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Abstract
We present an innovative adjusted bid price mechanism that incorporates economic multiplier effects in public food procurement processes. The approach provides a comprehensive view of the net cost to a state and allows public agencies to make better-informed local procurement decisions. The transparent and easy-to-implement method offers significant implications for policy debates surrounding public food procurement, local competitiveness, and sustainable food systems. The mechanism is empirically applied to detailed food purchase data by public agencies on state bids in New York State to highlight the extent and implications of its application relative to current policy.

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Introduction

There is growing recognition of the role public procurement can play in promoting sustainable local food systems and strengthening local economies. Indeed, a wide literature suggests that growing local food systems can contribute to economic development, job creation, and community resilience (e.g., Peters and Thilmany, 2022; Schmit et al., 2021; McFadden et al., 2016; Hughes and Boys, 2015; Pinchot, 2014). Public agencies around the world are increasingly utilizing their purchasing power to support local food producers, foster economic development, improve food security, and enhance environmental sustainability (Louro Caldeira et al., 2017). This is evidenced by the growing number of public institutions, such as schools, hospitals, and government agencies, that are actively integrating local food procurement strategies into their operations.

Love et al. (2020) argue that significant policy interventions are necessary to shift public procurement purchasing behavior towards more local and resilient supply chains, given that the current market structure has been developed to prioritize efficiency and cost-effectiveness. While traditional public food procurement law in the United States generally limits awards to the lowest cost bidder, several states and substate municipal authorities are implementing revisions to food procurement law that provide geographic preferences when awarding contracts, including tie-breaker preferences, price percentage allowances, and local food purchase quotas (CFSAC, 2021; Denning et al., 2010). Similar amendments to New York State (NYS) law consider allowances for "Best Value"[1], local purchasing preferences[2], and prioritizing food contractors selling NYS food products.[3] In line with state amendments, New York City (NYC) has their own local law to promote the purchase of local food products.[4]

Beyond public procurement law, other policy levers to increase demand for locally produced and/or grown products and support business development in NYS have established minimum percentages (i.e., quotas) of local spending to qualify for a particular benefit. For example, the establishment of the NYS Farm Brewery License in 2013 allowed farm brewers to produce beer and/or cider if a minimum percentage of ingredients are procured from NYS sources; e.g., 60% of hops for beer and 100% of apple/pome fruits for cider.[5] To the consideration of public procurement, the 30% NYS Initiative was established in 2018 and provides an additional state reimbursement of $0.19 per lunch meal to school food authorities (a 316% increase) if at least 30% of food procurement dollars are spent on NYS food products (Bilinski et al., 2022).[6]

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[1] State Finance Law (SFL) § 163(1)(j).

[2] General Municipal Law (GML) § 103(8-a)(a).

[3] SFL § 165(4)(b)(iv) and GML § 103(8-a)(c)(iii).

[4] 2011 New York City Local Law No. 50, NYC Administration Code § 6-130.

[5] Alcoholic Beverage Control (ABC), Chapter 3-B, Article 4, § 51-A. The law also mandates that the use of local inputs increases over time, but with clauses that allow for exemptions in years with limited supply.

[6] Other examples of recent programs supporting public procurement of local foods include Farm to Institution New York State, which aims to create a more robust market for NYS grown products by connecting farmers with institutional buyers (American Farmland Trust, 2021), and the Good Food Purchasing Program, which establishes procurement guidelines for public institutions to prioritize local, sustainable, and fair food purchasing (Center for Good Food Purchasing, 2021).

While the 30% NYS Initiative has been shown to have a net benefit to the state in the short run (Krasnoff et al., 2022), quota systems on procurement have an unintended consequence of restricting competition among suppliers. Suppliers benefiting from these protections can raise their prices and, hence, the cost of local food procurement without any incentive to improve practices. For agencies with fixed budgets, this necessarily means serving fewer people. Reduced competition also diminishes suppliers' incentive to innovate to enhance product quality, efficiency, or both. The resulting loss of competitiveness means that anti-competitive policies like quotas often do long-run harm to the very firms they aim to help in the short-run. Furthermore, to the degree that local spending quotas face supply constraints in the quantity or quality of inputs, business expansion and/or innovation may be impeded and, therefore, limit the favorable economic impacts promoted by the quotas in the first place.

