School Nutrition Expenditures, Local Agricultural Revenues, and Farm-to-School Policies

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Abstract

School meal provision represents one of the largest food markets in the country. 31 million students eat lunch or breakfast at 100,000 schools each year, with the federal government spending $13B annually on subsidized breakfast and lunch programs. 42,000 of these schools engage in farm-to-school nutrition sourcing policies. Little is known about how much school systems source their food locally or about the average relationship between farm-to-school policy adoption and local sourcing of school food. I link 17 years of school district nutrition expenditures across the state of Georgia to a unique commodity-by-county survey of agricultural revenues to assess how much school systems source food from within their county and neighboring counties. I then incorporate four years of survey-based information on district farm-to-school policies to test how farm-to-school programs differentially impact local sourcing patterns. Identification comes from spatiotemporal variation in school district adoption of the policy, where I present results of a simple difference-in-differences regression model, spatially-lagged regression models, and a plausibly causal triple difference specification exploiting variation in expenditures associated with an unrelated nutrition policy shift. Preliminary results suggest that $8B, or 4.7% of all agricultural revenues in the state from 2001-2017, may be attributed to nutrition spending by schools. Meanwhile, roughly $800M in local revenues may be attributed specifically to farm-to-school sourcing policies over the sample period.

Keywords: Farm-to-Schools; School Nutrition; Food and agricultural policy; Community development.
JEL:

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1 Introduction

The public K-12 student body in Georgia totaled 1.8 million in 2016, of which 1.1 million received free or reduced price lunch and breakfast. This represents at least 3% of the state's meal consumption.[1] Local, state, and federal nutrition expenditures for these meals amounted to $13.8 billion from 2001 to 2017. In recognition of the economic importance of school-provided meals, every state has implemented some form of farm-to-school incentive program, with 42% of schools participating in some form of farm-to-school policy in 2014-15.[2] Farm-to-school policies, however, are adopted by school districts. These heterogeneous district policies typically emphasize sourcing school food from local food vendors, especially of food considered more nutritious, and student educational programs that promote healthful dietary practices. To date, no study has assessed the average long-term role that these diverse policies play on local agricultural revenues.

This study asks whether these district policies relate to changes in local agricultural revenues, where local refers to the same county and contiguous counties. I also show evidence on the baseline role that school district nutrition expenditures play on local agricultural revenues. Finally, I provide suggestive evidence as to the types of agricultural products that are most associated both with farm-to-school policies and school district nutrition expenditures in general.

To answer these questions, I rely on variation in the timing of farm-to-school policy adoption and the approximate number of meals likely affected by the policy changes. I secure causal identification with two statistical models: a panel with spatial lags and regionally-correlated standard errors and a triple-difference model relying on school-level adoption of the Community Eligibility Provision of the Healthy Hunger Free Kids Act.

I find that as much as 5% of agricultural revenues in a county may be attributed to school nutrition expenditures. Moreover, roughly 6% of the inflation-adjusted nutrition expenditures from 2001-2017, or $800 million, were diverted to more local sources as a result of farm-to-school policy adoption. Farm-to-school adoption is strongly associated with local revenue increases of animal products, fruits and vegetables, and agrotourism. This study contributes to a sparse literature on the role that school nutrition expenditures and sourcing policies play on local agricultural revenues.

[1] One third of meals for 1.8M/10.5M people in the state for 180 out of 365 days in the year (assuming only one meal per student per day).

[2] Christensen et al. (2018)

2 Prior Work

A large literature has investigated farm-to-school policies. Joshi et al. (2008) provide an early synopsis of this literature, categorizing farm-to-school studies by those relating to changes in students and parents, those relating to changes in teacher, administration, and cafeteria practices, and those relating to farmer behaviors. For concision, I will focus on the latter category. Many survey-based studies have sought to conceptualize the economic context of farm-to-school policies, examining scalability of farm-to-school policies, institutional factors surrounding the policies, and the barriers to success of the programs; several studies rely on the 2015 USDA Farm to School Census or the USDA Census of Agriculture's 2015 Local Food Marketing Practices Survey.[3] These surveys, however, are cross sections of one year. Relatively few studies focus on actual observed economic impacts of farm-to-school policies, perhaps because doing so requires solid identification that purges selection bias, spatial autocorrelation, policy spillovers, and even reverse causation.[4]

Christensen et al. (2018) provides an overview of eight studies assessing the economic impacts of farm-to-school programs. Six of the studies were not peer-reviewed, employ varying methods that complicate cross-state comparisons, rely on short (typically one-year) time windows, and often do not use primary data. The authors highlight two case studies of special merit, one in Georgia and the other in Minnesota. In these studies, information on school district expenditures on local food was combined with surveys of farmers supplying to school districts. These measures were inputted into a software known as IMPLAN (IMpact Analysis for PLANing) that allows for disentangling direct, indirect, and induced economic impacts both with and without opportunity costs. The key finding of these studies is that each dollar spent on farm-to-school programs has an implied multiplier effect of 1.5 on output with opportunity costs and 2 without opportunity costs.[5] In a related work, Christensen et al. (2019) show that farm-to-school purchases from direct local vendors instead of intermediate suppliers is cheaper for school districts.

This study adds to the previous work in several ways. First, I provide estimates of agricultural

[3] Botkins and Roe (2018), Deller et al. (2017), Holland et al. (2015), Hoffman et al. (2017), Lee et al. (2019),Thompson et al. (2014)

[4] O'Hara and Benson (2019) show that local production conditions are associated with patterns of local-food purchasing by districts, suggesting the presence of reverse causation whereby supply and local production determines the extent to which school districts purchase locally (and not a farm-to-school policies).

[5] The average multipliers in the Minnesota and Georgia studies. These measures closely resemble the spending multipliers found in the six unpublished studies briefly discussed in the paper, which find spending multipliers of 1.1-2.4.

revenues related to nutrition spending across all farmers and all school districts in the state. The case studies mentioned in Christensen et al. (2018) average information from only seven Georgia farms and five farms near Minnesota. Moreover, whereas food expenditure data in the Georgia case study was based on the stated farm-to-school nutrition expenditures of 61 school districts in one survey year (2014-15), I incorporate all nutrition expenditures across all districts over 17 academic years.[6] This broader reach allows estimation of baseline local food purchases by school districts that do not engage in farm-to-school policies. Next, I observe detailed commodity revenue information, allowing me to separately estimate effects over commodity groups and by specific commodity. Only one study surveyed by this paper investigated how farm-to-school purchases may be broken up by type of commodity, and that study relied on purchase information in a relatively small geographic region during only the first year of a grant-funded policy roll-out.[7] Finally, I incorporate variation in nutrition expenditures associated with a policy unrelated to farm-to-school adoption to secure causal identification purged of selection bias and reverse causation.

