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. In 2015, 42,000 schools serving 23.6 million students engaged in farm-to-school nutrition sourcing policies. Yet, little is known about how much school systems actually 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 policy and variation in expenditures associated with the community eligibility provision of the Healthy Hunger Free Kids Act. Results suggest that as much as \$966M of school nutrition expenditures flow to producers within the same county. Of this, perhaps as much as \$680M, or 0.6% of all agricultural revenues in the state from 2001-2017, are associated with adoption of farm-to-school policies by school districts.

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

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1 Introduction

In recognition of the economic importance of school-provided meals to local businesses, every state has implemented some form of farm-to-school incentive program, with 42,000 schools participating in some form of farm-to-school policy in 2014-15.¹ These policies are diverse in scope and characteristics. They exist at the state, school district, and school level; they also emphasize different elements of the farm-to-school movement. In general, however, these programs consist of three key policies: serving food sourced from local providers, edible school garden activities, and food educational initiatives such as field trips to local farms and food tastings.

In Georgia, meal provision for the 1.8 million public K-12 students represents at least 3% of the state's meal consumption; local, state, and federal nutrition expenditures for these meals amounted to \$13.8 billion from 2001 to 2017.² Of all students in the state, 1.1 million received free or reduced price lunch and breakfast, while 1.3 million students were served by schools with some form of farm-to-school policy. Despite the fact that more students receive exposure to a farm-to-school policy than free-and-reduced price lunch or breakfast, relatively fewer studies have investigated how farm-to-school policies affect students or local economies. In particular, 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 are associated with changes in local agricultural revenues.³ 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 share of students induced into free meal status by the Community Eligibility Provision, which increased school nutrition expenditures. I secure plausibly-causal identification with two statistical models: a triple-difference model relying on school-level

¹Christensen et al. (2018); USDA (2017). Incentive programs at the state level often consist of recognition and awards for commitment to the movement. For example, Georgia gives the "Golden Radish" award to school districts meeting certain criteria for excellence in commitment to farm-to-school programs. See more here.

²One 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, which notably excludes breakfast).

³For traction I adopt a definition of local corresponding to the same county and contiguous counties. The definition of "local" varies by program. According to the 2015 farm-to-school census, 27.2% of Georgia farm-to-school programs use a definition of local corresponding to a region within a 100 mile radius, 36% use a definition of local corresponding to the entire state, 18% use a definition of local corresponding to a region of nearby states, and 9% use some other definition of local.

adoption of the Community Eligibility Provision (CEP) of the Healthy Hunger Free Kids Act and a two-stage least squares model that uses expenditure changes associated with the CEP to predict local agricultural revenue changes. I find that as much as 7% of school district expenditures flow to producers within the same county. Of this local share, perhaps as much as 70% of the expenditures are associated with adoption of farm-to-school policies. Specifically, \$680M out of \$966M local expenditures may be attributed to farm-to-school policy adoption. These figures represent 0.4% and 0.6%, respectively, of all agricultural revenues in the state from 2001-2017. These local expenditures are more strongly associated with revenue increases of fruits and vegetables than with animal products. This study contributes to a sparse literature on the role that school nutrition expenditures and sourcing policies play on local agricultural revenues.

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.⁴ These surveys, however, are cross sections of one year. Moreoever, relatively few studies focus on observable economic impacts of farm-to-school policies rather than school survey-based expenditure information. In part, the paucity of studies directly linking expenditures to local revenues relates to identification hurdles. Selection bias, spatial autocorrelation, policy spillovers, and even reverse causation each contribute to the confounding of correlational estimations.⁵

 $^{^{4}}$ Botkins and Roe (2018), Deller et al. (2017), Holland et al. (2015), Hoffman et al. (2017), Lee et al. (2019), Thompson et al. (2014)

 $^{{}^{5}}$ 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).

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.⁶ 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 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.⁷ 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.⁸ Finally, I incorporate variation in nutrition expenditures associated with a policy unrelated to farm-to-school adoption to secure identification plausibly purged of selection bias and reverse causation.

⁶The 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.

⁷The expenditure data is from the federally-mandating accounting ledgers of school districts, ensuring accurate reporting.

⁸Watson et al. (2018)

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.⁹ I describe each data source below.

3.1 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.¹⁰ A wide range of information on heterogeneous school district farm-to-school policies is included on these applications for the 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.¹¹ 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.¹² A map depicting all school districts ever adopting some form of farm-toschool 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 Farmto-School Census, which reports a wide range of information on county-level nutrition expenditures on farm-to-school foods.¹³

⁹In general, school districts and counties are geographically the same. Some counties, however, have school districts specific to a city within the county. Figure 1 depicts the overlap of school districts and counties.

¹⁰The 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.

¹¹The 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.

¹²Golden Radish Infographic.

¹³USDA (2017).

