

RESEARCH ARTICLE

A roadmap for modeling institutional and values-based procurement decisions in food supply chains

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(Received 11 March 2023; revised 25 October 2024; accepted 17 January 2025; first published online 03 April 2025)

Abstract

Public food procurement incentives and targeted policies by state and Federal governments are one of the most frequently enacted strategies to leverage food spending to promote cobenefits related to economic, environmental, and social outcomes. Here we use an optimization model to explore potential outcomes of policy alternatives and integrate cobenefit dimensions into schools' agri-food supply chains via Farm to School procurement incentives. We find that in the absence of policy supports, school food authorities are unlikely to participate in local food procurement programs. We then place the findings in context by inferring the level of financial incentives that are needed to reduce barriers to schools' participation. Our findings have implications for community and economic development policies, particularly those seeking to support agriculturally dependent areas via elevated institutional food procurement using the case of policies framed for a school setting.

Keywords: Agricultural policy; farm to school; food policy; local food; public food procurement; state policy; supply chains

JEL codes: O13, Q13, Q18

Introduction

"Local" public food procurement is perhaps the most frequently leveraged food-based strategy implemented in the United States (U.S.) to achieve public sector sustainability goals (Botkins and Roe 2018; Jablonski et al. 2023; NFSN and CAFS 2021). The National School Lunch Program (part of a suite of child nutrition programs available in schools), provided 4.9 billion lunches at a total cost of \$14.2 billion in FY 2019 (prior to the COVID-19 pandemic) (USDA ERS 2022; USDA FNS 2024). There is growing pressure from advocates to use these funds to support multiple "values-based"

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goals¹ (Campbell 2023), including "kids win farmers win communities win" outcomes (NFSN 2021). As a signal of the momentum to support such initiatives, the Good Food Purchasing Program, the most widely adopted values-based procurement program in the U.S., included 63 institutions and 11 local coalitions representing 25 cities and more than \$1.1 billion in annual food expenditures as of 2022 (Center for Good Food Purchasing 2023).

Yet, school food service directors are under considerable pressure to use their budget efficiently and responsibly, whereas local procurement in schools is likely more expensive, including the higher transaction costs associated with managing multiple smaller vendors (Long et al. 2021). Further, the costs of producing meals in schools may already exceed the pre-determined rate at which school meal programs can claim cost reimbursement from the federal government-even before a school food authority (SFA)² considers the potential elevated costs of integrating local items (School Nutrition Association 2024). These pressures create a complex environment for school food decisionmakers and raise questions about how school food decisionmakers react to policy changes in the face of competing incentives. To explore these ideas, we model an SFA's optimization problem, with the primary intention of offering a template for such analysis, but also, parameterizing it with data from SFAs and the literature to provide step-by-step guidance on how one might apply the model to a specific setting. This contributes to the field by providing a roadmap for framing such analysis, and offering both observed outcomes in response to existing procurement policies that are unique to school food, as well as offering a framework to consider future responses to proposed policies.

There has been increasing attention on large, public institutional buyers of local food, such as schools and hospitals to increase the buying dollars and potential impact of local and regional food marketing efforts. The National School Lunch Program (NSLP), for example, is typically the second largest food and nutrition assistance program in the U.S., after the Supplemental Nutrition Assistance Program (USDA ERS 2022; USDA FNS 2020). Of the \$7.3 billion that SFAs spent on all types of food during the 2018–19 school year, \$1.3 billion (approximately 20%) was spent on local products (USDA FNS 2021b, 2021a).³ School nutrition programs are a reasonable proxy for institutional food procurement in the sense that the constraints they face in food purchasing are likely similar to those experienced by hospitals, municipalities, and other large buyers with complex purchasing platforms and processes. For the purposes of this research, we assume SFAs strive to minimize their costs subject to mandatory operational constraints (e.g., they must achieve a certain level of product variety), as well as policy-based constraints that can be turned "on" or "off" to simulate different policy environments.

Community investment in local food systems has been found to produce economic (e.g., Hughes et al. 2017; Jablonski, Schmit, and Kay 2016), social (e.g., Brown and Miller 2008; Marsden, Flynn, and Harrison 2000), and environmental (e.g., Pretty et al. 2001, 2005) benefits. King et al. (2010) find that local communities retain larger shares of wages, income, and farm revenues when farmers sell products through local supply chains versus mainstream channels. If schools purchase food from farmers or local food businesses with strong economic ties to their local communities, a larger share of their food dollars is

¹"Values-based" procurement is where criteria such as environmental or local economic impacts are integrated into institutional food purchasing decisions in addition to price.

²School food authorities are the entities that administer nutrition programs at the school district level. ³School food authorities may develop their own definitions of "local" foods. Some choose to define local food as originating within a certain radius of the school district, while others may use geopolitical boundaries, such as originating within the same county or state (USDA FNS 2021b).

cycled back into their local economies relative to purchases made from larger food distribution companies (Christensen, Jablonski, and O'Hara 2019; Gunter and Thilmany 2012; Jablonski, Schmit, and Kay 2016; Kluson 2012; O'Hara and Pirog 2013; Roche, Conner, and Kolodinsky 2015; Shideler et al. 2018; Tuck et al. 2010). Attention to distributive, equity, or co-beneficial outcomes can contribute to more holistic wealth creation in agriculturally dependent areas (Ashley and Maxwell 2002; Aubry and Kebir 2013; Harrison et al. 2019; Marsden et al. 2000b, 2000a; Pender et al. 2012; Renting et al. 2003), many of which have experienced economic decline in the past several decades (Alig et al. 2004; Cromartie 2017). Recently, Kashyap et al. (2024) found that there are key relationships between community wealth and Farm to School programs. Subsequently, Fresco et al. (2021) urge food economists to investigate institutional and governance decisions using a multidisciplinary approach, integrating social embeddedness and community values in supply chain scenarios.

SFAs have potential to contribute to local economic development and other positive outcomes but also face complex decision-making environments with competing demands on their limited resources. This research asks: What are the cost and socio-economic tradeoffs of SFA food procurement choices in different policy environments? The primary contribution of this study is framing a roadmap for parameterizing optimization models to simulate the decision-making environment of public institutions that adopt values-based procurement. Walking through the development of an optimization model from 1) conceptualization, to 2) compiling and ground-truthing a collection of data compiled from literature and program data, to 3) parameterizing the model in a way that characterizes public procurement decisions provides a step-by-step process via which others assessing potential impacts of values-based procurement decisions can answer novel questions about economic and social trade-offs among policies for various actors in the supply chain. The optimization model focuses on fully considering the options and constraints faced by an SFA and is informed by primary data (the best choice when available) and recent literature from various local food supply chain studies (where representative numbers are the second-best option). As there are a number of economic and other factors that vary greatly across the different supply chain options, we pay particular attention to integrating the best available empirical data from the literature, case studies, and primary data analysis to represent trade-offs among factors that may drive school decisions (e.g., price, labor needs, social outcomes).

This is a pilot model unique in its approach to integrate food system literature and evolving policies to frame a conceptual model that allows one to explore trade-offs of SFA decision-making, so we encourage the reader to focus on the magnitude and direction of results rather than on specific values. While some data in the objective function and constraints are meant to frame a representative SFA and its supply chain choices, other constraints were created to represent the types of policy "levers" being used to nudge SFAs to balance costs with other values-based outcomes (local economic activity, price risk). Our hope is that, guided by this framework, practitioners can re-parameterize and customize the model and its constraints to better reflect the conditions in their local SFAs and run various scenarios that reflect potential policy choices being considered for school food purchasing behavior in their area or state.

Local food procurement in schools: farm to school

In the U.S., Farm to School (FTS) – including an emphasis on local procurement – is increasingly promoted as a values-based procurement strategy to meet sustainable development goals (Kashyap et al. 2023; Long et al. 2021). The 2023 FTS Census, which

surveyed SFAs about their FTS activities during the 2022–2023 school year, reported that 74% of all food authorities surveyed participated in FTS (USDA FNS 2023b). Of schools that participated, 63% participated in local procurement activities, spending \$1.8 billion on locally grown and raised items (USDA FNS 2023b). Further, procurement is a frequently pursued and enacted subnational legislation (NFSN and VLSCAFS 2021). Accordingly, FTS procurement is the focus of this article.

Challenges associated with FTS procurement have been well-documented and include availability, price and budget constraints, communication barriers, lack of supply chain infrastructure, lack of staff time to prepare local foods, and concerns about food safety (Botkins and Roe 2018; Long et al. 2021; Stokes 2014; USDA FNS 2021a). Although the U.S. has had a specific FTS grant program since 2012 (part of the 2010 Healthy Hunger Free Kids Act), state incentives far exceed federal FTS funds (O'Hara et al. 2022). Most state policies have focused on alleviating the cost implications related to relatively higher prices for local food procurement (NFSN and VLSCAFS 2021), as local food is generally perceived to be more expensive or inflated by relatively higher transaction costs than its traditionally sourced counterpart (Donaher and Lynes 2017; Fox and Gearan 2019).

