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REPORT

FINAL REPORT

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

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

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Quinn Moore

April Yanyuan Wu

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Office of Policy Support
3101 Park Center Drive
Alexandria, VA 22302
Project Officer: Chan Chanhatasilpa
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Submitted by:
Mathematica Policy Research
111 East Wacker Drive, Suite 920
Chicago, IL 60601-4303
Telephone: (312) 994-1002
Facsimile: (312) 994-1003
Project Director: Eric Zeidman
Reference Number: 40030

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Objective

An important objective of second Access, Participation, Eligibility and Certification Study (APEC-II) modeling work is developing statistical models for producing State-level estimates of improper payments for the National School Lunch Program (NSLP) and School Breakfast Program (SBP). These estimates are valuable to the U.S. Department of Agriculture, Food and Nutrition Service (FNS) because they enable the agency to (1) assess variation in such payments across States and (2) identify States with high levels of improper payments. In addition, having separate State-level estimates of certification error, meal claiming error, and overall error allows FNS to provide information to States on which components of their school meal programs are generating the most error and would benefit most from improvement efforts. However, generating precise sample-based State estimates of improper payments requires collecting primary data from a large number of districts in a State. Because of that, it is not feasible to produce precise sample-based estimates for all States using traditional sample-based analytic techniques.

For these reasons, in the APEC-II study, we developed statistical models to estimate State-level improper payments by building on the national models described in the APEC-II statistical model technical report (U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, July 2015). The process of developing State-level models involved (1) modifying the statistical models of national improper payments of each type to be appropriate for State-level estimates and (2) validating these modified models.

Approach for developing State-level statistical models

The State-level improper payment models were built on the national models we developed in the APEC-II study (see U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, January 2016). To estimate improper payments at the national level, we developed separate statistical models of improper payments due to different types of error in schools participating and not participating in the Community Eligibility Provision (CEP). The development of the State-level model was in the same spirit: we developed three model systems for separately estimating certification error in non-CEP schools, certification error in CEP schools, and meal claiming error at the State level.

The State-level models retained certain key features of the national models, such as estimating a district-level econometric model of error rates from nationally representative districts. This feature enables us to estimate improper payments for each district using readily available administrative data. As with the national models, we first disaggregated overall findings on the SY 2012–2013 improper payment rates from APEC-II into a set of district-level improper payment rates. We then estimated a series of regression models that captured the relationship between the characteristics of these districts and their estimated improper payment rates. The estimated coefficients from these models were used in conjunction with values of district characteristics from administrative data to predict certification error for each district. We then computed improper payments in each district by multiplying each estimated error rate by the appropriate number of meals served (separately for NSLP and SBP). Each State's total was computed by summing across all districts in the State.

The State-level models were based on the final model system specifications used to generate national estimates. As with the national models, we computed standard errors and confidence intervals for predictions of improper payments at the State level by using bootstrapping methods. We considered two types of sampling and estimation errors: (1) the 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.

Building State-level models based on the national models, especially while specifying the State models at the district level offers several advantages. First, the models enable us to incorporate key data, available only at the district level, that are likely to be predictive of improper payments. In addition, the models are simple for FNS to apply to any State and in any future year because the relevant data are readily available. Once the models are estimated and validated, the cost of producing estimates is not expected to vary across States. Finally, the similarity between State models and the national models enable FNS use the same data source to produce State- and national-level estimates.

Validating model-based State-level estimates

Validation of the State-level models is necessary to assess whether the models produce State estimates of improper payment rates that should be expected to match each State's true improper payment rates. The ideal validation exercise would require sample-based State estimates for large numbers of States, which was not feasible within the limits of the study's resources. Given the constrains, we use two approaches to validate the State-level models: (1) a joint test of the accuracy of the model's district-level predictions and (2) a simulation testing the accuracy of simulated States of different sizes.

A joint test of the model's predictions at the district level involves jointly comparing sample-based estimates of each district's improper payments to its respective model-based estimates across all districts in the sample. The joint validation uses information from all sample districts to provide a single assessment of the model-based estimates for a given error type.

An important limitation of the joint district test is that it is not a direct test of the model's ability to produce State-level estimates. When constructing State-level estimates, some inaccuracies in district-level estimates will cancel out. For example, consider two districts, one with a model-based estimate that understates its true improper payment amount and one with a model-based estimate that overstates its true improper payment amount. If the inaccuracy of the model-based estimates is the same magnitude for these two districts, the sum of model-based estimates will be accurate. As a result, a rejection of the district-level model does not necessarily imply that the State-level estimates are inaccurate.

To address this limitation, we conduct a simulation that sums district improper payment estimates, as is done in constructing State estimates. As part of the simulation, we randomly selected groups of districts from the APEC-II sample to construct simulated States of different sizes: 10, 30, 50 and 100 districts, representing a range in the number of districts across States (the actual range is from 25 districts in Nevada to 1,247 districts in Texas). For each simulated State, we compare the model-based improper payment rate estimate to the sample-based

estimate. These simulated findings give an indication of model performance when summing across district-level estimates to construct State-level estimates.

Results of the State model estimation

State estimates generated from our modeling efforts show that there is considerable variation in improper payment rates across States for these three sources of improper payments. For certification error in non-CEP schools, for the NSLP, State model-based total improper payment rate estimates range from 2.8 percent to 16.0 percent. For the SBP, the range is 2.5 percent to 15.2 percent. For improper payment rates due to certification error in CEP schools, for both the NSLP and SBP, the State model-based total improper payment rate estimates range from 0.6 to about 3 percent. For meal claiming error, for the NSLP, State model-based total improper payment rate estimates range from 2.5 percent to 9.7 percent. For the SBP, the range is 4.2 percent to 17.7 percent.

Despite the wide range in State model-based improper payment rate estimates, many States have model-based improper payment rate estimates that are relatively close to the national improper payment rate. For example, for meal claiming error, for the NSLP, 32 States have model-based improper payment rate estimates within one percentage point of the national model-based improper payment rate of 5.33 percent.

We also found that the precision of these State estimates varies considerably. Using certification error in non-CEP schools as an example, for the NSLP, the median half-width of a 95 percent confidence interval around the State improper payment estimate is 3.02 percentage points; the range is 1.9 to 7.2 percentage points. For the SBP, the median half-width of a 95 percent confidence interval around the State improper payment estimate is 3.8 percentage points; the range is 2.1 to 8.9 percentage points.

Results of the State model validation

Findings from the joint test of district-level predictions indicate that the district-level predictions are not sufficiently accurate to ensure the accuracy of State-level estimates. However, a joint district validation is stronger than what is required for the model's stated purpose: a model that produces accurate district-level estimates is expected to produce accurate State-level estimates, but a model that is inaccurate at the district level may still result in an accurate estimate when aggregated to the State level. That is because district-level inaccuracies might cancel one another out when district-level estimates are summed to the State level.

Findings from the simulation testing the accuracy of simulated States of different sizes suggest that, on average, differences in model-based and sample-based State-level estimates should be expected to be small, particularly for States with larger numbers of districts. In fact, we find no statistically significant differences between model-based and sample-based estimates for any type of improper payment, regardless of the number of districts in the simulated State or the assumed correlation of differences within State. However, we did find that more simulated States had statistically significant differences in model-based and sample-based estimates than would be expected by chance.

As previously mentioned, the ideal validation exercise would require sample-based State estimates for large numbers of States, which was not feasible within the limits of the study's resources. Although the simulation validation test suggests that there are no statistically significant differences between model-based and sample-based estimates for any type of improper payment, the interpretation of the State-model estimates still warrants caution.

Conclusions

On average, the State-level models developed for APEC-II are likely to provide reasonable estimates of State improper payments. Thus, the model-based estimates can give useful information to help FNS target efforts to reduce improper payments and provide States with information on the types of error for which they are at highest risk.

Although the model-based State estimates are a useful tool among other tools for FNS to assess broadly how well States are doing in terms of administrating the program, it is important to interpret the estimates cautiously, keeping in mind their limitations:

- **The model-based estimates are typically not precise.** The width of the 95 percent confidence intervals around the estimates is as large as 29 percentage points for meal claiming error in the SBP.
- **The model based estimates are likely inaccurate for some States.** Findings from the validation analysis indicate that on average, simulated States have model-based improper payment estimates that are not significantly different than sample-based improper payment estimates. However, some individual simulated States did have statistically significant differences in model-based and sample-based estimates.
- **The model-based estimates may become less accurate over time**. The model-based estimates assume a stable relationship between improper payment rates and district characteristics 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. The further out into the future the SY 2012–2013 statistical model results are used to predict improper payments, the less reasonable the assumption becomes.

Based on these limitations, the model-based State improper payment estimates should be regarded as inexact indicators of risk for State improper payments, not as deterministic levels of improper payments in a State at a given time. Thus, it would be appropriate to use the model-based estimates for low-stakes efforts to reduce improper payments, such as targeting technical assistance and identifying the school meal program components that would benefit most from improvement efforts. It would not be appropriate to use the model-based estimates for high-stakes endeavors, such as awarding bonuses or penalties on the basis of State improper payment estimates.

I. INTRODUCTION

Summary

- The State-level improper payment models are based on the national models developed in the APEC-II study. Additional explanatory variables were included in some State-level models to improve their ability to capture State-level variation related to State program characteristics.
- Two approaches were used to validate the State-level models: (1) a joint test of the accuracy of the models' district-level predictions and (2) a simulation testing the accuracy of simulated States of different sizes.
- The joint test of the accuracy of the model's district-level predictions is congruent with the study's sampling strategy and model estimation approach, but it is not a direct test of the model's ability to produce State-level estimates.
- To address this limitation, we conducted a simulation in which we randomly selected groups of districts from the APEC-II sample in order to construct simulated States of different sizes; the model- and sample-based estimates of improper payment rates for simulated States were then compared.

An important objective of APEC-II modeling work is developing statistical models for producing State-level estimates of improper payments for the National School Lunch Program (NSLP) and School Breakfast Program (SBP). These estimates are valuable to the U.S. Department of Agriculture, Food and Nutrition Service (FNS) because they enable the agency to (1) assess variation in such payments across States and (2) identify States with high levels of improper payments. In addition, having separate State-level estimates of certification error, meal claiming error, and overall error allows FNS to provide information to States on which components of their school meal programs are generating the most error and would benefit most from improvement efforts. However, generating precise sample-based State estimates of improper payments requires collecting primary data from a large number of districts in a State. Because of that, it is not feasible to produce precise sample-based estimates for all States using traditional sample-based analytic techniques.

For these reasons, in the APEC-II study, we developed statistical models to estimate State-level improper payments by building on the national models described in the APEC-II statistical model technical report (U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, January 2016). The process of developing State-level models involved (1) modifying the statistical models of national improper payments of each type to be appropriate for State-level estimates and (2) validating these modified models.

The State-level statistical models we developed retained certain key features of the national models, such as estimating a district-level econometric model of error rates. As with the national models, State-level models relate district-level estimates for improper payment rates to district characteristics obtained from administrative data. Some State-level models included not only the

variables selected for inclusion in the national models but additional explanatory variables so as to improve the ability to capture State-level variation related to State program characteristics. After estimating the model using APEC-II data, those models were used to predict error rates for each district in the State, which then were aggregated at the State level.

Validation of the State-level model is necessary to assess whether the models produce State estimates of improper payment rates that should be expected to match each State's true erroneous payment rates. Through validating the national models of improper payments, we were able to compare model-based estimates to the APEC-II sample-based estimates. No such sample-based State estimates exist, so validation of the State-level models uses alternative methodologies. Specifically, we assess the accuracy of the models at the district level and also conduct simulations assessing the accuracy of sums of districts of different sizes.

In this technical report, we describe the approach to modeling State-level improper payments due to certification error in non-community eligibility provision (CEP) schools, certification error in CEP schools, and non-certification error in all schools. We also discuss the process for using these models to predict future improper payment amounts and rates at the State level and assess the models' performance relative to the main APEC-II study findings for school year (SY) 2012–2013.

A. Approach for developing State-level statistical models

The State-level improper payment models were built on the national models we developed in the APEC-II study (see U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, January 2016). To estimate improper payments at the national level, we developed separate statistics models of improper payments due to different types of error. The development of the State-level model was in the same spirit: we developed three model systems for separately estimating certification error in non-CEP schools, certification error in CEP schools, and meal claiming error at the State level.

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 based on a comprehensive survey of the households' income and size. 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). 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 (for detailed description of how we define each type of error, please refer to U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, July 2015, Chapter I and II). As with the national models, for each type of error, we developed separate State-level models for the NSLP and SBP.

The State-level models retained certain key features of the national models, such as estimating a district-level econometric model of error rates from nationally representative districts. This feature enables us to estimate improper payments for each district using readily available administrative data. As with the national models, 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 that captured the relationship between the characteristics of these districts and their estimated improper payment rates. The estimated coefficients from these models were used in conjunction with values of district characteristics from administrative data to predict certification error for each district. We then computed improper payments in each district by multiplying each estimated error rate by the appropriate number of meals served (separately for NSLP and SBP). Each State's total was computed by summing across all districts in the State.

When developing the national models, we considered and tested a number of model systems with different specifications of improper payment rates. We selected a preferred model system and specification for each type of improper payment using cross-validation model performance analysis, evaluating the difference between the predicted model system's improper payment rate and the observed APEC-II improper payment rate estimates as well as goodness of fit measures for the regression equations in the system. The State-level models were built on our final selection of model system and specification of the national models. Therefore, variables included in State models are similar (often identical) to those in national models; additional explanatory variables are included in some State-level models to improve the ability to capture State-level variation related to State program characteristics. For instance, we added State direct certification performance rate as an explanatory variable to meal claiming error models.

As with the national models, we computed standard errors and confidence intervals for predictions of improper payments at the State level by using bootstrapping methods. We considered two types of sampling and estimation errors: (1) the 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.

States with very large districts might be expected to have particularly big bootstrapped standard error because the bootstrapping process pulls random draws of districts within the State in which all districts are treated equally. States with very large districts might be expected to have particularly high bootstrapped variances if a large district has a predicted improper payment rate estimate that is different from typical districts in the rest of the State. For example, New York might have large bootstrapped variance estimates because some bootstrapped samples include New York City while others do not. To address this concern, we specified that certain very large districts be included in all bootstrapped samples used for estimating the variance of State-level estimates. The ten districts we identified to be included in all bootstrapped samples are identical to those were certainty selections for APEC-II sample, including larger districts in New York City, Chicago, San Diego and other cities.[1]

[1] The ten districts included in certainty selection bootstrapping procedure are District of Columbia Public Schools, Milwaukee Public School District, Clark County School District, Gwinnett County, Charlotte-Mecklenburg Schools,

Building State-level models based on the national models, especially while specifying the State models at the district level offers several advantages. First, the models enable us to incorporate key data, available only at the district level, that are likely to be predictive of improper payments. In addition, the models are simple for FNS to apply to any State and in any future year because the relevant data are readily available. Once the models are estimated and validated, the cost of producing estimates is not expected to vary across States. Finally, the similarity between State models and the national models enable FNS use the same data source to produce State- and national-level estimates.

B. Validating model-based State-level estimates

In the APEC-II design report (see U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, 2012) we evaluated several alternatives for validating the State-level estimates model, including single state validation, joint state validation, and joint district validation. Based on simulations to assess the statistical power of these three approaches, we concluded that only joint district validation has sufficient precision to provide a meaningful assessment of the model's validity. We use two approaches to validating the State-level models: (1) a joint test of the accuracy of the model's district-level predictions and (2) a simulation testing the accuracy of simulated States of different sizes.

A joint test of the model's predictions at the district level involves jointly comparing sample-based estimates of each district's improper payments to its respective model-based estimates across all districts in the sample. The joint validation uses information from all sample districts to provide a single assessment of the model-based estimates for a given error type. This model validation method has several advantages. First, the test is better aligned with the study's sampling strategy and model estimation approach so this method is a natural approach, considering that districts are both the study's primary sampling units and the model's unit of analysis. Therefore, validating the model at the district level provides an indirect assessment of its ability to produce accurate State-level estimates. Because the model also produces district-level estimates, which are used to aggregate to State estimates, validating those components would build confidence that the model is working as intended. Second, the sample of about 130 districts available in APEC-II (55 districts for CEP school certification error analysis) means that we can conduct a greater number of tests, and that can potentially increase the precision of the estimates. Finally, FNS might benefit from knowing whether the models are capable of producing district-level estimates even though that is not the primary focus of the validation.

The joint district validation requires calculating model-based and sample-based district-level estimates. Essentially, the test considers whether the observed differences between the model-based and sample-based estimates, taken together, are consistent with the expected uncertainty in each of the estimates. The Wald statistic was calculated and a chi-squared test was performed on the Wald statistics at the 95 percent confidence level to determine whether the observed differences in estimates are consistent with an accurate model.

(continued)

Memphis City, City of Chicago School District, San Diego USD, Baltimore City, and New York City school district.

An important limitation of the joint district test is that it is not a direct test of the model's ability to produce State-level estimates. A model that produces accurate district-level estimates is expected to produce accurate State-level estimates, but a model that is inaccurate at the district level can still result in an accurate estimate when aggregated to the State level. When constructing State-level estimates, some inaccuracies in district-level estimates will cancel out. For example, consider two districts, one with a model-based estimate that understates its true improper payment amount and one with a model-based estimate that overstates its true improper payment amount, if the inaccuracy of the model-based estimates is the same magnitude for these two districts, the sum of model-based estimates will be accurate. As a result, a rejection of the district-level model does not necessarily imply that the State-level estimates are inaccurate.

To address this limitation, we conduct a simulation in which we randomly select groups of districts from the APEC-II sample to construct simulated States of different sizes. For each simulated State, we compare the model-based improper payment rate estimate to the sample-based estimate. These simulated findings give an indication of model performance when summing across district-level estimates to construct State-level estimates.

C. Organization of the report

The remainder of the report is organized as follows. In Chapter II, we describe the State-level statistical models we developed, including data sources, model specifications, the results of the estimation of these models, and model performance when the estimates were aggregated at the State level. Chapter III describes the model validation strategy and assesses the validation results. In the final chapter (Chapter IV), we summarize the approach to creating and validating State-level models and limitations of the approach.

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Summary

- The statistical models used to estimate State-level improper payments were built on the national models developed in the APEC-II study.
- There is substantial variation across States in model-based total improper payment rates due to certification error in non-CEP schools. For the NSLP, State model-based estimates of the total improper payment rate range from 2.8 percent to 16.0 percent. For the SBP, the range is 2.5 percent to 15.2 percent. The precision of these State estimates also varies widely.
- There is also some variation across States in model-based improper payment rates due to certification error in CEP schools, although all State model-based estimates are relatively low. The precision of these State estimates varies somewhat.
- For meal claiming error, there is substantial variation across States in the rate of model-based total improper payments due to meal claiming error. For the NSLP, estimates of the State model-based total improper payment rate range from 2.5 percent to 9.7 percent. For the SBP, the range is 4.2 percent to 17.7 percent. The precision of these State estimates also varies widely.