3 Data

I rely on six sources of information on school districts and one statewide survey of county-level agricultural revenues. Although I observe farm-to-school policies at the district level, I aggregate to the county level of analysis for estimations on local agricultural revenues. I describe each data source below.

3.1 School District Information

3.1.1 Farm-to-School Policies

Information on the adoption of farm-to-school policies comes from school district applications for a statewide incentive program known as the Golden Radish Award.[8] A wide range of information on heterogeneous school district farm-to-school policies is included on these applications for the

[6]The expenditure data is from the federally-mandating accounting ledgers of school districts, ensuring accurate reporting.

[7]Watson et al. (2018)

[8]The program recognizes districts with five different levels of engagement to farm-to-school policies. These levels are platinum, gold, silver, bronze, and honorary. An additional "outstanding" award is given to one district. The application portal is here.

award, which is administered by a non-profit organization known as Georgia Organics in cooperation with the Georgia Departments of Education, Health, and Agriculture. Of special interest on the application is the first year a district implemented farm-to-school policies, which often predates the first application for a Golden Radish Award.[9] The program has expanded dramatically; 30 school districts received some form of Golden Radish recognition in fiscal year (FY) 2014 while over 75 school districts did so in FY 2017. The Golden Radish incentive program appears to affect school district culture, with 40 school districts institutionalizing farm-to-school language in their school district policies.[10] A map depicting all school districts ever adopting some form of farm-to-school policy is presented in Figure 1. Table 1 shows certain key summary statistics broken up by farm-to-school policy adoption status. I supplement this information with the 2015 USDA Farm-to-School Census, the only census of its kind, which records district-reported nutrition expenditures on farm-to-school foods.[11]

3.1.2 Community Eligibility Provision Adoption

The Georgia Department of Education maintains lists of schools and school districts that are eligible for participation in the Community Eligibility Provision of the Healthy Hunger Free Kids Act (HHFKA).[12] These spreadsheets list all schools that actually participate in the CEP program from FY 2016 to FY 2019. Measures of the number of eligible students, the number of students in participating schools, and the number of marginal students induced into free lunch by the program are depicted in Table 1. These figures are broken up across districts that ever have or do not ever have a farm-to-school policy.

3.1.3 Nutrition Expenditures

The Fiscal Research Center of the Andrew Young School of Policy Studies at Georgia State University maintains records of governmental expenditures in every school district across the state. I

[9] The survey also includes information on the district-wide number of farm visits, days serving local food, local meals, farm promotions, farm-based classroom lessons, schools with gardens, professional development staff, and local food taste tests among others. Information from these other questions is often missing, available for a relatively short sample window, and self-reported, with possibly heterogeneous definitions and reporting standards across districts. Information on these variables is presented in Appendix Table 1.

[10] Golden Radish Infographic.

[11] Data Portal.

[12] On this public web-page.

obtained records on nutritional expenditures broken up by local, state, and federal funding source from FY 2000 to FY 2017. Due to stipulations of tracking federal funding, these data are some of the most accurate expenditure accounts kept by the state of Georgia.[13] The data can be broken up by school and by nutrition expenditure code, which tracks the different types of nutritional outlay. However, over 95% of nutrition expenditures are on food, so I disregard the funding categories. I also disregard records by school due to missing values. Table 1 displays nutrition expenditures from state, local, and federal sources broken up by farm-to-school policy adoption status. Clearly, districts that adopt farm-to-school policies are statistically different from those that do not, being larger on average.

3.1.4 Student Enrollment and Demographics

Supplemental information on the total number of students across each school and school district was obtained through public records posted to the website of the Georgia Department of Education.[14] This information was linked to CEP status and other relevant characteristics using the Stata add-on Education Data Portal package developed by Matt Chinggos and others at the Urban Studies Institute.[15] This information is summarized in Table 1.

3.2 Agricultural Revenues

The Farm Gate Values Survey, maintained by the Center for Agribusiness Economic Development at the University of Georgia, maintains records of agricultural revenues across 160 Georgia counties from 2000-2018. The information is collected by agents within each county and accurately reflects total revenues in each county region.[16] The information includes revenues across 89 different commodity categories, with many commodity categories further broken down by type of grow

[13]Conversations with Nicholas Warner at the Fiscal Research Center.

[14]The data reporting tab on this webpage sub-links for reports on enrollment and free-and-reduced price lunch status.

[15]Education Data Portal (Version 0.3.0), Urban Institute, Center on Education Data and Policy, accessed May, 1st, 2019, https://educationdata.urban.org/documentation/US Department of Education Common Core of Data/

[16]In 2017, the FarmGate Values Survey reports slightly over $10 billion in revenues for agricultural products, while for the same year the US Census of Agriculture reports that the market value of all agricultural products sold in the state was $9.5 billion. This suggests that the Farm Gate Values survey accurately captures all agricultural products sold, and that the survey may in fact be a more accurate accounting of farm revenues than the national agricultural census.

technique. For this analysis I eliminate products likely unrelated to school nutrition.[17] The third panel of Table 1 displays information on agricultural revenues broken up by type of product. Although school districts that adopt farm-to-school policies are clearly not comparable to those that do not, agricultural revenues across both types of county are remarkably similar and not statistically distinguishable from each other in any commodity category used by this study. The products included in different classes of commodity, such as fruit, vegetable, dairy, or meat, are listed in Table A1.

4 Empirical Strategy

This paper exploits variation in the timing of farm-to-school policy adoption and student population affected to assess the role school nutrition expenditures and sourcing policies play on local agricultural revenues. I present the results of four statistical models: a naive panel fixed-effects OLS regression resembling a difference-in-differences model, a spatial lagged panel fixed effects model, and a triple difference model relying on exogenous adoption of the Community Eligibility Provision across schools. Strengths, weaknesses, and identifying assumptions of each model are discussed below.

4.1 Naive OLS Regression Model

I first present a straightforward empirical model relying on variation in the timing of farm-to-school policy adoption across school districts. Let y_{ipt} represent agricultural revenues in county i for agricultural product p in year t, where product p is often defined as all agricultural products.

$$y_{ipt} = \beta FTS_{it} + Z_{it}\gamma' + \eta_i + \tau_t + \epsilon_{ipt}. \tag{1}$$

In Equation 1, FTS_{it} is a variable representing adoption of farm-to-school policies by school districts within a county. Because school districts do not perfectly correspond to counties, this term is a continuous variable representing the proportion of a county's public K-12 population served

[17] Products considered not relevant to school nutrition expenditures are excluded from the analysis in all regressions. These products include timber, camping, Christmas trees, corn mazes, crop insurance, fishing, horses, goats, flight quail, meat quail, tobacco, wildlife observation, government payments, and hunting leases for deer, duck, and turkey.

by farm-to-school-adopting districts in a school year.[18] Z_{it} controls for time-varying total student population within the county. η_i is a county fixed effect and τ_t is a year fixed effect. These fixed effects control for baseline differences in agricultural revenues across counties and secular changes in agricultural revenues across the state over time.