In 2017 and 2018, 23 states passed legislation to encourage FTS procurement (NFSN and CAFS 2019). Many of these state-level policies provide reimbursements to SFAs if they participate in certain local purchasing behaviors. For example, Colorado House Bill (CO HB) 19-1132, passed in May 2019, authorized a \$500,000-capped reimbursement program for SFA spending on Colorado-grown or -processed foods (Colorado General Assembly 2019). It effectively reduces the costs of Colorado-grown or -processed products for eligible SFAs by providing a \$0.05 per meal incentive. As another example, Chapter 56 of the Laws of 2022 for New York State increases the reimbursement schools receive for school lunches from 5.9 cents per meal to 25 cents per meal for any SFA that ensures their school lunches are made up of at least 30% eligible New York produced and processed products (NYSDAM n.d.). To date, incentives have been developed without a full understanding of how SFAs make decisions, how they balance costs, and what level of premium might be required to achieve multiple values-based goals. To our knowledge, this is the first empirical research to ask these questions.

Previous agri-supply chain and farm to school research

Many FTS studies provide qualitative descriptions of constraints faced by SFAs that want to purchase more local food (Botkins and Roe 2018; Stokes 2014), but few quantify the trade-offs between constraints and outcomes for SFAs. Optimization models are a useful tool for this type of evaluation because they allow the researcher to estimate the potential impacts of changing various policy and market constraints and purchasing decisions on an SFA's budget and the quantity of meals purchased.

We could identify only one previous study that used an optimization model to look specifically at FTS supply chains. Long et al. (2021) used an optimization model to assess Colorado SFA purchasing of local, fresh fruits and vegetables subject to a variety of constraints, such as price and seasonality. They found that a \$0.05 per meal incentive would increase fresh fruit and vegetable purchasing 11–12% August through October and 0–1% in November and December. Our research builds on this work, but instead of focusing on amounts of specific products purchased, our model examines the choices a school makes regarding the type of distributor from which to purchase product.

While the literature using optimization models to assess FTS programs is sparse, previous research has used them to examine trade-offs in agri-food supply chains more generally. Monroy et al. (2008) used an optimization model to assess management policy

impacts on the efficiency of the milk-cheese supply chain for Guayanés cheese in the Guayana region of Venezuela. Wang et al. (2009) used an optimization model to assess supply and demand impacts of supply chain structure in a supply chain on green agricultural products. Zhong et al. (2015) compared the economic and environmental trade-offs of the switchgrass for feedstock and switchgrass for biofuel supply chains. These examples demonstrate the suitability of optimization models for assessing the impacts of changes along complex food supply chains to an outcome of interest. Here, we apply the optimization model framework to the school setting to assess how a per-meal incentive policy, along with several alternative policy options, could affect SFAs' choice of food suppliers. This is an important decision because different types of supply chains have different levels of efficiency and relative prices, as well as different positive and negative externalities.

Data and model selection

Our optimization model explores additional economic and environmental co-benefits relative to efficiency loses in the form of cost savings for four commonly used procurement supply chains. We chose a linear optimization model (as opposed to non-linear) for a few reasons. The linear optimization model requires fewer input parameters than a non-linear version of the model, so it is a better fit for state and local policy settings in which users of the model may not have access to the information needed to parameterize the non-linear version of the model. An SFA typically purchases food for a set number of meals that is determined by the number of students served by the SFA. The range of number of meals over which the constraints vary is restricted for each SFA by its student population, although by linearizing the model, we do give up information on how constraints vary within that range as SFAs allocate the fixed number of meals to different purchasing routes. Overall, though, the linear model still gives a realistic range of estimates for the choices and trade-offs faced by SFAs when choosing how many meals to purchase from different supply chain routes.

We structured the choice variables of the model based on conceptual models of supply chain routes laid out by Angelo et al. (2016) and Christensen et al. (2019). We compiled data to populate the model in a number of ways because of the diverse array of parameters and measures needed to characterize the factors integrated into the optimization model.

We used total annual food expenditures by SFAs and meal counts, obtained from the 2015 U.S. Department of Agriculture (USDA) Food and Nutrition Service (FNS) FTS Census and school district budgets. The FTS Census is an online survey completed by school food service directors, who self-report data on their programs (USDA FNS 2015b). We also obtained data from published and industry sources on FTS procurement, supply chain pathways, food marketing and product variety, and local versus conventional food price premia. We used an annual Sysco shareholder report (Sysco 2014), results of the Wallace Center and Michigan State University's Food Hub Benchmarking Survey (Colasanti et al. 2018), and Colorado State University's Market Channel Assessments (Jablonski et al. 2017) to compile information for supply chain cost structure, which allowed us to calculate objective function parameters. To estimate a local price premium, we used the USDA Agricultural Marketing Service (AMS) Custom Average Pricing Tool, which tracks farm gate price averages by commodities and product characteristics over specified time periods, and Iowa FTS records (Iowa Department of Education 2020; US Department of Agriculture Agricultural Marketing Service 2020). There is more information about each data source and how the data are integrated into the model constraints in the next section.

Choice Variable (number of meals)	Pathway Name	Supply Chain Pathway (from Figure 1)
Z ₁	Direct Local	$A \to F$
Z ₂	Non-Traditional Local	$A \to C \to F$
Z ₃	Traditional Local	$A \to D \to F$
Z ₄	Traditional Non-Local	$B\toD\toF$

Table 1. Supply chain pathways on choice variables

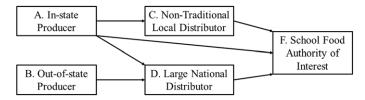


Figure 1. Choice variable supply chains for products purchased by school food authorities.

School food authority food cost minimization model

SFAs manage many competing demands to successfully produce meals that meet state and federal standards. An optimization model is an appropriate method for modeling SFA food purchasing behavior because it allows us to compare resource use among different choices and the marginal impact of changes in policies on resources. We first introduce the generic, non-parameterized objective function and subsequently explain how we structured the model and arrived at parameter values for the objective function and constraints.

The SFA's generic cost minimization objective function is:

Minimize
$$\sum c_1 z_1 + c_2 z_2 + c_3 z_3 + c_4 z_4$$
 w.r.t. z_{1-4} .

s.t.

 $\begin{array}{l} d_{1}z_{1}+d_{2}z_{2}+d_{3}z_{3}+d_{4}z_{4} \geq d_{5} \mbox{ (Quantity)} \\ e_{3}z_{3}-e_{4}z_{4} \leq e_{5} \mbox{ (Labor : FoodPrep)} \\ f_{1}z_{1}-f_{2}z_{2}+f_{3}z_{3}+f_{4}z_{4} \geq f_{5} \mbox{ (AssortmentBreadth)} \\ g_{1}z_{1}+g_{2}z_{2} \geq g_{3} \mbox{ (AssortmentDepth)} \\ h_{1}z_{1}+h_{2}z_{2}+h_{3}z_{3}-h_{4}z_{4} \geq h_{5} \mbox{ (IntensityofLocal)} \\ i_{1}z_{1}+i_{2}z_{2}-i_{3}z_{3}-i_{4}z_{4} \geq i_{5} \mbox{ (EconomicImpact)} \\ j_{1}z_{1}-j_{2}z_{2}+j_{3}z_{3}+j_{4}z_{4} \leq j_{5} \mbox{ (PriceRisk)} \end{array}$

The variable *c* is the cost per meal of purchasing from a supply chain pathway j, and z is the number of meals purchased through a supply chain pathway j. The choice variables are the number of meals purchased from each supply chain pathway: direct local (j = 1), nontraditional local (j = 2), traditional local (j = 3), and traditional non-local (j = 4)

Scenario	Quantity La	abor	Assortment Breadth	Assortment Depth	Local Intensity	Economic Impact	Price Risk
BAU	On	On	On	On	Off	Off	Off
CO HB 19-1132	On	On	On	On	Off	Off	Off
25% Local	On	On	On	On	On	Off	Off
High Econ. Imp.	On	On	On	On	Off	On	Off
Low Price Risk	On	On	On	On	Off	Off	On
Combo	On	On	On	On	On	On	On

Table 2. Constraint combinations for various scenarios

(Figure 1; Table 1). Choice variable pathways contain more specific vendor types as defined in the 2015 FTS Census. We defined the choice variable vendor groups to match the methodology of Christensen et al. (2019). The direct local category includes food purchased from food producers, farmers' markets, or CSAs. The nontraditional local category includes purchases indirectly made from local farms and ranches through intermediated distribution relationships with food hubs, producer cooperatives, food buying cooperatives, and State FTS program offices. The traditional local category includes purchases indirectly made from local farms and ranches through relationships with mainline distributors, processors/manufacturers, Department of Defense Program vendors, USDA Foods, and food service management companies. The traditional non-local category includes the same group of vendors as the traditional local grouping, but this category of variables represents those distributors' non-local product offerings.