II. STATE-LEVEL STATISTICAL MODELS

The statistical models to estimate State-level improper payments were built on the national models we developed in the APEC-II study (see U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, July 2015). We developed three model systems for separately estimating certification error in non-CEP schools, certification error in CEP schools, and meal claiming error at the State level. As with the national models, for each type of error, we developed separate State-level models for the NSLP and SBP. The models relate district-level estimates for improper payment rates to district and State characteristics obtained from administrative data. After estimating the models using APEC-II data, the models were used to predict error rates for each district in the State, which then were aggregated at the State level.

In this chapter, we describe the State-level 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. We also estimate the performance of these State models when applied to the Verification Collection Report (VCR; also known as the FNS-742) data for SY 2012–2013.

A. State-level statistical models for certification error in non-CEP schools

Building on the national models, for certification errors for non-CEP schools, improper payment rates were decomposed into four rates each for NSLP and SBP: three for overpayments and one for underpayments. Table II.1 summarizes the error rates to model.

Table II.1. Rates of improper payment due to certification error in non-CEP schools

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 all school 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 all school breakfasts

The national model of certification error for non-CEP schools is based on the specification that includes core variables from the VCR data plus one additional variable selected from the VCR. The core variables 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, as well as variables representing verification results. Several variables included in the final specification reflect district and State program characteristics, including enrollment, percentage of students certified for free meals, percentage of students certified for reduced price meals, and type of district (public or private). Also included is the State direct certification performance rate, which measures percentage of SNAP-participating children directly certified for free school meals. No additional data reflecting State program characteristics likely to be correlated with non-CEP certification error are available in the VCR or other readily available data sources. Therefore, no additional explanatory variables were included in the State-level models for non-CEP certification error; for this type of error, our State-level models are identical to the national models. The variables included in this specification are listed in Table II.2. The specifications for NSLP and SBP programs included the same variables.

Table II.2. Independent variables included in State-level models used in estimating certification error for non-CEP schools, NSLP and SBP

		Overpayment (L/B)			Underpayment(L/B)
		% CF-RPE	% CF-PE	% CRP-PE	% Under
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 applications for reduced price meals 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 applications for reduced price meals that did not respond in verification			X	
(13)	Interaction of (1) and (12)			X	
(14)	Percentage of verified applications for reduced price meals that did not respond 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

		Overpayment (L/B)			Underpayment(L/B)
		% CF-RPE	% CF-PE	% CRP-PE	% Under
(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 provisions	X (for NSLP)			
(26)	Total number of certified applications (in thousands)	X (for SBP)			
(27)	Number of applications certified categorically eligible		X		X
(28)	Percentage of students certified without an application			X	

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

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

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

% Under = Percentage of underpayment for school meals (lunches or breakfasts)

As with national models, we used these State-level models to estimate the relationship between the explanatory variables and improper payment rates (Appendix Tables A.1A and A.1B present the findings from the model regression equations). By combining these estimated relationships with district-level data on all of the explanatory variables included in the model, the models were able generate estimates of improper payment rates for all districts with each State. We then computed improper payments in each district by multiplying each estimated error rate by the appropriate number of meals served. We did this separately for NSLP and SBP. Then each State's total of improper payment due to certification error in non-CEP schools was computed by summing across all districts in the State (for more detailed descriptions of how we apply models to national data, see U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, July 2015, Chapter IV).

We used bootstrapping to generate the standard errors and confidence intervals for the State estimates. As with the national models, we considered two types of sampling error simultaneously: (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 improper payments from applying model-based estimates to national data, which is subject to sampling error from the VCR data.

In Tables II.3 and II.4, we present State estimates of predicted improper payments resulting from certification error for non-CEP schools as derived from our State models. We do this separately for NSLP and SBP. Figures II.1 and II.2 are a graphic representation of the tabular data in Tables II.3 and II.4. States near the top of the figures have higher error rates.

There is substantial variation across States in model-based total improper payment rates due to certification error in non-CEP schools. For the NSLP, State model-based total improper payment rate estimates range from 2.8 percent to 16.0 percent. For the SBP, the range is 2.5 percent to 15.2 percent.

Despite the wide range in State model-based improper payment rate estimates due to certification error in non-CEP schools, many States have model-based improper payment rate estimates that are relatively close to the national improper payment rate:

- For the NSLP, 19 States have model-based improper payment rate estimates within one percentage point of the national model-based improper payment rate of 9.27 percent. There are eight States with model-based estimates that are more than one percentage point greater than the national improper payment rate, and among these eight States, five have estimates at least two percentage points greater than the national improper payment rate. There are 22 States with model-based estimates that are more than one percentage point less than the national improper payment rate, and among these, six have estimates at least two percentage points less than the national improper payment rate.
- For the SBP, 19 States have model-based improper payment rate estimates within one percentage point of the national model-based improper payment rate of 8.45 percent. There are 13 States with model-based estimates that are more than one percentage point greater than the national improper payment rate, and among these 13 States, 9 have estimates at least two percentage points greater than the national improper payment rate. There are 17 States with model-based estimates that are more than one percentage point less than the national improper payment rate, and among these, 10 have estimates at least two percentage points less than the national improper payment rate.

The precision of these State estimates varies widely. For the NSLP, the median half-width of a 95 percent confidence interval around the State improper payment estimate is 3.0 percentage points; the range is 1.9 to 7.2 percentage points. For the SBP, the median half-width of a 95 percent confidence interval around the State improper payment estimate is 3.8 percentage points; the range is 2.1 to 8.9 percentage points.

Table II.3. State estimates of improper payments based on imputation model, certification error for non-CEP schools, NSLP

	Percentage of all reimbursements in error		
State	Overpayment	Underpayment	Total improper payment
Alabama	6.765 (1.102) [4.605, 8.924]	2.065 (0.524) [1.037, 3.093]	8.830 (1.201) [6.477, 11.183]
Arkansas	4.759 (1.315) [2.183, 7.335]	2.250 (0.674) [0.929, 3.571]	7.009 (1.523) [4.024, 9.994]
Arizona	6.691 (2.059) [2.655, 10.728]	1.426 (0.753) [-0.049, 2.901]	8.118 (2.181) [3.844, 12.391]
California	5.938 (1.280) [3.430, 8.446]	2.634 (0.631) [1.397, 3.871]	8.572 (1.454) [5.721, 11.422]
Colorado	5.538 (0.986) [3.605, 7.471]	3.404 (0.813) [1.811, 4.997]	8.942 (1.329) [6.337, 11.547]
Connecticut	7.588 (1.408) [4.828, 10.348]	1.878 (0.846) [0.220, 3.537]	9.467 (1.546) [6.437, 12.496]
District of Columbia	4.666 (2.709) [-0.643, 9.975]	1.320 (1.903) [-2.410, 5.050]	5.986 (3.170) [-0.227, 12.199]
Delaware	6.918 (1.525) [3.929, 9.908]	1.469 (0.839) [-0.176, 3.114]	8.387 (1.805) [4.849, 11.926]
Florida	12.061 (3.355) [5.485, 18.637]	2.891 (1.540) [-0.128, 5.909]	14.951 (3.641) [7.815, 22.087]
Georgia	6.628 (1.205) [4.267, 8.989]	3.069 (0.614) [1.865, 4.273]	9.697 (1.289) [7.171, 12.223]
Iowa	6.126 (0.886) [4.388, 7.863]	2.133 (0.509) [1.135, 3.131]	8.258 (0.962) [6.373, 10.144]
Idaho	4.860 (1.150) [2.606, 7.114]	3.109 (0.696) [1.745, 4.472]	7.969 (1.367) [5.289, 10.648]
Illinois	5.342 (0.984) [3.414, 7.270]	7.091 (0.644) [5.829, 8.353]	12.434 (1.210) [10.063, 14.804]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Indiana	5.424 (0.973) [3.518, 7.331]	2.033 (0.445) [1.161, 2.905]	7.458 (1.060) [5.380, 9.535]
Kansas	10.303 (3.454) [3.532, 17.073]	0.330 (1.568) [-2.744, 3.403]	10.633 (3.692) [3.396, 17.869]
Kentucky	6.705 (1.103) [4.544, 8.867]	2.259 (0.655) [0.975, 3.543]	8.965 (1.211) [6.591, 11.338]
Louisiana	5.862 (1.963) [2.015, 9.708]	1.936 (0.694) [0.576, 3.295]	7.797 (2.067) [3.745, 11.849]
Massachusetts	8.665 (2.223) [4.307, 13.023]	1.468 (0.624) [0.244, 2.691]	10.133 (2.143) [5.933, 14.333]
Marvland	6.720 (1.064) [4.634, 8.805]	3.336 (0.715) [1.934, 4.737]	10.055 (1.285) [7.537, 12.573]
Maine	5.533 (1.576) [2.443, 8.623]	1.201 (0.725) [-0.221, 2.622]	6.734 (1.698) [3.405, 10.062]
Michigan	7.032 (1.292) [4.500, 9.563]	1.211 (0.758) [-0.275, 2.696]	8.242 (1.393) [5.512, 10.972]
Minnesota	5.433 (0.966) [3.540, 7.325]	2.325 (0.593) [1.162, 3.488]	7.758 (1.079) [5.643, 9.872]
Missouri	5.252 (1.892) [1.544, 8.960]	1.347 (0.710) [-0.043, 2.738]	6.599 (1.974) [2.731, 10.468]
Mississippi	6.538 (1.953) [2.710, 10.366]	1.042 (0.618) [-0.169, 2.254]	7.580 (2.004) [3.652, 11.509]
Montana	3.535 (2.211) [-0.799, 7.868]	2.902 (1.331) [0.294, 5.510]	6.437 (2.714) [1.118, 11.756]
North Carolina	6.265 (1.335) [3.648, 8.882]	2.653 (0.555) [1.565, 3.740]	8.918 (1.429) [6.117, 11.719]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
North Dakota	7.479 (2.194) [3.178, 11.779]	2.912 (1.386) [0.195, 5.629]	10.391 (2.480) [5.530, 15.252]
Nebraska	5.120 (1.816) [1.561, 8.680]	3.045 (0.994) [1.096, 4.994]	8.165 (1.947) [4.348, 11.981]
New Hampshire	5.414 (2.171) [1.160, 9.669]	1.935 (1.403) [-0.814, 4.685]	7.349 (2.632) [2.192, 12.507]
New Jersey	10.685 (3.077) [4.654, 16.716]	0.000 (0.746) [-1.484, 1.440]	10.685 (3.103) [4.582, 16.744]
New Mexico	7.293 (1.615) [4.128, 10.459]	2.591 (0.891) [0.846, 4.337]	9.885 (1.870) [6.219, 13.550]
Nevada	7.567 (1.807) [4.026, 11.108]	8.392 (1.216) [6.009, 10.775]	15.959 (2.235) [11.580, 20.339]
New York	1.046 (1.014) [-0.942, 3.033]	1.725 (0.548) [0.650, 2.800]	2.770 (1.186) [0.445, 5.096]
Ohio	6.302 (1.251) [3.850, 8.754]	1.359 (0.533) [0.315, 2.403]	7.662 (1.280) [5.152, 10.171]
Oklahoma	5.746 (1.176) [3.440, 8.051]	2.151 (0.582) [1.010, 3.292]	7.897 (1.302) [5.346, 10.448]
Oregon	6.022 (2.159) [1.791, 10.253]	1.795 (1.029) [-0.221, 3.811]	7.817 (2.356) [3.199, 12.434]
Pennsylvania	6.157 (1.232) [3.741, 8.572]	1.780 (0.595) [0.615, 2.945]	7.937 (1.398) [5.196, 10.678]
Rhode Island	10.056 (3.377) [3.437, 16.675]	1.272 (1.049) [-0.784, 3.328]	11.328 (3.391) [4.682, 17.974]
South Carolina	7.478 (1.243) [5.042, 9.914]	2.261 (0.667) [0.954, 3.567]	9.738 (1.382) [7.030, 12.447]
South Dakota	6.062 (1.145) [3.819, 8.306]	2.404 (0.638) [1.153, 3.655]	8.466 (1.333) [5.854, 11.078]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Tennessee	6.254 (1.385) [3.540, 8.968]	1.990 (0.676) [0.665, 3.315]	8.244 (1.433) [5.435, 11.053]
Texas	7.724 (1.622) [4.545, 10.904]	3.752 (1.055) [1.685, 5.819]	11.476 (1.805) [7.938, 15.014]
Utah	6.148 (1.186) [3.823, 8.473]	3.650 (0.675) [2.326, 4.974]	9.798 (1.316) [7.219, 12.377]
Virginia	7.089 (1.289) [4.563, 9.616]	2.520 (0.834) [0.886, 4.155]	9.610 (1.535) [6.602, 12.618]
Vermont	6.356 (2.471) [1.513, 11.199]	1.141 (1.437) [-1.675, 3.958]	7.497 (2.744) [2.119, 12.875]
Washington	8.784 (2.163) [4.545, 13.023]	1.048 (0.967) [-0.848, 2.943]	9.832 (2.424) [5.080, 14.584]
Wisconsin	5.795 (1.071) [3.696, 7.894]	2.496 (0.517) [1.482, 3.509]	8.291 (1.167) [6.004, 10.578]
West Virginia	7.552 (1.646) [4.326, 10.777]	1.959 (0.815) [0.362, 3.556]	9.511 (1.780) [6.021, 13.000]
Wyoming	5.794 (2.074) [1.729, 9.859]	3.543 (1.164) [1.261, 5.824]	9.336 (2.197) [5.031, 13.642]

Note: For each State, the table shows: (1) the improper payment rate (either over-, under-, or total), (2) standard error (in parentheses), and (3) 95 percent confidence interval around the improper payment rate estimate [in brackets].

Table II.4. State estimates of improper payments based on imputation model, certification error for non-CEP schools, SBP

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Alabama	4.695 (1.239) [2.265, 7.124]	1.237 (0.469) [0.318, 2.155]	5.931 (1.254) [3.474, 8.388]
Arkansas	5.477 (1.688) [2.169, 8.785]	1.353 (0.479) [0.415, 2.291]	6.830 (1.757) [3.387, 10.273]
Arizona	6.325 (2.491) [1.444, 11.206]	1.129 (0.697) [-0.238, 2.496]	7.454 (2.508) [2.538, 12.370]
California	6.134 (1.551) [3.093, 9.175]	2.155 (0.603) [0.974, 3.337]	8.289 (1.656) [5.044, 11.535]
Colorado	4.450 (1.178) [2.140, 6.759]	2.891 (1.075) [0.784, 4.998]	7.341 (1.659) [4.088, 10.593]
Connecticut	9.029 (1.999) [5.110, 12.947]	1.685 (0.720) [0.275, 3.095]	10.714 (2.033) [6.728, 14.699]
District of Columbia	14.463 (4.361) [5.917, 23.010]	0.718 (1.528) [-2.276, 3.711]	15.181 (4.555) [6.253, 24.108]
Delaware	6.127 (1.822) [2.557, 9.698]	1.104 (0.763) [-0.391, 2.599]	7.231 (2.002) [3.307, 11.155]
Florida	9.565 (2.761) [4.153, 14.977]	2.440 (1.107) [0.269, 4.610]	12.005 (2.945) [6.232, 17.777]
Georgia	5.695 (1.399) [2.953, 8.436]	1.880 (0.633) [0.639, 3.120]	7.574 (1.565) [4.507, 10.642]
Iowa	6.164 (1.128) [3.954, 8.374]	1.787 (0.435) [0.935, 2.638]	7.951 (1.224) [5.552, 10.350]
Idaho	2.999 (1.307) [0.438, 5.561]	1.949 (0.657) [0.660, 3.237]	4.948 (1.405) [2.195, 7.701]
Illinois	3.564 (0.951) [1.700, 5.428]	5.720 (0.521) [4.698, 6.742]	9.284 (1.050) [7.226, 11.342]