Identifying Assumptions: To predict the causal effect of farm-to-school policies on local agricultural revenues, Equation 1 requires that counties with more farm-to-school adopting districts would have had similar counter-factual post-adoption trends in agricultural revenues as counties with no (or fewer) adopting districts. An important potential violation of this assumption would be if county populations have changing preferences over time that are correlated both with agricultural revenues and the timing of farm-to-school policy adoption. For example, counties with more adopters of the policy may experience simultaneous increases in purchases from farmers markets, or retailers may change their sourcing patterns at the same time as the policy adoption.

Equation 1 also requires that the expectation of the error term, ϵ_{ipt}, is zero conditional on the model covariates. This is unlikely due to spatial correlation and policy spillovers. To start with spatial correlation, agricultural revenues are inherently place-based; agglomeration effects, land suitability and availability, and distance to markets all affect the location and magnitude of agricultural revenues. The county unit of observation does not perfectly overlap with these locational factors, so we may expect regionally-correlated agricultural revenues to violate the assumptions of the model. Moreover, time-varying factors in productivity may cause regional perturbations in the error term, also violating the model's assumptions. Next, policy spillovers occur when school districts sourcing from "local" vendors source from nearby counties. This tendency would attenuate the estimated policy change related to farm-to-school adoption because counties without the policy change may experience simultaneous increases in agricultural revenues.

4.2 Spatial Lag Model

To address potential issues with spatial correlation and policy spillovers raised in subsection 4.1, I present a spatial lag model that allows for regionally-correlated agricultural revenues and regionally-

[18][Forthcoming] In Appendix Table ??, I show the results when applying different definitions of farm-to-school policy adoption within a county. These alternative definitions include a binary equal to one if at least half a county's population is served by a farm-to-school adopting school district in a school year, the proportion of expenditures a district reports as local on the the 2015 Farm to School Census, and the absolute number of students in a county served by a farm-to-school-adopting districts in a school year.

correlated error terms. Let y_{ipt} represent agricultural revenues in county i for agricultural product p in year t, where product p is often defined as all agricultural products.

$$y_{ipt} = \lambda \sum_{j=1}^{n} w_{ij} \cdot y_{jpt} + \beta FTS_{it} + Z_{it}\gamma' + \eta_i + \tau_t + \epsilon_{ipt}. \tag{2}$$

In Equation 2, $\sum_{j=1}^{n} w_{ij} * y_{jpt}$ is a weighting term that controls for variation in agricultural revenues in all counties in the state, y_{jpt}, where the weighting term w_{ij} is the inverse distance between county i and county j. The term λ measures the correlation in agricultural revenues across county i and counties j. As before, FTS_{it} is a variable representing adoption of farm-to-school policies by school districts within a county, Z_{it} controls for time-varying county characteristics, η_i is a county fixed effect, and τ_t is a year fixed effect. In this model, ϵ_{ipt} is a spatially autoregressive error term that allows agricultural revenue perturbations to be affected by error term disturbances in nearby counties, where I define "nearby" counties $j \in \{1, ..., n\}$ as all contiguous counties.[19]

Next, I present a spatial lag model that allows direct testing of effects of nutrition expenditures and farm-to-school policy adoption on the agricultural revenues of contiguous counties. Let $\mathbf{Y}$ represent y_{ipt} and $\mathbf{W}$ represent the lagging weights $\sum_{j=1}^{n} w_{ij}$. Consider the following (equivalent) spatial regression specifications:

$$\begin{aligned} y_{ipt} = \lambda \sum_{j=1}^{n} w_{ij} \cdot y_{jpt} + \beta_1 FTS_{it} + \beta_2 \sum_{j=1}^{n} w_{ij} \cdot FTS_{jt} \\ + Z_{it}\gamma_1' + \sum_{j=1}^{n} w_{ij} \cdot Z_{jt}\gamma_2' + \eta_i + \tau_t + \epsilon_{ipt} \end{aligned} \tag{3}$$

$$\mathbf{Y} = \lambda \mathbf{WY} + \beta \mathbf{WFTS} + \gamma \mathbf{WZ} + \epsilon \tag{4}$$

[19]Note that the error term disturbances are allowed to be correlated only with contiguous counties, while the dependent variable is lagged across all counties in inverse proportion to distance. I adopt different contiguity matrices because the year controls handle error term disturbances that are constant across all counties but do not control for sub-regional fluctuations (for example, in the case of a drought). The contiguous-county error matrix allows for such correlations. Spatially correlated agricultural revenues, meanwhile, are influenced by markets in proportion to their distance to those markets and not simply by the average revenues in contiguous counties, so it seems more reasonable to adopt an inverse-distance contiguity matrix.

In Equation 4, the weighting term $\sum_{j=1}^{n} w_{ij} * y_{jpt}$ is the same as before. Likewise, FTS_{it} is a variable representing adoption of farm-to-school policies by school districts within a county, Z_{it} controls for time-varying county characteristics, η_i is a county fixed effect, τ_t is a year fixed effect, and ϵ_{ipt} is a spatially autoregressive error term that allows agricultural revenue perturbations to be affected by error term disturbances in nearby counties. The two new terms, $\sum_{j=1}^{n} \cdot FTS_{jt}$ and $\sum_{j=1}^{n} \cdot Z_{jt}$, allow testing for policy spillover effects in nearby counties. β_2 measures the extent to which farm-to-school policy adoption affects agricultural revenues in nearby counties, while γ_2 is the relationship between each time-varying covariate in the vector Z_{jt} and agricultural revenues. Of special interest, γ allows testing the extent to which local nutrition expenditures impact agricultural revenues of contiguous counties.

Identifying Assumptions: To predict the causal effect of farm-to-schools policies on local agricultural revenues, Equation 4 requires that counties with more nearby farm-to-school adopting districts would have had similar counter-factual post-adoption trends in agricultural revenues as counties with no (or fewer) nearby adopting districts. As before, one violation of this assumption is the selection bias associated with adopting districts having unrelated increases in agricultural revenues correlated with the timing of farm-to-school policy adoption. To assess the importance of this form of selection bias, we next turn to an empirical model relying on exogenous changes in another school nutrition policy, the community eligibility provision of the Healthy Hunger Free Kids Act.