An alternative approach to achieve the same desired outcome of boosting the competitiveness of local vendors in state procurement processes is to require that agencies consider economic multiplier effects. Multiplier effects are generated when local dollars recirculate through an economy due to backward-linked local industry input purchases and local spending by employees and business owners via households. This follow-on spending generates additional, subsequent tax revenues for local and state governments. Accordingly, adjusting the bid price of a vendor for these fiscal impacts resolves a dynamic externality, the fact that there are spillover effects from current procurement on future fiscal revenues and spending. Put differently, the bidded cost represents a gross cost to the state while the true (net) cost accounts for added state tax revenues vis a vis the multiplier effects. Food procurement law that allows for price percentage preferences for local food products at least indirectly, albeit inadequately, encompasses the concept of economic multiplier benefits, however with price percentages (i.e., allowable increases in costs if the products are local) defined as a result primarily of political debate rather than sound science.

We contribute significantly to this policy debate by developing an adjusted bid price mechanism whereby procurement bids are adjusted formulaically and transparently for multiplier differences among vendors. Such an exercise requires care and expertise since estimating multiplier effects attributable to specific suppliers for bid adjustment depends on firm-level spending patterns and to the degree to which that spending is local, rather than by utilizing average industry spending patterns from which most multiplier effect estimation originates (Rickard et al., 2016). We provide a clear approach to estimate precise bid adjustments so that it is a transparent and easy-to-implement adjustment method rooted in corrected market pricing rather than ad hoc regulatory or statutory restrictions on trade. Ultimately, our proposed framework allows agencies to compare adjusted bid prices across bidders when making procurement decisions.

We continue with the derivation of the economic model that defines adjusted bid prices, followed by empirical applications of the model using detailed food purchase data from state bid contracts. We close with conclusions and implications of our work and directions for future research.

Economic Model

Input-Output (IO) models distinguish the effects of a shock by the economic sectors of a geographically defined economy. IO methods estimate the extent of these impacts and trace how the changes impact different sectors of the economy. The analytical strength of this methodology is its ability to estimate indirect and induced economic effects stemming from the direct expenditures that lead to additional purchases by final users in an economy.

The direct effects are the initial set of expenditures applied to the IO multipliers; in our case, they represent the bid value (B) for one or a collection of food products sold by a vendor to public agencies through a bid process. The indirect effects are the additional business-to-business purchases that take place up the supply chain within the region stemming from the initial input (i.e., the direct effect). Induced effects are values of industry activity that stem from household spending of increased labor income that result from the initial input purchases and follow-on indirect effects.

For any individual sector, call it sector j, the sales or output multiplier is defined as the direct plus indirect plus induced sales throughout the economy resulting from a one dollar increase in sales to final demand in sector j. By comparing these multipliers across sectors, one can identify those sectors in which a change in sales to final demand generate the largest combined direct plus indirect plus induced change in sales in all sectors of the economy.[7]

Technically, our analysis utilizes IMPLAN's Social Accounting Matrix (SAM) model as our starting point, rather than an IO model. A SAM incorporates not only economic data for an economy, but social data as well, including national and household income statistics (Van Wyk et al., 2015). Accordingly, the SAM has an input-output model at its core but has additional capacity to disaggregate households, firms, and other institutions such that the impacts and multipliers based on the SAM reflect ripple effects throughout the economy with somewhat greater precision than do those based on an IO model alone (Miller and Blair 2009, Ch. 11).[8]

As introduced above, common bid processes for food procurement in NYS use a request for bid (RFB) process that follows a competitive offering to procure the best "price" for the public agency for specific products.[9] A "Request for Proposal" (RFP) is allowed under certain circumstances and for particular agencies (e.g., school food authorities) that provides a competitive offering process to procure the best "value" for the public agency for specific products and evaluation criteria (e.g., points awarded based on geographic preference). In this case, price is one but not the only consideration, and with, arguably, ad hoc scoring systems to define winning bidders.