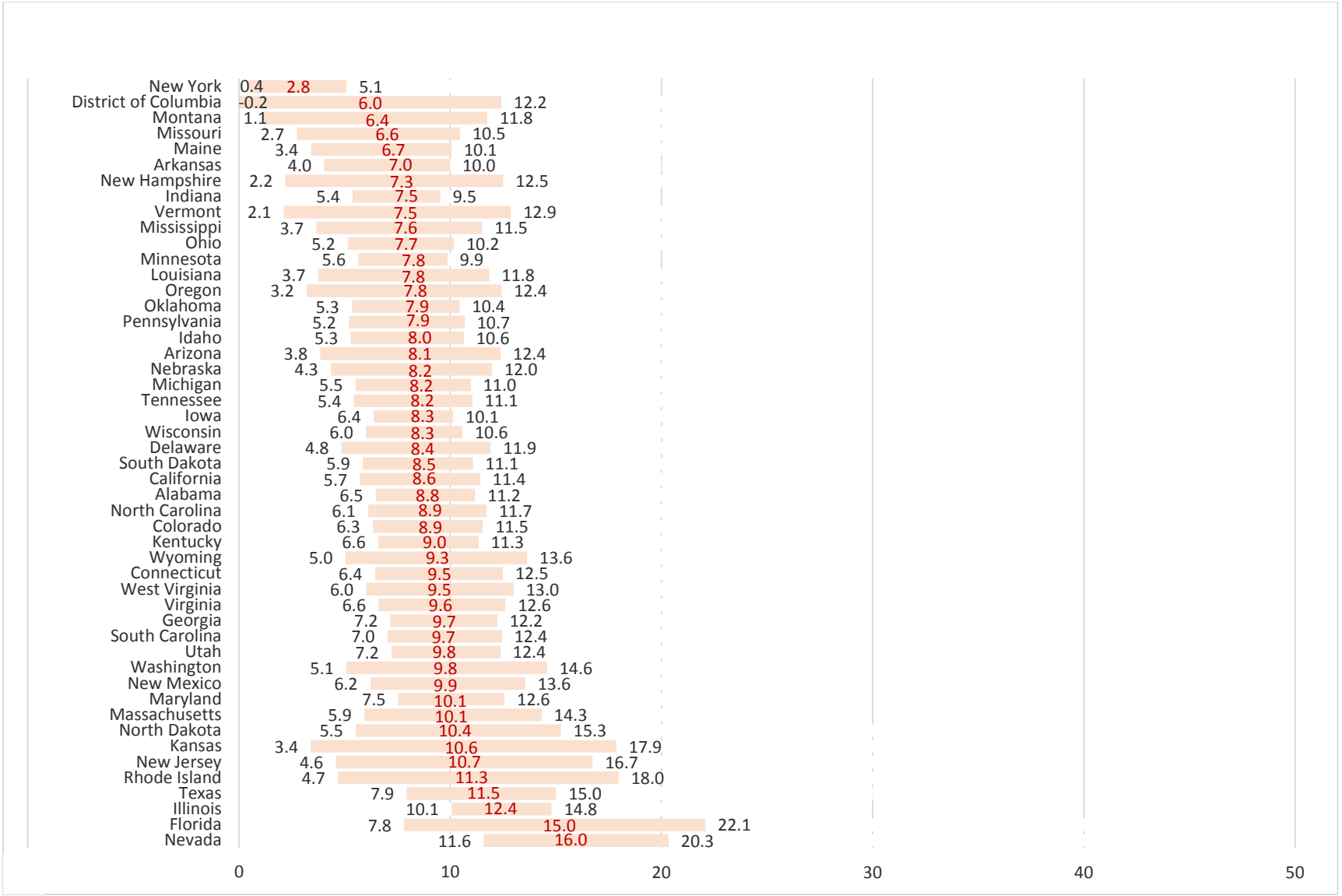
State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Indiana	5.673 (1.301) [3.123, 8.223]	1.460 (0.342) [0.790, 2.129]	7.133 (1.316) [4.555, 9.711]
Kansas	11.094 (3.690) [3.861, 18.326]	0.567 (1.018) [-1.428, 2.563]	11.661 (3.853) [4.110, 19.212]
Kentucky	6.619 (1.500) [3.679, 9.560]	1.633 (0.603) [0.451, 2.814]	8.252 (1.575) [5.166, 11.338]
Louisiana	4.779 (2.324) [0.224, 9.334]	1.689 (0.781) [0.159, 3.219]	6.468 (2.401) [1.762, 11.174]
Massachusetts	5.875 (1.539) [2.860, 8.891]	0.645 (0.534) [-0.402, 1.691]	6.520 (1.576) [3.430, 9.609]
Maryland	5.692 (1.213) [3.315, 8.068]	2.863 (0.661) [1.567, 4.159]	8.554 (1.394) [5.821, 11.287]
Maine	3.947 (1.925) [0.175, 7.719]	0.799 (0.862) [-0.891, 2.490]	4.746 (2.015) [0.797, 8.695]
Michigan	9.068 (1.874) [5.394, 12.741]	1.363 (0.668) [0.054, 2.673]	10.431 (1.944) [6.621, 14.241]
Minnesota	6.858 (1.472) [3.973, 9.743]	1.996 (0.427) [1.160, 2.832]	8.854 (1.526) [5.864, 11.844]
Missouri	6.445 (2.333) [1.873, 11.018]	1.023 (0.555) [-0.064, 2.111]	7.469 (2.343) [2.876, 12.061]
Mississippi	5.200 (2.240) [0.809, 9.590]	0.399 (0.503) [-0.586, 1.384]	5.598 (2.244) [1.200, 9.997]
Montana	5.489 (3.090) [-0.567, 11.546]	1.902 (0.907) [0.125, 3.679]	7.391 (3.261) [0.999, 13.783]
North Carolina	4.364 (1.568) [1.291, 7.436]	1.640 (0.433) [0.791, 2.488]	6.003 (1.609) [2.850, 9.156]
North Dakota	9.898 (3.006) [4.005, 15.790]	2.285 (1.077) [0.173, 4.397]	12.183 (3.180) [5.950, 18.415]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Nebraska	7.549 (2.452) [2.743, 12.355]	2.576 (0.841) [0.928, 4.223]	10.125 (2.589) [5.051, 15.199]
New Hampshire	3.475 (3.092) [-2.585, 9.536]	1.152 (1.517) [-1.821, 4.125]	4.628 (3.300) [-1.840, 11.095]
New Jersey	9.837 (2.426) [5.082, 14.593]	0.000 (0.535) [-1.096, 1.003]	9.837 (2.465) [4.959, 14.623]
New Mexico	7.354 (1.824) [3.778, 10.929]	1.780 (0.859) [0.096, 3.464]	9.134 (1.916) [5.379, 12.888]
Nevada	5.871 (1.883) [2.181, 9.561]	7.313 (1.070) [5.216, 9.411]	13.185 (2.148) [8.975, 17.394]
New York	1.404 (1.036) [-0.626, 3.434]	1.117 (0.407) [0.319, 1.916]	2.521 (1.099) [0.368, 4.674]
Ohio	7.420 (1.572) [4.338, 10.502]	1.293 (0.440) [0.430, 2.156]	8.713 (1.597) [5.584, 11.842]
Oklahoma	7.017 (1.536) [4.006, 10.028]	1.976 (0.507) [0.981, 2.970]	8.993 (1.591) [5.875, 12.110]
Oregon	3.875 (2.607) [-1.233, 8.984]	0.713 (0.880) [-1.011, 2.437]	4.589 (2.622) [-0.550, 9.727]
Pennsylvania	5.096 (1.628) [1.906, 8.286]	1.030 (0.602) [-0.149, 2.209]	6.126 (1.696) [2.801, 9.451]
Rhode Island	7.525 (2.387) [2.846, 12.203]	0.403 (0.939) [-1.439, 2.244]	7.927 (2.671) [2.692, 13.163]
South Carolina	6.202 (1.395) [3.468, 8.936]	1.509 (0.507) [0.514, 2.503]	7.711 (1.401) [4.964, 10.457]
South Dakota	6.655 (1.613) [3.493, 9.817]	1.516 (0.508) [0.521, 2.511]	8.171 (1.703) [4.832, 11.510]
Tennessee	4.529 (1.457) [1.673, 7.386]	0.777 (0.604) [-0.407, 1.961]	5.307 (1.575) [2.220, 8.394]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Texas	8.382 (2.143) [4.182, 12.583]	3.243 (0.959) [1.363, 5.123]	11.626 (2.210) [7.294, 15.957]
Utah	6.113 (1.409) [3.351, 8.874]	2.884 (0.567) [1.772, 3.996]	8.997 (1.537) [5.984, 12.010]
Virginia	6.975 (1.531) [3.974, 9.976]	2.421 (0.731) [0.989, 3.854]	9.396 (1.736) [5.994, 12.799]
Vermont	11.938 (3.820) [4.450, 19.425]	1.038 (0.958) [-0.839, 2.916]	12.976 (3.964) [5.206, 20.746]
Washington	8.206 (2.574) [3.160, 13.251]	0.724 (0.730) [-0.707, 2.155]	8.929 (2.670) [3.697, 14.162]
Wisconsin	6.285 (1.308) [3.721, 8.848]	2.206 (0.406) [1.410, 3.002]	8.491 (1.384) [5.778, 11.203]
West Virginia	7.925 (2.146) [3.719, 12.131]	1.550 (0.671) [0.234, 2.866]	9.475 (2.250) [5.066, 13.885]
Wyoming	7.882 (2.807) [2.380, 13.384]	2.971 (0.868) [1.270, 4.671]	10.853 (2.922) [5.127, 16.579]

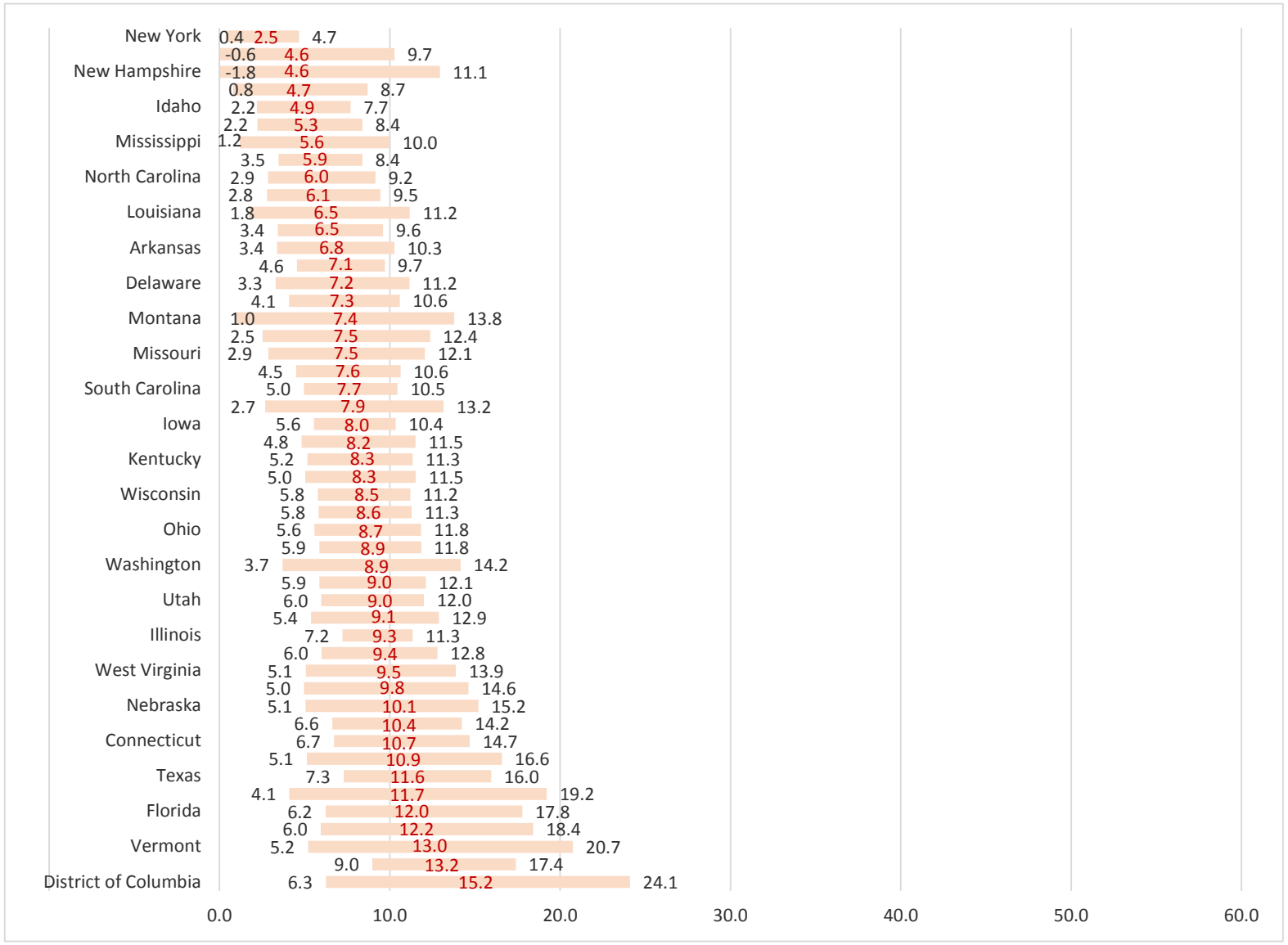
Note: For each State, the table shows: (1) the improper payment rate (either over-, under-, or total), (2) standard error (in parentheses), and (3) 95 percent confidence interval around the improper payment rate estimate [in brackets].

Figure II.1. Model-based State estimates of improper payments due to certification error for non-CEP schools, NSLP



Note: Values in red represent the State improper payment rate estimates. Values in black represent the upper and lower bounds of the 95 percent confidence interval around the State estimate. The lower bound of the confidence interval that goes below the zero is not graphed in the figure.

Figure II.2. Model-based State estimates of improper payments due to certification error for non-CEP schools, SBP



Note: Values in red represent the State improper payment rate estimates. Values in black represent the upper and lower bounds of the 95 percent confidence interval around the State estimate. The lower bound of the confidence interval that goes below the zero is not graphed in the figure.

B. State-level statistical models for certification error in CEP schools

For SY 2012–2013, CEP was implemented in six States plus the District of Columbia. We developed statistical models of certification error in CEP schools and used them to generate model-based estimates for these States. As with the national models, the models used to develop State-level estimates of certification error in CEP schools include two certification error rates, as shown in Table II.5.

Table II.5. Rates of improper payment due to certification error in 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

These rates can take either positive or negative values, depending on whether the district had overpayments or underpayments (that is, depending on whether its 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 explanatory variables included in State-level CEP models are identical to those in national models, which are based on the specification that includes only core variables from the VCR, shown in Table II.6. These variables capture CEP implementation characteristics (such as the percentage of students in schools operating CEP and the percentage of schools operating CEP), characteristics related to direct certification (the State direct certification performance rate calculated annually in the Report to Congress on direct certification implementation, and whether the district was privately operated), and local economic conditions (the school-age poverty rate at the county level). No other data source available at national level reflects State program characteristics.

Table II.6. 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.

We used these State-level models to estimate the relationship between the explanatory variables and improper payment rates for CEP schools (Appendix Table 2 presents the findings from the model regression equations). As with the national improper payment estimation process, we had to impute which districts were operating CEP in SY 2012–2013 and CEP reimbursements because we have no CEP information from the SY 2012–2013 VCR file (see

U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, July 2015, Chapter IV).

By combining the models' estimated relationships with information on all of the explanatory variables included in the model for districts we identified as operating CEP, the models were able to generate updated estimates of improper payment rates for all identified CEP districts. We then computed improper payments in each district by multiplying each estimated error rate by the imputed number of meals served for CEP schools. We did this separately for NSLP and SBP. Then, for the six States and DC, the total of improper payment due to certification error in CEP schools is computed by summing across all CEP districts in these States. We bootstrapped the standard errors and confidence intervals for each State estimate; the bootstrapping process is analogous to the one described above for certification error in non-CEP schools.

In Tables II.7 and II.8, we present State estimates of predicted improper payments resulting from certification error for CEP schools as derived from our State models. It is shown for NSLP and for SBP. Figures II.3 and II.4 are a graphic representation of the tabular data in Tables II.7 and II.8. States near the top of the figures have higher error rates.

There is variation across States in model-based improper payment rates due to certification error in CEP schools, although all State model-based estimates are relatively low. For both the NSLP and SBP, the State model-based total improper payment rate estimates range from 0.6 to about 3 percent. For both programs, 1 State has a model-based estimate less than 1 percent and one State has a model based-estimate near 3 percent; the remaining 5 States have rates within 1 percentage point of the national improper payment rate.

The precision of these State estimates varies somewhat. For the NSLP, the median half-width of a 95 percent confidence interval around the State improper payment estimate is 1.6 percentage points; the range is from 0.9 to 2.0 percentage points. For the SBP, the median half-width of a 95 percent confidence interval around the State improper payment estimate is 1.7 percentage points; the range is 1.0 to 2.0 percentage points.

Table II.7. State estimates of improper payments based on imputation model, certification error for CEP schools, NSLP

	Percentage of all reimbursements in error		
State	Overpayment	Underpayment	Total improper payment
District of Columbia	0.000 (0.001) [-0.003, 0.003]	2.986 (0.913) [1.197, 4.775]	2.986 (0.913) [1.197, 4.775]
Illinois	0.079 (0.347) [-0.602, 0.759]	0.487 (0.590) [-0.671, 1.644]	0.566 (0.476) [-0.368, 1.499]
Kentucky	0.000 (0.079) [-0.155, 0.155]	2.659 (1.020) [0.659, 4.658]	2.659 (1.005) [0.689, 4.628]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Michigan	0.000 (0.148) [-0.289, 0.289]	2.414 (0.879) [0.692, 4.136]	2.414 (0.896) [0.658, 4.170]
New York	0.000 (0.262) [-0.513, 0.513]	1.896 (0.719) [0.487, 3.305]	1.896 (0.701) [0.523, 3.269]
Ohio	0.015 (0.239) [-0.454, 0.483]	1.089 (0.918) [-0.710, 2.888]	1.104 (0.836) [-0.535, 2.742]
West Virginia	0.000 (0.116) [-0.227, 0.227]	2.460 (0.723) [1.043, 3.878]	2.460 (0.688) [1.111, 3.809]

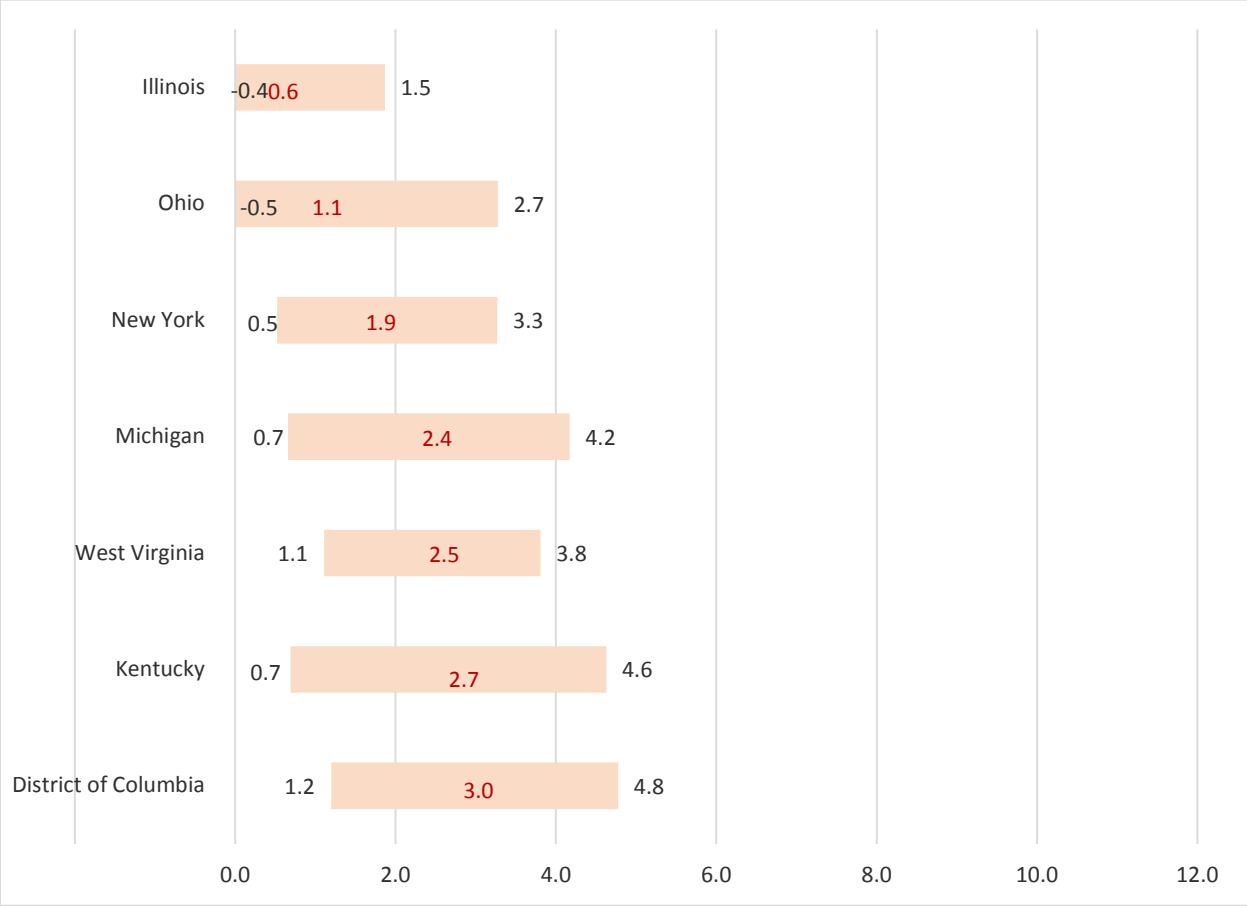
Note: For each State, the table shows: (1) the improper payment rate (either over-, under-, or total), (2) standard error (in parentheses), and (3) 95 percent confidence interval around the improper payment rate estimate [in brackets].