4.3 Community Eligibility Provision

To secure causal identification, I employ a triple difference model that exploits simultaneous variation in two policies. The first is school-district adoption of farm-to-school policies. The second is the Community Eligibility Provision (CEP) of the Healthy Hungry Free Kids Act (HHFKA), which allows schools with over 40% of their student population qualifying for some form of federal aid to serve free lunch to all their students, saving administrative burden. Although many schools are eligible CEP schools, only some actually participate. Participating schools experience an increase in the number of meals that they serve to students as marginal students are induced into eating cafeteria food. These increased nutritional outlays are primarily financed by the federal government, making it unlikely that coincidental local tax changes may indirectly affect agricultural revenues. Causal identification comes from the fact that, when faced with the need and ability to purchase more school food, farm-to-school districts may be more likely to source it locally. Figure 2 shows the increase in expenditures among districts with CEP-participating schools. Table A3 provides empirically demonstrates that CEP adoption reliably increases nutrition expenditures every definition of CEP participation.

Let y_{ipt} represent agricultural revenues in county i for agricultural product p in year t, where product p is often defined as all agricultural products.

$$y_{ipt} = \beta FTS_{it} \cdot CEP_{it} + Z_{it}\gamma' + \eta_i + \tau_t + \epsilon_{ipt} \tag{5}$$

In Equation 5, terms FTS_{it}, Z_{it}, η_i, τ_t, and ϵ_{ipt} are defined as before. The term CEP_{it} represents the share of students marginally induced into free meals according to school-level adoption of the Community Eligibility Provision.[20] Rather than identifying CEP_{it} off potentially endogenous participation in the program, the term represents the county share of students induced into "free meal" status by adoption of the program. For example, a county in which every student qualifies for free-and-reduced price lunch before the HHFKA, and in which all schools adopt the CEP, would receive a value of 0 because no student is marginally induced into free-meal status. Likewise, a school district in which no student elects to receive free-and-reduced price meals before the HHFKA, where all schools within the county adopt the CEP, would have a CEP_{it} value of one. In practice, neither situation occurs.

One might also consider a spatially-lagged version of Equation 5. Let y_{ipt} represent agricultural revenues in county i for agricultural product p in year t, where product p is often defined as all agricultural products.

$$y_{ipt} = \lambda \sum_{j=1}^{n} w_{ij} \cdot y_{jpt} + \beta_1 FTS_{it} \cdot CEP_{it} + \beta_2 \sum_{j=1}^{n} w_{ij} \cdot FTS_{jt} \cdot CEP_{it}$$

[20]For each county, $\text{CEP}_{it} \equiv \sum_{s=1}^{n} (1 - FRL_{st}) \cdot Participation_{st} \cdot \frac{SchoolEnrollment_{st}}{CountyEnrollment_{it}}$ over all schools in a district $s \in \{1, ..., S\}$ where $Participation_{st}$ is a binary variable representing school s participation in the CEP program in year t.

$$+Z_{it} \cdot CEP_{it}\gamma_1' + \sum_{j=1}^{n} w_{ij} \cdot Z_{jt} \cdot CEP_{it}\gamma_2' + \eta_i + \tau_t + \epsilon_{ipt} \tag{6}$$

In Equation 6, terms FTS_{it}, CEP_{it}, Z_{it}, η_i, τ_t, and ϵ_{ipt} are defined as before. This regression model synthesizes the causal identification strategies presented in Equation 4 and Equation 5, allowing potentially unbiased estimation of the effect of nutrition expenditures on local agricultural revenues and the effect of farm-to-school policy adoption on local agricultural revenues, where local includes both the same county and contiguous counties. A pitfall of this well-identified model is that CEP variation is only present for a short period of the sample (3 out of 17 years), so it is less likely that significant relationships will be observed.

Identifying Assumptions: To estimate the causal relationship between nutrition expenditures and farm-to-school policy adoption and local agricultural revenues, Equation 5 and Equation 6 require that there are no county-specific factors correlated both with the share of students induced into "free" meal status and farm-to-school policy adoption across districts. Such correlated factors must also impact local agricultural revenues. In Equation 6, the correlated factors must be county-specific, as local revenues are allowed to fluctuate with regional agricultural revenues and regional disturbances in agricultural revenues. It seems unlikely that some factor may be correlated with both of these variables simultaneously and not be controlled by county fixed effects, time-varying county characteristics, and regional lags and correlated errors. The primary shortcoming of this identification model, rather, is that a relatively small share of students are induced into free meal status over a relatively short time frame. This weakness reduces the likelihood of observing statistically significant relationships.

5 Results

5.1 Local Economic Effects of Nutrition Expenditures

I find strong evidence that school nutrition expenditures increase local agricultural revenues. Perhaps as much as $0.60 of each dollar spent on school food is recouped by local farmers. Farm-to-school policies, moreover, likely increased local agricultural revenues for animal products, fruits and vegetables, and agrotourism. Table 2 presents results across all empirical specifications from section 4, including five regression models testing for local agricultural revenue increases from baseline school district nutrition expenditures and five regression models testing for local agricultural revenue increases related to adoption of farm-to-school policies. I discuss the findings of each specification below.

Columns (1) and (2) of Table 2 present the results of a naive panel fixed effects model, where in column (2) the variable representing farm-to-school policies is an interaction between farm-to-school adoption and post-adoption year weighted to the county by student population. The first row in these models shows that nutrition expenditures are highly correlated with agricultural revenues in the same county. However, the coefficients of 1.3 and 1.1 suggest that each dollar spent by school districts on food increased agricultural revenues in the same county by *more than* 1 dollar. It is unclear whether this finding relates is an approximation of the spending spillovers of 1.5 estimated in Christensen et al. (2018) or if it relates to the influence of selection bias and cross-district spending spillovers. The coefficient on farm-to-school policy adoption, "FtS Policy," is large and almost significant at the 90% level of confidence. The point estimate 6884, which is expressed in thousands, suggests that each post-policy adoption year is associated with increases in local agricultural revenues of \$6.8M. Scaling this average implies agricultural revenue increases of \$1.8B related to farm-to-school policies.[21] Although this is small in comparison to the \$167B in agricultural revenues from 2001-2017, it represents about 6% of nutrition expenditures over the sample, \$13.8B.