The constraints are divided into mandatory operational constraints (i.e., quantity, labor: food prep, assortment breadth, assortment depth) that are turned "on" in every model scenario and optional policy constraints (i.e., intensity of local, economic impact, price risk) that can be turned "on" and "off" depending on the policy environment the modeler wants to simulate. The quantity constraint forces the SFA in the model to purchase a minimum number of meals. The labor constraint captures the differences in preparation time among supply chain routes. The assortment breadth constraint captures the costs to schools associated with product variety available from different distributor types. The assortment depth constraint refers to the assortment of products available within a single food category which could be changed to reflect an SFA's higher or lower preferences for specialty or local products. The intensity of local constraint is meant to represent a policy lever, whereby SFAs commit to purchasing a certain portion of their food from local sources. The economic impact constraint consists of economic impact multipliers for different supply chain routes that capture economic impacts to local economies from the local food sector versus the traditional wholesale sector. The price risk constraint captures differences in price volatility faced by schools among different supply chain routes.

Model scenarios

We ran the model under several scenarios to see how various policy levers would impact FTS procurement behavior (Table 2). Most of the scenarios consisted of "operationalizing" various policy lever constraints. For the first scenario, Business as Usual, we included no policy constraints. In the second, CO HB 19-1132, we modeled purchasing behavior under

a \$0.05 per meal reimbursement for local purchasing behavior, such as that authorized in Colorado in May 2019. Under this scenario, we lowered the objective parameters by \$0.05 per meal for z_1 , z_2 , and z_3 . We based the third scenario, 25% Local, on the Denver Food Vision 2030 winnable goal (signed by Denver's Mayor in 2017), in which at least 25% of all meals purchased had to come from z_1, z_2 , or z_3 . This scenario is reflective of many policies passed by cities across the U.S. For this scenario, we returned the objective function parameters to their original values and varied the intensity of local constraints. For the fourth scenario, High Economic Impact, we "turned off" the intensity of local constraint and activated the economic impact constraint. This reflects goals and priorities of many mayors and governors to maximize economic outcomes. In the fifth scenario, Low Price Risk, we "turned off" the intensity of local and economic impact constraints and turned on the price risk constraint. This scenario is important for decisionmakers such as Congress and the USDA that prioritize programs that subsidize insurance products and other programs to support farm viability outcomes. For the sixth and final scenario, Combination, we combined all seven constraints, four baseline constraints and three policy lever constraints, along with the original objective function parameters to see the impact of a bundle of policies on school purchasing.

Meal cost parameterization

The model-building process developed and described in this manuscript is intended to serve as a roadmap, and part of the local context needed in the model development process is selecting the data with which to parameterize the model. Herein our goal was to understand trade-offs associated with a specific state-level policy (CO HB 19-1132) by modeling the SFA (the entity that makes many school food purchasing decisions) decision-making environment. Accordingly, we incorporated Colorado-specific data to the extent possible. When data for our preferred geographic context was not available, we supplemented with national data or data from another state. Though integrating data from multiple locations is imperfect, given the proliferation of values-based procurement policies, there are conversations underway at the national and subnational level about how to improve school food data collection moving forward to address these data deficiencies (USDA FNS 2023a). Thus, as local data availability continues to improve, it should ease the ability to parametrize this road map model.

Traditional non-local meal cost

To begin, we calculate a baseline average meal cost for SFAs that do not procure locally, essentially representing the lowest average food cost for school meals. We consulted the 2015 FTS Census to identify Colorado schools that did not participate in any FTS activity in the 2013–14 school year. To capture some of the variety in size among Colorado's 178 school districts, while also not skewing our baseline by scale, we chose the four median Colorado school districts by pupil population from the list of schools that did not participate in FTS activities: Big Sandy 100J, Swink 33, Ridgway, and Kiowa C-2 (Colorado Department of Education 2020a; USDA FNS 2015a).⁴

We consulted publicly available school budgets and Colorado Department of Education meal count records to calculate an average food cost per meal for each of the four districts

⁴These school districts tended to be smaller and more rural than many other districts in Colorado, so it should be noted that they are not representative of the state's districts as a whole.

(Big Sandy School District 2018; Colorado Department of Education 2020b; Kiowa C-2 School District 2017; Ridgway School District R-2 2013; Swink School District 2015).⁵ School district operating budgets often aggregate breakfast and lunch supplies into one line item for food service supplies, so we consider all meals (breakfast and lunch) served by the SFA in our model. We took the average of the four meal costs and used that value as our baseline meal cost: \$1.84.⁶ We used this number to parameterize the cost of the traditional non-local supply chain route, c_4 in the objective function.

Traditional local meal cost

Next, we modified the traditional non-local supply chain route meal cost for each choice variable based on information compiled about profit margins of supply chain routes. Ideally, we would have information about three finance categories that constitute total sales for each supply chain route: cost of goods, operating expenses, and profit. However, in the publicly available reports we consulted, the profit and operating expense figures were aggregated (Colasanti et al. 2018; Jablonski et al. 2017; Sysco 2014). Therefore, we aggregated profit and operating expenses in our parameter calculations. While this limited our ability to precisely estimate parameters, we still provide approximations of relative meal costs. We found it encouraging that several sources corroborated our margin calculations for various supply chain routes (Draganska and Jain 2005; Hansen 2003; Plakias et al. 2020), which we describe next.

Sysco (Houston, TX) is a publicly traded company that served approximately 17.4% of the food service market in the U.S. and Canada in 2013, making it one of the largest broadline food distribution companies in either country. In its Annual Shareholders' Report from fiscal year 2014, Sysco emphasized a business strategy of supply chain consolidation and centralization built on customer relationships, product variety, prices, reliability, and punctuality. These features of its business model make it representative of a broadline distributor participating in the traditional non-local (c_4) and, since their customers have demanded more local options, traditional local (c_3) supply chain routes. We used information from the Shareholders' Report to parameterize the traditional supply chain routes (c_{3-4}) in our optimization model. We consulted the fiscal year 2014 report to align with the timeline of the 2015 FTS Census data. We broke the baseline meal price of \$1.84 down into the profit/operating expenses and cost of goods sold categories for the traditional non-local supply chain route (c_4). Sysco's total sales in that year were \$46.5 million, the cost of goods sold was \$38.3 million, and the gross profit (including operating expenses) was \$8.1 million. Eighty-three percent of total sales was paid by Sysco to acquire

⁵Different budget years were available from school websites, so we chose the fiscal year closest to the 2013–14 school year, since that is the data year for the FTS Census that was used to estimate other factors in the model. We carefully matched meal count records with the same year we compiled school food expenditures from budgets. We saw that SFAs likely benefit from economies of scale in lunch production costs because those with more students tended to have lower average meal costs.

⁶Previous literature suggests that the national average baseline meal price may be slightly lower than the \$1.84 figure used in our model. For example, Newman (2012) documented a price range of \$1.17 to \$1.38 as part of a USDA Economic Research Service (ERS) analysis of 2005 meal cost data from 400 schools nationally. Adjusting for food price inflation (https://www.usinflationcalculator.com/inflation/food-inflation-in-the-united-states/), this range would increase to \$1.42–\$1.68 in the 2013–14 school year we base this model on (21.4% higher) A few reasons for the additional difference in meal cost could be regional and temporal price variation, meal counting practices (more meals may be prepared and paid for than are "counted" as being served), and inclusion of "other food service supplies" in the school food budget line.

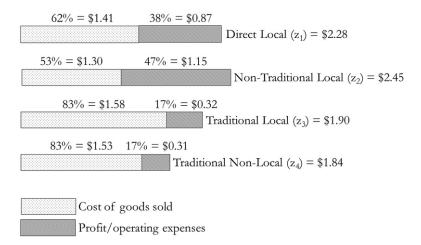


Figure 2. Cost structure breakdown for each supply chain route with baseline objective function parameter values. (Source: Cost structures calculated from results from the following: Direct Local from Jablonski et al. 2017 and Sysco 2014. Non-Traditional Local from Iowa Department of Education 2020, Colasanti et al. 2018, and Sysco 2014. Traditional Local from Iowa Department of Education 2020, Colasanti et al. 2018, and Sysco 2014. Traditional Non-Local from Sysco 2014).

the product, leaving 17% to cover profit and operating expenses, a number which we used as a proxy for marketing and distribution costs.

