data, weighted by the number of students who receive free and reduced-price meals to reflect the APEC-II sampling strategy and the fact that these students are responsible for the vast majority NSLP and SBP reimbursements that serve as the denominator for all calculations of improper payment rates. We found that whereas most of the values are quite comparable, they are not identical. Therefore, the difference between the sample-based estimate of error and the model-based estimate of error is expected.

Table A.3. Comparison of variables' means in the APEC-II sample vs. VCR sample

Model	Variable name	APEC-II sample means	VCR means (weighted by number of students eligible for free and reduced-price meals
Meal claiming model	Enrollment (in 10,000's)	4.37	9.72
Meal claiming model	Average school size	646.29	644.69
Meal claiming model	Percentage of students certified for free meals	52.75	52.95
Meal claiming model	Percentage of students certified for free meals interacts with the dummy variable of > 50%	38.80	37.65
Meal claiming model	Percentage of students certified as free not subject to verification	31.93	29.83
Meal claiming model	Percentage of applications with benefits changed in verification (excluding those who did not respond)	25.47	25.69
Meal claiming model	Publicly operated	0.97	0.98
Certification error for non-CEP schools model	Used alternate random verification sample	0.20	0.21
Certification error for non-CEP schools model	Percentage of verified applications for free meals that had benefits reduced or terminated in verification	28.19	25.53
Certification error for non-CEP schools model	Percentage of verified applications for reduced-price meals that had benefits increased in verification	5.93	6.41
Certification error for non-CEP schools model	Percentage of verified free applications that did not respond in verification	31.75	30.35
Certification error for non-CEP schools model	Percentage of verified reduced-price applications that had benefits reduced or terminated in verification	27.14	25.51
Certification error for non-CEP schools model	Percentage of all verified applications that had benefits changed in verification	27.69	25.69
Certification error for non-CEP schools model	Percentage of verified applications for reduced-price meals that did not respond in verification	38.45	36.21
Certification error for non-CEP schools model	Percentage of verified reduced-price applications that had benefits changed in verification	27.14	25.51
Certification error for non-CEP schools model	Percentage of verified all applications that did not respond in verification	34.47	33.06
Certification error for non-CEP schools model	Percentage of students certified without an application	29.29	29.83
Certification error for non-CEP schools model	Percentage of students certified categorically	4.04	4.00
Certification error for non-CEP schools model	Enrollment (in 10,000s)	4.74	9.72
Certification error for non-CEP schools model	Percentage of students certified for free meals	50.97	52.95
Certification error for non-CEP schools model	Percentage of students certified for reduced-price meals	7.54	8.53

Model	Variable name	APEC-II sample means	VCR means (weighted by number of students eligible for free and reduced-price meals
Certification error for non-CEP schools model	Publicly operated	0.89	0.97
Certification error for non-CEP schools model	State direct certification performance rate	87.38	87.79
Certification error for non-CEP schools model	Any special provision schools	5.49	22.04
Certification error for non-CEP schools model	Number of applications certified as categorically eligible	1531.12	1723.26
Certification error for non-CEP schools model	Total number of certified applications (in1,000s)	6.64	10.37
Certification error for CEP schools model	Percentage of CEP students	74.02	37.86
Certification error for CEP schools model	Percentage of CEP schools	77.87	46.56
Certification error for CEP schools model	Publicly operated	0.89	0.97
Certification error for CEP schools model	Percentage of SNAP recipients directly certified for free meals	97.67	96.72
Certification error for CEP schools model	Percentage of 5- to 17-year-olds living in poverty	26.90	26.60

3. Overpayment estimates for certification error for non- CEP schools

Reviewer 1 expressed concern about estimating overpayments because of the relatively large difference between the sample-based and model-based estimates in APEC-II modeling.

Mathematica’s response

The decomposition analysis we conducted (results shown in Table A.1) helped demonstrate which component of overpayment is or is not closely estimated. We found that the component that differs most between the APEC-I and APEC-II model-based estimates is the estimate for improper payment amount/rate due to students certified for reduced-price meals but actually not eligible for school meal benefits.

In addition to that decomposition analysis, we conducted an analysis that tests a different strategy for disaggregating improper payments. We decomposed the improper payment rate into improper payments due to reporting error (over/underpayments) and those due to administrative error (over/underpayments), and explored whether a different modeling strategy might reduce the difference in model- and sample-based overpayment estimates.