Columns (3) through (6) of Table 2 display results of empirical specifications discussed in subsection 4.2. In these models, variations in county agricultural revenues are lagged by revenues in all other counties in the state in proportion to the inverse distance between county i and j. Moreover, error term disturbances in contiguous counties are allowed to be correlated. Columns (3) and (5) show the baseline relationship between nutrition expenditures in county i and agricultural revenues in both county i and in counties j that are contiguous to county i. The point estimates suggest that roughly \$0.63-\$0.68 of every dollar spent on school nutrition is recouped by farmers in the same county, while perhaps as much as \$0.37 is recouped by farmers in bordering counties. Since these terms add up to one, and it seems unlikely that *all* nutrition expenditures occur so locally, these estimates may be influenced by selection or spending multipliers. Columns (4) and

[21] The average effect over 68 counties with an average of 4.2 post-policy years, or 288 total post-policy district years, can be converted to the total implied effect by multiplying the point estimate times 288 district years and then 1000 from scaling the values.

(6) jointly estimate the effect of nutrition expenditures and farm-to-school policies on agricultural revenues in local and nearby counties. Although these models do not control for selection into the farm-to-school policies, they accurately control for regionally correlated revenue levels and error-term disturbances. The farm-to-school policy variable is consistent across both models, suggesting large local economic effects of roughly \$900M. The coefficient on "FtS Policy" in the sixth row suggests that perhaps \$30M in nutrition spending was recouped by neighboring counties, although this term is not significant.

The final four columns of Table 2 display results of the empirical specifications discussed in subsection 4.3. These estimates rely on variation in nutrition spending resulting from a federal policy change that is unrelated to farm-to-school adoption, plausibly purging the selection bias associated with school districts adopting farm-to-school programs. The variable CEP is the share of a county's students that are induced into free lunch status by the new policy.[22] The interpretation of the coefficients in these models is a bit clunky; technically, the coefficient of 38,000 in the third row means that, if every student in a typical district were induced into free lunch status by the CEP, then the resulting increase in nutrition expenditures would lead to a \$38M increase in local agricultural revenues. Since the proportion of students induced into free lunch status is relatively small, this point estimates in columns (7) through (10) must be scaled down according to the observed share of marginally induced free lunch students. The implied actual change in local agricultural revenues associated with this policy is therefore the \$38M point estimate times the sum of observed shares of students induced into free lunch eligibility in each district in each year.[23] This implied increase resulting from CEP policies is \$425M, or roughly 1.4% of all agricultural revenues from FY 2015 to FY 2017 (\$30B). The interpretation procedure for the $CEP * FtS$ coefficients is similar. The coefficient 8813, for example, means that if every student in a typical farm-to-school district were induced into free lunch status by the CEP, then local agricultural revenues would increase by \$8.8M, while agricultural revenues in adjacent counties would increase by \$23M. From these coefficients, the implied increase in agricultural revenues in local and contiguous counties resulting from farm-to-school policies is approximately \$765M.[24] The point estimates on the farm-

[22] As shown in Table A3, school-level adoption of the CEP policy in general is strongly statistically associated with increases in nutrition expenditures.

[23] Actual change $\equiv$ \$38M $\cdot \Sigma CEP_{it}$.

[24] The scaling process involves both extrapolating to all farm-to-school district policy years and scaling back by the portion exclusively attributable to the CEP. The calculation is \$8.8M $\cdot \frac{\Sigma FtS_{it}}{\Sigma CEP_{it}} + \$22.6M \cdot \frac{\Sigma FtS_{it}}{\Sigma CEP_{it}}$.

to-school policy adoption interacted with the share of marginally induced CEP students are not significant, but the implied economic effects are nevertheless similar to those obtained in columns (4) and (6).

5.2 Local Economic Effects of Nutrition Expenditures by Commodity Type

I present a subset of regression models across animal products, fruits and vegetables, and agrotourism in Table 3, Table 4, and Table 5. Animal products, which includes revenues for beef, catfish, chicken, dairy, eggs, fishing, and pork, appear related to baseline nutrition expenditures, although the exact magnitude of the coefficient fluctuates between the (insignificant) point estimate of \$0.38 per dollar spent to the (significant) \$0.55 observed in column (5). Farm-to-school policies appear strongly associated with increases in local revenues for animal products, although it is unclear how much of the significant effects in columns (3) and (4) may be attributed to selection. The results of Table 4 similarly suggest that nutrition expenditures increase local agricultural revenues on fruits and vegetables, with perhaps \$0.40 cents of each dollar spent by school districts recouped by local farmers. The coefficients on the farm-to-school policy variables, however, bounce back and forth depending on whether spillover estimates are incorporated in the model, in one case achieving significance in opposite directions for local vs. contiguous counties (column (4)). It is unclear how these results should be interpreted. Table 2 shows how revenues for agrotourism are associated with farm-to-school policy adoption. Since school field trips to farms is a major element of farm-to-school policies, with a typical district engaging in 13 separate such field trips in any given year, it seems likely that agrotourism revenues might be associated with policy adoption. Indeed, each point estimate in the table is positive, providing some suggestive evidence that these field trips did increase revenues for local farmers.

5.3 Discussion of Implied Revenue Changes

There are several relevant horizons over which to view the implied local agricultural revenue changes. For one, the annual revenues for all agricultural products has hovered around \$10B throughout the 2010s, up \$1.8B from the (inflation-adjusted) annual revenues in 2001. The annual school nutrition expenditures over the same period have gone up from \$650M to roughly \$900M, totaling \$13.8B over the entire sample. The total agricultural revenues generated from 2001-2017, meanwhile, is \$167B.

If the baseline estimates on the effect of nutrition expenditures in Table 2, which hover around \$0.60, are to be believed, then perhaps as much as \$8B, or around 4.7% of all agricultural revenues from 2001-2017, may be attributed to school district nutrition spending. Interestingly, this number is quite similar to the 3% figure presented in the second sentence of this paper, which assumes that all students have only one meal at school. If we relax this assumption, perhaps allowing half of students to also eat breakfast at school and supposing that school cafeterias have on average more food waste than typical food providers,[25] then 4.7% seems like a reasonable estimate of the effect of school nutrition expenditures on agricultural revenues.

6 Conclusion

This paper provides strong evidence that school nutrition expenditures play an important role in local agricultural markets. I estimate that these expenditures account for roughly 4% of all agricultural revenues in the state from 2001-2017, or \$8B. This figure is, interestingly, 58% of all nutrition expenditures in the state, suggesting that a majority of school nutrition expenditures remain in the state. According to my estimates, roughly half of nutrition expenditures ending up in farmer pocketbooks were spent on animal products, while perhaps a third were spent on fruits and vegetables. I find weaker but mostly positive evidence that farm-to-school policies are associated with increases in local agricultural revenues. Averaging over three credible statistical models that control for spatial heterogeneity, perhaps \$800m in local agricultural revenues, or 6% of all nutrition expenditures, may be attributable to differential sourcing policies on the part of school districts. The findings suggest that school nutrition expenditures are economically meaningful drivers of agricultural markets, and local sourcing policies may be a valuable tool for assisting local farmers.