Table II.8. State estimates of improper payments based on imputation model, certification error for CEP schools, SBP

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
District of Columbia	0.000 (0.001) [-0.003, 0.003]	3.098 (0.949) [1.237, 4.958]	3.098 (0.949) [1.237, 4.958]
Illinois	0.086 (0.359) [-0.618, 0.790]	0.522 (0.622) [-0.698, 1.741]	0.608 (0.502) [-0.376, 1.591]
Kentucky	0.000 (0.078) [-0.153, 0.153]	2.776 (1.067) [0.685, 4.868]	2.776 (1.053) [0.713, 4.840]
Michigan	0.000 (0.152) [-0.299, 0.299]	2.511 (0.918) [0.711, 4.311]	2.511 (0.937) [0.674, 4.348]
New York	0.000 (0.276) [-0.541, 0.541]	1.953 (0.743) [0.497, 3.408]	1.953 (0.726) [0.530, 3.376]
Ohio	0.017 (0.254) [-0.480, 0.515]	1.116 (0.951) [-0.748, 2.980]	1.133 (0.864) [-0.560, 2.827]
West Virginia	0.000 (0.113) [-0.221, 0.221]	2.550 (0.747) [1.085, 4.015]	2.550 (0.714) [1.151, 3.949]

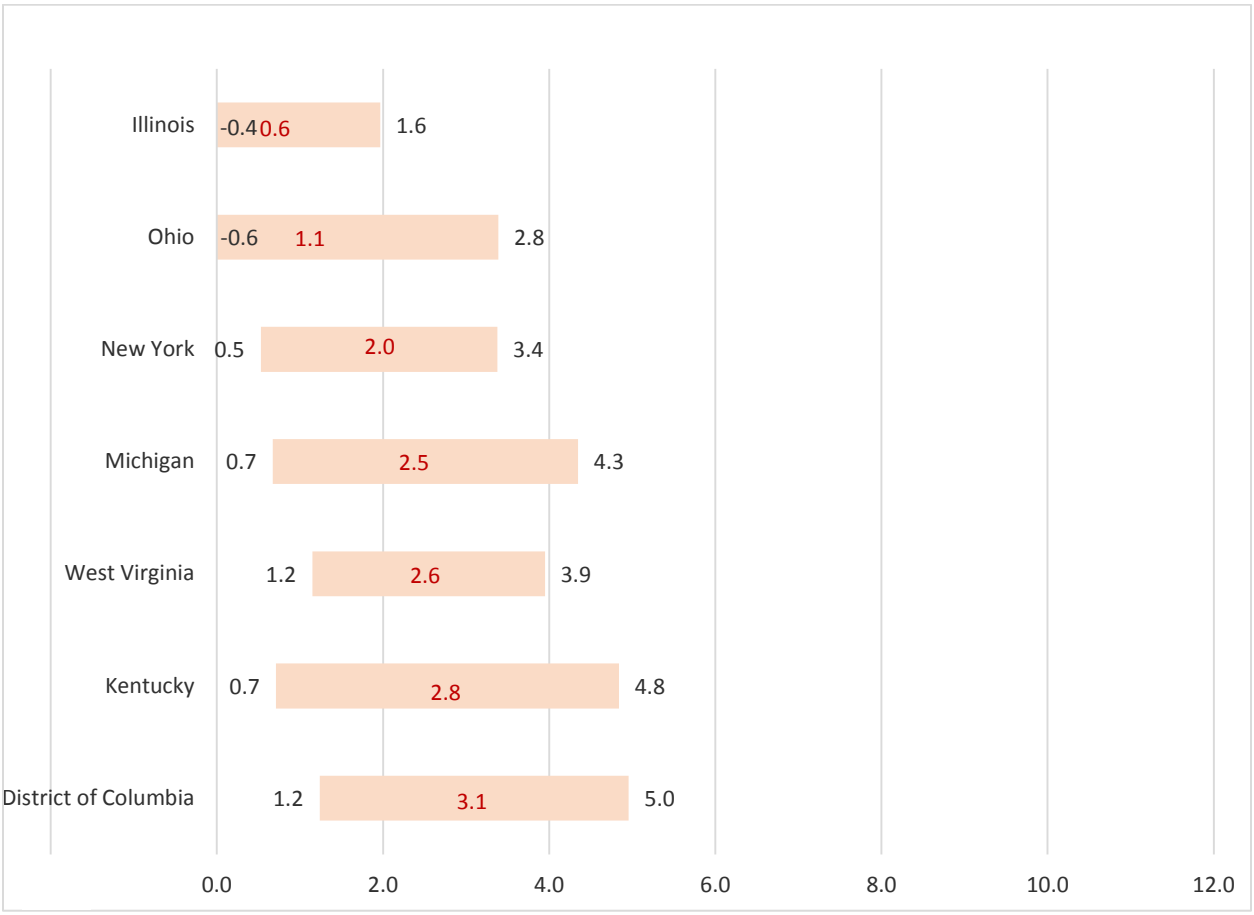
Note: For each State, the table shows: (1) the improper payment rate (either over-, under-, or total), (2) standard error (in parentheses); and (3) 95 percent confidence interval around the improper payment rate estimate [in brackets].

Figure II.3. Model-based State estimates of improper payments due to certification error for CEP schools, NSLP



Note: Values in red represent the State improper payment rate estimates. Values in black represent the upper and lower bounds of the 95 percent confidence interval around the State estimate. The lower bound of the confidence interval that goes below the zero is not graphed in the figure.

Figure II.4. Model-based State estimates of improper payments due to certification error for CEP schools, SBP



Note: Values in red represent the State improper payment rate estimates. Values in black represent the upper and lower bounds of the 95 percent confidence interval around the State estimate. The lower bound of the confidence interval that goes below the zero is not graphed in the figure.

C. State-level statistical models for certification error for all schools

We generated State-level estimates of predicted improper payments resulting from certification error for all schools by adding improper payment estimates due to certification error in non-CEP schools and CEP schools. In Tables II.9 and II.10, we present State estimates of predicted improper payments resulting from certification error for all schools. We do this separately for NSLP and SBP. Figures II.5 and II.6 rank the States according to their improper payment rates.

The estimates of certification error for all schools are nearly identical to estimates shown earlier for non-CEP schools. The estimates for all schools differ from estimates of certification error for non-CEP schools only for the States that operated CEP schools in SY 2012–2013. For these six States and DC, the model-based improper payment rates for all schools due to certification error are somewhat lower than those for non-CEP schools after accounting for lower improper payment rates of CEP schools.

Table II.9. State estimates of improper payments based on imputation model, certification error for all schools, NSLP

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Alabama	6.765 (1.102) [4.605, 8.924]	2.065 (0.524) [1.037, 3.093]	8.830 (1.201) [6.477, 11.183]
Arkansas	4.759 (1.315) [2.183, 7.335]	2.250 (0.674) [0.929, 3.571]	7.009 (1.523) [4.024, 9.994]
Arizona	6.691 (2.059) [2.655, 10.728]	1.426 (0.753) [-0.049, 2.901]	8.118 (2.181) [3.844, 12.391]
California	5.938 (1.280) [3.430, 8.446]	2.634 (0.631) [1.397, 3.871]	8.572 (1.454) [5.721, 11.422]
Colorado	5.538 (0.986) [3.605, 7.471]	3.404 (0.813) [1.811, 4.997]	8.942 (1.329) [6.337, 11.547]
Connecticut	7.588 (1.408) [4.828, 10.348]	1.878 (0.846) [0.220, 3.537]	9.467 (1.546) [6.437, 12.496]
District of Columbia	1.337 (0.752) [-0.137, 2.811]	2.509 (0.870) [0.803, 4.215]	3.846 (1.031) [1.825, 5.867]
Delaware	6.918 (1.525) [3.929, 9.908]	1.469 (0.839) [-0.176, 3.114]	8.387 (1.805) [4.849, 11.926]
Florida	12.061 (3.355) [5.485, 18.637]	2.891 (1.540) [-0.128, 5.909]	14.951 (3.641) [7.815, 22.087]
Georgia	6.628 (1.205) [4.267, 8.989]	3.069 (0.614) [1.865, 4.273]	9.697 (1.289) [7.171, 12.223]
Iowa	6.126 (0.886) [4.388, 7.863]	2.133 (0.509) [1.135, 3.131]	8.258 (0.962) [6.373, 10.144]
Idaho	4.860 (1.150) [2.606, 7.114]	3.109 (0.696) [1.745, 4.472]	7.969 (1.367) [5.289, 10.648]
Illinois	3.959 (0.724) [2.540, 5.377]	5.355 (0.434) [4.505, 6.205]	9.314 (0.845) [7.658, 10.971]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Indiana	5.424 (0.973) [3.518, 7.331]	2.033 (0.445) [1.161, 2.905]	7.458 (1.060) [5.380, 9.535]
Kansas	10.303 (3.454) [3.532, 17.073]	0.330 (1.568) [-2.744, 3.403]	10.633 (3.692) [3.396, 17.869]
Kentucky	5.036 (0.921) [3.230, 6.842]	2.359 (0.578) [1.226, 3.491]	7.395 (1.068) [5.302, 9.487]
Louisiana	5.862 (1.963) [2.015, 9.708]	1.936 (0.694) [0.576, 3.295]	7.797 (2.067) [3.745, 11.849]
Massachusetts	8.665 (2.223) [4.307, 13.023]	1.468 (0.624) [0.244, 2.691]	10.133 (2.143) [5.933, 14.333]
Maryland	6.720 (1.064) [4.634, 8.805]	3.336 (0.715) [1.934, 4.737]	10.055 (1.285) [7.537, 12.573]
Maine	5.533 (1.576) [2.443, 8.623]	1.201 (0.725) [-0.221, 2.622]	6.734 (1.698) [3.405, 10.062]
Michigan	5.175 (1.086) [3.047, 7.304]	1.528 (0.646) [0.261, 2.795]	6.704 (1.116) [4.515, 8.892]
Minnesota	5.433 (0.966) [3.540, 7.325]	2.325 (0.593) [1.162, 3.488]	7.758 (1.079) [5.643, 9.872]
Missouri	5.252 (1.892) [1.544, 8.960]	1.347 (0.710) [-0.043, 2.738]	6.599 (1.974) [2.731, 10.468]
Mississippi	6.538 (1.953) [2.710, 10.366]	1.042 (0.618) [-0.169, 2.254]	7.580 (2.004) [3.652, 11.509]
Montana	3.535 (2.211) [-0.799, 7.868]	2.902 (1.331) [0.294, 5.510]	6.437 (2.714) [1.118, 11.756]
North Carolina	6.265 (1.335) [3.648, 8.882]	2.653 (0.555) [1.565, 3.740]	8.918 (1.429) [6.117, 11.719]
North Dakota	7.479 (2.194) [3.178, 11.779]	2.912 (1.386) [0.195, 5.629]	10.391 (2.480) [5.530, 15.252]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Nebraska	5.120 (1.816) [1.561, 8.680]	3.045 (0.994) [1.096, 4.994]	8.165 (1.947) [4.348, 11.981]
New Hampshire	5.414 (2.171) [1.160, 9.669]	1.935 (1.403) [-0.814, 4.685]	7.349 (2.632) [2.192, 12.507]
New Jersey	10.685 (3.077) [4.654, 16.716]	0.000 (0.746) [-1.484, 1.440]	10.685 (3.103) [4.582, 16.744]
New Mexico	7.293 (1.615) [4.128, 10.459]	2.591 (0.891) [0.846, 4.337]	9.885 (1.870) [6.219, 13.550]
Nevada	7.567 (1.807) [4.026, 11.108]	8.392 (1.216) [6.009, 10.775]	15.959 (2.235) [11.580, 20.339]
New York	0.926 (0.904) [-0.846, 2.698]	1.744 (0.503) [0.758, 2.731]	2.670 (1.071) [0.571, 4.769]
Ohio	5.410 (1.093) [3.268, 7.552]	1.321 (0.469) [0.401, 2.241]	6.731 (1.139) [4.499, 8.963]
Oklahoma	5.746 (1.176) [3.440, 8.051]	2.151 (0.582) [1.010, 3.292]	7.897 (1.302) [5.346, 10.448]
Oregon	6.022 (2.159) [1.791, 10.253]	1.795 (1.029) [-0.221, 3.811]	7.817 (2.356) [3.199, 12.434]
Pennsylvania	6.157 (1.232) [3.741, 8.572]	1.780 (0.595) [0.615, 2.945]	7.937 (1.398) [5.196, 10.678]
Rhode Island	10.056 (3.377) [3.437, 16.675]	1.272 (1.049) [-0.784, 3.328]	11.328 (3.391) [4.682, 17.974]
South Carolina	7.478 (1.243) [5.042, 9.914]	2.261 (0.667) [0.954, 3.567]	9.738 (1.382) [7.030, 12.447]
South Dakota	6.062 (1.145) [3.819, 8.306]	2.404 (0.638) [1.153, 3.655]	8.466 (1.333) [5.854, 11.078]
Tennessee	6.254 (1.385) [3.540, 8.968]	1.990 (0.676) [0.665, 3.315]	8.244 (1.433) [5.435, 11.053]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Texas	7.724 (1.622) [4.545, 10.904]	3.752 (1.055) [1.685, 5.819]	11.476 (1.805) [7.938, 15.014]
Utah	6.148 (1.186) [3.823, 8.473]	3.650 (0.675) [2.326, 4.974]	9.798 (1.316) [7.219, 12.377]
Virginia	7.089 (1.289) [4.563, 9.616]	2.520 (0.834) [0.886, 4.155]	9.610 (1.535) [6.602, 12.618]
Vermont	6.356 (2.471) [1.513, 11.199]	1.141 (1.437) [-1.675, 3.958]	7.497 (2.744) [2.119, 12.875]
Washington	8.784 (2.163) [4.545, 13.023]	1.048 (0.967) [-0.848, 2.943]	9.832 (2.424) [5.080, 14.584]
Wisconsin	5.795 (1.071) [3.696, 7.894]	2.496 (0.517) [1.482, 3.509]	8.291 (1.167) [6.004, 10.578]
West Virginia	3.620 (0.997) [1.665, 5.574]	2.220 (0.551) [1.141, 3.299]	5.840 (1.118) [3.648, 8.031]
Wyoming	5.794 (2.074) [1.729, 9.859]	3.543 (1.164) [1.261, 5.824]	9.336 (2.197) [5.031, 13.642]

Note: For each State, the table shows: (1) the improper payment rate (either over-, under-, or total), (2) standard error (in parentheses), and (3) 95 percent confidence interval around the improper payment rate estimate [in brackets].

Table II.10. State estimates of improper payments based on imputation model, certification error for all schools, SBP

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Alabama	4.695 (1.239) [2.265, 7.124]	1.237 (0.469) [0.318, 2.155]	5.931 (1.254) [3.474, 8.388]
Arkansas	5.477 (1.688) [2.169, 8.785]	1.353 (0.479) [0.415, 2.291]	6.830 (1.757) [3.387, 10.273]
Arizona	6.325 (2.491) [1.444, 11.206]	1.129 (0.697) [-0.238, 2.496]	7.454 (2.508) [2.538, 12.370]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
California	6.134 (1.551) [3.093, 9.175]	2.155 (0.603) [0.974, 3.337]	8.289 (1.656) [5.044, 11.535]
Colorado	4.450 (1.178) [2.140, 6.759]	2.891 (1.075) [0.784, 4.998]	7.341 (1.659) [4.088, 10.593]
Connecticut	9.029 (1.999) [5.110, 12.947]	1.685 (0.720) [0.275, 3.095]	10.714 (2.033) [6.728, 14.699]
District of Columbia	4.031 (1.194) [1.692, 6.370]	2.434 (0.849) [0.771, 4.097]	6.465 (1.300) [3.918, 9.012]
Delaware	6.127 (1.822) [2.557, 9.698]	1.104 (0.763) [-0.391, 2.599]	7.231 (2.002) [3.307, 11.155]
Florida	9.565 (2.761) [4.153, 14.977]	2.440 (1.107) [0.269, 4.610]	12.005 (2.945) [6.232, 17.777]
Georgia	5.695 (1.399) [2.953, 8.436]	1.880 (0.633) [0.639, 3.120]	7.574 (1.565) [4.507, 10.642]
Iowa	6.164 (1.128) [3.954, 8.374]	1.787 (0.435) [0.935, 2.638]	7.951 (1.224) [5.552, 10.350]
Idaho	2.999 (1.307) [0.438, 5.561]	1.949 (0.657) [0.660, 3.237]	4.948 (1.405) [2.195, 7.701]
Illinois	2.585 (0.686) [1.241, 3.929]	4.257 (0.377) [3.517, 4.997]	6.842 (0.729) [5.414, 8.270]
Indiana	5.673 (1.301) [3.123, 8.223]	1.460 (0.342) [0.790, 2.129]	7.133 (1.316) [4.555, 9.711]
Kansas	11.094 (3.690) [3.861, 18.326]	0.567 (1.018) [-1.428, 2.563]	11.661 (3.853) [4.110, 19.212]
Kentucky	4.853 (1.069) [2.759, 6.948]	1.938 (0.565) [0.830, 3.046]	6.791 (1.165) [4.507, 9.075]
Louisiana	4.779 (2.324) [0.224, 9.334]	1.689 (0.781) [0.159, 3.219]	6.468 (2.401) [1.762, 11.174]