Table A.4 summarizes the results from cross-validation for the NSLP. This table is identical to Table IV.2 in the National Modeling report, except we added the cross-validation results from the new specification—decomposing the improper payment rate into improper payments due to reporting error (over/underpayments) and those due to administrative error (over/underpayments). We refer to this new specification as model system 5.

For model system 5, we developed five specifications, analogous to other model systems:

- Core variables only
- Core variables plus one additional variable from the VCR
- Core variables plus three additional variables from the VCR
- Core variables plus one additional variable from any data set
- Core variables plus three additional variables from any data set

For each specification of each model system, Table A.4 shows the percentage of NSLP reimbursements in error (overall, overpayments, and underpayments) averaged across the cross-validation testing samples, the percentage of NSLP reimbursements in error as estimated in the APEC-II study, and the difference in these rates.

The cross-validation results show that the new model system (decomposing the improper payment rate into improper payments due to reporting error and those due to administrative error) does not perform as well as the one we chose as our final specification (the specification of model system 4, which includes the core explanatory variables plus one additional variable from the VCR) for the NSLP. The best performing specification of model system 5 is the one including the core explanatory variables plus one additional variable from VCR data. Comparing the estimates from this specification to the APEC-II sample-based estimates of the improper payment rate for the NSLP, we found that the predicted overall certification error rate is about 32 percent higher than the APEC-II sample's estimated error rates, and the predicted overpayment rate is 31 percent higher than the sample-based estimate of the overpayment rate, whereas the difference for the underpayment is about 41 percent higher than the sample-based estimate of the underpayment rate.

We also conducted the same exercise for the SBP and found that the best performing specification of model system 5 is slightly better than what we chose as the final specification for the SBP, but the improvement is small. Therefore, the new strategy of disaggregating improper payments suggests similar performance in SBP estimation but worse performance in NSLP estimation. Our final specifications are still the only ones that consistently minimize the relative differences between cross-validation predicted certification error rates and those of the APEC-II sample estimated error rates.

We took this exercise one step further as a validation test for our conclusion above by applying the estimated parameters from the new strategy of disaggregating improper payments to national data to generate national estimates of overpayments, underpayments, and overall improper payments of SY 2012–2013. Table A.6 shows national estimates derived from the new model system, along with the main findings from the APEC-II study for SY 2012–2013. This external validity test further confirms that the new strategy of disaggregating improper payments does not improve the model's performance. The national estimates based on this new model perform worse in estimating the NSLP and produce almost identical results for the SBP compared with the sample-based estimates of the APEC-II study.

Table A.4. Cross-validation results for model systems of certification error in non-CEP schools, NSLP

Model system 1	Cross-validation testing sample predicted improper payment rates			APEC-II estimated improper payment rates			Comparison		
Model specification	IPR	OPR	UPR	IPR	OPR	UPR	Difference in IPR	Difference in OPR	Difference in UPR
Model system 1									
Core	0.13	0.09	0.05	0.10	0.07	0.03	1.34	1.23	1.69
Core + 1 from VCR	0.12	0.08	0.04	0.10	0.07	0.03	1.19	1.16	1.32
Core + 3 from VCR	0.13	0.09	0.04	0.10	0.07	0.03	1.28	1.26	1.41
Core + 1 from any source	0.12	0.09	0.04	0.10	0.07	0.03	1.24	1.23	1.34
Core + 3 from any source	0.12	0.09	0.04	0.10	0.07	0.03	1.24	1.25	1.29
Model system 2									
Core	0.09	0.07	0.01	0.10	0.07	0.03	0.87	1.04	0.47
Core + 1 from VCR	0.08	0.07	0.01	0.10	0.07	0.03	0.83	0.99	0.48
Core + 3 from VCR	0.09	0.08	0.01	0.10	0.07	0.03	0.94	1.13	0.50
Core + 1 from any source	0.09	0.07	0.01	0.10	0.07	0.03	0.87	1.04	0.46
Core + 3 from any source	0.09	0.08	0.01	0.10	0.07	0.03	0.89	1.06	0.48
Model system 3									
Core	0.07	0.06	0.01	0.10	0.07	0.03	0.68	0.78	0.47
Core + 1 from VCR	0.07	0.05	0.01	0.10	0.07	0.03	0.67	0.76	0.48
Core + 3 from VCR	0.07	0.06	0.01	0.10	0.07	0.03	0.71	0.81	0.50
Core + 1 from any source	0.07	0.05	0.01	0.10	0.07	0.03	0.67	0.76	0.46
Core + 3 from any source	0.07	0.06	0.01	0.10	0.07	0.03	0.73	0.85	0.48
Model system 4									
Core	0.12	0.08	0.05	0.10	0.07	0.03	1.20	1.04	1.69
Core + 1 from VCR	0.11	0.07	0.04	0.10	0.07	0.03	1.06	0.99	1.32
Core + 3 from VCR	0.12	0.08	0.04	0.10	0.07	0.03	1.20	1.14	1.41
Core + 1 from any source	0.11	0.07	0.04	0.10	0.07	0.03	1.10	1.04	1.34
Core + 3 from any source	0.11	0.08	0.04	0.10	0.07	0.03	1.12	1.08	1.29
Model system 5 (decomposed the improper payment rate into improper payments due to reporting error (over/underpayments) and those due to administrative error (over/underpayments)									
Core	0.14	0.10	0.05	0.10	0.07	0.03	1.42	1.33	1.73
Core + 1 from VCR	0.13	0.09	0.04	0.10	0.07	0.03	1.32	1.31	1.41
Core + 3 from VCR	0.14	0.10	0.04	0.10	0.07	0.03	1.40	1.38	1.49
Core + 1 from any source	0.15	0.10	0.05	0.10	0.07	0.03	1.45	1.35	1.78
Core + 3 from any source	0.14	0.10	0.04	0.10	0.07	0.03	1.38	1.40	1.37