[25] Kropp et al. (2018) shows that farm to school programs increase fruit and vegetable consumption, but do not appear to impact food waste patterns.

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Tables

Table 1: School District and County Characteristics by Farm-to-School Policy Status

	(1) Farm-to-Schools		(2) Not Farm-to-Schools		(3) T-test of Means
District Characteristics (2001-2017)					
Total Enrollment	325.9	(486.9)	66.10	(69.53)	-259.8***
Free-and-Reduced Lunch Share	0.614	(0.139)	0.699	(0.133)	0.0842***
Rural-Urban Status	31.57	(9.214)	37.18	(4.840)	5.603***
% CEP Schools	0.434	(0.452)	0.572	(0.444)	0.138
CEP Population	12112.9	(25510.0)	3383.1	(4672.1)	-8729.8**
Marginal CEP Students	521.6	(865.3)	271.5	(480.6)	-250.1*
% Marginal CEP Students	0.0331	(0.0496)	0.0448	(0.0666)	0.0117
Nutritional Expenditures (2001-2017)					
Nutrition Expenditures	9423.6	(13207.0)	2140.5	(2078.6)	-7283.1***
Federal Nutrition Revenue	7813.5	(10945.6)	1743.7	(1679.9)	-6069.8***
Local Nutrition Revenue	2109.8	(4248.2)	349.6	(587.4)	-1760.3***
State Nutrition Revenue	261.4	(381.6)	57.28	(59.10)	-204.1***
County Agricultural Revenues (2000-2018)					
All Revenues	62078.5	(78315.1)	61559.4	(71870.8)	-519.1
Animal Products	43250.6	(77299.2)	36796.5	(60137.3)	-6454.1
Fruits and Vegetables	15022.4	(20775.5)	20596.7	(28615.2)	5574.2
Agrotourism	283.8	(483.1)	368.3	(1345.7)	84.53
Meats	37124.2	(66703.6)	31504.8	(53829.2)	-5619.4
Dairy	1412.4	(4093.8)	2317.3	(6096.7)	904.9
School Visits	15.41	(39.91)	8.340	(34.19)	-7.067
Other Revenues	4338.6	(5287.1)	6664.8	(7485.0)	2326.2*
Placebo Revenues	6477.6	(8333.4)	13574.6	(12885.0)	7097.0***
Farm-to-School Policy Variables (2001-2017)					
Farm-to-School Enrollment	107.1	(212.0)			
Marginal CEP Students in FtS District	443.1	(720.8)			
% Marginal CEP Students in FtS District	0.0264	(0.0392)			
District Observations	58		96		154
County Observations	63		96		159

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Mean coefficients reported in columns (1) and (2); standard deviations in parentheses. All dollar amounts expressed in thousands of 2017 dollars. Table A1 lists the commodities included in each category.

Table 2: Agricultural Revenues 2001-2017

	OLS		Spatial Lag 1		Spatial Lag 2		CEP 1		CEP 2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Within-County Effects										
Nutrition Expenditures	1.289***	1.079***	0.678*	0.571	0.631	0.552	0.621	0.669*	0.603	0.624
	(2.87)	(2.70)	(1.75)	(1.46)	(1.57)	(1.37)	(1.59)	(1.72)	(1.50)	(1.56)
FtS Policy		6884.6		3345.3*		3260.3				
		(1.39)		(2.04)		(1.74)				
CEP							38678.9*		37626.2	
							(2.03)		(1.71)	
CEP*FtS								13814.9		8813.1
								(0.32)		(0.20)
Contiguous County Effects										
Nutrition Expenditures					0.372	0.165			0.135	0.332
					(0.45)	(0.19)			(0.16)	(0.40)
FtS Policy						120.9				
						(0.04)				
CEP									1886.5	
									(0.05)	
CEP*FtS										22595.6
										(0.23)
Implied Δ Revenue		1.8B		897M		906M	425M	336M	434M	765M
N	2,669	2,669	2,669	2,669	2,669	2,669	2,669	2,669	2,669	2,669

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-statistics in parentheses. Year and county fixed effects included in all models. Clustered standard errors at the county level in models (1) and (2). Standard errors clustered across contiguous counties in models (3) - (10). Time-varying control variables include the total number of students in each district. Models (3) - (10) include dependent variable lags across inverse distance bandwidths, controlling for agricultural revenues in county i by agricultural revenues in all counties j in proportion to the inverse distance between county i and county j. $FtSPolicy$ is the proportion of students in a county served by a farm-to-school policy in their school district. CEP is the proportion of students in a county that are induced into free lunch by their schools participation in the Community Eligibility Provision of the HHFKA. $CEP * FtS$ is the proportion of students in a county that are induced into free lunch by their schools participation in the Community Eligibility Provision of the HHFKA while also being served by farm-to-school districts. Coefficients on nutrition expenditures are scaled to the dollar, while coefficients on FtS Policy, CEP, and CEP*FtS are scaled to the each thousand dollars. Implied Δ Revenue is the estimated change in statewide agricultural revenues associated with the policy coefficient(s) of interest in each model.

Table 3: Agricultural Revenues - Animal Products 2001-2017

	OLS		Spatial Lag 1	Spatial Lag 2	CEP 1	CEP 2
	(1)	(2)	(3)	(4)	(5)	(6)
Within-County Effects						
Nutrition Expenditures	0.693*	0.564*	0.420	0.382	0.549*	0.467
	(1.85)	(1.74)	(1.30)	(1.15)	(1.72)	(1.41)
FtS Policy		4230.9	3966.4***	4530.3***		
		(0.86)	(2.96)	(2.93)		
CEP*F2S					17145.5	21577.6
					(0.48)	(0.58)
Contiguous County Effects						
Nutrition Expenditures				0.592		0.813
				(0.85)		(1.18)
FtS Policy				-2605.8		
				(-0.96)		
CEP*F2S						-75704.2
						(-0.93)
N	2,669	2,669	2,669	2,669	2,669	2,669

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-statistics in parentheses. Year and county fixed effects included in all models. Clustered standard errors at the county level in models (1) and (2). Standard errors clustered across contiguous counties in models (3) - (6). Time-varying control variables include the total number of students in each district. Models (3) - (6) include dependent variable lags across inverse distance bandwidths, controlling for agricultural revenues in county i by agricultural revenues in all counties j in proportion to the inverse distance between county i and county j. $FtSPolicy$ is the proportion of students in a county served by a farm-to-school policy in their school district. CEP is the proportion of students in a county that are induced into free lunch by their schools participation in the Community Eligibility Provision of the HHFKA. $CEP * FtS$ is the proportion of students in a county that are induced into free lunch by their schools participation in the Community Eligibility Provision of the HHFKA while also being served by farm-to-school districts. Coefficients on nutrition expenditures are scaled to the dollar, while coefficients on FtS Policy, CEP, and CEP*FtS are scaled to the each thousand dollars.