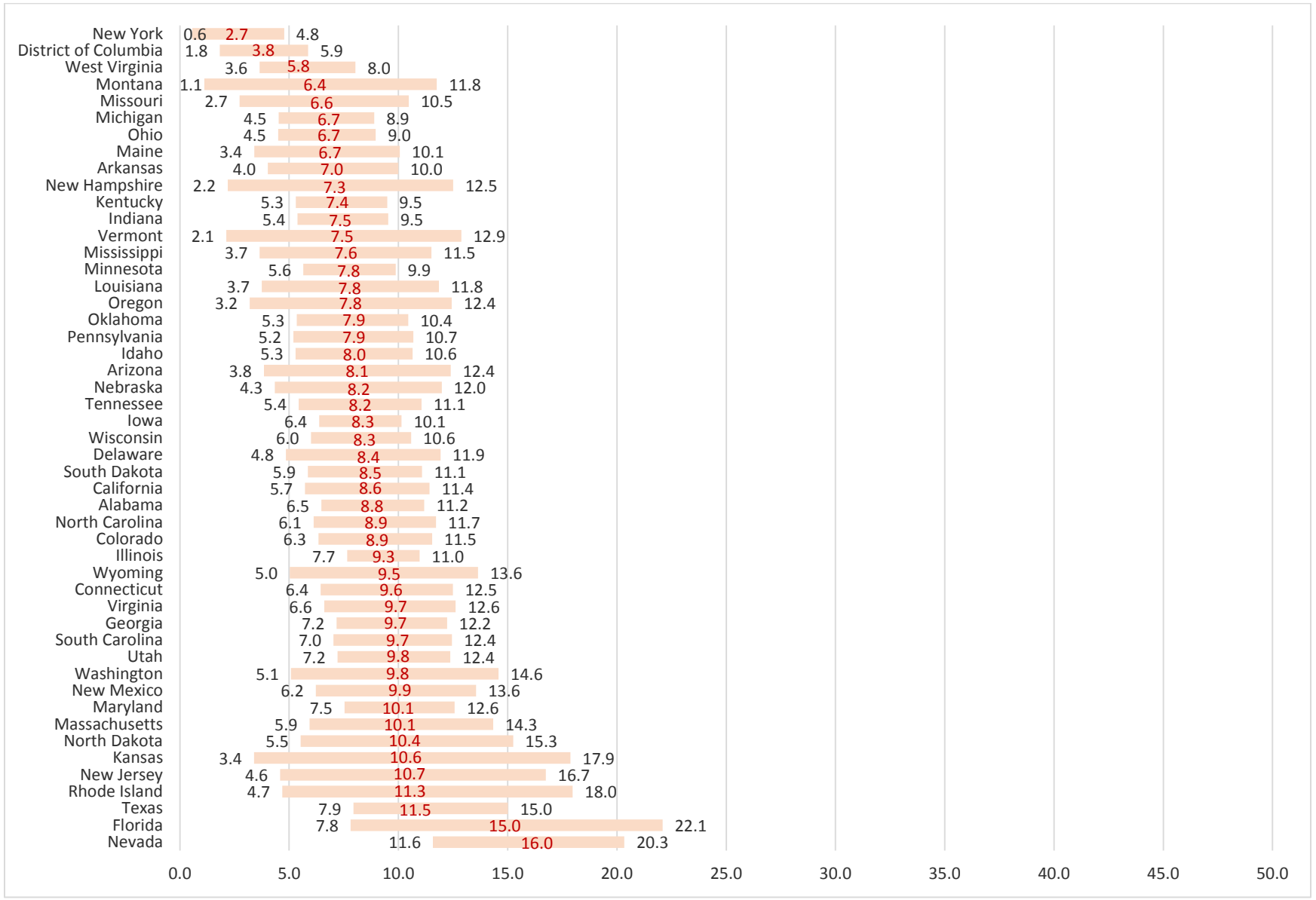
State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Massachusetts	5.875 (1.539) [2.860, 8.891]	0.645 (0.534) [-0.402, 1.691]	6.520 (1.576) [3.430, 9.609]
Maryland	5.692 (1.213) [3.315, 8.068]	2.863 (0.661) [1.567, 4.159]	8.554 (1.394) [5.821, 11.287]
Maine	3.947 (1.925) [0.175, 7.719]	0.799 (0.862) [-0.891, 2.490]	4.746 (2.015) [0.797, 8.695]
Michigan	6.482 (1.473) [3.594, 9.370]	1.690 (0.612) [0.492, 2.889]	8.172 (1.473) [5.284, 11.060]
Minnesota	6.858 (1.472) [3.973, 9.743]	1.996 (0.427) [1.160, 2.832]	8.854 (1.526) [5.864, 11.844]
Missouri	6.445 (2.333) [1.873, 11.018]	1.023 (0.555) [-0.064, 2.111]	7.469 (2.343) [2.876, 12.061]
Mississippi	5.200 (2.240) [0.809, 9.590]	0.399 (0.503) [-0.586, 1.384]	5.598 (2.244) [1.200, 9.997]
Montana	5.489 (3.090) [-0.567, 11.546]	1.902 (0.907) [0.125, 3.679]	7.391 (3.261) [0.999, 13.783]
North Carolina	4.364 (1.568) [1.291, 7.436]	1.640 (0.433) [0.791, 2.488]	6.003 (1.609) [2.850, 9.156]
North Dakota	9.898 (3.006) [4.005, 15.790]	2.285 (1.077) [0.173, 4.397]	12.183 (3.180) [5.950, 18.415]
Nebraska	7.549 (2.452) [2.743, 12.355]	2.576 (0.841) [0.928, 4.223]	10.125 (2.589) [5.051, 15.199]
New Hampshire	3.475 (3.092) [-2.585, 9.536]	1.152 (1.517) [-1.821, 4.125]	4.628 (3.300) [-1.840, 11.095]
New Jersey	9.837 (2.426) [5.082, 14.593]	0.000 (0.535) [-1.096, 1.003]	9.837 (2.465) [4.959, 14.623]
New Mexico	7.354 (1.824) [3.778, 10.929]	1.780 (0.859) [0.096, 3.464]	9.134 (1.916) [5.379, 12.888]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Nevada	5.871 (1.883) [2.181, 9.561]	7.313 (1.070) [5.216, 9.411]	13.185 (2.148) [8.975, 17.394]
New York	1.233 (0.916) [-0.564, 3.029]	1.219 (0.382) [0.471, 1.967]	2.452 (0.981) [0.529, 4.374]
Ohio	6.262 (1.341) [3.634, 8.890]	1.265 (0.404) [0.474, 2.057]	7.527 (1.388) [4.806, 10.248]
Oklahoma	7.017 (1.536) [4.006, 10.028]	1.976 (0.507) [0.981, 2.970]	8.993 (1.591) [5.875, 12.110]
Oregon	3.875 (2.607) [-1.233, 8.984]	0.713 (0.880) [-1.011, 2.437]	4.589 (2.622) [-0.550, 9.727]
Pennsylvania	5.096 (1.628) [1.906, 8.286]	1.030 (0.602) [-0.149, 2.209]	6.126 (1.696) [2.801, 9.451]
Rhode Island	7.525 (2.387) [2.846, 12.203]	0.403 (0.939) [-1.439, 2.244]	7.927 (2.671) [2.692, 13.163]
South Carolina	6.202 (1.395) [3.468, 8.936]	1.509 (0.507) [0.514, 2.503]	7.711 (1.401) [4.964, 10.457]
South Dakota	6.655 (1.613) [3.493, 9.817]	1.516 (0.508) [0.521, 2.511]	8.171 (1.703) [4.832, 11.510]
Tennessee	4.529 (1.457) [1.673, 7.386]	0.777 (0.604) [-0.407, 1.961]	5.307 (1.575) [2.220, 8.394]
Texas	8.382 (2.143) [4.182, 12.583]	3.243 (0.959) [1.363, 5.123]	11.626 (2.210) [7.294, 15.957]
Utah	6.113 (1.409) [3.351, 8.874]	2.884 (0.567) [1.772, 3.996]	8.997 (1.537) [5.984, 12.010]
Virginia	6.975 (1.531) [3.974, 9.976]	2.421 (0.731) [0.989, 3.854]	9.396 (1.736) [5.994, 12.799]
Vermont	11.938 (3.820) [4.450, 19.425]	1.038 (0.958) [-0.839, 2.916]	12.976 (3.964) [5.206, 20.746]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Washington	8.206 (2.574) [3.160, 13.251]	0.724 (0.730) [-0.707, 2.155]	8.929 (2.670) [3.697, 14.162]
Wisconsin	6.285 (1.308) [3.721, 8.848]	2.206 (0.406) [1.410, 3.002]	8.491 (1.384) [5.778, 11.203]
West Virginia	3.593 (1.105) [1.427, 5.758]	2.097 (0.508) [1.102, 3.092]	5.689 (1.178) [3.381, 7.998]
Wyoming	7.882 (2.807) [2.380, 13.384]	2.971 (0.868) [1.270, 4.671]	10.853 (2.922) [5.127, 16.579]

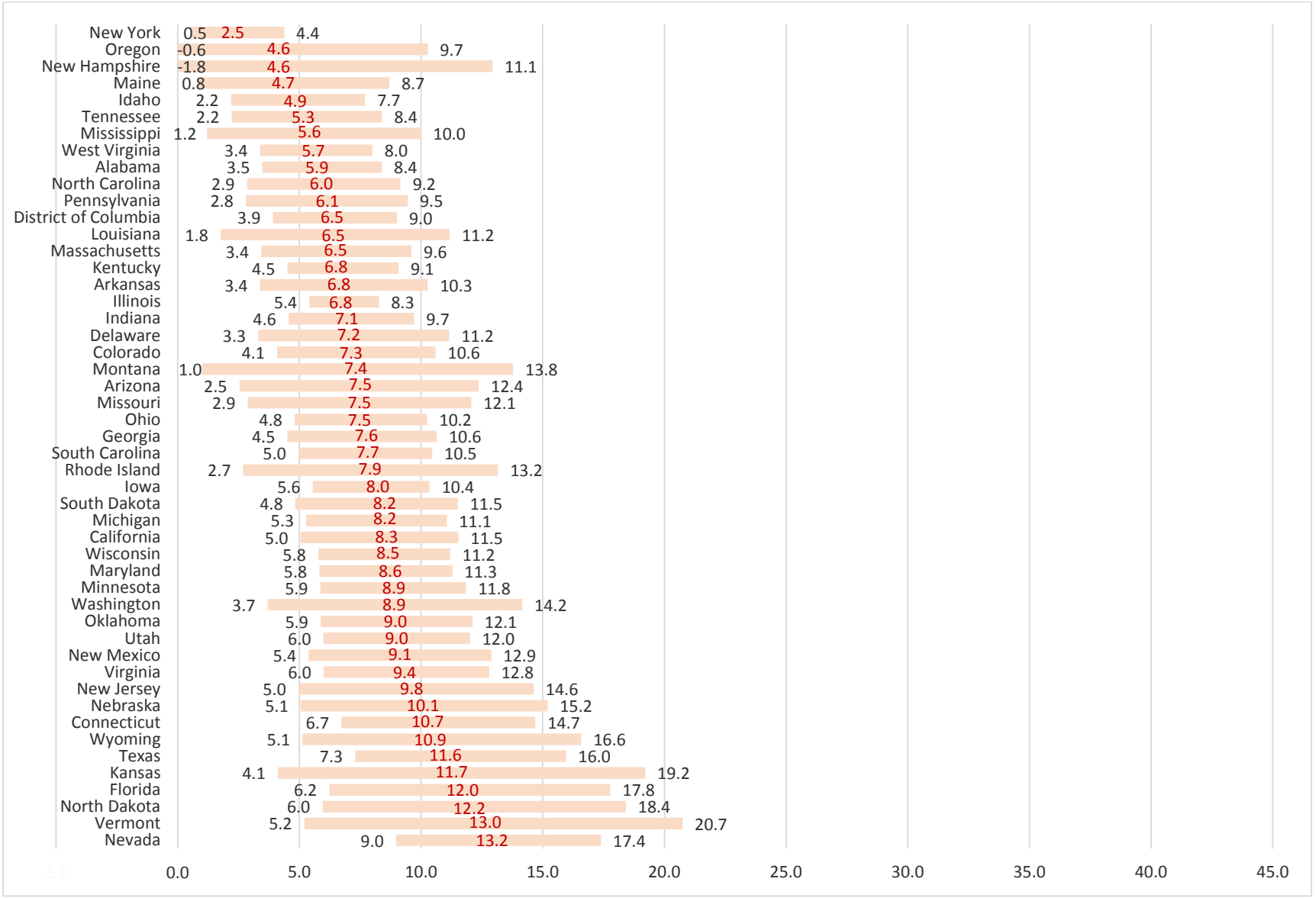
Note: For each State, the table shows: (1) the improper payment rate (either over-, under-, or total), (2) standard error (in parentheses), and (3) 95 percent confidence interval around the improper payment rate estimate [in brackets].

Figure II.5. Model-based State estimates of improper payments due to certification error for all schools, NSLP



Note: Values in red represent the State improper payment rate estimates. Values in black represent the upper and lower bounds of the 95 percent confidence interval around the State estimate. The lower bound of the confidence interval that goes below the zero is not graphed in the figure.

Figure II.6. Model-based State estimates of improper payments due to Certification error for all schools, SBP



Note: Values in red represent the State improper payment rate estimates. Values in black represent the upper and lower bounds of the 95 percent confidence interval around the State estimate. The lower bound of the confidence interval that goes below the zero is not graphed in the figure.

D. State-level statistical models for meal claiming error

As with the national models, we decomposed meal claiming error into two separate categories—overpayment and underpayment—for both the NSLP and SBP, as shown in Table II.11.

Table II.11. Rates of improper payment due to meal claiming error

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

Following the same approach we used for the national models, we modeled both NSLP and SBP overpayments and underpayments using a single-equation approach. For both NSLP and SBP, the specification we selected for the national models included only core variables. The core variables capture:

- **Student certification characteristics.** Schools with a higher percentage 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. 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.

In addition to these core variables included in the national models, we included in the State models the State direct certification performance rate, calculated annually in the Report to Congress on direct certification implementation. This variable captures characteristics related to direct certification at the State-level. Table II.12 lists all variable included in these State-level models.

Table II.12. Independent variables included in models used in estimating meal claiming error

	% Underpayment		% Overpayment	
	NSLP	SBP	NSLP	SBP
Enrollment	X	X	X	X
Average size (enrollment/number of school)	X	X	X	X
Percentage of students certified for free meals				
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	X	X
Percentage of students certified as free not subject to verification	X	X	X	X
Percentage of application with benefits changed in verification	X	X	X	X
Publicly operated	X	X	X	X
State direct certification performance rate	X	X	X	X

As in the certification error modeling, we used these State-level models to estimate the relationship between the explanatory variables and improper payment rates for meal claiming error (Appendix Table 3 presents the findings from the model regression equations). Estimated coefficients from these models were used in conjunction with values of district characteristics to predict meal claiming error in each district. These improper payment rates then were translated into amounts and rates of improper payments in each district. Finally, we aggregated the district-level estimates to the State level and bootstrapped standard error and confidence interval for each State estimate.

In Tables II.13 and II.14, we present State estimates of predicted improper payments resulting from meal claiming error, separately for NSLP and SBP. Figures II.7 and II.8 are a graphic representation of the tabular data in Tables II.13 and II.14. States near the top of the figures have higher error rates.

There is substantial variation across States in model-based total improper payment rates due to meal claiming error. For the NSLP, State model-based total improper payment rate estimates range from 2.5 percent to 9.7 percent. For the SBP, the range is 4.2 percent to 17.7 percent.

Despite the wide range in State model-based improper payment rate estimates due to meal claiming error, many States have model-based improper payment rate estimates that are relatively close to the national improper payment rate:

- For the NSLP, 32 States have model-based improper payment rate estimates within one percentage point of the national model-based improper payment rate of 5.33 percent. There are 8 States with model-based estimates that are more than 1 percentage point greater than the national improper payment rate, and among these 8 States, 3 have estimates at least 2

percentage points greater than the national improper payment rate. There are 9 States with model-based estimates that are more than 1 percentage point less than the national improper payment rate, and among these, 4 have estimates at least 2 percentage points less than the national improper payment rate.

- For the SBP, 13 States have model-based improper payment rate estimates within one percentage point of the national model-based improper payment rate of 10.97 percent. There are 19 States with model-based estimates that are more than one percentage point greater than the national improper payment rate, and among these 19 States, 15 have estimates at least two percentage points greater than the national improper payment rate. There are 17 States with model-based estimates that are more than 1 percentage point less than the national improper payment rate, and among these, 9 have estimates at least two percentage points less than the national improper payment rate.

The precision of these State estimates varies widely. For the NSLP, the median half-width of a 95 percent confidence interval around the State improper payment estimate is 2.1 percentage points; the range is 1.3 to 5.3 percentage points. For the SBP, the median half-width of a 95 percent confidence interval around the State improper payment estimate is 5.5 percentage points; the range is 2.9 to 14.7 percentage points.

Table II.13. State estimates of improper payments based on imputation model, meal claiming error, NSLP