Source: FNS-742 Verification Collection Reports (VCR) and APEC-II study.

IPR = percentage of total reimbursements in error; OPR = percentage of overpayments in error; UPR = percentage of underpayments in error

Highlighted row represents final model system specification selected for analysis.

Table A.5. Cross-validation results for model systems of certification error in non-CEP schools, SBP

Model system 1	Cross-validation testing sample predicted error rates			APEC-II sample-based estimated error rates			Comparison		
Model specification	IPR	OPR	UPR	IPR	OPR	UPR	Difference in IPR	Difference in OPR	Difference in UPR
Model system 1									
Core	0.10	0.07	0.04	0.11	0.08	0.03	0.91	0.84	1.07
Core + 1 from VCR	0.10	0.07	0.03	0.11	0.08	0.03	0.89	0.87	0.94
Core + 3 from VCR	0.10	0.07	0.03	0.11	0.08	0.03	0.88	0.92	0.80
Core + 1 from any source	0.10	0.07	0.03	0.11	0.08	0.03	0.88	0.86	0.93
Core + 3 from any source	0.10	0.07	0.03	0.11	0.08	0.03	0.84	0.87	0.76
Model system 2									
Core	0.09	0.07	0.01	0.11	0.08	0.03	0.76	0.89	0.43
Core + 1 from VCR	0.09	0.07	0.01	0.11	0.08	0.03	0.76	0.90	0.44
Core + 3 from VCR	0.09	0.08	0.02	0.11	0.08	0.03	0.81	0.96	0.44
Core + 1 from any source	0.09	0.07	0.01	0.11	0.08	0.03	0.76	0.90	0.42
Core + 3 from any source	0.09	0.07	0.01	0.11	0.08	0.03	0.77	0.91	0.43
Model system 3									
Core	0.07	0.05	0.01	0.11	0.08	0.03	0.59	0.65	0.43
Core + 1 from VCR	0.07	0.05	0.01	0.11	0.08	0.03	0.59	0.66	0.44
Core + 3 from VCR	0.07	0.06	0.02	0.11	0.08	0.03	0.63	0.71	0.44
Core + 1 from any source	0.07	0.06	0.01	0.11	0.08	0.03	0.61	0.69	0.42
Core + 3 from any source	0.07	0.06	0.01	0.11	0.08	0.03	0.61	0.69	0.43
Model system 4									
Core	0.11	0.07	0.04	0.11	0.08	0.03	0.95	0.90	1.07
Core + 1 from VCR	0.10	0.07	0.03	0.11	0.08	0.03	0.90	0.88	0.94
Core + 3 from VCR	0.10	0.08	0.03	0.11	0.08	0.03	0.92	0.98	0.80
Core + 1 from any source	0.10	0.07	0.03	0.11	0.08	0.03	0.90	0.89	0.93
Core + 3 from any source	0.10	0.07	0.03	0.11	0.08	0.03	0.87	0.91	0.76
Model system 5 (decomposed the improper payment rate into improper payments due to reporting error (over/underpayments) and those due to administrative error (over/underpayments)									
Core	0.11	0.07	0.04	0.11	0.08	0.03	0.95	0.88	1.14
Core + 1 from VCR	0.11	0.07	0.04	0.11	0.08	0.03	0.96	0.91	1.07
Core + 3 from VCR	0.11	0.08	0.03	0.11	0.08	0.03	0.95	0.97	0.91
Core + 1 from any source	0.11	0.07	0.03	0.11	0.08	0.03	0.94	0.89	1.06
Core + 3 from any source	0.10	0.07	0.03	0.11	0.08	0.03	0.91	0.93	0.86