Our proposed procurement process explicitly accounts for NYS economic multiplier effects of food procurement when selecting winning bidders based on level of local economic activity of the direct, indirect, and induced effects. The additional economic activity has value to the state, that we measure as the additional state tax revenues generated. In other words, the cost of the bid is a gross cost (B) to the state (i.e., paid by the state agency procuring the food with public dollars), while the net cost (B^*) is B less the tax revenues accruing from local business activity through the

[7] Final demand is the value of goods and services produced and sold to final users during the calendar year. Final use means that the good or service will be consumed and not incorporated into another product.
[8] A typical SAM provides a mapping into a functional category for households usually based on household income class. The IMPLAN SAM serves this purpose with nine household income categories; however, with a shortcoming in the SAM accounts that restricts the full evaluation of income distribution effects (Alward and Lindall 1996).
[9] Technically, there are additional terms and conditions for vendors to qualify for selection, such as product specifications, food safety and insurance requirements, and delivery specifications, among others. None of these conditions change as part of the alternative bid selection process proposed.

direct, indirect, and induced effects. As such, determining winning bidders based on B^* (but still paying B) provides a more complete picture of net costs to the state and incentivizes local firm participation in public food procurement.

This context is illustrated in Figure 1 where we consider two bidders: one with an entirely nonlocal food product who bids B_{NL} and one with a local food product who bids B_L. In this case, $B_L > B_{NL}$ and under a traditional RFB process the winning bidder is the nonlocal bid. Since no multiplier effects accrue to the first product $B_{NL}^* = B_{NL}$; i.e., the gross and net cost to the state are the same. However, given multiplier effects related to local spending in the production of the second product, the net cost to the state is B_L^* and $B_L^* < B_L$. If $B_L^* < B_{NL}$, as depicted in Figure 1, the winning bidder under our proposed bid algorithm is the local bid. The increase in cost to the agency relative to the traditional RFB process is $\Delta = B_L - B_{NL}$. If $B_L^* > B_{NL}$, the winning bidder remains the nonlocal product and if $B_L^* < B_L < B_{NL}$, the winning bid in either case is the local bid with no increase in costs to the agency.

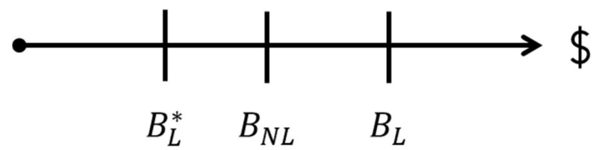

Figure 1. Example gross (B) and net (B^*) bid costs by local (L) and nonlocal (NL) food products.

Disaggregating Food Product Spending
Industry spending patterns in IMPLAN depict gross intermediate input purchases per dollar of output that are invariant across defined local economies (e.g., fruit farming in Washington State has an identical intermediate input spending pattern as in New York). Furthermore, the percentages of inputs purchased locally (i.e., Regional Purchase Coefficients or RPCs) are based on gravity flow models that restrict all purchasers (industries and institutions) to source identical local proportions; e.g., a school food authority and private processor procure the same percentage of fresh (raw) apples locally (IMPLAN, 2020). The combination of spending patterns and to the degree that spending accrues locally defines the size of the industry multipliers.

The challenge in estimating economic impacts of food product purchases is in the proper delineation of specific expenditures and value added outlays that can differ by firm. Collecting primary data for each food product and firm may result in differences in impact; however, the ability to and extent of such model customization is cost prohibitive (McFadden et al., 2016; Schmit et al., 2019; Jablonski et al., 2022). Further, numerous food products are contained within aggregated industry production functions in IMPLAN; e.g., "canned fruits and vegetables manufacturing" encompasses many different food products. To appropriately account for the local production of food products procured by public agencies, we margin all expenditures back to the raw/farm product level and require additional input from vendors to incorporate specific RPCs for food product and food product ingredients. In so doing, we customize both the production function for each food product and the respective RPCs following a standardized process using supplemental vendor supplied information.