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Alabama	3.865 (0.603) [2.684, 5.046]	0.810 (0.248) [0.323, 1.297]	4.675 (0.642) [3.417, 5.933]
Arkansas	5.234 (0.835) [3.598, 6.870]	0.806 (0.300) [0.218, 1.394]	6.040 (0.841) [4.391, 7.689]
Arizona	5.417 (0.984) [3.488, 7.347]	1.156 (0.415) [0.343, 1.970]	6.574 (1.090) [4.438, 8.710]
California	6.055 (0.902) [4.288, 7.822]	0.994 (0.317) [0.372, 1.615]	7.048 (0.950) [5.186, 8.910]
Colorado	6.181 (1.322) [3.591, 8.772]	1.525 (0.632) [0.287, 2.764]	7.707 (1.505) [4.757, 10.657]
Connecticut	4.932 (1.024) [2.925, 6.939]	0.444 (0.432) [-0.402, 1.291]	5.376 (1.075) [3.270, 7.482]
District of Columbia	2.956 (0.771) [1.444, 4.468]	0.107 (0.275) [-0.431, 0.645]	3.063 (0.831) [1.435, 4.691]
Delaware	3.370 (0.768) [1.865, 4.875]	0.607 (0.553) [-0.476, 1.691]	3.977 (0.863) [2.286, 5.669]
Florida	3.871 (0.710) [2.480, 5.262]	0.455 (0.239) [-0.014, 0.925]	4.327 (0.749) [2.858, 5.795]
Georgia	2.954 (0.859) [1.271, 4.638]	0.384 (0.334) [-0.270, 1.038]	3.338 (0.918) [1.538, 5.137]
Iowa	4.379 (0.808) [2.796, 5.961]	0.838 (0.377) [0.100, 1.576]	5.217 (0.855) [3.541, 6.892]
Idaho	4.869 (0.964) [2.981, 6.758]	1.292 (0.424) [0.461, 2.124]	6.161 (1.064) [4.076, 8.247]
Illinois	3.978 (2.050) [-0.040, 7.995]	1.101 (1.016) [-0.891, 3.093]	5.079 (2.351) [0.472, 9.686]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Indiana	4.875 (0.741) [3.421, 6.328]	1.070 (0.380) [0.326, 1.815]	5.945 (0.798) [4.380, 7.510]
Kansas	3.912 (0.987) [1.977, 5.847]	0.348 (0.466) [-0.566, 1.262]	4.260 (1.143) [2.019, 6.501]
Kentucky	2.719 (0.782) [1.187, 4.251]	0.268 (0.364) [-0.446, 0.983]	2.987 (0.875) [1.272, 4.702]
Louisiana	4.345 (0.993) [2.400, 6.291]	1.224 (0.523) [0.199, 2.249]	5.570 (1.128) [3.358, 7.781]
Massachusetts	4.772 (0.857) [3.092, 6.452]	0.944 (0.332) [0.295, 1.594]	5.716 (0.911) [3.931, 7.501]
Maryland	4.259 (0.694) [2.898, 5.619]	0.787 (0.261) [0.275, 1.299]	5.046 (0.721) [3.633, 6.459]
Maine	4.482 (1.253) [2.027, 6.937]	1.514 (0.562) [0.412, 2.615]	5.996 (1.394) [3.262, 8.729]
Michigan	3.247 (0.884) [1.514, 4.980]	0.187 (0.328) [-0.455, 0.829]	3.434 (0.993) [1.489, 5.379]
Minnesota	5.168 (0.918) [3.368, 6.968]	1.138 (0.419) [0.317, 1.960]	6.307 (1.001) [4.346, 8.268]
Missouri	4.708 (0.931) [2.884, 6.533]	1.084 (0.378) [0.344, 1.824]	5.792 (0.996) [3.841, 7.744]
Mississippi	4.156 (0.886) [2.419, 5.893]	0.789 (0.329) [0.144, 1.434]	4.946 (0.942) [3.100, 6.791]
Montana	7.239 (1.975) [3.368, 11.111]	1.858 (0.868) [0.158, 3.559]	9.098 (2.177) [4.832, 13.364]
North Carolina	3.871 (0.644) [2.608, 5.133]	1.046 (0.341) [0.378, 1.714]	4.916 (0.742) [3.462, 6.370]
North Dakota	6.278 (1.416) [3.503, 9.052]	0.578 (0.576) [-0.551, 1.707]	6.856 (1.498) [3.919, 9.793]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Nebraska	4.265 (0.998) [2.309, 6.221]	0.666 (0.658) [-0.623, 1.956]	4.931 (1.192) [2.595, 7.267]
New Hampshire	7.254 (2.299) [2.748, 11.761]	2.417 (1.093) [0.275, 4.559]	9.672 (2.677) [4.425, 14.919]
New Jersey	4.929 (0.764) [3.432, 6.426]	0.862 (0.398) [0.082, 1.641]	5.790 (0.810) [4.203, 7.378]
New Mexico	6.372 (1.138) [4.142, 8.602]	0.734 (0.402) [-0.054, 1.522]	7.106 (1.136) [4.880, 9.332]
Nevada	4.826 (1.165) [2.542, 7.111]	0.777 (0.398) [-0.004, 1.558]	5.603 (1.277) [3.100, 8.106]
New York	4.962 (0.983) [3.035, 6.890]	0.586 (0.637) [-0.662, 1.835]	5.548 (1.167) [3.261, 7.836]
Ohio	4.217 (0.695) [2.856, 5.578]	0.779 (0.308) [0.176, 1.382]	4.996 (0.714) [3.597, 6.394]
Oklahoma	5.012 (0.736) [3.570, 6.454]	0.423 (0.237) [-0.041, 0.886]	5.435 (0.744) [3.977, 6.892]
Oregon	4.513 (1.349) [1.870, 7.156]	1.727 (0.624) [0.504, 2.950]	6.240 (1.558) [3.186, 9.294]
Pennsylvania	5.472 (1.243) [3.036, 7.909]	1.607 (0.662) [0.310, 2.904]	7.080 (1.421) [4.294, 9.866]
Rhode Island	4.356 (1.065) [2.268, 6.444]	0.543 (0.293) [-0.031, 1.117]	4.899 (1.177) [2.592, 7.206]
South Carolina	4.381 (0.678) [3.053, 5.709]	0.707 (0.208) [0.300, 1.114]	5.088 (0.698) [3.719, 6.457]
South Dakota	5.208 (0.956) [3.335, 7.082]	1.063 (0.616) [-0.144, 2.270]	6.272 (1.102) [4.113, 8.431]
Tennessee	1.963 (0.796) [0.402, 3.524]	0.486 (0.395) [-0.289, 1.260]	2.449 (0.874) [0.735, 4.162]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Texas	5.038 (0.982) [3.113, 6.963]	0.000 (0.276) [-0.546, 0.536]	5.038 (1.042) [2.990, 7.076]
Utah	5.360 (1.078) [3.247, 7.472]	0.770 (0.330) [0.124, 1.417]	6.130 (1.137) [3.901, 8.359]
Virginia	4.675 (1.025) [2.666, 6.685]	0.634 (0.251) [0.142, 1.127]	5.309 (1.051) [3.249, 7.370]
Vermont	5.081 (1.079) [2.967, 7.196]	0.849 (0.494) [-0.121, 1.818]	5.930 (1.153) [3.670, 8.190]
Washington	4.976 (0.974) [3.068, 6.884]	1.261 (0.404) [0.469, 2.054]	6.237 (1.067) [4.146, 8.328]
Wisconsin	3.717 (0.637) [2.469, 4.966]	1.032 (0.594) [-0.133, 2.197]	4.749 (0.805) [3.172, 6.326]
West Virginia	2.867 (0.948) [1.008, 4.726]	0.268 (0.539) [-0.789, 1.324]	3.134 (1.153) [0.875, 5.394]
Wyoming	5.518 (1.350) [2.873, 8.164]	0.602 (0.539) [-0.455, 1.659]	6.120 (1.439) [3.300, 8.940]

Note: For each State, the table shows: (1) the improper payment rate (either over-, under-, or total), (2) standard error (in parentheses), and (3) 95 percent confidence interval around the improper payment rate estimate [in brackets].

Table II.14. State estimates of improper payments based on imputation model, meal claiming error, SBP

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Alabama	12.141 (2.118) [7.989, 16.293]	0.135 (0.051) [0.035, 0.234]	12.276 (2.122) [8.117, 16.434]
Arkansas	11.477 (2.519) [6.539, 16.415]	0.131 (0.064) [0.007, 0.256]	11.608 (2.525) [6.660, 16.557]
Arizona	14.686 (3.266) [8.285, 21.087]	0.023 (0.068) [-0.110, 0.155]	14.709 (3.283) [8.274, 21.143]
California	13.304 (3.280) [6.876, 19.732]	0.093 (0.059) [-0.023, 0.208]	13.396 (3.291) [6.946, 19.847]
Colorado	13.214 (4.518) [4.359, 22.069]	0.142 (0.102) [-0.058, 0.341]	13.355 (4.530) [4.476, 22.235]
Connecticut	7.483 (2.151) [3.267, 11.699]	0.247 (0.095) [0.061, 0.433]	7.730 (2.162) [3.492, 11.968]
District of Columbia	7.514 (3.743) [0.179, 14.850]	0.146 (0.063) [0.022, 0.269]	7.660 (3.744) [0.321, 14.998]
Delaware	10.720 (3.234) [4.381, 17.060]	0.244 (0.073) [0.100, 0.388]	10.965 (3.243) [4.608, 17.321]
Florida	11.018 (2.710) [5.706, 16.330]	0.169 (0.056) [0.060, 0.278]	11.187 (2.714) [5.868, 16.506]
Georgia	10.205 (2.637) [5.036, 15.374]	0.296 (0.089) [0.121, 0.471]	10.501 (2.643) [5.321, 15.681]
Iowa	8.598 (2.146) [4.392, 12.805]	0.329 (0.105) [0.123, 0.535]	8.928 (2.161) [4.691, 13.164]
Idaho	13.465 (3.199) [7.195, 19.735]	0.270 (0.103) [0.067, 0.472]	13.735 (3.202) [7.460, 20.010]
Illinois	12.597 (4.161) [4.441, 20.753]	0.105 (0.064) [-0.022, 0.231]	12.702 (4.157) [4.555, 20.848]

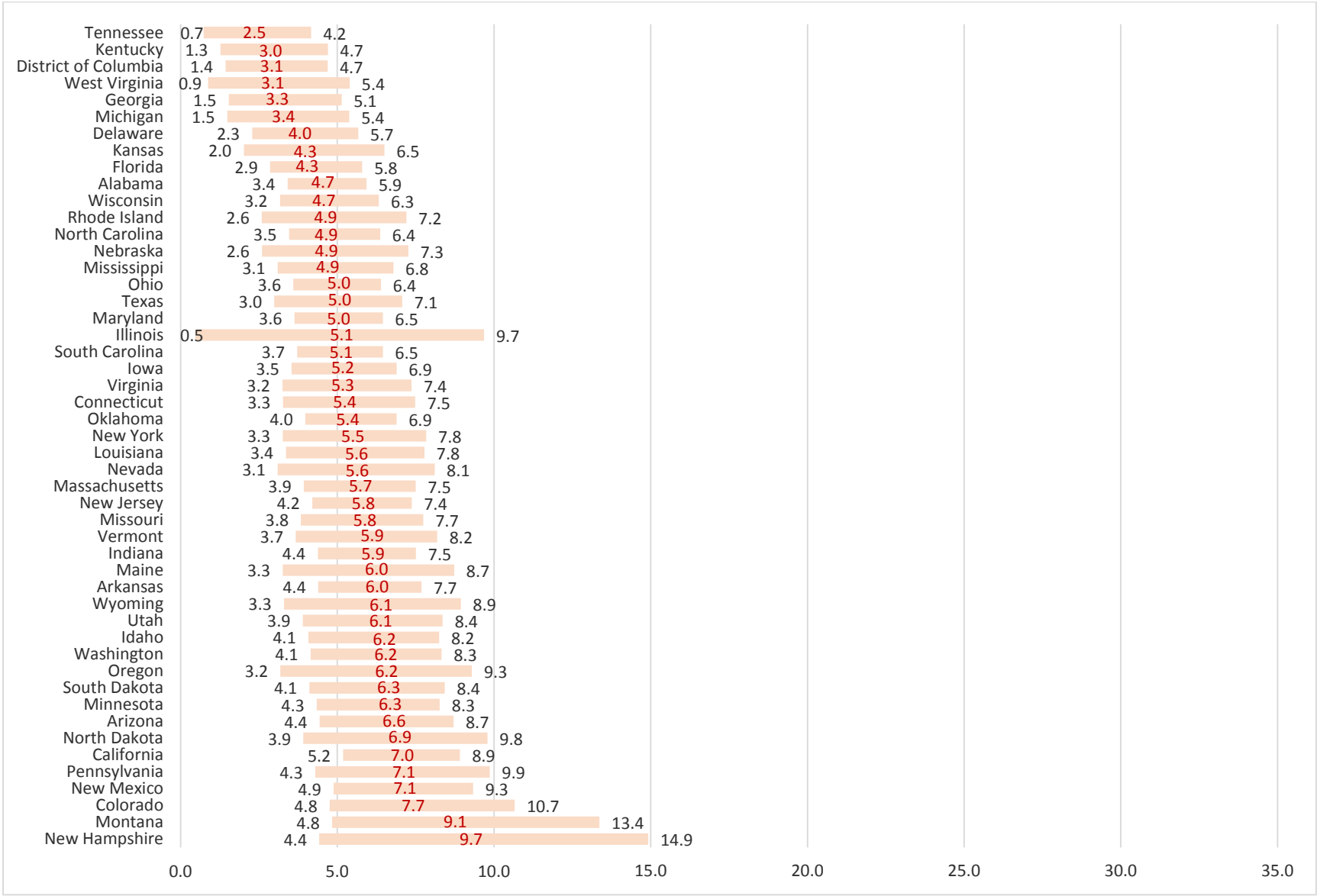
State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Indiana	11.907 (2.029) [7.929, 15.884]	0.198 (0.065) [0.070, 0.326]	12.105 (2.038) [8.110, 16.100]
Kansas	5.742 (2.764) [0.324, 11.160]	0.364 (0.127) [0.114, 0.614]	6.106 (2.788) [0.642, 11.569]
Kentucky	8.916 (3.466) [2.124, 15.708]	0.312 (0.091) [0.133, 0.491]	9.228 (3.473) [2.421, 16.035]
Louisiana	13.304 (3.108) [7.212, 19.396]	0.034 (0.073) [-0.108, 0.176]	13.338 (3.113) [7.236, 19.439]
Massachusetts	11.524 (1.900) [7.800, 15.249]	0.136 (0.057) [0.023, 0.248]	11.660 (1.906) [7.925, 15.395]
Maryland	9.549 (1.813) [5.996, 13.103]	0.265 (0.083) [0.101, 0.428]	9.814 (1.825) [6.238, 13.390]
Maine	13.997 (4.426) [5.322, 22.672]	0.210 (0.120) [-0.024, 0.444]	14.207 (4.424) [5.537, 22.877]
Michigan	9.722 (4.388) [1.122, 18.321]	0.199 (0.077) [0.049, 0.349]	9.920 (4.384) [1.328, 18.512]
Minnesota	10.595 (2.343) [6.002, 15.187]	0.296 (0.093) [0.114, 0.478]	10.891 (2.354) [6.276, 15.505]
Missouri	12.721 (2.833) [7.169, 18.274]	0.127 (0.075) [-0.021, 0.274]	12.848 (2.834) [7.293, 18.404]
Mississippi	13.023 (2.683) [7.765, 18.281]	0.048 (0.062) [-0.073, 0.169]	13.071 (2.686) [7.806, 18.336]
Montana	13.872 (6.487) [1.159, 26.586]	0.086 (0.143) [-0.193, 0.366]	13.959 (6.498) [1.223, 26.694]
North Carolina	13.512 (2.504) [8.603, 18.421]	0.229 (0.078) [0.076, 0.382]	13.741 (2.509) [8.823, 18.659]
North Dakota	5.630 (3.363) [-0.962, 12.222]	0.317 (0.128) [0.067, 0.567]	5.947 (3.393) [-0.703, 12.597]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Nebraska	6.435 (2.612) [1.315, 11.556]	0.335 (0.125) [0.091, 0.580]	6.771 (2.632) [1.612, 11.930]
New Hampshire	17.604 (7.476) [2.952, 32.256]	0.123 (0.165) [-0.200, 0.447]	17.727 (7.487) [3.053, 32.402]
New Jersey	9.877 (1.466) [7.004, 12.750]	0.178 (0.061) [0.059, 0.297]	10.055 (1.475) [7.164, 12.946]
New Mexico	10.291 (3.877) [2.693, 17.889]	0.063 (0.067) [-0.069, 0.195]	10.354 (3.887) [2.736, 17.971]
Nevada	14.033 (3.573) [7.029, 21.036]	0.247 (0.090) [0.071, 0.423]	14.280 (3.577) [7.268, 21.291]
New York	4.181 (2.770) [-1.247, 9.610]	0.000 (0.070) [-0.146, 0.128]	4.181 (2.773) [-1.262, 9.607]
Ohio	10.783 (2.082) [6.702, 14.865]	0.189 (0.055) [0.080, 0.297]	10.972 (2.086) [6.884, 15.060]
Oklahoma	9.844 (1.803) [6.310, 13.377]	0.162 (0.058) [0.048, 0.277]	10.006 (1.809) [6.459, 13.552]
Oregon	15.320 (4.575) [6.353, 24.287]	0.176 (0.118) [-0.055, 0.406]	15.496 (4.578) [6.524, 24.468]
Pennsylvania	13.939 (3.208) [7.651, 20.226]	0.148 (0.085) [-0.018, 0.314]	14.087 (3.218) [7.779, 20.395]
Rhode Island	10.799 (2.515) [5.870, 15.727]	0.134 (0.096) [-0.054, 0.322]	10.933 (2.510) [6.013, 15.853]
South Carolina	13.169 (2.312) [8.637, 17.701]	0.156 (0.054) [0.051, 0.262]	13.325 (2.320) [8.779, 17.872]
South Dakota	8.763 (3.463) [1.977, 15.550]	0.262 (0.102) [0.062, 0.462]	9.026 (3.477) [2.210, 15.841]
Tennessee	10.068 (3.291) [3.617, 16.519]	0.290 (0.089) [0.116, 0.465]	10.359 (3.297) [3.898, 16.820]

State	Percentage of all reimbursements in error		
	Overpayment	Underpayment	Total improper payment
Texas	8.833 (2.434) [4.064, 13.603]	0.158 (0.060) [0.041, 0.275]	8.991 (2.433) [4.222, 13.761]
Utah	9.398 (2.633) [4.239, 14.558]	0.369 (0.116) [0.142, 0.597]	9.767 (2.640) [4.593, 14.942]
Virginia	9.250 (2.403) [4.540, 13.960]	0.360 (0.106) [0.151, 0.568]	9.610 (2.409) [4.888, 14.332]
Vermont	8.629 (2.644) [3.446, 13.811]	0.310 (0.103) [0.108, 0.513]	8.939 (2.660) [3.726, 14.152]
Washington	13.512 (2.836) [7.953, 19.071]	0.194 (0.083) [0.031, 0.357]	13.706 (2.843) [8.134, 19.279]
Wisconsin	9.647 (2.572) [4.606, 14.688]	0.243 (0.075) [0.095, 0.390]	9.890 (2.577) [4.838, 14.941]
West Virginia	11.092 (5.424) [0.461, 21.724]	0.325 (0.110) [0.110, 0.540]	11.417 (5.424) [0.786, 22.049]
Wyoming	5.439 (3.679) [-1.771, 12.650]	0.418 (0.154) [0.117, 0.719]	5.857 (3.709) [-1.413, 13.127]

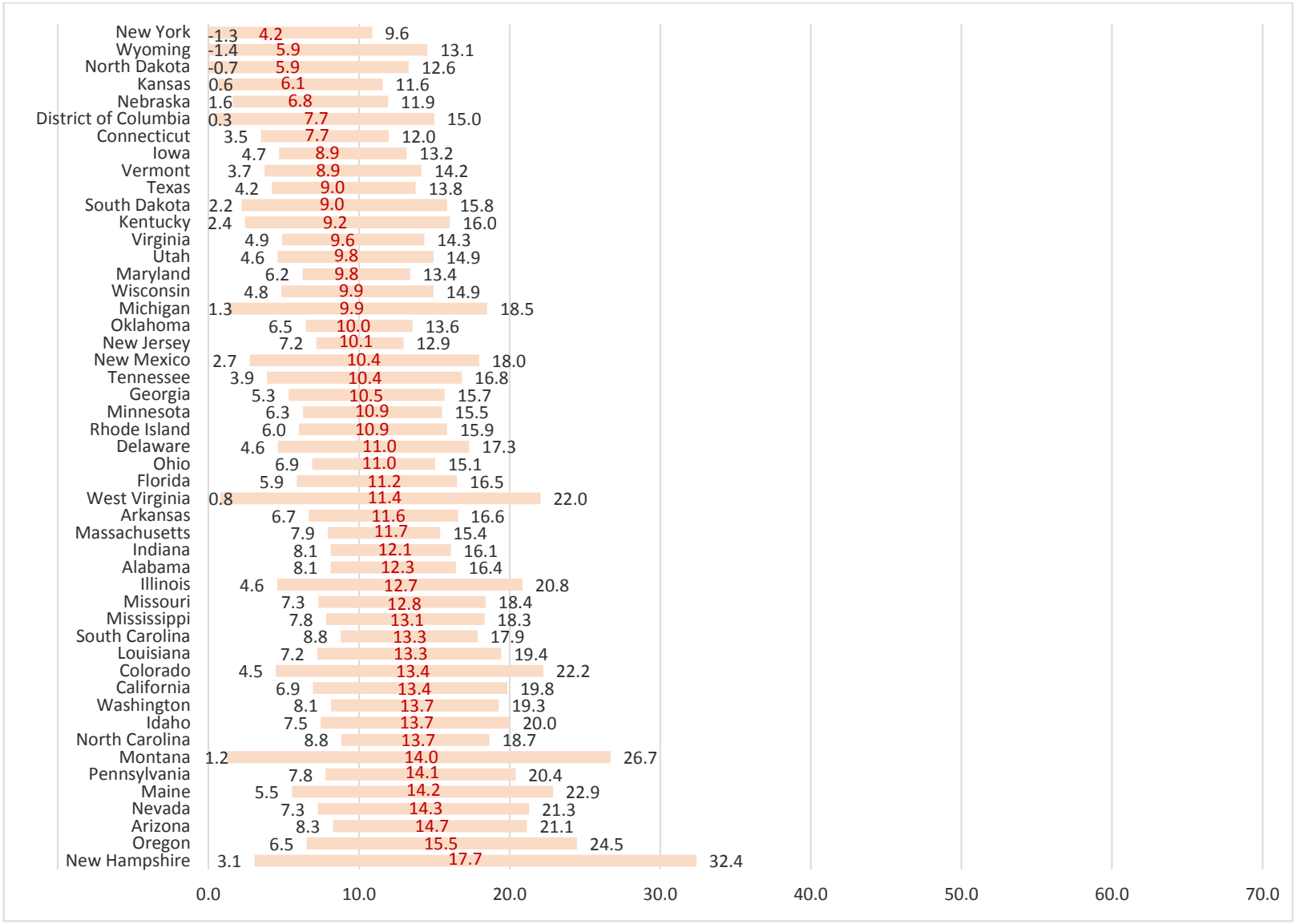
Note: For each State, the table shows: (1) the improper payment rate (either over-, under-, or total), (2) standard error (in parentheses), and (3) 95 percent confidence interval around the improper payment rate estimate [in brackets].