Source: FNS-742 Verification Collection Reports (VCR) and APEC-II study.

IPR = percentage of total reimbursements in error; OPR = percentage of overpayments in error; UPR = percentage of underpayments in error

Highlighted row represents final model system specification selected for analysis.

Table A.6. Comparison of national estimates of improper payments based on APEC-II study, on the new imputation model, and on our preferred model, certification error for non-CEP schools

	APEC-II study		New model-based estimation		Preferred model-based estimation	
	NSLP	SBP	NSLP	SBP	NSLP	SBP
Percentage of all reimbursements in error						
Overpayments	7.16	7.97	8.48	6.58	6.71	6.44
Underpayments	2.86	3.32	2.56	2.01	2.56	2.01
Total improper payments	10.01	11.3	11.05	8.59	9.27	8.45

4. Underpayment estimates for certification error for non-CEP schools

Reviewer 1 wondered why the performance of model system 4 is better than that of model system 2 for projecting underpayments. Model system 4 uses a more aggregated measure of underpayments, whereas model system 2 disaggregates underpayments into three components. Reviewer 1 thought that we used a Tobit specification for estimating underpayments and suggested using some other approaches to modeling the three sources of underpayments instead of reducing the problem to predicting overall underpayments. Reviewer 1 also suggested that we compare model-based estimates of three components of underpayment to the corresponding sample-based estimates.

Mathematica's response

To clarify, we did not use a Tobit model for the final estimation. We used Ordinary Least Squares (OLS), but we also conducted sensitivity tests using a Tobit-based model. The cross-validation results show that the performance of models using OLS is superior to those using Tobit-based specifications.

We conducted the decomposition analysis suggested by Reviewer 1. Table A.7 summarizes the results.

Table A.7. Model- and sample-based estimates of NSLP and SBP underpayments, by type of underpayment (in percent)

	APEC-II model-based estimates	APEC-II sample-based estimates
Certified reduced-price, free eligible, NSLP	0.52%	0.46%
Certified not eligible, free eligible, NSLP	0.34	1.77
Certified not eligible, reduced-price eligible, NSLP	0.23	0.45
Total improper underpayment rate, NSLP	1.10	2.68
Certified reduced-price, free eligible, SBP	0.52	0.57
Certified not eligible, free eligible, SBP	0.15	2.24
Certified not eligible, reduced-price eligible, SBP	0.10	0.57
Total improper underpayment rate, SBP	0.77	3.38

When underpayments are disaggregated into three components, the component that differs most between the APEC-II model-based estimate and the APEC-II sample-based estimate is the estimate for improper payment rate due to certified not eligible but actually eligible for free meals. The APEC-II imputation model tends to underestimate this component for both the NSLP and the SBP. A close look at the data shows that, in 50.4 percent of the districts in the APEC-II sample, lunch was not served to students who were certified as not eligible but were actually eligible for free meals; the corresponding number for the SBP is 55.1 percent. The skewness and the nonlinearity of the distribution pose a significant challenge for modeling work. We tested different modeling strategies to address the nonlinearity of the sampling distribution, including a Tobit model and two-stage approaches in which the first stage estimates the probability of any improper payments, but we found that model system 4, which uses a more aggregated measure of underpayments, performs the best.

5. Potential for back-casting

Reviewer 1 and Reviewer 2 suggested that we use the APEC-II model to back-predict the error rates for earlier periods.