Table 4: Agricultural Revenues - Fruits and Vegetables 2001-2017

	OLS		Spatial Lag 1	Spatial Lag 2	CEP 1	CEP 2
	(1)	(2)	(3)	(4)	(5)	(6)
Within-County Effects						
Nutrition Expenditures	0.612**	0.545*	0.379**	0.274	0.426***	0.267
	(2.29)	(1.89)	(2.34)	(1.36)	(2.67)	(1.32)
FtS Policy		2198.5*	1317.2**	-1645.0*		
		(1.67)	(2.09)	(-1.76)		
CEP*F2S					18076.7	-17913.7
					(1.02)	(-0.81)
Contiguous County Effects						
Nutrition Expenditures				0.125		0.285
				(0.35)		(0.82)
FtS Policy				4764.9***		
				(3.44)		
CEP*F2S						71007.1*
						(1.81)
N	2,669	2,669	2,669	2,669	2,669	2,669

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-statistics in parentheses. Year and county fixed effects included in all models. Clustered standard errors at the county level in models (1) and (2). Standard errors clustered across contiguous counties in models (3) - (6). Time-varying control variables include the total number of students in each district. Models (3) - (6) include dependent variable lags across inverse distance bandwidths, controlling for agricultural revenues in county i by agricultural revenues in all counties j in proportion to the inverse distance between county i and county j. $FtSPolicy$ is the proportion of students in a county served by a farm-to-school policy in their school district. CEP is the proportion of students in a county that are induced into free lunch by their schools participation in the Community Eligibility Provision of the HHFKA. $CEP * FtS$ is the proportion of students in a county that are induced into free lunch by their schools participation in the Community Eligibility Provision of the HHFKA while also being served by farm-to-school districts. Coefficients on nutrition expenditures are scaled to the dollar, while coefficients on FtS Policy, CEP, and CEP*FtS are scaled to the each thousand dollars.

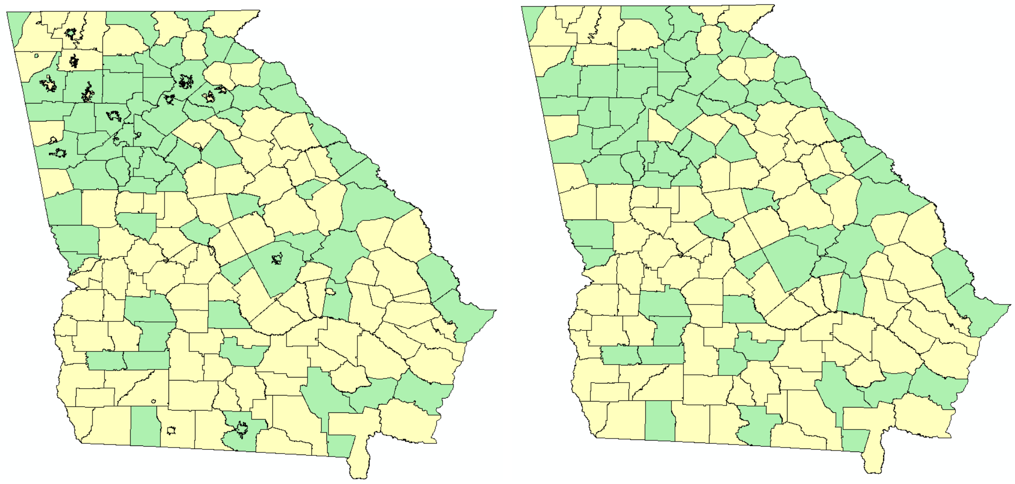
Table 5: Agricultural Revenues - Agrotourism 2001-2017

	OLS		Spatial Lag 1	Spatial Lag 2	CEP 1	CEP 2
	(1)	(2)	(3)	(4)	(5)	(6)
Within-County Effects						
Nutrition Expenditures	-0.0299	-0.0333	-0.0337	-0.0356	-0.0312	-0.0350
	(-0.86)	(-0.96)	(-1.31)	(-1.38)	(-1.22)	(-1.37)
FtS Policy		111.3*	107.5	78.91		
		(1.93)	(0.98)	(0.66)		
CEP*F2S					1368.8	420.8
					(0.48)	(0.15)
Contiguous County Effects						
Nutrition Expenditures				0.0194		0.0114
				(0.34)		(0.20)
FtS Policy				-29.33		
				(-0.13)		
CEP*F2S						7949.3
						(1.17)
N	2,669	2,669	2,669	2,669	2,669	2,669

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-statistics in parentheses. Year and county fixed effects included in all models. Clustered standard errors at the county level in models (1) and (2). Standard errors clustered across contiguous counties in models (3) - (6). Time-varying control variables include the total number of students in each district. Models (3) - (6) include dependent variable lags across inverse distance bandwidths, controlling for agricultural revenues in county i by agricultural revenues in all counties j in proportion to the inverse distance between county i and county j. $FtSPolicy$ is the proportion of students in a county served by a farm-to-school policy in their school district. CEP is the proportion of students in a county that are induced into free lunch by their schools participation in the Community Eligibility Provision of the HHFKA. $CEP * FtS$ is the proportion of students in a county that are induced into free lunch by their schools participation in the Community Eligibility Provision of the HHFKA while also being served by farm-to-school districts. Coefficients on nutrition expenditures are scaled to the dollar, while coefficients on FtS Policy, CEP, and CEP*FtS are scaled to the each thousand dollars.