Nontraditional local meal cost

We calculated a 33% premium for local food versus conventionally procured food based on the price differences in a bundle of ingredients used in a school meal from the Iowa FTS report (Appendix A). We chose Iowa because Colorado data were unavailable, and Iowa's FTS program archives include online purchasing reports with volume and price information (Iowa Department of Education 2020). Iowa SFAs used a food hub to procure their local food (Thilmany 2020). Thus, the 33% premium we calculated represents the \$0.61 difference in cost between the traditional non-local route (c_4) at \$1.84 per meal and the nontraditional local route (c_2), which includes food hubs as distributors, at \$2.45 per meal (Figure 2).

We assumed that the 33% premium was partially due to the increase in the cost of the product paid by the distributor to the farmer, and partially due to increased per unit operating expenses for these smaller scale distributors. Choosing how to distribute the 33% percent premium into profit/operating expenses and cost of goods was an important step to appropriately estimate the meal costs for the remaining supply chain routes (c_1 and c_3). Food hubs attribute approximately 47% of their total sales to profit and operating expenses, compared to 17% for large traditional distributors (Figure 2; Colasanti et al. 2018). The difference of 30% represents a portion of the 33% premium difference between these two supply chain routes. The 3% of the 33% premium remaining after the estimated profit/operating expenses difference was subtracted was attributed to the difference in cost of goods, implying the difference in the price paid to the farmer for the local product over the conventional product. We calculated the proportion of the \$0.61 premium of c_2 over c_4

that goes to each type of expense and observed that \$0.55 goes to operating expenses/profit, which is relatively higher than mainline distributors by our estimate, and \$0.06 goes to the cost of goods, or as a premium on the farm gate price, representing some of the potential local benefit to producers in the community.

To calculate the meal cost for the traditional local supply chain route (c_3), we assumed the farmer expects the same absolute price premium per meal for a local product as if they were selling through a food hub (\$0.06), but the traditional supplier can market and distribute more efficiently, eliminating the portion of the price difference between c_2 and c_4 that went to operating expenses/profit. Summing the baseline traditional non-local meal cost of \$1.84 and the local farm gate premium of \$0.06 gave the traditional local meal cost of \$1.90.

Direct local meal cost

The final meal cost parameter relates to the direct local supply chain route (c_1) . In previous market channel research sponsored by the USDA, Colorado State University found that, for farmers selling to "other" types of institutions (which includes schools), approximately 62% of the cost of the food goes to costs of production up through harvest, while the remaining 38% constitutes marketing, distribution, and operating expenses, as well as profits (Jablonski et al. 2017). Even though this is not a benchmark directly comparable to the Sysco numbers, it is a relevant comparator for a farm marketing directly to schools. This figure is also within the range of 13–62% for marketing costs of farms selling direct to consumers documented by King et al. (2010) in the 15 case studies that formed the basis for their USDA ERS supply chain report. We performed the same calculation that we did for the nontraditional local supply chain route, subtracting the 17% profit/operating costs margin of the large national distributor from the 38% margin for the local producer selling directly. The 21% difference was added to the local product farm gate price premium of 3% for a total of a 24% premium captured by the farmer using this supply chain route. Using the traditional non-local distributor baseline price of \$1.84, we added the 24% premium for a final meal price of \$2.28 for the direct local supply chain route (c_1) . A summary of the objective function parameters can be found in Table 2.

Constraint parameterization

Once we established estimates for school meal costs purchased through various supply chain routes, we turned to formulating constraints representing resource and cost constraints that may affect the objective function. Based on a literature review of factors SFAs consider when procuring food, we incorporated the following constraints into our model: quantity, labor, assortment breadth, assortment depth, intensity of local procurement, economic impact, and price risk (Carpenter and Moore 2006; Chiang and Wilcox 1997; Conner et al. 2012; Feenstra and Ohmart 2012; Gordon et al. 2007; Hancock 2017; Izumi, Wright, and Hamm 2010; Meyer and Conklin 1998; Motta and Sharma 2016; Newman 2012; Woodward-Lopez et al. 2014).⁷ We classified the quantity,

⁷There are some factors included in the literature that we did not explicitly include in the model with individual constraints but whose importance we still want to acknowledge: budget, assortment cost, seasonality, kitchen equipment, food quality, and communication along the supply chain. We consider each of these factors and explain why we omitted them when we discuss model limitations.

labor, assortment breadth, and assortment depth as baseline constraints faced regardless of broader social equity considerations. But we included levers that may "nudge" a buyer to consider the intensity of local procurement, economic impact, and price risk as policy constraints that represent levers being more commonly employed in public procurement processes.⁸ We detail theoretical underpinnings and parameterization of each constraint below. Ge et al. (2015, 2016) used a similar methodology, compiling relevant conceptual framing and parameters from the literature, calculating, and assuming parameters for optimization models. We followed their example for all parameters to make information as easy as possible for the reader to follow.

Quantity constraint

The quantity constraint forces the SFA in the model to purchase a minimum number of meals. We set the quantity constraint at the number of meals (or amount of food in meal equivalents) purchased by SFAs annually. Because the model is cost minimizing, a quantity-unconstrained model would purchase zero meals. Schools participating in the NSLP and Breakfast Program must maintain daily meal count records to claim their federal reimbursements. We used this meal count number, aggregated to the annual level, to parameterize the quantity constraint. The annual meal count for any SFA could be used to minimally constrain the total number of meals sourced from all four supply chain routes. We use the average of annual meal counts from the 2013–14 academic year of the four median Colorado school districts by pupil size, which amounts to 46,085 meals (Colorado Department of Education 2020a, 2020b). The final quantity constraint is:

 $z_1 + z_2 + z_3 + z_4 \ge 46,085.$

Labor constraint

The labor constraint captures the differences in preparation time among supply chain routes. To a lesser degree, it could also be a proxy for administrative labor, or transaction costs, associated with local procurement. We set the labor constraint at the maximum per meal labor cost, so it does not constrain the model because we wanted to focus on the impacts of the policy constraints. Preparing raw ingredients and cooking preparation require more staff time than the increasingly common practice of warming preprocessed batches of food. Since most farms and some statewide food distributors of local products sell raw ingredients that require additional labor before the product can be served we must consider labor, and Woodward-Lopez et al. (2014) found that, on average, scratch cooking cost \$0.02 per meal more than the base labor cost of \$0.14 per meal across 10 California school districts. Based on that study, we assumed that the two more specialized local routes (z_1 and z_2) would cost \$0.02 per meal more in labor costs for extra preparation time than the two traditional supply chain routes (z_3 and z_4). The labor constraint is:

⁸With the exception of the quantity constraint, we chose right-hand side constraining values so the baseline constraints would not be binding for two reasons. First, we wanted to clearly delineate the impact of turning on each policy constraint. Second, reliable numbers for right-hand side constraint bounds were difficult to find. For example, with the food preparation labor constraint, we were able to find information about the relative (left-hand side parameters), but it was difficult to make an accurate assumption about the exact number of labor hours to which an SFA's food preparation should be constrained. Therefore, we did not want to place too much emphasis on that constraint when interpreting model output, especially since our focus was on policy constraints rather than baseline constraints.

$$0.16z_1 + 0.16z_2 + 0.14z_3 + 0.14z_4 \le 0.16^*(1z_1 + 1z_2 + 1z_3 + 1z_4).$$

Linearized, it becomes:

$$-0.02z_3 - 0.02z_4 \le 0$$

Assortment breadth constraint

Our assortment constraints includes both assortment breadth and assortment depth. School meals eligible for reimbursement must include five meal components: vegetable, fruit, grain, meat/meat alternative, and milk (USDA FNS 2020). Also, previous research found that students are more satisfied with lunch service when meals are palatable, culturally appropriate, and contain a variety of ingredients (Meyer 2000; Meyer and Conklin 1998). If participation rates are high, then schools can achieve economies of scale and reduce their per meal cost of production. It is thus in the financial interest of SFAs to procure a large assortment of ingredients to keep students interested in their menus (Conner et al. 2012; Ralston et al. 2017). The assortment breadth constraint captures the costs to schools associated with product variety available from different distributor types. Larger broadline distributors generally carry product lines with more items than small distributors, and schools have fewer transaction costs by procuring from a distributor who can provide all the ingredients they need for their menu. It is also more expensive for distributors to carry such large product varieties, but we assumed that these additional costs are already reflected in the costs charged to schools.