Mathematica's response

We applied the APEC-II model estimated coefficients to the earlier wave (2005–2006) VCR data. This exercise can provide information on whether there is any variation in predictions over time. However, it will not provide additional information on the validity of the model for SY 2012–2013 or for school years following SY 2012–2013. If the relationships between the model's explanatory variables and improper payment rates change in future years, the validity of the models will degrade. The only way to verify that these relationships have not changed is to conduct a model validation analysis using data from future school years.

The results from the back-casting exercise are summarized in Table A.8. The three sets of estimates—estimates based on the APEC-I model, on the APEC-II model, and on the APEC-I study sample-based estimates—on overpayments (both amounts and rates) are quite consistent. However, when we apply the APEC-II model estimated coefficients to the earlier wave (2005–2006) VCR data, the underpayments tend to be overestimated. The finding is not surprising, as undercertification error rates increased from SY 2005–2006 to SY 2012–2013. Therefore, the estimated coefficients based on the APEC-II model represent relationships associated with a higher error rate. For this reason, the point estimate based on the APEC-II model is higher than the point estimates based on both the APEC-I model and the APEC-I sample.

Table A.8. Comparison of national estimates of improper payments based on the APEC-I model, on the APEC-II model, and on the APEC-I study sample-based estimates, certification error for non-CEP schools

	APEC-II model-based estimates	APEC-I model-based estimates	APEC-I sample-based estimates
Improper payments (in millions of dollars)			
Overpayments	555	578	573
Underpayments	646	152	186
Total improper payments	1,201	730	759
Total reimbursements	8,029	8,029	8,060
Percentage of all reimbursements in error			
Overpayments	6.91	7.20	7.11
Underpayments	8.05	1.89	2.31
Total improper payments	14.96	9.09	9.42

6. District versus State variation

Reviewer 1 suggested that further decomposition of the total district-level variation to within- and cross-State variation might provide insight into the model fit. The reviewer also questioned whether FNS should focus on error rates at the State or district level. Reviewer 3 also asked how much variation in the error rate is within districts instead of between districts.

Mathematica’s response

We appreciated both reviewers’ comments. Reviewer 1’s intuition is correct, and the methodology suggested is sound. Unfortunately, the APEC-II sample includes relatively few districts per State, so it is difficult to develop reliable estimates of within-State correlation. An analysis based on the APEC-II sample that was conducted as part of the State model validation exercise suggests that the within-State correlation is likely to be in the range of 0.05 to 0.10. This suggests that variation within a State is substantial. Furthermore, this finding may support the reviewer’s conjecture that improper payments may vary more by district than by State.

7. Potential issues with CEP modeling

Because of the timing of the CEP reform, data constraints, and the fact that districts within the States that elected to use the CEP in SY 2012–2013 may differ from typical CEP districts after the program was rolled out nationwide, both Reviewer 1 and Reviewer 2 expressed concern about the credibility of using the CEP model to estimate and forecast errors for the CEP schools going forward. Reviewer 1 also expressed confusion about how the error rate is defined in CEP models. Reviewer 3 recommended that, before the next APEC wave, some follow-up work investigating what predicts errors in CEP schools would be useful.

Mathematica’s response

We share the reviewers’ concerns about the usefulness of the CEP model in predicting improper payments in CEP schools in future years. As noted in the report, there are a number of important caveats to keep in mind when interpreting predictions from the CEP models, particularly the caveats related to constraints in the availability of data and potential nonrepresentativeness of the States and districts that implemented the CEP in SY 2012–2013. However, FNS is required to provide estimates of improper payments for future years, and the current models provide the best estimates possible given the constraints under which they operate. In the national report, we added more discussion of this point to underscore the limitations of the current CEP models. We also added discussion on the potential impact of these limitations as the use of the CEP expands.

8. Potential issues with Provision 2 and 3 schools

Reviewer 1 is concerned that our models did not include Provision 2 and 3 schools. The reviewer believes that our justification that these schools will be gone in the future is weak given that they are operating now and would influence today's error rates, which are the ones we are trying to understand.

Mathematica's response

We did include Provision 2 and 3 schools in the analysis; improper payments related to these schools are incorporated into the non-CEP improper payment rates. In addition, in certification error for non-CEP school modeling, we included a control that represents the proportion of special provision schools in the district. We revised the text in the report to make this point clear.