Figure II.7. Model-based State estimates of improper payments due to meal claiming error, NSLP



Note: Values in red represent the State improper payment rate estimates. Values in black represent the upper and lower bounds of the 95 percent confidence interval around the State estimate. The lower bound of the confidence interval that goes below the zero is not graphed in the figure.

Figure II.8. Model-based State estimates of improper payments due to meal claiming error, SBP



Note: Values in red represent the State improper payment rate estimates. Values in black represent the upper and lower bounds of the 95 percent confidence interval around the State estimate. The lower bound of the confidence interval that goes below the zero is not graphed in the figure.

E. Model components driving cross-State differences in improper payment rates estimation

Given the large variation by State in model-based improper payment rates related to each type of error, we conducted a decomposition analysis to assess factors associated with State variation in estimate of improper payment rates. The decomposition analysis is meant to provide context for the mechanics of the model-based estimates, illustrating how differences in explanatory variables affect estimates of improper payment. Findings from this analysis should not be interpreted causally or used to guide policy decisions. The models cannot be used to provide the actual change in improper payment rates that would be caused by targeting certain changes in the levels of explanatory variables. Rather, the models provide estimates of improper payment rates given the observed relationship between improper payment rates and explanatory variables in SY 2012–2013. The State model-based estimates can be thought of as a "best guess" of the actual State improper payment rate given the characteristics of the State's districts and the observed relationship between district characteristics and improper payment rates nationally in SY 2012–2013.

Table II.15 summarizes the findings comparing estimates of NSLP meal claiming error in New Hampshire (the State with the highest estimates of meal claiming improper payment rates) to those of average States nationally. The first row of this table shows the difference between the national estimate of the meal claiming improper payment rate and New Hampshire's estimate of the meal claiming improper payment rates. The remaining rows show how much of the total difference in the estimates of meal claiming improper payment rates is associated with average characteristics of districts in New Hampshire relative to the average characteristics of districts nationwide. In other words, these rows show which observed district characteristics lead the model to calculate a relatively high estimate of the meal claiming improper payment rate for New Hampshire.

The second column of Table IV.15 shows the average district characteristics for the nationwide sample on all explanatory variables included in the meal claiming model, as well as the predicted model-based improper payment rate for a district with those characteristics. The third column provides analogous values for New Hampshire. We estimated counterfactual improper payment rate estimates replacing the mean value of each variable included in the model (listed in Column 1) nationwide with the mean value of New Hampshire for that specific variable. This counterfactual answers the question "What would the nationwide average be if the mean explanatory variable value was the same as observed in New Hampshire?" Column four summarizes the difference between the predicted national improper payment rate and each predicted counterfactual rate, while Column five summarizes the percentage of total difference in the nationwide and New Hampshire rates explained by each explanatory variable.

Table II.15. Decomposition: Nationwide vs. New Hampshire, meal claiming error, NSLP

			Difference in total improper payments rate due to difference in explanatory variables	
	Nationwide	New Hampshire	Difference	Percentage of total difference
Total improper payment rate	**5.37**	**9.67**	**-4.30**	**100.00**
Enrollment (in 10,000)	8.27	0.53	0.14	-3.27
Average school size	670.48	529.35	0.09	-2.18
% free eligible students	51.76	27.89	-0.75	17.52
Percentage of certified as free not subject to verification	29.30	14.61	-1.23	28.61
% applications benefits changed in verification	25.86	21.07	-0.25	5.79
Publicly operated	0.98	1.00	-0.01	0.26
State direct certification performance rate	87.78	58.00	-2.29	53.27

Our analysis suggests that for meal claiming error for NSLP, the two factors that are most strongly related to New Hampshire's high model-based estimate of the NSLP improper payment rate are the (lower) percentage of students certified for free meals not subject to verification (derived from the VCR) and the (lower) percentage of eligible students directly certified for free meals (the State direct certification performance rate from the Report to Congress on direct certification implementation). The percentage of students certified for free meals not subject to verification is associated with lower overpayment rates. However, the mean of this variable for New Hampshire districts is substantially lower than the national mean (14.61 percent versus 29.3 percent). The percentage of eligible students directly certified for free meals (State direct certification performance rate) is associated with lower overpayment and underpayment rates, but the mean of this variable for New Hampshire districts is substantially lower than the national mean (58 percent versus 88 percent, respectively).

Given New Hampshire's pattern of explanatory variables and the observed relationship between explanatory variables and improper payment rates, New Hampshire is expected to have a meal claiming improper payment rate that is higher than the national average, as reflected in the higher-than-average, model-based, meal claiming, improper payment estimate for New Hampshire. However, the model-based estimate is not precisely estimated, and New Hampshire's actual improper payment rate could take a wide range of values, as reflected in the wide confidence interval around the model-based estimate of improper payments. Moreover, as noted earlier, the model cannot be used to infer the change in the actual improper payment rate that would result from a change in an explanatory variable. As a result, policies intended to reduce improper payment rates should focus on changes that are likely related to improper payment rates in that State. Policies should not focus exclusively on factors included in the model with the expectation that changes in these factors alone will cause particular changes in the actual improper payment rate.

Table II.16 summarizes the results for SBP for meal claiming error. For SBP, the factor that is most strongly related to New Hampshire's high model-based SBP improper payment rate estimate is the percentage of eligible students directly certified for free meals (from the Report to Congress on direct certification implementation). The percentage of eligible students directly certified for free meals is associated with lower overpayment rates, however the mean of this variable for New Hampshire districts is substantially lower than the national mean (88 percent versus 58 percent). It is worth noting that the factors mentioned above are only indirectly related to meal claiming error in a policy sense. As discussed in greater detail in the national modeling report, the meal claiming error models would be better able to predict meal claiming error if there were a national data source that collected information that has a more direct connection to meal claiming error, such as administrative review data on the accuracy of district meal claiming processes.

Table II.16. Decomposition: Nationwide vs. New Hampshire, meal claiming error, SBP

			Difference in total improper payments rate due to difference in explanatory variables	
	Nationwide	New Hampshire	Difference	Percentage of total difference
Total improper payment rate	**11.04**	**17.73**	**-6.68**	**100.00**
Enrollment (in 10,000)	7.93	0.56	-0.44	6.61
Average school size	652.57	525.16	0.83	-12.45
% free eligible students	53.17	29.37	-1.77	26.46
Percentage of certified as free not subject to verification	30.00	15.56	1.79	-26.80
% applications benefits changed in verification	25.83	21.18	-0.22	3.22
Publicly operated	0.98	1.00	-0.14	2.03
State direct certification performance rate	88.01	58.00	-6.75	100.93

Tables IV.17 and IV.18 provide decomposition results pertaining to certification error for non-CEP schools for Nevada, the State with the highest estimate of the improper payment rate. We found that the factor most strongly related to Nevada's high estimate of the model-based improper payment rate for both the NSLP and the SBP is the number of applications certified for free meals based on categorical eligibility.

While the decomposition analysis illustrates how district characteristics affect the estimates for each individual State, these results should be interpreted cautiously because the decomposition analysis is not intended to examine any causal relationships. To further illustrate this point, we compared the estimated rate for certification error for non-CEP schools in New York (the State with the lowest estimate of the improper payment rate) to those of average States nationally. Tables II.19 and 20 summarize the results for the NSLP and the SBP, respectively. We found that the factor most strongly related to New York's low model-based estimate of the improper payment rate for both the NSLP and the SBP is the percentage of students certified for

reduced-price meals, rather than number of applications certified for free meals based on categorical eligibility. The factors that affect the estimates are different for different States.

We also conducted the same analysis for certification error for CEP schools, and found that the factor most strongly related to District of Columbia's high model-based improper payment rate estimate for both NSLP and SBP in CEP schools is percentage of CEP schools in the district.

Table II.17. Decomposition: Nationwide vs. Nevada, certification error for non-CEP schools, NSLP

			Difference in total improper payments rate due to difference in explanatory variables	
	Nationwide	Nevada	Difference	Percentage of total difference
Total improper payment rate	**9.15**	**16.58**	**-7.43**	**100.00**
Used alternate random verification sample	0.22	0.03	-0.91	12.27
Percentage of verified reduced-price applications that had benefits changed in verification	25.86	27.92	-0.08	1.07
Percentage of all verified applications that had benefits changed in verification	26.17	30.11	0.25	-3.30
Percentage of verified reduced-price applications that did not respond in verification	35.95	55.10	-1.05	14.13
Percentage of verified all applications that did not respond in verification	32.85	49.71	0.83	-11.19
Percentage of students certified free without an application	28.18	25.98	-0.20	2.65
Percentage of students certified categorically	3.96	2.89	-0.43	5.77
Enrollment by 10K	8.13	24.99	-0.42	5.68
Percentage of students certified for free meals	51.03	44.84	0.36	-4.87
Percentage of students certified for reduced price meals	8.26	6.50	-0.99	13.33
Publicly operated	0.98	1.00	-0.19	2.52
State direct certification performance rate	87.50	89.00	-0.08	1.04
Number of applications certified categorically eligible	1444.86	6910.75	-5.19	69.88
Any special provision	18.26	10.92	-0.05	0.71
Percentage of verified free applications that had benefits reduced or terminated in verification	26.05	31.44	0.23	-3.14
Percentage of verified free applications that did not respond in verification	30.09	46.22	0.49	-6.66
Percentage of verified RP applications that had benefits reduced or terminated in verification	19.35	23.32	-0.01	0.12

Table II.18. Decomposition: Nationwide vs. Nevada, certification error for non-CEP schools, SBP

	Difference in total improper payments rate due to

			difference in explanatory variables	
	Nationwide	Nevada	Difference	Percentage of total difference
Total improper payment rate	**8.92**	**13.25**	**-4.33**	**100.00**
Used alternate random verification sample	0.21	0.03	0.73	-16.85
Percentage of verified reduced-price applications that had benefits changed in verification	25.95	27.86	-0.04	0.90
Percentage of all verified applications that had benefits changed in verification	26.19	30.06	0.12	-2.74
Percentage of verified reduced-price applications that did not respond in verification	36.29	55.17	-0.87	20.01
Percentage of verified all applications that did not respond in verification	33.06	49.75	0.42	-9.68
Percentage of students certified free without an application	28.81	26.10	-0.44	10.18
Percentage of students certified categorically	4.06	2.89	0.19	-4.46
Enrollment by 10K	7.82	25.13	-0.45	-10.41
Percentage of students certified for free meals	52.47	44.96	0.33	-7.59
Percentage of students certified for reduced price meals	8.22	6.49	-0.75	17.19
Publicly operated	0.98	1.00	-0.03	0.62
State direct certification performance rate	87.70	89.00	-0.20	4.55
Number of applications certified categorically eligible	1468.04	6949.44	-3.54	81.59
Total number of certified applications (in thousands)	9.05	36.71	-0.54	12.51
Percentage of verified free applications that had benefits reduced or terminated in verification	26.09	31.39	0.05	-1.15
Percentage of verified free applications that did not respond in verification	30.30	46.25	-0.18	4.06
Percentage of verified reduced-price applications that had benefits increased in verification	6.51	4.60	-0.05	1.22
Percentage of verified RP applications that had benefits reduced or terminated in verification	19.44	23.26	-0.002	0.05

Table II.19. Decomposition: Nationwide vs. New York, certification error for non-CEP schools, NSLP

			Difference in total improper payments rate due to difference in explanatory variables	
	Nationwide	New York	Difference	Percentage of total difference
Total improper payment rate	**9.15**	**3.074**	**6.074**	**100.00**
Used alternate random verification sample	0.22	0.16	-0.285	-4.698
Percentage of verified reduced-price applications that had benefits changed in verification	25.86	14.92	0.421	6.927
Percentage of all verified applications that had benefits changed in verification	26.17	15.19	-0.683	-11.243

Percentage of verified reduced-price applications that did not respond in verification	35.95	55.31	-1.061	-17.475
Percentage of verified all applications that did not respond in verification	32.85	52.46	0.967	15.915
Percentage of students certified free without an application	28.18	32.08	0.349	5.745
Percentage of students certified categorically	3.96	1.76	-0.880	-14.482
Enrollment by 10K	8.13	72.82	-1.620	-26.668
Percentage of students certified for free meals	51.03	51.41	-0.022	-0.364
Percentage of students certified for reduced price meals	8.26	23.18	8.422	138.649
Publicly operated	0.98	0.95	0.341	5.613
State direct certification performance rate	87.50	100.00	-0.646	-10.636
Number of applications certified categorically eligible	1444.86	2138.22	-0.658	-10.838
Any special provision	18.26	201.62	1.306	21.502
Percentage of verified free applications that had benefits reduced or terminated in verification	26.05	15.27	-0.467	-7.686
Percentage of verified free applications that did not respond in verification	30.09	48.78	0.573	9.430
Percentage of verified RP applications that had benefits reduced or terminated in verification	19.35	10.75	0.019	0.311

Table II.20. Decomposition: Nationwide vs. New York, certification error for non-CEP schools, SBP

			Difference in total improper payments rate due to difference in explanatory variables	
	Nationwide	New York	Difference	Percentage of total difference
Total improper payment rate	**8.921**	**2.955**	**5.965**	**100.00**
Used alternate random verification sample	0.21	0.15	0.229	3.835
Percentage of verified reduced-price applications that had benefits changed in verification	25.95	14.89	0.228	3.815
Percentage of all verified applications that had benefits changed in verification	26.19	15.12	-0.340	-5.694
Percentage of verified reduced-price applications that did not respond in verification	36.29	56.31	-0.920	-15.415
Percentage of verified all applications that did not respond in verification	33.06	53.34	0.510	8.549
Percentage of students certified free without an application	28.81	32.72	0.638	10.703
Percentage of students certified categorically	4.06	1.75	0.383	6.415
Enrollment by 10K	7.82	74.88	1.747	29.285
Percentage of students certified for free meals	52.47	52.44	0.001	0.024

Percentage of students certified for reduced price meals	8.22	23.71	6.675	111.897
Publicly operated	0.98	0.95	0.061	1.024
State direct certification performance rate	87.70	100.00	-1.863	-31.226
Number of applications certified categorically eligible	1468.04	2196.34	-0.470	-7.875
Total number of certified applications (in thousands)	9.05	36.51	-0.538	-9.020
Percentage of verified free applications that had benefits reduced or terminated in verification	26.09	15.20	-0.103	-1.721
Percentage of verified free applications that did not respond in verification	30.30	49.64	-0.213	-3.577
Percentage of verified reduced-price applications that had benefits increased in verification	6.51	4.14	-0.065	-1.098
Percentage of verified RP applications that had benefits reduced or terminated in verification	19.44	10.75	0.005	0.080

III. VALIDATION OF STATE-LEVEL STATISTICAL MODEL ESTIMATES

Summary

- Two approaches were used to validate the State-level models: (1) a joint test of the accuracy of the model's district-level predictions and (2) a simulation testing the accuracy of simulated States of different sizes.
- The joint test of the model's predictions at the district level shows that there are significant differences at the five percent level between model-based and sample-based estimates of improper payment rates due to certification error in non-CEP schools, certification error in CEP schools, and meal claiming error. However, a joint district validation is stronger than what is required for the model's stated purpose: a model that produces accurate district-level estimates is expected to produce accurate State-level estimates, but a model that is inaccurate at the district level may still produce an accurate estimate when estimates are aggregated to the State level.
- In response to this limitation, we conducted a simulation in which we used randomly selected groups of districts from the APEC-II sample to construct simulated States of different sizes; we then compared model- and sample-based estimates of the improper payment rate for each simulated State.
- When averaging estimates across simulated States, we found no statistically significant differences between model-based and sample-based estimates for any type of improper payment, regardless of the number of districts in the simulated State or the assumed correlation of differences within State. However, under most assumptions, the number of statistically significant simulated State differences is greater than what would be expected by chance.

The ideal validation exercise would require sample-based State estimates for large numbers of States; however, this approach as not feasible within the limits of the study's resources. Thus, we use two approaches to validate the State-level models: (1) a joint test of the accuracy of the model's district-level predictions and (2) a simulation testing the accuracy of simulated States of different sizes. In this chapter, we discuss each validation strategy for State-level models and summarize the validation results.

A. Validation based on joint comparison for multiple districts

A joint test of the model's predictions at the district level involves jointly comparing sample-based estimates of district-level improper payments to their respective model-based estimates across all districts in the APEC-II sample. Since districts are both the study's primary sampling units and the model's unit of analysis, validating the model at the district level provides an indirect assessment of its ability to produce accurate State-level estimates. A model that produces accurate district-level estimates is expected to produce accurate State-level estimates. Thus, the joint validation uses information from all sample districts to provide a single assessment of the model-based estimates for a given error type.