Accordingly, to capture assortment breadth, we follow results from the work of Chiang and Wilcox (1997), who used an ordinary least squares regression to estimate the relationship between percent profit margin and product variety in a grocery retail setting, where profit margin was defined as the product category's average retail margin as a percent of price and variety was defined as the average number of SKUs stocked in a given category. Their regression analysis, based on data about number of SKUs and profit margins provided by a midwestern retailer, yielded the following relationship: variety = 141.52 - 233.1% * profit margin (Chiang and Wilcox 1997)⁹. We used the Chiang and Wilcox regression to calculate product variety for the supply chain routes based on their gross profit margins, and set the assortment breadth constraint at an intermediate value (rounded the highest value of the routes not maintained by a mainline distributor, routes 1 and 2, up to the nearest 10) that would not likely be satisfied by only purchasing from the local routes, but at a value that could be satisfied easily by purchasing some meals from traditional suppliers. Doing so directs the model toward supply chain routes 3 and 4, which also happen to be the cheapest and therefore most desirable when unconstrained. The final assortment breadth constraint is:

$$52.94z_1 + 30.73z_2 + 101.89z_3 + 101.89z_4 \ge 60^*(1z_1 + 1z_2 + 1z_3 + 1z_4).$$

Linearized, it becomes:

$$-7.06z_1 - 29.27z_2 + 41.89z_3 + 41.89z_4 \ge 0.$$

⁹While prices have certainly increased, and we examined the distributor context instead of the retailer context, we assumed that general relationships between profit and product variety would hold.

Assortment depth constraint

Although not a common term used in local and direct produce marketing, we integrated an assortment depth constraint to capture the availability of differentiated or niche products that specialized distributors, such as food hubs or farmers, sell and that might have special properties, such as being produced locally, which are inherent to geography or production processes (Belletti et al. 2017). While the assortment breadth constraint refers to the assortment of products available across categories, the assortment depth constraint refers to the assortment of products available within a single category which could be changed to reflect an SFA's higher or lower preferences for specialty or local products. Carpenter and Moore's (2006) study of 454 grocery consumers, assessed the assortment of products for different types of retailers, from which we could draw parallels between the types of retailers they selected and the types of distributors represented in our optimization model. We set the assortment depth constraint at the per meal minimum by adding an additional 9% of assortment depth to the z_1 parameter. The final assortment depth constraint is:

 $4.75z_1 + 4.36z_2 + 4.00z_3 + 4.00z_4 \ge 4.0^*(1z_1 + 1z_2 + 1z_3 + 1z_4).$

Linearized, it becomes:

$$0.75z_1 + 0.36z_2 \ge 0.$$

Intensity of local policy constraint

Local and fair trade (share of sales captured by various members of the supply chain) are potential types of values-based procurement that SFAs may explore, especially if directed to by state or local policy initiatives (Maloni and Brown 2006). The intensity of local procurement activity constraint is meant to represent a policy lever, whereby SFAs commit to purchasing a certain portion of their food from local sources. As an example, the City of Denver committed to a goal of 25% local food procurement by the year 2030 in its Food Vision at the time of analysis in 2020 (Hancock 2017). We based the intensity of local constraint parameter on this particular policy, although the constraint could be tailored to any procurement policy under consideration. The intensity of local procurement activity constraint is:

$$1z_1 + 1z_2 + 1z_3 \ge .25^*(1z_1 + 1z_2 + 1z_3 + 1z_4).$$

Linearized, it becomes:

$$0.75z_1 + 0.75z_2 + 0.75z_3 - 0.25z_4 \ge 0.$$

Economic impact policy constraint

Potatoes are the highest-value fruit and vegetable crop grown in Colorado (by volume and sales), and they are available year-round, so we used data from the potato sector to parameterize two of the economic impact constraints and all of the price risk constraints (US Department of Agriculture National Agricultural Statistics Service 2020). The economic impact constraint consists of economic impact multipliers for different supply chain routes that capture economic impacts to local economies from the local food sector versus the traditional wholesale sector. The traditional local and non-local parameters came from 2016 IMPLAN data for the San Luis Valley, Colorado¹⁰ wholesale trade sector,

¹⁰Saguache, Alamosa, Rio Grande, Conejos, Costilla, and Mineral Counties were included in the multicounty San Luis Valley region.

which was the North American Industry Classification System (NAICS) sector that most closely aligned with a large food distributor's economic activity. We chose to focus on the San Luis Valley region of Colorado because it is the state's largest potato-growing region.

The local direct and nontraditional local parameters came from customized local food sector multiplier calculations created using IMPLAN data and customized to reflect local food sector activity using USDA Agricultural Resource Management Survey data from 2013 to 16 (Thilmany & Watson, 2019).¹¹ While the custom local food multipliers were not Colorado-specific, the Colorado and San Luis Valley wholesale trade multipliers were all calculated based on multicounty regions in rural and rural-adjacent areas, so there are some parallels between the regions represented in this constraint.¹² We multiplied each supply chain route's multiplier by the cost per meal for that route, which gave us 3.71 for z₁, 4.08 for z₂, 2.83 for z₃, and 2.74 for z₄. We set the economic impact constraint to the target level of economic impact (multiplier times meal price) so that only purchasing meals via local routes would necessarily satisfy the economic impact target; purchasing some meals from other routes could satisfy the target. We constrained the model to a minimum average economic impact per meal of 3.5 to ensure the SFA would engage with the direct local or non-traditional local routes while also maintaining some flexibility to purchase ingredients through more efficient channels. A policymaker or SFA that wanted to boost the economic impact of its food purchases could adjust the right-hand side parameter upward, while those more concerned with efficiency could lower it. The economic impact constraint is:

 $\begin{aligned} &(1.6251^*2.28)z_1 + (1.6640^*2.45)z_2 + (1.4872^*1.90)z_3 \\ &+ (1.4872^*1.84)z_4 \geq 3.5^*(1z_1 + 1z_2 + 1z_3 + 1z_4). \end{aligned}$

Linearized, it becomes:

$$0.21z_1 + 0.58z_2 - 67z_3 - .76z_4 \ge 0.$$

Price risk policy constraint

The price risk constraint captures differences in price volatility faced by schools among different supply chain routes. We calculated standard deviations of farm gate and terminal market prices in a separate analysis of potato markets to more generally represent price risk at different levels of the supply chain (with shorter, local chains being exposed to less risk) (Love and Thilmany 2022). We sourced price data from the USDA AMS custom price report tool (USDA AMS 2019). If schools purchase through a more price-volatile market channel, the prices they pay are likely less reliable, and their risk increases. The farm gate price standard deviation was 0.038, which corresponds to the z_1 route, and the terminal market price standard deviation was 0.087, which corresponds to the z_3 and z_4 routes. We added an additional 10% price risk to z_2 as compared to z_1 to represent the loss of control

¹¹The multicounty designation was the appropriate geographical scope to use for these multipliers because FTS transactions often take place across county lines (Plakias et al. 2020). The "both direct and intermediated" multiplier is most appropriate among the categories (that also included "direct only" or "intermediated only") for the local direct supply chain route because farmers who sell to institutions, such as schools, are likely to have large and complex enough operations to sell both through both direct and intermediated market channels. The "intermediated" multiplier is most appropriate for the nontraditional local supply chain route because farmers are selling their products through another entity (e.g., food hub, co-op) in this marketing channel.

¹²Urban areas tend to have higher economic impact multipliers than rural areas.

over pricing that schools have when additional steps of the supply chain are added. We set the price risk constraint by rounding up to the nearest hundredth from the routes not maintained by the mainline distributor (1 and 2), so the SFA would have to purchase some meals from those routes to satisfy the constraint. We set the right-hand side constraint value between the standard deviations of the two channels at 0.05, which allows us to capture the SFA's tolerance for some of the price risk present in the middle stages of the supply chain and also their tendency towards lower-volatility channels. The price risk constraint is:

$$0.038z_1 + 0.0418z_2 + 0.087z_3 + 0.087z_4 \le 0.05^*(1z_1 + 1z_2 + 1z_3 + 1z_4).$$

Linearized, it becomes:

$$-0.012z_1 - 0.0082z_2 + 0.037z_3 + 0.037z_4 \le 0.$$

A summary of all parameter variables, values, data sources, and methodologies used to calculate parameter values can be found in Table 3.