3.2 Community Eligibility Provision Adoption

Part of the Healthy Hunger-Free Kids Act, the Community Eligibility Provision is a universal free-meal option available to schools or entire school districts with at least 40% of their students qualifying for free lunch through categorical eligibility. The fraction that is categorically eligible, or the Identified Student Percentage (ISP), is the share of students receiving any other form of federal financial assistance. Depending on the ISP, a school district receives federal reimbursement of between 64% and 100% of their nutrition expenditures.¹⁴ The Georgia Department of Education maintains lists of schools and school districts that are eligible for participation in the Community Eligibility Provision, including information on schools or districts that actually participate in these programs from FY 2016-2019.¹⁵ 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.

3.3 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 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.¹⁶ 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 school-level records because these are mostly missing. 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.

¹⁴Gordanier et al. (2019). A school barely qualifying, with 40% ISP, receives reimbursement equal to 64% of expenditures. All schools with ISP above 62.5% receive full reimbursement for their breakfasts and lunches. ¹⁵On this public web-page.

¹⁶According to conversations with Nicholas Warner at the Fiscal Research Center.

3.4 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.¹⁷ This information was linked to supplemental information sourced from the Common Core of Data using the Stata add-on Education Data Portal package developed by the Urban Studies Institute.¹⁸ This information is summarized in Table 1.

3.5 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.¹⁹ The information includes revenues across 89 different commodity categories, with many commodity categories further broken down by type of grow technique. For this analysis I eliminate products likely unrelated to school nutrition.²⁰ The third panel of Table 1 displays information on agricultural revenues broken up by type of product. Although school districts adopting farm-to-school policies differ from those that do not, agricultural revenues across both types of county are similar and not statistically distinguishable from each other in any commodity category used by this study. The products included in each class of commodity, such as fruit, vegetable, dairy, or meat, are listed in Table A1.

¹⁷The data reporting tab on this webpage sub-links for reports on enrollment and free-and-reduced price lunch status.

¹⁸Education 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/

¹⁹In 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.

²⁰Products 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.

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 plausibly 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-toschool 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.

$$y_{ipt} = \beta FTS_{it} + Z_{it}\gamma' + \eta_i + \tau_t + \epsilon_{ipt}.$$
(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 by farmto-school-adopting districts in a school year. Z_{it} controls for time-varying total student population within the county and free and reduced lunch shares. 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 entire 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. Finally, there is evidence that local production increases may in fact cause these policy shifts, as school districts re-allocate expenditures where local supply permits.²¹ This reverse causation is another important potential violation of the identification assumption.

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-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.

$$y_{ipt} = \lambda \sum_{j=1}^{n} w_{ij} \cdot y_{jpt} + \beta FTS_{it} + Z_{it}\gamma' + \eta_i + \tau_t + \epsilon_{ipt}.$$
(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 student population and free and reduced

²¹O'Hara and Benson (2019).

price lunch shares, 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.²²

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 **Y** represent y_{ipt} and **W** represent the lagging weights $\sum_{j=1}^{n} w_{ij}$. Consider the following (equivalent) spatial regression specifications:

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

$$\mathbf{Y} = \lambda \mathbf{W} \mathbf{Y} + \beta \mathbf{W} \mathbf{F} \mathbf{T} \mathbf{S} + \gamma \mathbf{W} \mathbf{Z} + \epsilon \tag{4}$$

In 3, 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 including total student population and free and reduced price lunch shares, 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.

²²Note 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.

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. Moreover, the possibility of reverse causation remains. To assess the importance of selection bias and reverse causation, I 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 plausibly causal identification, I employ a related empirical 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. Plausibly 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 empirically demonstrates that CEP adoption reliably increases nutrition expenditures across 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.²³ 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.

$$y_{it} = \beta_1 FTS_{it} + \beta_2 CEP_{it} + \beta_3 FTS_{it} \cdot CEP_{it} + \lambda_1 x_{it} + \lambda_2 \sum_{j=1}^n w_{ij} \cdot y_{jt}$$
$$+ \psi_1 \sum_{j=1}^n w_{ij} \cdot FTS_{jt} + \psi_2 \sum_{j=1}^n w_{ij} \cdot CEP_{jt} + \psi_3 \sum_{j=1}^n w_{ij} \cdot FTS_{jt} \cdot CEP_{jt}$$
$$+ Z_{it}\gamma_1' + \eta_i + \tau_t + \epsilon_{it}$$

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 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 three-year period out of the 17 year sample.

Identifying Assumptions: To estimate the causal relationship between nutrition expenditures and farm-to-school policy adoption and local agricultural revenues, Equation 5 and Equation

²³For 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.

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.