To formally explain the method, we offer the following example. Suppose we are interested in comparing an improper payment rate for a particular type of error for *n* districts. Let sample-based estimates for district *i* be $\widehat{s_i}$ and model-based estimates be $\widehat{m_i}$. We tested whether each of the model-based estimates differs from its respective sample-based estimate:

$$\hat{\boldsymbol{\gamma}} = \begin{bmatrix} \hat{m}_1 - \hat{s}_1 \\ \vdots \\ \hat{m}_n - \hat{s}_n \end{bmatrix} = \mathbf{0}$$

In order to determine whether the differences between model-based and sample-based estimates are jointly statistically significant, we calculated the Wald statistic:

$$W = \widehat{\gamma}' \widehat{\Sigma_{\gamma}^{-1}} \widehat{\gamma},$$

where $\hat{\boldsymbol{\Sigma}}_{\gamma}$ is an estimate of the variance-covariance matrix associated with the vector of estimate differences. We then performed a chi-squared test on the Wald statistic *W* to determine whether the observed differences in estimates are consistent with an accurate model.

Using the Wald statistic, **we find significant differences at the five percent level between model-based and sample-based estimates of improper payment rates due to certification error in non-CEP schools, certification error in CEP schools, and meal claiming error.** Thus, for each type of error, we reject that the district-level differences between the model-based and sample-based improper payment rate estimates are jointly equal to 0. Results for three types of error all indicate that the model-based State estimates do not match well with the sample-based State estimates based on primary data.

B. Validation based on simulated States of different sizes

An important limitation of the joint district test is that it is not a direct test of the model's ability to produce State-level estimates. A joint district validation is stronger than what is required for the model's stated purpose: a model that produces accurate district-level estimates is expected to produce accurate State-level estimates, but a model that is inaccurate at the district level may still result in an accurate estimate when aggregated to the State level. When constructing State-level estimates, some inaccuracies in district-level estimates will cancel out. For example, consider two districts, one which has a model-based estimate that understates its true improper payment amount and one which has a model-based estimate that overstates its true improper payment amount. If the inaccuracy of the model based estimates is the same magnitude for these to district, then the sum of model-based estimates will be accurate. As a result, a rejection of the district-level model does not necessarily imply that the State-level estimates are inaccurate.

In response to this limitation, we conducted a simulation in which we randomly selected groups of districts from the APEC-II sample to construct simulated States of different sizes. We tested the equality of the model-based improper payment rate estimates and the sample-based estimates across simulated States. These simulated findings give an indication of model performance when summing across district-level estimates to construct State-level estimates.

Formally explaining the method, we are interested in comparing an improper payment rate for a simulated State with n districts. First, we randomly selected (with replacement) n districts from the APEC-II sample to construct a simulated State. We repeated this selection 1,000 times. We conducted these 1,000 random draws for simulated States of sizes 10, 30, 50 and 100 (50 for certification error in CEP schools, given the small sample size), representing a range in the number of districts across States (the actual range is from 25 districts in Nevada to 1,247 districts in Texas).

For each simulated State we are able to construct a sample-based improper payment rate estimate as well as a model-based estimate. This is done by summing the relevant improper payment rates across the districts randomly selected to make up the simulated State. We calculated the differences between model-based and sample-based estimates as well as the variance associated with each difference.

One challenge with estimating the variances of the differences is accounting for within-State correlation of the difference terms. The APEC-II sample includes relatively few districts per State, so it is difficult to develop reliable estimates of this term. However, analysis using the APEC-II sample suggests that the within-State correlation is likely to be in the range of 0.05 to 0.10. For the purposes of this validation, we consider a range of values for the correlation parameter, including 0.00, 0.05, 0.10, and 0.20. Larger values of this correlation will lead to larger variances.

We are interested (1) whether the State-level model-based estimates are accurate on average, and (2) the extent to which model-based estimates are accurate for individual States. To assess whether model-based estimates are accurate on average, we calculated the average difference between model-based and sample-based estimates across the 1,000 simulated States with the same number of districts, as well as the average variance of difference. We then

conducted a *t*-test evaluating whether the average difference across simulated States is equal to 0. To assess the extent to which model-based estimates are accurate for individual States, we also conducted *t*-tests for each individual simulated State. We compared the number of simulated States with statistically significant differences to the number that would be expected by chance.

Table III.1 summarizes the validation test results based on simulated States with different numbers of districts. When averaging the estimates across simulated States, we find no statistically significant differences between model-based and sample-based estimates for any type of improper payment, regardless of the number of districts in the simulated State or the assumed correlation of differences within State. Moreover, the sizes of these differences are generally small in practical terms and decrease as the number of districts in the simulated States increases. For example, simulated States with 10 districts average a 1.41 percentage point difference between sample-based and model-based non-CEP certification improper payment rate estimates for the SBP; the average for simulated States with 100 districts is 0.03 percentage points. Thus, on average, the model can be expected to produce estimates that are similar to the sample-based estimates.

Table III.1. Validation results based on simulated states of different size

	Difference between model-based and sample-based estimates	p-value, assuming within-State correlation is:			
		0.00	0.05	0.10	0.20
Certification error for non-CEP schools, NSLP					
Districts in simulated State					
10	2.44	0.787	0.788	0.790	0.793
30	2.15	0.810	0.813	0.817	0.823
50	2.02	0.805	0.811	0.816	0.825
100	1.90	0.766	0.779	0.791	0.809
Certification error for non-CEP schools, SBP					
Districts in simulated State					
10	1.41	0.849	0.851	0.852	0.855
30	0.46	0.948	0.949	0.950	0.952
50	0.22	0.972	0.973	0.974	0.976
100	-0.03	0.995	0.995	0.996	0.996
Certification error for CEP schools, NSLP					
Districts in simulated State					
10	0.11	0.861	0.866	0.870	0.878
30	0.33	0.345	0.391	0.429	0.487
50	0.35	0.188	0.264	0.323	0.410
100	0.35	0.156	0.238	0.302	0.394
Certification error for CEP schools, SBP					
Districts in simulated State					
10	0.15	0.811	0.818	0.825	0.836
30	0.38	0.297	0.347	0.387	0.450
50	0.40	0.149	0.225	0.286	0.376
100	0.40	0.121	0.201	0.266	0.361

	Difference between model-based and sample-based estimates	p-value, assuming within-State correlation is:			
		0.00	0.05	0.10	0.20
Meal claiming error for all schools, NSLP					
Districts in simulated State					
10	-0.03	0.990	0.990	0.990	0.991
30	-0.16	0.929	0.932	0.935	0.939
50	-0.20	0.904	0.910	0.915	0.923
100	-0.20	0.884	0.895	0.904	0.917
Meal claiming error for all schools, SBP					
Districts in simulated State					
10	0.48	0.930	0.931	0.933	0.935
30	0.57	0.918	0.920	0.922	0.926
50	0.62	0.901	0.904	0.907	0.912
100	0.49	0.904	0.908	0.911	0.916

When examining differences between model-based and sample-based estimates for individual simulated States, findings vary depending on the improper payment rate, number of districts, and assumed correlation of differences within State (Table III.2). Under most assumptions, the number of statistically significant simulated State differences is greater than would be expected by chance. For example, 10 percent of simulated States with 100 districts had model-based non-CEP certification improper payment rates for the NSLP that were significantly different (at the 5 percent level) than the model-based rate, assuming a within-State correlation of 0.10; 5 percent would be expected by chance. The percentage of simulated States with statistically significant differences decreases with the number of districts in the simulated State and with the assumed correlation of differences within State. These percentages are somewhat lower for meal claiming error than for certification error. Therefore, although the model can be expected to produce estimates that are similar to the sample-based estimates on average, we also expect the model to produce estimates that are significantly different than the sample-based estimate for some States.

In summary, since we do not have the sample-based State estimates for the appropriate validation, we use two other validation methodologies to examine external validity of State-level statistical model estimates. Findings from the joint test of district-level predictions indicate that the district-level predictions are not sufficiently accurate to ensure the accuracy of State-level estimates. However, a joint district validation is stronger than what is required for the model's stated purpose. Findings from the simulation testing the accuracy of simulated States of different sizes suggest that no statistically significant differences between model-based and sample-based estimates for any type of improper payment, regardless of the number of districts in the simulated State or the assumed correlation of differences within State. However, we did find that more simulated States had statistically significant differences in model-based and sample-based estimates than would be expected by chance. Therefore, the interpretation of the State-model estimates still warrants caution.

Table III.2. Percentage of simulated states with significant differences between sample-based estimates and model-based estimates

	Percentage of simulated States with statistically significant differences, assuming with State correlation is:			
	0.00	0.05	0.10	0.20
Districts in simulated State				
10	26%	24%	21%	16%
30	32%	26%	20%	12%
50	27%	21%	16%	8%
100	17%	13%	10%	4%
Districts in simulated State				
10	36%	34%	32%	27%
30	34%	28%	25%	19%
50	29%	25%	20%	13%
100	16%	13%	10%	5%
Districts in simulated State				
10	12%	11%	10%	8%
30	12%	6%	4%	1%
50	23%	9%	3%	0%
100	29%	10%	3%	0%
Districts in simulated State				
10	13%	12%	10%	9%
30	17%	9%	5%	2%
50	29%	14%	6%	1%
100	37%	15%	5%	0%
Districts in simulated State				
10	25%	22%	20%	15%
30	17%	12%	9%	5%
50	14%	7%	4%	2%
100	8%	3%	1%	0%
Districts in simulated State				
10	30%	27%	25%	21%
30	32%	26%	21%	14%
50	30%	24%	19%	12%
100	27%	23%	19%	15%

IV. CONCLUSION

Summary

- Building on national models, we developed models to estimate improper payments due meal claiming error and to certification error in non-CEP schools and in CEP schools. State estimates generated from the models show that there is considerable variation in improper payment rates across States for these three sources of improper payments.
- We used two methods to validate the State model-based estimates. Findings from the joint test of district-level predictions—which is stronger than what is required for the model's purpose—indicate that the district-level predictions are not sufficiently accurate to ensure the accuracy of State-level estimates. Findings from the simulation test suggests that there are no statistically significant differences between model-based and sample-based estimates for any type of improper payment.
- Although the model-based State estimates are a useful tool for FNS to broadly assess how well States are doing in terms of administering the program, the estimates are limited. The key limitations are that the model-based estimates are imprecise and likely inaccurate for some States. The estimates are likely to become less accurate over time as the relationships between improper payment rates and State and district characteristics change.
- Based on these limitations, the model-based estimates of State improper payments should be interpreted cautiously. They should be regarded as inexact indicators of risk for State improper payments, not as precise, deterministic levels of improper payments in a State at a given time.

State-level estimates of improper payments by type of error allow FNS to identify States with high levels of improper payments and provide States with information on the types of error for which they are at highest risk and, thus, the school meal program components that would benefit most from improvement efforts. To fulfill this need, we developed statistical models to estimate State-level improper payments by building on the national models described in the APEC-II statistical model technical report (U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support, July 2015). We developed models to estimate improper payments due to certification error in non-CEP schools and in CEP schools, and those due to meal claiming error. State estimates generated from our modeling efforts show that there is considerable variation in improper payment rates across States for these three sources of improper payments.

We used two methods to validate the State model-based estimates: (1) a joint test of the accuracy of the model's district-level predictions and (2) a simulation testing the accuracy of simulated States of different sizes. Findings from the joint test of district-level predictions indicate that the district-level predictions are not sufficiently accurate to ensure the accuracy of State-level estimates. However, a joint district validation is stronger than what is required for the model's stated purpose: a model that produces accurate district-level estimates is expected to

produce accurate State-level estimates, but a model that is inaccurate at the district level may still result in an accurate estimate when aggregated to the State level. That is because district-level inaccuracies might cancel one another out when district-level estimates are summed to the State level.

Findings from the simulation testing the accuracy of simulated States of different sizes suggest that, on average, differences in model-based and sample-based estimates should be expected to be small, particularly for States with larger numbers of districts. In fact, we find no statistically significant differences between model-based and sample-based estimates for any type of improper payment, regardless of the number of districts in the simulated State or the assumed correlation of differences within State. However, we did find that more simulated States had statistically significant differences in model-based and sample-based estimates than would be expected by chance.

We conclude from this validation analysis that on average, the State-level models developed for APEC-II are likely to provide reasonable estimates of State improper payments. Therefore, the model-based State estimates can give useful information to help FNS target efforts to reduce improper payments and provide States with information on the types of error for which they are at highest risk.

Although the model-based State estimates are a useful tool, among other tools, for FNS to assess broadly how well States are doing in terms of administrating the program, it is important to interpret the estimates cautiously, keeping in mind their limitations:

- **The model-based estimates are typically not precise.** The width of the 95 percent confidence intervals around the estimates is as large as 29 percentage points for meal claiming error in the SBP.
- **The model based estimates are likely inaccurate for some States.** Findings from the validation analysis indicate that on average, simulated States have model-based improper payment estimates that are not significantly different than sample-based improper payment estimates. However, some individual simulated States did have statistically significant differences in model-based and sample-based estimates.
- **The model-based estimates may become less accurate over time.** The model-based estimates assume a stable relationship between improper payment rates and district characteristics over time. This is probably a reasonable assumption in the short run of a few years. However, the further out into the future the SY 2012–2013 statistical model results are used to predict improper payments, the less reasonable the assumption becomes.

Based on these limitations, the model-based State improper payment estimates should be regarded as inexact indicators of risk for State improper payments, not as deterministic levels of improper payments in a State at a given time. Thus, it would be appropriate to use the model-based estimates for low-stakes efforts to reduce improper payments, such as targeting technical assistance and identifying the school meal program components that would benefit most from improvement efforts. It would not be appropriate to use the model-based estimates for high-stakes endeavors, such as awarding bonuses or penalties on the basis of State improper payment estimates.

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APPENDIX A

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Table A.1a. 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)	- -

Variables		% Underpayment_L	% CF_RPE_L	% CF_PE_L	% CRP_PE_L
Verification variables (core)					
(14)	Percentage of verified RP 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)
(17)	Interaction of (1) and (16)	- -	- -	- -	0.0157 (1.022)
Certification variables (core)					
(18)	Percentage of students certified without an application	-0.0246 (0.0489)	-0.0474 (0.0840)	-0.140 (0.154)	- -
(19)	Percentage of students certified categorically	-0.394** (0.157)	-0.0269 (0.265)	-0.00297 (0.496)	- -
District characteristics (core)					
(20)	Enrollment (by 10k)	-0.0913** (0.0454)	0.0377 (0.0960)	0.169 (0.144)	-0.228 (0.304)
(21)	Percentage of students certified for free meals	-0.0107 (0.0388)	-0.0661 (0.0668)	0.122 (0.123)	-0.199 (0.268)
(22)	Percentage of students certified for reduced price meals	0.205 (0.148)	0.407 (0.261)	-0.941** (0.458)	-0.852 (1.081)
(23)	Publicly operated	1.755 (3.798)	7.197 (6.723)	7.941 (12.23)	22.48 (32.57)
Policy variables (core)					
(24)	State direct certification performance rate	0.00227 (0.0406)	-0.287*** (0.0716)	0.0548 (0.129)	0.443 (0.346)
Additional variables					
(25)	Percentage of students certified without an application	- -	- -	- -	0.547 (0.385)

Variables		% Underpayment_L	% CF_RPE_L	% CF_PE_L	% CRP_PE_L
Verification variables (core)					
(26)	Number of applications	0.00131***	-	-0.000464	-
	certified categorically eligible	(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 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 A.1b. Coefficient estimates from estimated regression equations, certification error for non-CEP schools for 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	- -	0.0018 (0.0525)	-0.0128 (0.0779)	- -
(11)	Interaction of (1) and (2)	- -	-0.295** (0.130)	0.190 (0.192)	- -
(12)	Percentage of verified free applications that did not respond in verification	- -	0.0290 (0.0478)	0.00779 (0.0714)	- -

Variables		% Underpayment_B	% CF_RPE_B	% CF_PE_B	% CRP_PE_B
Verification variables (core)					
(13)	Interaction of (1) and (12)	-	-0.0825	-0.0580	-
		-	(0.0925)	(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)
(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	-0.0448	0.140	-0.352
		(0.0354)	(0.0919)	(0.132)	(0.271)
(22)	Percentage of students certified for reduced price meals	0.188	0.356	-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					

Variables		% Underpayment_B	% CF_RPE_B	% CF_PE_B	% CRP_PE_B
Verification variables (core)					
(25)	Percentage of students certified without an application	- -	- -	- -	0.850** (0.386)
(26)	Number of applications certified categorically eligible	0.00113*** (0.000123)	- -	-0.000641 (0.000459)	- -
(27)	Total number of certified applications (in thousands)	- -	-0.111 (0.112)	- -	- -
Constant					
	Constant	0.156 (4.006)	34.00*** (9.95)	-9.360 (14.85)	-33.81 (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

Table A.2. Coefficient estimates from estimated regression equations, certification error for CEP schools for 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	-0.003	-0.003
	(019)	(.020)
Percentage SNAP recipients directly certified for free meals	-0.001	-0.001
	(.001)	(.001)
Percentage of 5- to 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

Table A.3. Coefficient estimates from estimated regression equations, meal claiming error, NSLP and SBP

	NSLP		SBP	
	% Overpayment	% Underpayment	% Overpayment	% Underpayment
Variable Name				
Enrollment (by 10k)	0.0155	0.0027	-0.0575	-0.00244
	(0.0184)	(0.007)	(0.0836)	(0.00169)
Average school size	0.00047	0.00019	0.00659	-0.00006
	(0.00187)	(0.0009)	(0.00766)	(0.000129)
Percentage of students certified for free meals	-0.0225	-0.0315	0.130	-0.00210
	(0.0651)	(0.0433)	(0.203)	(0.00623)
Interaction term: percentage of students certified for free meals interacts with the dummy variable of > 50%	0.0128	0.00264	-0.129	-0.00218
	(0.0344)	(0.0215)	(0.123)	(0.00381)
Percentage of certified as free not subject to verification	-0.0945***	0.0107	0.125	-0.00133
	(0.0284)	(0.0112)	(0.173)	(0.00172)
Percentage of applications with benefits changed in verification (excluding those who did not respond to the verification)	-0.0556*	0.00358	-0.0518	0.00561*
	(0.0314)	(0.0106)	(0.0736)	(0.00292)
Publicly operated	5.726***	-5.042	9.424**	0.183
	(2.015)	(4.627)	(4.698)	(0.160)
Percentage SNAP recipients directly certified for free meals	-0.0325	-0.0444*	-0.231	0.00645
	(0.0649)	(0.0261)	(0.177)	(0.00481)
Constant	6.334	10.57	13.70	-0.433
	(7.072)	(7.264)	(22.48)	(0.446)
Observations	143	143	141	141
R-squared	0.107	0.155	0.040	0.132

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

Robust standard errors in parentheses.

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

R-squared for logit and Tobit models (first stage % overpayment and second stage % overpayment low probability group) is pseudo R-squared.

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