Formal statement of parameterized optimization model

The formal statement of the full, parameterized optimization problem is:

$$\text{Minimize} \sum 2.28z_1 + 2.45z_2 + 1.90z_3 + 1.84z_4$$

w.r.t.z, s.t.

$$1z_1 + 1z_2 + 1z_3 + 1z_4 \ge 46,085$$
 (Quantity)

$$.16z_1 + .16z_2 + .14z_3 + .14z_4 \le .16^*(1z_1 + 1z_2 + 1z_3 + 1z_4)$$
 (Labor : FoodPrep)

$$52.94z_1 + 30.73z_2 + 101.89z_3 + 101.89z_4 \ge 60^*(1z_1 + 1z_2 + 1z_3 + 1z_4)$$

(AssortmentBreadth)

 $4.75z_1 + 4.36z_2 + 4.00z_3 + 4.00z_4 \ge 4.0^*(1z_1 + 1z_2 + 1z_3 + 1z_4) \text{ (AssortmentDepth)}$

$$1z_1 + 1z_2 + 1z_3 \ge .25^*(1z_1 + 1z_2 + 1z_3 + 1z_4)$$
 (IntensityofLocal)

$$(1.6251^{*}2.28)z_{1} + (1.6640^{*}2.45)z_{2} + (1.4872^{*}1.90)z_{3}$$

$$+(1.4872^*1.84)z_4 \ge 3.5^*(1z_1+1z_2+1z_3+1z_4)$$

(EconomicImpact)

$$0.038z_1 + 0.0418z_2 + 0.087z_3 + 0.087z_4$$
le; $0.05^*(1z_1 + 1z_2 + 1z_3 + 1z_4)$ (PriceRisk)

Once we linearized all constraints and simplified terms, we derived the following model, programed in R and solved using the nonlinear optimizer "lpSolve," employing the simplex method. The linearized model is:

$$Minimize \sum 2.28z_1 + 2.45z_2 + 1.90z_3 + 1.84z_4 \quad w.r.t.z$$

s.t.

 $1z_1+1z_2+1z_3+1z_4 \ge 46,085$ (Quantity) $-0.02z_3-0.02z_4 \le 0$ (Labor : FoodPrep)

$$-7.06z_1 - 29.27z_2 + 41.89z_3 + 41.89z_4 \ge 0$$
 (AssortmentBreadth)

Table 3. Parameter names, values, data sources, and methodology

Parameter Variable	Value (z1; z2; z3; z4; constraint)	Methodology	Data Source	Geographic Area of Data
Objective Function Cost	2.28; 2.45; 1.90; 1.84	Calculated from literature	(Colasanti et al., 2018; Iowa Department of Education, 2020; Jablonski et al., 2017; Sysco, 2014; USDA AMS, 2019)	National; Iowa; Colorado; National; National
Quantity	1; 1; 1; 1; 46,085	Secondary data from source	(Colorado Department of Education, 2020a, 2020b)	Compositve of Colorado School Districts
Labor	-0.02; -0.02; 0; 0; 0	Drawn from literature	(Woodward-Lopez et al., 2014)	California school districts
Assortment Breadth	-7.06; -29.27; 41.89; 41.89; 0	Calculated from literature	(Chiang & Wilcox, 1997)	Indiana-based retailer
Assortment Depth	0.75; 0.46; 0; 0; 0	Calculated from literature	(Carpenter & Moore, 2006)	National
Local Intensity	0.75; 0.75; 0.75; -0.25; 0	Drawn from policy	(Hancock, 2017)	Denver, Colorado
Economic Impact	0.21; 0.58; -0.67; -0.76; 0	Calculated for Local Food Impact Calculator from USDA ARMS and IMPLAN data	(Thilmany & Watson, 2019)	Colorado multi-county; Colorado multi-county; National; National
Price risk	-0.012; -0.0082; 0.037; 0.037; 0	Calculated	(USDA AMS, 2019)	Colorado

 $\begin{array}{l} 0.75z_1+.36z_2 \geq 0 \mbox{ (AssortmentDepth)} \\ 0.75z_1+0.75z_2+0.75z_3-0.25z_4 \geq 0 \mbox{ (IntensityofLocal)} \\ 0.21z_1+0.58z_2-0.67z_3-0.76z_4 \geq 0 \mbox{ (EconomicImpact)} \\ -0.012z_1-0.0082z_2+0.037z_3+0.037z_4 \leq 0 \mbox{ (PriceRisk)} \end{array}$

Sensitivity analysis

We conducted a sensitivity analysis on the objective function parameters because since so many estimates were used for parameterization and we wanted to assess the robustness of findings. We varied the objective function parameters one at a time from 50% of their baseline values to 50% over their baseline values. We ran the model 10 times for each scenario in the sensitivity analysis: once with all objective function parameter values at 50% of their original values, four times with a single objective function parameter value at 50% of its original value each time (and the others remaining at their original values), once with all objective function parameter values at 50% above their original values, and four times with a single objective function parameter value at 50% above its original value each time (and the others remaining at their original value each time (and the others remaining at their original value each time (and the others remaining at their original value each time (and the others remaining at their original value each time (and the others remaining at their original value each time (and the others remaining at their original value each time (and the others remaining at their original values).

We did not conduct sensitivity analysis on the constraint parameters. The baseline constraints do not bind (which was an intentional choice because we wanted to focus on the model response to policy constraints), and the policy constraints were set with particular policies/scenarios in mind. Notably, we had to change the appropriate economic impact constraint parameter when that policy was enacted during a scenario because the constraint was partially based on the price per meal. We then observed changes in model solution and duals and reported the range of choice variable, constraint dual, and activity dual values for each scenario.

Results

As the data used to parameterize the objective function and baseline constraints were often from different geographies than the data used to parameterize the policy constraints, we encourage readers to consider our results primarily in terms of directionality and relative magnitude (though specific model results are in parentheses for reference). We walk through the model results to demonstrate how one might interpret model output.

Under the Business as Usual and CO HB 19-1132 scenarios, the SFA purchased all meals through the most cost-effective traditional non-local route (Table 4). Importantly, we find that the \$0.05 per local meal credit provided by CO HB 19-1132 was not enough to change the school's purchasing behavior. Under the 25% Local scenario, the SFA purchased some of its meals (25%) through the most cost-effective local route, the traditional local route, and the remaining meals through the traditional non-local route. Under the High Economic Impact scenario, the SFA purchased most of its meals (78%) through the direct local route and the remaining meals through the traditional non-local route. This supply chain has the second-highest economic impact per meal, but it is relatively more cost-effective than the nontraditional local route, which has the highest economic impact per meal. Under the Low Price Risk scenario, the SFA purchased most of its meals (76%) through the direct local route, which was the more cost-effective of the two routes that had a lower price risk. It purchased the remaining meals through the traditional

Scenario	Direct Local (z ₁) Meals Purchased (% of Total)	Non-Traditional Local (z ₂) Meals Purchased (% of Total)	Traditional Local (z ₃) Meals Purchased (% of Total)	Traditional Non- Local (z ₄) Meals Purchased (% of Total)
BAU	0 (0%)	0 (0%)	0 (0%)	46,085 (100%)
CO HB 19-1132	0 (0%)	0 (0%)	0 (0%)	46,085 (100%)
25% Local	0 (0%)	0 (0%)	11,521 (25%)	34,564 (75%)
High Econ. Imp.	36,108 (78%)	0 (0%)	0 (0%)	9,977 (22%)
Low Price Risk	34,799 (76%)	0 (0%)	0 (0%)	11,286 (24%)
Combination	36,108 (78%)	0 (0%)	0 (0%)	9,977 (22%)

Table 4. Supply chain route purchasing decisions under various scenarios

Note: The scenarios are Business as Usual (baseline objective function parameter values, no policy constraints), CO HB 19-1132 (objective function parameter values lowered by \$0.05 each, no policy constraints), 25% Local (baseline objective function parameter values, policy constraint: school districts are required to purchase 25% of their meals from a local source), High Economic Impact (baseline objective function parameter values, policy constraint: school districts are required to achieve an average per meal level of economic impact), Low Price Risk (baseline objective function parameter values, policy constraint: school districts are required to purchase in a way that achieves a per meal level of price volatility for farmers), and Combination (baseline objective function parameter values, all policy constraints from previous three scenarios are in effect).

non-local route. The Combination scenario showed that the most binding constraint was the economic impact constraint, and it should be noted that the SFA's purchasing behavior in the Combination scenario was identical to that under the High Economic Impact scenario.

All three policy levers nudged the SFA to purchase different amounts through each supply chain route. Some amount of traditional non-local was purchased in every scenario, and nontraditional local was never purchased, despite the application of several different policy constraints that encouraged local over traditional purchasing. Thus, policy levers can make some difference, but it is important to consider the implicit "cost" of such choices that may make certain options clear cost "winners," while others remain unachievable.