4.4 Two Stage Least Squares – Share of CEP Students

The empirical strategies laid out in subsection 4.4 may still be susceptible to bias from reverse causation. To eliminate this bias, I employ a two stage least squares regression relying on variation in the share of students induced into free and reduced price lunch status. Farm-to-school adoption may be endogeneous because districts select into the policies, so I do not include any interaction with farm-to-school policy adoption. 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. Let x_{it} represent total school district nutritional expenditures in county *i* and year *t*.

$$x_{it} = \beta CEP_{it} + Trend'_i\delta + \eta_i + \tau_t + u_{it}$$
$$y_{it} = \gamma x_{it} + Trend'_i\delta + \eta_i + \tau_t + \epsilon_{it}$$

In the above two stage least squares model, terms CEP_{it} and η_i are defined as before. τ_t is a year dummy. $Trend_i$ is a district-specific trend control. Rather than identifying CEP_{it} off potentially endogenous student population or district decisions to participate in the program, the term represents the county share of students induced into "free meal" status by adoption of the program.²⁴ Intuitively, this empirical model uses variation in the share of students induced into free meal status to predict the change in nutrition expenditures, and this change in nutrition

²⁴The formula for this variable is: $CEP_{it} = \frac{\sum_{s} CEP_{st}(1-FRL_{st})}{Enrollment_{it}}$.

expenditures is then used to predict changes in within-county agricultural revenues. The two-stage least squares provides an estimate of the baseline relationship between agricultural revenues and nutrition expenditures with which to compare previous estimates.

Identifying Assumptions: A causal interpretation requires that the share of students induced into free lunch status strongly predicts nutrition expenditures. As before, Figure 2 shows the increase in expenditures among districts with CEP-participating schools. Table A3 demonstrates that CEP adoption reliably increases nutrition expenditures across every definition of CEP participation. Moreover, the share of students induced into free lunch status must affect local agricultural revenues only through the changes in nutrition expenditures, otherwise known as the exclusion restriction. Although the exclusion restriction cannot be directly tested, it seems unlikely that small variations in the free-and-reduced lunch population across CEP-participating schools would directly affect local agricultural revenues except through school nutrition expenditures.

5 Results

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. Across all specifications, I find weak statistical evidence that school nutrition expenditures are associated with local agricultural revenues. For each dollar spent on school nutrition, agricultural revenues in the same county are \$0.13 to \$0.19 higher. This relationship is not necessarily causal; since the Farm to School Census found that 17% of district expenditures in farm to school districts goes to local farmers, these point estimates are not unreasonable but are likely biased by selection and possible reverse causation. Additionally, these findings should be relatively higher because the spending multiplier on local food is 1.5 according to Christensen et al. (2018).

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 coefficient on farm-to-school policy adoption, "FtS Policy," is relatively large but not statistically significant.

The point estimate 1913, which is expressed in thousands, suggests that each post-policy adoption year is associated with increases in local agricultural revenues of \$1.9M. Scaling this average across all policy years implies agricultural revenue increases of \$550M related to farm-to-school policies.²⁵ Although this is small in comparison to the \$167B in agricultural revenues from 2001-2017, it represents about 3.9% of all 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 \$0.15-\$0.18 of every dollar spent on school nutrition is recouped by farmers in the same county, while a surprisingly negative \$0.94 is lost by farmers in bordering counties. It is unclear why local expenditures are associated with negative revenues in bordering counties. although this may relate to unobservable agricultural differences in urban and suburban regions with greater nutrition expenditures. Columns (4) and (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. Controlling for these error disturbances dramatically improves the precision of the estimated relationship between farmto-school policy adoption and local agricultural revenues; these point estimates are similar to those of column (2), although they're not quite statistically significant. The farm-to-school policy variable is consistent across both models, suggesting large local economic effects of slightly over \$550M. The coefficient on "FtS Policy" in the sixth row suggests that perhaps \$6.5M in nutrition spending was lost 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 4.4. 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

²⁵The 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 because the point estimates are expressed in thousands.

associated with school districts adopting farm-to-school programs or reverse causation. The variable CEP is the share of a county's students that are induced into free lunch status by the new policy.²⁶ Clearly, increasing shares of students induced into free meal status is strongly and statistically significantly associated with increases in local agricultural revenues. The coefficient of 43,000 in column (8), for example, means that going from no students induced into free lunch to all students induced into free lunch would increase local revenues by \$43M. Of course, it is impossible for the CEP variable to increase by more than 0.4, and on average this variable is in fact 0.005. Therefore, on average, the share of marginally induced free lunch students was associated with a \$215,000 increase in local agricultural revenues. Scaling by all marginally induced free lunch CEP students, this is a total change of 3.3M. In contrast, the smaller point estimate of 3,365 in column (8) suggests that each year of farm-to-school adoption is associated with \$3.36M increase in local agricultural revenues. Over all farm to school years, this represents \$967M in increased local revenues. This value should be corrected by the point estimate of CEP * FtS, -76,000. Since the average value of CEP * FtS is 0.001 and the total of all such interactions is 3.8, the figure of \$967M should be scaled back to 678M.²⁷ That is, the linear combination of the terms in row (2) and row (4) in columns (8) and (10) suggests that farm to school programs are associated with agricultural revenue increases of roughly \$680M.