Figures

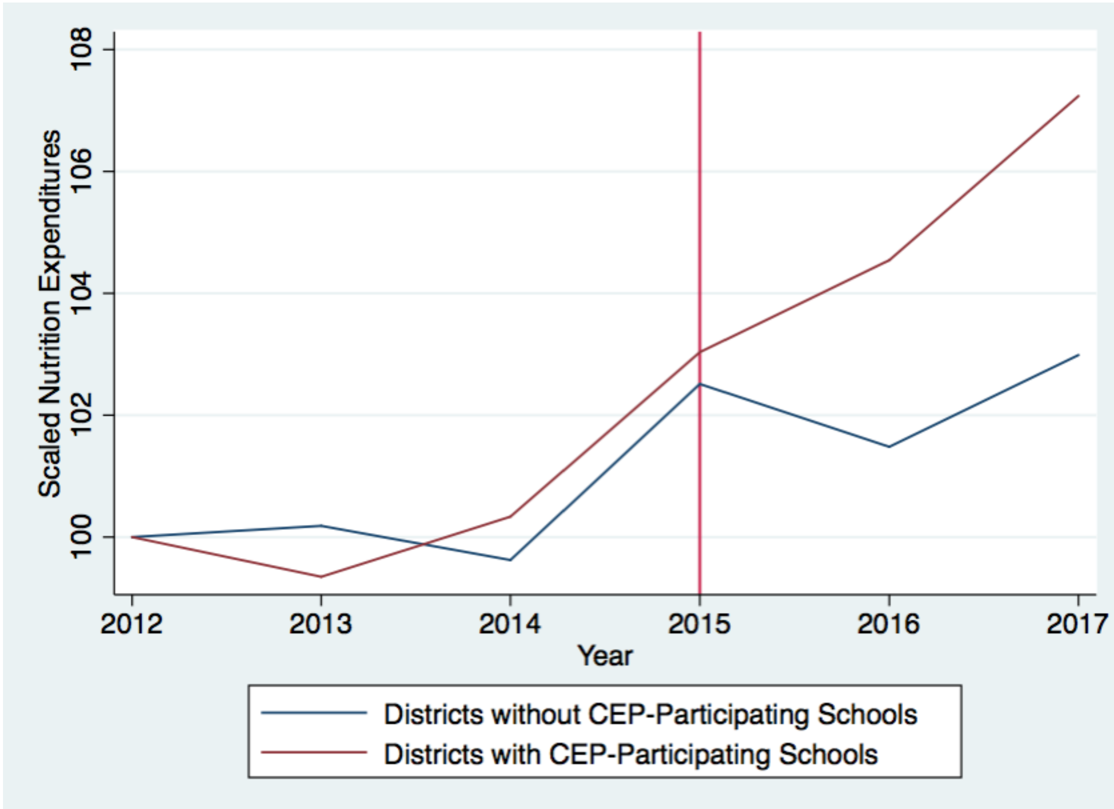
Figure 1: Farm-to-School Policy Adoption



(a) Farm-to-school Districts   (b) Farm-to-school Counties

Note: Beige represents school districts that never adopt a farm-to-school policy or counties with no school district adopting a farm-to-school policy. Green regions represent school districts or counties with farm-to-school policies.

Figure 2: Nutrition Expenditures in Georgia 2012-2017



Note: District nutrition expenditures are scaled such that 2012 expenditures are equal to 100. Lines represent averages over all school districts with CEP-participating schools or without CEP-participating schools. All values expressed in 2017 dollars. The vertical red line represents the last year in which no school participated in the CEP program.

Appendix

Table A1: Commodities Included in Each Agricultural Category

Main Categories	Commodities
Animal Products	Beef, Catfish, Chicken, Dairy, Eggs, Fishing, Pork
Fruits & Vegetables	Apples, Banana Peppers, Barley, Bell Peppers, Blackberries, Blueberries, Broccoli, Cabbage, Cantaloupe, Carrots, Collards, Container Nursery, Corn, Cucumbers, Eggplant, English Peas, Field Nursery, Green House, Grapes, Green Onions, Hay, Honey Bees, Hot Peppers, Irish Potatoes, Kale, Lettuce, Lima Beans, Mustard, Organics, Oats, Okra, Onions, Peaches, Peanuts, Pecans, Pole Beans, Pumpkin, Rye, Snap Beans, Sorghum, Southern Peas, Soybeans, Spinach, Strawberries, Sweet Corn, Tomato, Turnip Greens, Turnip Roots, Watermelon, Winter Squash, Yellow Squash, Zucchini
Agrotourism	Corn Maze, Guide Services, Hayrides, School tours, Special Attractions, Special Events
Other	Other , Silage, Pine Straw, Straw, Turfgrass
Placebo Commodities	Timber, Camping, Christmas Trees, Cotton, Hunting Leases, Tobacco
Unused Commodities	Horses, Wildlife Observation, Goats, Quail, Sheep

Table A2: Golden Radish Application Information 2014-2018

	Mean	SD	% Missing
Days Local	118.2	(67.97)	70.55
Local Meals	1110443.7	(1890232.2)	70.74
Taste Tests	134.1	(590.8)	72.09
Farmer Field Trips	13.75	(21.75)	72.75
Local Food Promotions	112.0	(321.1)	71.32
Local Food Lessons	97.21	(408.3)	73.41
Schools with Gardens	12.73	(19.51)	71.65
Food Activities	50.99	(138.3)	73.74
Activities with Committee Members	24.27	(51.85)	73.19
Professional Development Trainings	16.94	(110.7)	73.41
Golden Radish Awards	197	-	
Year-District Observations	910		

Mean coefficients reported; standard deviations in parentheses.

Table A3: Community Eligibility Provision Predicts Nutrition Expenditures 2001-2017

	(1)	(2)	(3)	(4)	(5)
CEP Students	80.88**				
	(2.18)				
Marginal CEP Students		1385.4**			
		(2.17)			
Marginal FtS CEP Students			1989.7*		
			(1.84)		
% Marginal CEP Students				3068731.1***	
				(4.37)	
% Marginal FtS CEP Students					7427600.5***
					(2.91)
Implied Δ Expenditures	8.3M	77.5M	49.7M	36M	20.7M
R2	0.704	0.699	0.700	0.693	0.693
N	2,669	2,669	2,669	2,669	2,669

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-statistics in parentheses. Year and county fixed effects included in all models. Clustered standard errors at the county level. Time-varying control variables include the total number of students in each district. $CEPStudents$ is the total number of students at CEP-participating schools in county i in year t. $MarginalCEPStudents$ is the number of students induced into free lunch status by CEP participation in county i in year t. $MarginalFtSCEPStudents$ is the number of students induced into free lunch status by CEP participation in county i in year t, where county i has school districts that participate in the farm-to-school program. $\%MarginalCEPStudents$ is the share of students induced into free lunch status in county i in year t. $\%MarginalFtSCEPStudents$ is the share of students induced into free lunch status in farm-to-school-participating schools in county i in year t. Implied Δ Expenditures is the estimated change in county nutrition expenditures associated with the coefficients of interest in each model, where the implied change in expenditures is calculated by multiplying the point estimate times the all-sample total of the dependent variables. For example, 8.3M in column (1) was calculated by multiplying 80 times the total number of students in CEP participating schools in the sample, which is 102,734.