The shadow values of constraints represent the costs to SFAs of participating in certain optimization-constraining behaviors, such as procurement policies (Table 5). Although a shadow value typically shows the change in value of the objective function if the right-hand side constraint value is increased by one, because of how we set up the constraints, a one-unit increase in the constraint value does not necessarily correspond to a one-unit increase or decrease in meals served. However, the shadow values do show us the relative expenses of certain policy measures in dollar amount per meal (the shadow value on the quantity constraint). Overall, we find that CO HB 19-1132 was the most affordable, followed by 25% Local, Low Price Risk, and High Economic Impact.

Activity duals show the effect on the objective function of forcing the school to purchase a meal through one of the non-optimal supply chain routes instead of the optimal routes chosen by the model (Table 6). Essentially, the activity duals tell us how expensive it would be (on the margin) for the SFA to make an alternative purchasing decision under a

Scenario	Quantity	Labor	Assortment Breadth	Assortment Depth	Local Intensity	Economic Impact	Price Risk
BAU	1.84	0	0	0	n/a	n/a	n/a
	1.84	0	0	0	n/a	n/a	n/a
25% Local	1.86	0	0	0	0.060	n/a	n/a
High Econ. Imp.		0	0	0	n/a	0.45	n/a
Low Price Risk	2.17	0	0	0	n/a	n/a	-8.98
Combination	2.18	0	0	0	0	0.45	0

Table 5.	Shadow	values	(\$)	for	constraints	under	various	scenarios

Note: The scenarios are Business as Usual (baseline objective function parameter values, no policy constraints), CO HB 19-1132 (objective function parameter values lowered by \$0.05 each, no policy constraints), 25% Local (baseline objective function parameter values, policy constraint: school districts are required to purchase 25% of their meals from a local source), High Economic Impact (baseline objective function parameter values, policy constraint: school districts are required to achieve an average per meal level of economic impact), Low Price Risk (baseline objective function parameter values, policy constraint: school districts are required to purchase a per meal level of price volatility for farmers), and Combination (baseline objective function parameter values, all policy constraints from previous three scenarios are in effect).

Scenario	Direct Local (z ₁) Dual	Non-Traditional Local (z ₂) Dual	Traditional Local (z ₃) Dual	Traditional Non-Local (z ₄) Dual
BAU	0.44	0.61	0.06	0
CO HB 19- 1132	0.39	0.56	0.01	0
25% Local	0.38	0.55	0	0
High Econ. Imp.	0	0.002	0.02	0
Low Price Risk	0	0.20	0.06	0
Combination	0	0.002	0.02	0

Table 6. Activity duals (\$) under various scenarios

Note: The scenarios are Business as Usual (baseline objective function parameter values, no policy constraints), CO HB 19-1132 (objective function parameter values lowered by \$0.05 each, no policy constraints), 25% Local (baseline objective function parameter values, policy constraint: school districts are required to purchase 25% of their meals from a local source), High Economic Impact (baseline objective function parameter values, policy constraint: school districts are required to achieve an average per meal level of economic impact), Low Price Risk (baseline objective function parameter values, policy constraint: school districts are required to purchase a per meal level of price volatility for farmers), and Combination (baseline objective function parameter values, all policy constraints from previous three scenarios are in effect).

certain policy scenario. For example, under the Business as usual (BAU) scenario if an SFA wanted to purchase a meal from route z_1 instead of the optimal route (z_4) , that meal would carry an additional cost (\$0.44 extra). This is helpful information for policymakers who are deciding how much they need to subsidize SFAs if they want to encourage them to procure food from certain routes under certain policies. Given data constraints at the time of

Scenario	Direct Local (z ₁) Meals Purchased (% of Total)	Non-Traditional Local (z ₂) Meals Purchased (% of Total)	Traditional Local (z ₃) Meals Purchased (% of Total)	Traditional Non- Local (z ₄) Meals Purchased (% of Total)
BAU	0–39,438	0–27,129	0-46,085	0–46,085
	(0–86%)	(0–59%)	(0-100%)	(0–100%)
CO HB 19-	0–39,438	0–27,129	0-46,085	0–46,085
1132	(0–86%)	(0–59%)	(0-100%)	(0–100%)
25% Local	0–39,438	0–27,129	0-46,085	0–34,564
	(0–86%)	(0–59%)	(0-100%)	(0–75%)
High Econ.	0-39,438	0–26,623	0-10,998	0-46,085
Imp.	(0-86%)	(0–58%)	(0-24%)	(0-100%)
Low Price	26,744–39,438	0-8,732	0-11,286	0-11,286
Risk	(58–86%)	(0-19%)	(0-24%)	(0-24%)
Combo	26,744–39,438	0-8,732	0-10,998	0-11,286
	(58–86%)	(0-19%)	(0-24%)	(0-24%)

Table 7. Sensitivity analysis of supply chain route purchasing decisions under various scenarios

parameterizing this model, we encourage decisionmakers to consider our results as a litmus test to understand the direction and relative magnitude of economic policy impacts on public institution decision-making rather than as precise cost implications.

Sensitivity analysis

As we varied the objective function parameters from 50% of their baseline values to 50% above their baseline values, we saw wide fluctuations as a 50% change was enough to make the parameter being altered either the most or least expensive option (Table 7). Generally, when meals from a certain supply chain route were cheaper, the SFA purchased more of them; when they were more expensive, the SFA purchased fewer of them. The model was unsolvable when all parameters were lowered to 50% of their baseline values in the High Economic Impact and Combination scenarios. It was also unsolvable when the Direct Local meal cost was lowered to 50% of its baseline value in the Combination scenario. We hypothesize that the newer, lower cost of the direct local meal in this step of the sensitivity analysis decreased the total dollar amount the school spent through this supply chain route, which lowered the expenditure to which the economic impact multiplier was applied. The lower price tag decreased the overall economic impact to a point where the minimum per meal level of economic impact laid out in the corresponding constraint could not be achieved.

Even with fluctuations in meal purchasing behavior, we observe that certain patterns hold. SFAs purchase fewer meals through the direct local and nontraditional local supply chain routes under the Business as Usual, CO HB 19-1132, and, sometimes, the 25% Local scenarios. The SFA purchases a maximum of 75% of its meals through the traditional non-local route in the 25% Local scenario, while it purchases fewer meals through broadline distributors and more meals directly from local sources in the High Economic Impact, Low Price Risk, and Combination scenarios. In every scenario except Low Price Risk and Combination, the minimum number of meals purchased under sensitivity analysis

Scenario	Quantity	Labor	Asst. Br.	Asst. Dp.	Local Int.	Ec. Imp.	Price. Risk
BAU	0.92-2.76	0	0-0.01	0	n/a	n/a	n/a
CO HB 19-1132	0.92-2.76	0	0-0.01	0	n/a	n/a	n/a
25% Local	0.93–2.78	0	0-0.01	0	0-0.98	n/a	n/a
High Econ. Imp.	2.17-2.76	0	0	0	n/a	0-0.67	n/a
Low Price Risk	1.09-3.26	0	0-0.04	0	n/a	n/a	-64.80-0
Combo	2.17-3.26	0	0-0.03	0	0	0-0.67	-64.80-0

Table 8. Sensitivity analysis of shadow values (\$) for constraints under various scenarios

Table 9. Sensitivity analysis of activity duals (\$) under various scenarios

Scenario	Direct Local (z ₁) Dual	Non-Traditional Local (z ₂) Dual	Traditional Local (z ₃) Dual	Traditional Non- Local (z ₄) Dual
BAU	0-1.58	0-1.84	0-1.01	0–0.89
CO HB 19-1132	0-1.51	0-1.76	0-0.94	0-0.91
25% Local	0-1.52	0-1.78	0-0.57	0–0.89
High Econ. Imp.	0-0.66	0-0.91	0-0.33	0-0.31
Low Price Risk	0	0-1.63	0-1.01	0–0.89
Combo	0	0-0.31	0-0.33	0-0.31

conditions was zero, indicating that pricing a certain supply chain route 50% higher was sufficient to cease purchases through that route.

Tables 8 and 9 provide the results for sensitivity analyses of the shadow values for constraints under various scenarios and activity duals under various scenarios. The activity duals show the financial incentive the SFA would need in order to be indifferent about its choice of supply chain route and purchase additional meals from suboptimal supply chain routes. These dollar values can be thought of as the range within which policymakers would have to subsidize school lunch programs on a per meal basis if they wanted SFAs to purchase from a certain supply chain route. All ranges have zero as a lower bound because the school would require no additional financial incentive if meals through a certain supply chain route were priced 50% lower than their current assumed value.

Discussion

We set out to examine the trade-offs faced by SFAs when deciding how to procure food, and particularly local food, with an emphasis on public policies intended to balance costs with the social co-benefits (economic impact, social embeddedness) associated with local FTS procurement activity. By assuming the SFA's goal was to minimize costs, we assumed that price was a primary motivating factor for SFAs when deciding how to make procurement decisions, but the literature makes a compelling case to motivate consideration of policies to address the externalities of low-cost food procurement systems.