Surprisingly, results in the second panel of Table 2 provide little clarity on the effect of agricultural spending on contiguous counties. The only statistically significant coefficients are the effects of increasing CEP shares, which are positive. These would suggest that increased nutrition expenditures from CEP adoption are associated with large increases to agricultural revenues in contiguous counties. The coefficient of 85,222 in column (9), for example, suggests that going from zero students induced into free lunch to all students induced into free lunch would increase revenues in contiguous counties by \$85M. Since the typical district's marginal share of CEP students is 0.005, this implies that a typical district's increase in nutrition expenditures associated with CEP adoption may have led to an average increase in agricultural revenues in contiguous counties of \$425,000. The total increase in revenues in contiguous counties would therefore be \$323M. The negative coefficient on the farm-to-schools variable in the second panel, meanwhile, may suggest

 $^{^{26}}$ As shown in Table A3, school-level adoption of the CEP policy in general is strongly statistically associated with increases in nutrition expenditures.

 $^{^{27}678.2 = 967 - 3.8 * 76}M$

that districts are substituting to more-local suppliers from more-distant providers, although this coefficient is not statistically distinguishable from zero.

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 an insignificant point estimate of \$0.08 per dollar spent to the \$0.229 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) through (6) may be attributed to selection and reverse causation. It seems plausible that a school district with nearby milk or egg production would be more inclined to enact farm-to-school policies. The fact that coefficients on the CEP share, in columns (5) and (6), are not significant may provide support for the notion that the farm-to-school variable is more endogenous and prone to reverse causation for animal products.

The results of Table 4 provide weaker evidence that nutrition expenditures increase local agricultural revenues on fruits and vegetables, with perhaps \$0.01 to \$0.14 cents of each dollar spent by school districts recouped by local farmers. The coefficients on the farm-to-school policy variables, however, are universally negative, often statistically significantly so. Unlike the results for animal products, however, increasing CEP shares are associated with increases to local agricultural revenues. It is unclear how to interpret these results. Table 5 shows how revenues for agrotourism are associated with farm-to-school policy adoption. Since school field trips to farms are 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. However, each point estimate on the farm-to-schools variable in the table is negative and statistically insignificant. Although the interaction CEP * FtS is significant and positive, it is unclear why this interaction should be positive because CEP shares are not related to field trip visits a priori.

Finally, to provide an estimate of the baseline relationship between nutrition expenditures and agricultural revenues, Table 6 depicts the results of a two stage least squares estimation procedure. Clearly, increasing shares of students receiving free lunch through the CEP is associated with dramatic increases to school nutrition expenditures. The first-stage coefficient of 2.6M suggest that a typical district's CEP share increased local nutrition expenditures by \$13,000 in each year. Moreover, I find evidence that these increasing expenditures were in part recouped by local farmers. The coefficient of 26.37 in column (1) suggests that a typical county's change to nutrition expenditures associated with the CEP increased local agricultural revenues by \$350,000. This value is roughly 7% of the average district expenditures in each county. If we extrapolate this value over the entire sample window, it suggests that \$966M of school district expenditures flowed to local within-county producers. This is 11.3% of all school district expenditures; interestingly, this figure is less than the local share found in the 2015 Farm to School Census, which was 17%.²⁸ Since my estimates relate to a local variable of only within the same county, this makes sense. The estimated relationship is strongest for fruits and vegetables, not animal products; this may suggest that within-county expenditure shifts are more likely drivers of fruit and vegetable revenues than animal product revenues, as economical large-scale feeding operations are less likely to be present locally.

5.1 Discussion of Implied Revenue Changes

The Farm to School Census reports that \$40M was spent on local food by Georgia school districts in 2015.²⁹ Extrapolating this value over the 17 year sample would be \$680M, although it is unlikely that this level of local investment was constant over the entire sample period. The point estimate on "FtS Policy" in the naive regression model, reported in column (2) of Table 2, would suggest that this figure is the reduced \$550M. Since this estimated relationship does not account for spatial correlation, spatial lags, selection bias, or reverse causation, it seems reasonable that the estimate is noisy, although it is surprising that is so close to the surveyed quantity. In columns (4) and (6) of Table 2, the point estimate on "FtS Policy" implies an increase of \$555M and \$627M in local revenues associated with farm-to-school policies. This figure is, again, smaller than what might be expected from the Farm to School Census, perhaps reflecting selection bias, reverse causation, or merely the local share of spending being lower in earlier years of the sample. When incorporating variation from the Community Eligibility Provision, I find implied local revenue shifts, that are very similar to the extrapolated figure from the Farm to School Census. These figures range from

²⁸USDA (2017).