9. Concerns with variable selection

Reviewer 1 commented on the variable selection process. He noted that if one is going to use the regressions to predict and decompose the differences between estimates, one would hope that these factors are somewhat uncorrelated; the reviewer asked whether we computed some F-tests on groups of variables to get a sense of which variables are contributing to the predicted value and which ones are not. Reviewer 3 also commented on the model specification, noting some confusion about which other variables are included in the model and why given variables are or are not included. In particular, Reviewer 3 was curious about the role of demographic variables and commented that some demographic variables, such as percent of nonwhite, can serve as a proxy for unobservable factors and will help to predict year-to-year changes in error rates. Reviewer 3 also asked Mathematica to clarify what "automated procedure" means.

Mathematica's response

Most of the variables we included in the model are core variables; these core variables are selected on the basis of their theoretical relationship to improper payment rates, not on observed correlations with improper payments. We conducted tests on building a model in which variables are selected purely on the basis of correlation. This model's performance is no better than the chosen specification (and it is likely to perform worse when applied to external data because it would be overfitted to the APEC-II sample). In revisions to the report, we clarified our discussion of how we selected the variables and discussed fittings of models built purely on correlations.

We agree with Reviewer 3 that some of the demographic variables can serve as proxy variables and contribute to the predictive power of the modeling. We can also confirm Reviewer 3's conjecture that these variables were not included as core variables in most cases because they are unlikely to change from year to year in response to changes in school meal policies. We clarified this point in the revised draft of the report.

The independent variables we considered for the model included indicators of the administrative features of the NSLP and the SBP in the district, other characteristics of the district, demographic characteristics of students and families in the district, and other policy variables that are likely to be relevant to the types of error being modeled. Particularly relevant to Reviewer 3's comment, we considered the following demographic characteristics from Common Core Data (CCD)/Private School Universe Survey (PSS) data:

- Grade span by district
- Enrollment by race/ethnicity/gender/grade
- Location of the district (for example, large city, mid-size city, large town, small town)
- Number of SFA administrators and support staff overall and per student
- Number of teachers, school administrators, and support services staff overall and per student
- Spending on food services, food service salaries, and administrative support services overall and per student

We also considered variables for local income, poverty rates, and unemployment rates from the Small Area Income/Poverty Estimates (SAIPE) and the Local Area Unemployment Statistics (LAUS) data.

We described, under our variable selection procedures that our strategy for selecting a set of variables and specifications consisted of the following elements:

- We first came up with a list of candidate explanatory variables in the model. This list included variables from the VCR as well as variables from the other data sources we acquired.
- Based on theoretical relevance and data availability, we selected from the VCR data a set of independent variables we defined as core variables that would definitely be included in the model.
- We used an automated procedure for selecting an additional set of variables to be included in the equation as independent variables; we constructed these independent variables by using the VCR data included in the set of candidate variables. We then repeated this process, including as candidate variables independent variables from all available data sets.
- We allowed each equation of each model system to have a unique set of independent variables. In other words, each equation includes the independent variables that best predict that equation's dependent variable.

We included demographic variables that we described in our variable selection procedure as additional variables. These variables were selected in a stepwise fashion based on correlations of all variables in the set being considered with each dependent variable, controlling for the core variables (that is, with the residual from the regression of each dependent variable on the core variables). The variables that explained the greatest proportion of the variation of this residual were included as additional independent variables in the model. For instance, to model certification error in non-CEP schools, we developed five specifications for each of the four model systems:

- Core variables only
- Core variables plus one additional variable from the VCR
- Core variables plus three additional variables from the VCR
- Core variables plus one additional variable from any data set
- Core variables plus three additional variables from any data set

After identifying the variables to include in the equation for each model system, we selected the model with the strongest within-sample cross-validation model performance. Based on the cross-validation results, we picked core variables plus one additional variable from the VCR as our preferred model specification.

In summary, we considered demographic characteristics when building the models. We have two reasons for not including the variables on demographic characteristics in our final model specification: (1) these variables did not explain the greatest proportion of the variation of the residual after controlling for the core variables, and (2) even if some demographic variables were selected, the model specification in which they are included was not selected on the basis of the implementation of the cross-validation procedure.

In the revision of the report, we clarified our variable selection procedures in response to Reviewer 3's comment. We also added a more detailed discussion of how the automated procedure works.

C. Model validation issues

1. Comparing the APEC-II sample-based estimates of the national error to the model-based estimates provides no insight into whether the model can accurately predict out of sample, in different time periods.

Reviewer 2 expressed concern about our validation approach not giving information on out-of-sample predictions for future years. This reviewer was particular concerned about the sampling error.