As discussed in the introduction, many schools, institutions, and municipalities are embedding values-based procurement strategies to achieve multiple sustainable development goals. The idea is that through increasing purchases of local, for example, there can be an array of potential positive externalities, including environmental, economic, and social co-benefits. In the absence of policies that internalize, communicate and/or elevate these potential co-benefits of FTS activity, schools are likely to continue to purchase food through the more cost-effective, traditional non-local supply chain route. Convenience, labor, and food cost all play a role in the efficiency of traditional non-local supply chain routes. If a policymaker wanted to shift the SFA's purchasing to a local supply chain route, our model suggests it would have to offer an incentive to make the SFA indifferent about a choice between the traditional non-local and traditional local routes. The necessary amount would depend on many local factors, but the model suggests a per-meal incentive of \$0.06 could be enough to change behavior under the conditions that were modeled (which are not tied to any one specific geographic place).

While the model may not reflect exact price premia estimates for supply chain route choices faced by specific Colorado SFAs, our results suggest that the reimbursement offered by CO HB 19-1132 may be slightly less than the amount required to change some SFAs' purchasing behavior from non-local to local unless they are motivated by intangible factors. Shifting schools' purchasing to local distributors or directly from local producers would require an even larger per-meal incentive estimated at an additional \$0.44 for direct local purchasing and \$0.61 for nontraditional local.

Across scenarios, it is consistent that nontraditional local is never purchased and some traditional non-local is always purchased; in other words, none of the policy levers make purchasing the most expensive option worthwhile since there is a cheaper alternative with some of the same benefits (direct local). The difference in positive externalities captured by the policy constraints in these scenarios is not large enough to be worth the extra cost of purchasing from the nontraditional local over the direct local supply chain. The cost-efficient traditional, non-local option is used to fill in whatever food is still needed once policy constraints have been met. This likely reflects the reality that schools will continue to purchase some amount of food from mainline distributors even as they prioritize or are "nudged" to purchase more local ingredients.

Implications

The results of our model provide decisionmakers with a road map for how to proactively develop a better-informed procurement policy that includes a realistic price incentive for SFAs to integrate values-based procurement into their purchasing decisions. To date, incentives have been developed without a full understanding of how SFAs make decisions, how they balance costs, and what level of premium might be required to achieve multiple values-based goals. Our process and model, together with locally relevant data where available, can help decisionmakers to more carefully consider trade-offs and co-benefits of purchasing incentives.

Limitations

This paper is intended to be a roadmap for building an optimization model that simulates institutional food purchasing behavior and incorporates values-based procurement decisions. We caution readers to think more about the process, data needs, and modeling methods than the results. Limitations of the model presented here primarily stem from data limitations, as most price data along the supply chain are proprietary, and it is difficult

to make price generalizations for the wide range of products procured for school lunches. Parameter values are assumed or gleaned from estimates reported in the literature, which are generalized for a wide variety of SFAs. The lack of consistent data across a particular geography limits our ability to draw conclusions beyond the magnitude and directionality of results. If policymakers want results that are better suited to local conditions, they could customize the model.

There are a few other limitations. Food prices and procurement policies are increasingly dynamic, and we only light touch on the variability of costs in one facet of the model. Another limitation is that the model is linear, and moreover, the original constraints are all linear, which is unlikely the case for several of the economic factors included in this model. We also do not control for whether production seasons and school food procurement seasonality align. We initially included a seasonality constraint in the model and then realized that other constraints were more likely to be binding.

As we alluded to while discussing model setup, a final limitation is that we did not explicitly model several factors that are thought to be important in school purchasing decisions: budget, assortment cost, seasonality, equipment, food quality, food safety, and communication along the supply chain. Transaction cost constraints would be particularly helpful for modeling SFA behavior, likely increasing the cost of purchasing food from producers via the direct local route relative to purchasing food from one food hub via the nontraditional local route. Including this constraint might shift purchases that are currently made through direct local to nontraditional local. We opted to leave an explicit budget constraint out of the model because the model is already minimizing costs, and we wanted to observe how total spending would change in various scenarios without limiting the model's behavior in this way.

Infrastructure and institutional capacity may also matter. SFAs with the equipment to do raw ingredient preparation are more likely to participate in FTS than SFAs without equipment, and the type of equipment may also matter. Additionally, the type of kitchen equipment to which schools have access can affect food preparation efficiency. Unfortunately, we were unable to find a national database with SFA cooking equipment availability at the county or SFA level.

We could not find reliable estimates of food quality by supply chain route, so we leave that task for future research. The literature suggests that more localized and specialized supply chain routes require different communication with vendors to handle more and smaller transactions compared to traditional routes, so the labor constraint could reflect some of the differences in administrative labor in addition to the food preparation labor that it was specifically parameterized to represent.

Future directions

Making parameter values more robust is a potential future research direction. The process of building an optimization model focused on values-based procurement highlights the need for high-quality data about institutional purchaser behavior and other supply chain actors, and there are a number of organizational efforts to address that limitation including the Good Food Purchasing program and efforts by the Urban School Food Alliance (Good Food Purchasing Program 2024; Urban School Food Alliance 2023).

Another future research goal would be to build a nonlinear version of the model, or at least incorporate some nonlinear constraints of interest, such as one for transaction costs associated with the administrative labor of procuring through different supply chain routes. An additional research direction would be to clarify the mechanisms by which local procurement produces positive externalities and quantify the magnitude and distribution of those effects in a welfare context. Although the model structure is simple, it provides a functional policy assessment framework on which to build as more information becomes available. We believe that as more procurement policies are implemented, it is important to have this type of evaluation framework.

Conclusion

This research provides evidence that schools generally purchase through commodity supply chains due to price considerations unless policy levers nudge them to purchase food locally. The literature documents that greater local economic impact is associated with local food procurement compared to non-local, but it is not clear what types of policies and what levels of financial incentives are needed to encourage more local procurement. Traditional commodity supply chains have developed over many years to feed people cost efficiently, but for those communities and states who want to incentivize community priorities, this paper provides a roadmap to consider trade-offs of such decisions.

Substantial changes to supply chain structure or agent motivations, built on policy interventions, are likely required to shift buying and purchasing transactions away from efficiently operated and price-effective commodity supply chains. Because the current market structure has developed over many years in response to increasing attention to price competitiveness and supply chain complexity, shifting behavior will not be easy. Perhaps some motivation for changing supply chain behavior could come from a goal to build resilient economies. As one example, the White House released a Food System Transformation policy platform aimed to make food supply chains fairer, more competitive, and more resilient, (The White House Briefing Room 2022; USDA 2022). In addition, USDA recently announced plans to invest \$1.7 billion in purchasing locally and regionally produced foods for emergency assistance (USDA 2024). Demonstrated investments in regional food supply chains mean the importance of tools to assess the impact of policy interventions on local and regional actors' behavior (such as SFAs) will likely increase in the future.

Using the optimization model tool can help decisionmakers understand the trade-offs and co-benefits for institutional purchasers and other supply chain actors when different policy levers are used. This information can be used to decide when policies that encourage a wider range of social outcomes can be effective, including how SFAs might respond to incentives. We provided a roadmap for building a values-based procurement optimization model, from conceptualization to parameterization and results interpretation, to illustrate how one might estimate the "economic implication" of policy levers being considered to spur local purchasing by schools in the U.S.

We show that the choice of policy lever impacts the type of local supply chain route from which the school chooses to purchase. Therefore, FTS policy advocates should consider not only what they are disincentivizing schools to do (procure conventionally), but also the specific local purchasing behaviors they want to encourage and what economic outcomes they should expect. Aligning institutional food procurement policies with a community's development goals is crucial if food systems are to be leveraged to play a central role in local economic development.

Data availability statement

The data that support the findings of this study are available from public sources as cited in the text.

Funding statement

This research was supported by Colorado State University's Office of the Vice President for Research Catalyst for Innovative Partnerships Program, the Foundation for Food and Agriculture Research, the Colorado Potato Administrative Committee, the Colorado Agricultural Experiment Station, and RTI International's Fellows Program. The content is solely the responsibility of the authors and does not necessarily represent the official views of the funding organizations.

Competing interests

The authors declare no competing interests.

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Cite this article: Love, E., B. B. R. Jablonski, D. Thilmany McFadden, and L. Bellows (2025). "A roadmap for modeling institutional and values-based procurement decisions in food supply chains." *Agricultural and Resource Economics Review* **54**, 109–137. https://doi.org/10.1017/age.2025.11