²⁹USDA (2017).

\$627M to \$683M, which are almost identical to \$680M. It should be the case, however, that these figures are higher than the extrapolated value in the farm-to-school census, as the census only received replies from 84% of Georgia school districts.³⁰ Despite this fact, it would make sense if these values are roughly similar if the share of local expenditures has increased over time and the 2015 surveyed value is not representative of all years from 2001-2017.

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 total agricultural revenues generated from 2001-2017 is \$167B. Meanwhile, the annual school nutrition expenditures over the same period have increased from \$650M to roughly \$900M, totaling \$13.8B over the entire sample. If the implied revenue shifts associated with farm-to-school policy adoption are credible. then perhaps as much as 4.9% of nutritional expenditures in the state may be attributed to farmto-school policy adoption. This figure is roughly 0.4% of all agricultural revenues in the state over the same period. Meanwhile, the estimates of Table 6 suggest that perhaps 7% of nutritional expenditures remain in the same county, or as much as 0.6% all agricultural revenues in the state. Although these estimations may be a small share of all agricultural revenues, they are a relatively large share of what is likely spent locally by school districts (5-7%). If we assume that the two stage least squares results in Table 6 are accurate, then farm-to-school policy adoption is actually responsible for 70% of all nutrition expenditures that remain in the same county. Interestingly, both the estimates reported in Table 2 and Table 6 are lower than the share of local expenditures reported in the Farm to School Census of 2015, which found that 17% of nutrition expenditures were spent locally in Georgia in 2015.³¹ This divergence, however, makes perfect sense. The Farm to School Census sample includes only 84% of school districts, likely excluding many that would do not engage in these policies. It also incorporates local expenditures that flow to nearby counties, while my estimation procedure focuses on within-county changes.

6 Conclusion

This paper provides evidence that school nutrition expenditures play an important role in local agricultural markets, whether these nutrition expenditures are associated with farm-to-school poli-

³⁰https://farmtoschoolcensus.fns.usda.gov/find-your-school-district/georgia

 $^{^{31}}$ USDA (2017).

cies or not. I estimate that 5 to 7% of school district nutrition expenditures flow to within-county producers. These expenditures account for roughly 0.6% of all agricultural revenues in the state from 2001-2017, or \$966M out of \$167B. Of this total, perhaps as much as \$680M, or 70% of the total amount of local expenditures, may be specifically attributable to farm-to-school policy adoption. My estimates for the share of local expenditures correspond almost precisely to the shares reported in the Farm to School Census after extrapolating over a longer sample. According to my estimates, roughly three quarters of the local share of school nutrition expenditures is spent on fruits and vegetables, while a smaller share of the remainder is spent on animal products. 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.

References

- Botkins, E. R. and Roe, B. E. (2018). Understanding participation in farm to school programs: Results integrating school and supply-side factors. *Food Policy*, 74:126 – 137.
- Christensen, L., Jablonski, B., Stephens, L., and Joshi, A. (2018). Evaluating the economic impacts of farm-to-school procurement. *Journal of Agriculture, Food Systems, and Community Development*, 8(C):73–94.
- Christensen, L. O., Jablonski, B. B. R., and O'Hara, J. K. (2019). School districts and their local food supply chains. *Renewable Agriculture and Food Systems*, 34(3):207–215.
- Deller, S., Canto, A., and Brown, L. (2017). Food access, local foods, and community health. Community Development, 48(5):657–680.
- Gordanier, J., Ozturk, O., Williams, B., and Zhan, C. (2019). Free lunch for all! the effect of the community eligibility provision on academic outcomes. *SSRN Electronic Journal*.
- Hoffman, J. A., Schmidt, E. M., Wirth, C., Johnson, S., Sobell, S. A., Pelissier, K., Harris, D. M., and Izumi, B. T. (2017). Farm to preschool: The state of the research literature and a snapshot of national practice. *Journal of Hunger & Environmental Nutrition*, 12(4):443–465.
- Holland, J. H., Thompson, O. M., Godwin, H. H., Pavlovich, N. M., and Stewart, K. B. (2015). Farm-to-school programming in south carolina: An economic impact projection analysis. *Journal* of Hunger & Environmental Nutrition, 10(4):526–538.
- Joshi, A., Azuma, A. M., and Feenstra, G. (2008). Do farm-to-school programs make a difference? findings and future research needs. *Journal of Hunger & Environmental Nutrition*, 3(2-3):229–246.
- Lee, E., Smathers, C., Zubieta, A., Ginnetti, S., Shah, A., and Freedman, D. (2019). Identifying indicators of readiness and capacity for implementing farm-to-school interventions. *Journal of School Health*, 89:373–381.
- O'Hara, J. K. and Benson, M. C. (2019). The impact of local agricultural production on farm to school expenditures. *Renewable Agriculture and Food Systems*, 34(3):216–225.
- Thompson, O. M., Twomey, M. P., Hemphill, M. A., Keene, K., Seibert, N., Harrison, D. J., and Stewart, K. B. (2014). Farm to school program participation: An emerging market for small or limited-resource farmers? *Journal of Hunger & Environmental Nutrition*, 9(1):33–47.
- USDA (2017). 2015 farm to school census.
- Watson, J., Treadwell, D., and Bucklin, R. (2018). Economic analysis of local food procurement in southwest florida's farm to school programs. *Journal of Agriculture, Food Systems, and Community Development*, 8(3):61–84.