Mathematica's response

We agree with the reviewer that the model validation applies only to SY 2012–2013. It is not possible to evaluate the validity of the model for future years without estimates of sample-based improper payment rates for future years. We discussed this limitation of the model and the validation approach in the report. We added text to underscore the point.

D. Interpretation issues

1. Using a static prediction model in a changing world

Reviewer 2 commented that the reports did not sufficiently address the problems that arise when a regression model from one period is used to forecast outcomes in the future.

Mathematica's response

We agree with Reviewer 2 that the regression parameters may not be stable over time both because administrative features of the program change (for example, the CEP and direct certification) and because the administrators are likely to react to the APEC-II study findings (for example, to reduce errors or attempt to increase the utilization of direct certification). We revised the reports to include a more targeted discussion on this limitation of the modeling work.

2. Interpretation of the State model validation findings

Both Reviewer 1 and Reviewer 2 expressed concern about the interpretation of the validation results of the State model. As one validation approach implies the negative results, both reviewers suggested that we downplay the current validation exercises.

Mathematica's response

We appreciate the comments from both reviewers. The ideal validation exercise would require sample-based State estimates for large numbers of States, which was not feasible given the limits of the study's resources. We revised the language in the reports to clearly reflect both the limitations of the methodology for the State model validation and the implications of these limitations for interpreting State estimates.

3. Interpretation of the decomposition analysis in the State model

Reviewer 1 praised our methodology for decomposing the differences in the State's error rate from the national error rate. At the same time, Reviewer 2 expressed some concern about the way we interpreted the decomposition results. Reviewer 3 also commented that Mathematica's State report had a useful Oaxaca style decomposition exercise but recommended revising the way these findings are presented.

Mathematica's response

We revised the language in the report so the text clearly states that the decomposition is not intended to examine any causal relationships. In this exercise, we tried only to show how district characteristics affect the estimates. We added additional analysis using additional States to illustrate how different district characteristics affect the estimates. We also revised the table and the accompanying text in response to these comments.

E. Other issues

1. Improving our knowledge of error rates in the future

Reviewer 2 noted that the APEC-I and the APEC-II follow very similar strategies and suggested that we include a brief discussion of how one might address the modeling and prediction problems in future analyses.

Mathematica's response

Limitations of the data represent the major hurdle for the modeling work. Better information, such as more detailed district-level data and representative CEP data, will allow more efficient modeling and more accurate estimation. Furthermore, building the model in the post-CEP environment will be helpful, as it will improve the confidence in predicting error rates in future years. In the revision of the reports, we added discussions on these issues.

2. The write-up of the reports

Reviewer 1 noted that some of the discussion of the technical methods and procedures could be relegated to appendixes but that some parts of the reports need more detail. Reviewer 3 commented that although the reports have, by and large, successfully described the methods and presented results, some improvements to readability, such as providing guideposts for the subsequent analysis, adding details for some technical analysis, and so on, could be made.

Mathematica's response

In response to these comments, we added text boxes at the beginning of each chapter that summarize the key points of each chapter at a glance.

3. Big picture questions raised by reviewers

Reviewer 3 raised several big picture questions. For instance, the reviewer asked about the implications of making districts and States accountable for improper payments. The reviewer noted that both APEC-I and APEC-II data were collected when there were no "stakes" on any of the variables collected. Despite this fact, the relationship between variables and errors evolved across the data collection waves. For instance, how will the models perform when stakes are placed on the variables? Which independent variables can be manipulated to get the largest reduction in error rates?

Mathematica's response

We agree with the reviewer that attaching stakes to model results is likely to result in changes in the way that data are reported and, as a result, changes in the applicability of the model. As noted in the caveats to the State report, we do not believe that attaching stakes to the State modeling results is an appropriate use of the estimates.

4. Concerns about program integrity

Reviewer 3 noted that although most States' overpayment rates are higher than their underpayment rates, the underpayment rates in a few States (including Illinois) are higher than the overpayment rates. The reviewer asked why this would be the case.

Mathematica's response

It is certainly possible for the underpayment rates of a district or State to be higher than its overpayment rates. Unfortunately, the APEC-II study was designed to provide estimates of the levels of improper payments, and we cannot give definitive answers on the reasons behind patterns of improper payments. Also, given the wide confidence intervals for the State estimates, it is possible that the underpayment rates are not actually lower than the overpayment rates.