Tables

	((1)		(2)	(3)
	Farm-te	o-Schools	Not Farm	n-to-Schools	T-test of Means
District Characteristics (2001-2017)					
Total Enrollment	325.9	(486.9)	66.10	(69.53)	-259.8^{***}
FRL Share	0.614	(0.139)	0.699	(0.133)	0.0842^{***}
Nutrition Expenditures	9423.6	(13207.0)	2140.5	(2078.6)	-7283.1^{***}
% CEP Schools	0.434	(0.452)	0.572	(0.444)	0.138
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)	-5191
Animal Products	43250.6	(77299.2)	36796 5	(60137.3)	-6454 1
Fruits and Vegetables	15022	(11235.2) (20775.5)	20596 7	(28615.2)	5574.2
Agrotourism	15 41	(20110.0) (39.91)	8 340	(20010.2) (34.19)	-7.067
Meats	37194.9	(66703.6)	31504.8	(53829.2)	-5619.4
Dairy	14124.2	(4093.8)	2317.3	(6096.7)	904 9
School Visits	15 41	(39.91)	8 340	$(34\ 19)$	-7.067
Other Bevenues	4338.6	(5287.1)	6664.8	(7485.0)	2326.2*
Placebo Revenues	6477.6	(8333.4)	13574.6	(12885.0)	2020.2
Tracebo revenues	0411.0	(0000.4)	10011.0	(12000.0)	1051.0
Farm-to-School Policy Variables (2002	L-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	75		105		180
County Observations	63		96		159

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

* 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.

le 2:	Agricultural Reve	nues 2001	-2017								
1		0	LS	Spatia	l Lag 1	Spatial	$ \operatorname{Lag}_{2} 2$	CE CE	P 1	CE	P 2
11		(1)	(2)	(3)	(4)	(Q)	(0)	(2)	(8)	(6)	(10)
	Within-County I Nutrition Expenditures FtS Policy	2 ffects 0.174 (0.386)	$\begin{array}{c} 0.147\\ (0.392)\\ 1913.4\\ (5072.9)\end{array}$	0.180 (0.404)	$\begin{array}{c} 0.152\\ (0.404)\\ 1927.2\\ (1894.4)\end{array}$	0.174 (0.406)	$\begin{array}{c} 0.148\\ (0.407)\\ 2178.1\\ (1903.2)\end{array}$	0.199 (0.404)	$\begin{array}{c} 0.165\\ 0.404)\\ 3365.0^{*}\\ (2038.0)\end{array}$	0.158 (0.408)	$\begin{array}{c} 0.132\\ (0.408)\\ 3282.3\\ (2074.4)\end{array}$
	CEP							25167.5 (19544.0)	43072.4^{**} (21809.2)	25984.1 (19471.9)	46586.1^{**} (21911.4)
	$\begin{array}{l} {\rm CEP} \times {\rm FtS} \\ {\rm Policy} \end{array}$								-75222.3^{*} (43600.1)		-76044.2^{*} (43686.6)
	Contiguous Coun Nutrition Expenditures FtS Policy	ıty Effects				-0.943 (0.907)	$\begin{array}{c} -0.831 \\ (0.911) \\ -6537.3 \\ (4854.7) \end{array}$			-1.239 (0.914)	$\begin{array}{c} -1.168 \\ (0.916) \\ -8274.6 \\ (5172.3) \end{array}$
	CEP									85222.5* (47895.0)	95942.9^{*} (53648.6)
1 11	$\begin{array}{l} {\rm CEP} \times {\rm FtS} \\ {\rm Policy} \\ {\rm Implied} \ \Delta \ {\rm Revenue} \\ {\rm N} \end{array}$	2,669	550M $2,669$	2,669	555M 2,669	2,669	627M 2,669	390M $2,669$	683M 2,669	402M 2,669	-39083.0 (114514.2) 656M 2,669
* $p < 0$ the tot; across c revenue of stude by thein free lum nutritio	1, ** $p < 0.05$, *** p al number of students contiguous counties in s in county <i>i</i> by agric ants in a county served r schools participation ch by their schools pa	 < 0.01. Stan < 0.01. Stan in each dist models (3) - ultural reven ultural reven in the Comi in the Comi ulto the didition of the didition 	dard errors rict and FR (10). Mode ues in all co co-school pol munity Eligi nut the Commu ollar, while	in parenthe L shares. (L L shares. (10) ls (3) - (10) unties j in their licy in their bility Provi nity Eligib nity Eligib	ses. Year ar Clustered st) include dep proportion 1 · school distu sion of the I dility Provisio on FtS Polio	d county fi andard error pendent van to the inver rict. CEP i Π HFKA. C Π HFKA. C T of the H Π T of CEP, an	xed effects i ors at the cc riable lags at se distance is the propo EP * FtS is HFKA while dCEP*FtS	ncluded in al nuty level ir cross inverse between coun rtion of studd i the proporti s also being s	I models. Tim 1 models (1) i distance band aty i and coun- aty i and coun- ents in a coun- terved by farm erved by farm	ne-varying con and (2). Stan lwidths, contra- lwidths, contra- ty that are in ty that are in ty in a county -to-school distra- to-usand dollars	trol variables include dard errors clustered olling for agricultural <i>icy</i> is the proportion threed into free lunch chat are induced into ricts. Coefficients on Implied Δ Revenue

is the estimated change in statewide agricultural revenues associated with the policy coefficient(s) of interest in each model. In models (1) through (6), this is

simply equal to the point estimate times in row (2) times the total number of farm-to-school policy county-years (i.e., 288). In models (7) and (9), implied change in revenue is the point estimate in row (3) times the sum of CEP shares (i.e., 15.5). In models (8) and (10), the implied revenue change is the point estimate in row (2) times 288 subtracted by the point estimate in (4) times the sum of all CEP*FtS combinations (i.e., 3.8).

2001-2
Revenues
Agricultural
5:
Table

	С	DLS	Spatial Lag 1	Spatial Lag 2	CEP 1	CEP 2
	(1)	(2)	(3)	(4)	(5)	(6)
Within-County	Effects					
Nutrition	0.229	0.165	0.193	0.160	0.199	0.0868
Expenditures	(0.285)	(0.287)	(0.333)	(0.332)	(0.333)	(0.333)
FtS Policy		4531.3	4630.8^{***}	4587.7^{***}	5175.6^{***}	4312.6**
		(4844.7)	(1553.7)	(1552.3)	(1678.4)	(1693.7)
CEP					12130.3	11682.8
0111					(18319.4)	(17957.1)
						· · · · ·
$CEP \times FtS$					-29202.4	-26095.5
Policy					(35897.5)	(35860.8)
Contiguous Cou	ınty Effe	ects				
Nutrition				0.314		-0.0336
Expenditures				(0.781)		(0.780)
FtS Policy				362.7		695.6
U				(4226.3)		(4497.0)
CEP						155718 3***
						(45202.6)
						()
$CEP \times FtS$						-168525.1^{*}
Policy						(96327.1)
N	$2,\!669$	$2,\!669$	2,669	2,669	2,669	2,669

 Table 3: Agricultural Revenues - Animal Products 2001-2017

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Year and county fixed effects included in all models. Time-varying control variables include the total number of students in each district and FRL shares. Clustered standard errors at the county level in models (1) and (2). Standard errors clustered across contiguous counties in models (3) - (6). 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-toschool 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.

	С	DLS	Spatial Lag 1	Spatial Lag 2	CEP 1	CEP 2
	(1)	(2)	(3)	(4)	(5)	(6)
Within-County	Effects					
Nutrition	0.0119	0.0486	0.113	-0.0399	0.137	-0.0120
Expenditures	(0.314)	(0.301)	(0.178)	(0.197)	(0.178)	(0.197)
FtS Policy		-2575.9 (1689.1)	-1858.9** (839.1)	-2416.0*** (879.7)	-891.6 (910.8)	-1645.2^{*} (957.3)
CEP					24775.8^{***} (9563.0)	24919.9^{**} (10286.5)
$\begin{array}{l} \text{CEP} \times \text{FtS} \\ \text{Policy} \end{array}$					-44989.4** (19067.2)	-32876.3 (21109.3)
Contiguous Cou	inty Effe	cts				
Nutrition				-0.920*		-0.966*
Expenditures				(0.000536)		(0.000537)
FtS Policy				-5820.6**		-8154.6***
				(2592.6)		(2863.0)
CEP						-16419.4 (30769.7)
$\begin{array}{c} \text{CEP} \times \text{FtS} \\ \text{Policy} \end{array}$	2 2 2 2	2.600	2.660	2.660	2.000	94053.6 (65743.7)
IN	2,669	2,669	2,669	2,669	2,669	2,669

Table 4:	Agricultural	Revenues	- Fruits and	Vegetables	2001-2017
TOUGHO TO	ingriourourou	rooronaoo	LIGIOD GIIG	1050000100	TOOT TOT!

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Year and county fixed effects included in all models. Time-varying control variables include the total number of students in each district and FRL shares. Clustered standard errors at the county level in models (1) and (2). Standard errors clustered across contiguous counties in models (3) - (6). 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-toschool 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.

	0	LS	Spatial Lag 1	Spatial Lag 2	CEP 1	CEP 2
	(1)	(2)	(3)	(4)	(5)	(6)
Within-County	Effects					
Nutrition	-0.0435	-0.0441	-0.0431	-0.0420	-0.0469^{*}	-0.0447*
Expenditures	(0.0337)	(0.0339)	(0.0264)	(0.0264)	(0.0263)	(0.0264)
FtS Policy		46.83 (117.1)	51.98 (123.7)	54.41 (123.4)	-83.06 (132.8)	-73.72 (134.2)
CEP					-6259.7^{***} (1411.5)	-6101.8*** (1421.9)
$CEP \times FtS$					5960.9**	6061.6**
Policy					(2837.8)	(2856.7)
Contiguous Co Nutrition Expenditures	unty Effec	ets		-0.0209 (0.0617)		-0.00485 (0.0615)
FtS Policy				-199.4		-259.0
1 0.5 1 01105				(326.2)		(345.9)
CEP						-1118.1 (3805.4)
$CEP \times FtS$						11489.3
Policy						(7836.7)
N	$2,\!669$	2,669	2,669	2,669	$2,\!669$	2,669

Table 5:	Agricultural	Revenues -	Agrotourism	2001-2017
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* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Year and county fixed effects included in all models. Time-varying control variables include the total number of students in each district and FRL shares. Clustered standard errors at the county level in models (1) and (2). Standard errors clustered across contiguous counties in models (3) - (6). 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-toschool 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.

		(-)	(-)
	(1)	(2)	(3)
	Total	Animal	Fruits and
	Revenues	Products	Vegetables
First Stage			
CEP Share	$2,696,274^{***}$	$2,696,274^{***}$	$2.696.274^{***}$
	(290860.1)	(290860.1)	(290860.1)
F-Stat of Excluded Instruments	17.01	17.01	17.01
	11101	11101	1
Second Stage			
Nutrition Expenditures	26.37^{*}	3.86	19.26^{*}
-	(15.79)	(5.59)	(10.88)
	~ /		· · ·
County Mean Agricultural Revenue	61.8M	39.4M	\$18.44M
County Mean Nutrition Expenditure	\$5.13M	\$5.13M	\$5.13M
Implied Average County Revenue Change	\$354,560	\$52,038	\$259,651
Implied Local Expenditure Share	6.9%	1.0%	5.0%
Implied Total Revenue Change	966M	\$138M	\$690M
Trend Controls	\checkmark	\checkmark	\checkmark
Year & District FEs	\checkmark	\checkmark	\checkmark
Observations	2,701	2,701	2,701

Table 6: Two Stage Least Squares: Agricultural Revenues 2001-2017

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Clustered standard errors at the county level. Controls include county-specific trends and year and district fixed effects. County mean agricultural revenue is the revenue across all relevant agricultural products in a county, while mean nutrition expenditures is the total nutrition expenditures by schools in a county. Implied Average County Revenue Change is the first-stage CEP coefficient times the average CEP share and the second stage coefficient, representing the increase in local agricultural revenues associated with increasing numbers of free lunch students through with the CEP across each county-year combination on average. Implied local expenditure share is the average proportion of nutrition expenditures that appear to be recouped by farmers in the same county. Implied Total Revenue Change is the total nutritional outlays over the entire sample (\$13.8B) times the implied local expenditure share.

Figures





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.



Figure 3: Total Agricultural Revenues by Product (in millions) 2001-2017

Note: Figure plots all-time revenues by product in the Farm Gate Values Survey in millions of dollars.

Appendix

Main Categories	Commodities
Animal Products	Beef, Catfish, Chicken, Dairy, Eggs, Fishing, Pork
Fruits & Vegetables	Apples, Banana Peppers, Barley, Bell Peppers, Blackber-
	ries, 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, Pump-
	kin, 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 A1: Commodities Included in Each Agricultural Category

	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		

 Table A2:
 Golden Radish Application Information 2014-2018

Mean coefficients reported; standard deviations in parentheses.

	(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	$77.5 \mathrm{M}$	$49.7 \mathrm{M}$	36M	$20.7 \mathrm{M}$
R2	0.704	0.699	0.700	0.693	0.693
N	2,669	$2,\!669$	$2,\!669$	2,669	2,669

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

* 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 county *i* in year *t*. %*MarginalFtSCEPStudents* 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 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.