To develop our model, we first define the spending patterns to produce food products; i.e., their intermediate input expenditures and value added allocations. Value added is gross regional product derived from the income paid to owners of the factors of production. It consists of employee compensation, proprietor income, other property type income, and net taxes on production and imports. For a particular product *i*, the value of its output (Y_i) equals the sum of the cost of intermediate inputs and the value added allocations. Consider one dollar of output of product *i* expressed as:

(1) $Y_i = GAV_i + VA_i$,

where GAV_i is the gross absorption value (or cost of all intermediate inputs) to produce one dollar of output *i*, VA_i is total value added per dollar of output, and $TAV_i + VA_i = 1$.[10] Allocations to *GAV* and *VA* vary across commodity. To estimate economic impacts accruing acutely to local food products, we first disaggregate *GAV* to its food product ingredients (*FPI*) and nonfood product ingredients (*NFPI*). Accordingly (1) is rewritten as:

(2) $Y_i = FPI_i + NFPI_i + VA_i$,

where $FPI_i + NFPI_i = TAV_i$.[11] Since food manufacturing sectors in IMPLAN encompass multiple food products, the spending pattern for product *i* is an industry average among them. The current version of IMPLAN has 56 food product sectors.[12] For practical application of our algorithm, food bidders are asked to map food products to one of 29 aggregated sectors (Table 1) and provide the percent of that product that is produced or grown in NYS.

If product *i* is a processed food product, bidders are also asked to classify the top two food product ingredients ($i1$ and $i2$) that make up food product *i* by the same aggregated commodity sectors (Table 1) and give the percentage of each of them in product *i* that is produced or grown in NYS. We assign portions of FPI_i to the two food product ingredients by weights W_{i1} and W_{i2} (where $W_{i1}+W_{i2} = 1$).[13] Substituting into equation (2) reveals:

(3) $Y_i = W_{i1}FPI_i + W_{i2}FPI_i + NFPI_i + VA_i$.

If $i1$ and $i2$ are also processed food products, further food product margining is necessary. For practical agency implementation, each of these products is automatically mapped in our algorithm to a raw (farm) food product category depending on the processed food product category of the ingredient defined by the vendor. Since some processed food product categories do not map uniquely to an individual farm sector, aggregated second round food product mapping rules are applied (Table 1).[14] Accordingly, we have:

[10] For example, consider food product *i* = pizza that falls under "frozen specialties manufacturing" in IMPLAN and our aggregated product category 18P (Table 1) with $GAV_i = 0.77$ and $VA_i = 0.23$.
[11] For example, for food product *i* = pizza, GAV_i is composed of $FPI_i = 0.56$ and $NFPI_i = 0.21$.
[12] Food product sectors in IMPLAN include 1-6, 9-14, and 65-108.
[13] For food product *i* = pizza, consider the primary food product ingredients as $i1$ = cheese with $W_{i1} = 0.67$ and $i2$ = tomato paste with $W_{i2}= 0.33$. Then, $W_{i1}FPI_i = 0.38$ and $W_{i2}FPI_i = 0.18$.
[14] Consider food product *i* = pizza (18P in Table 1) whose primary ingredients are $i1$ = cheese (20P) and $i2$ = tomato paste (17P). The algorithm automatically maps the second round margining to milk from farms (10F) and fruits and vegetables from farms (IMPLAN 3 and 4), respectively. See Table 1 for all second round mapping allocations.

Table 1. Food product mapping and IMPLAN Regional Purchase Coefficients (RPC).

Food product category (second round mapping)[a]	Implan Sector	Mapped Sector [b]	RPC[c]
Oilseeds	1	1F	14.71
Grains	2	2F	22.81
Vegetables & melons	3	3F	20.55
Fruit	4	4F	14.31
Tree nuts	5	5F	0.15
Greenhouse/nursery products	6	6F	19.82
Sugar cane/beet farming	9	7F	0.00
Other crops	10	8F	37.23
Beef cattle	11	9F	32.68
Milk from farms	12	10F	88.54
Poultry & eggs	13	11F	17.47
Other animals from farms	14	12F	21.62
Fresh fish	17	13F	10.59
Flour, rice, malt, wet corn, breakfast cereals (2)	65-68, 71	14P	16.86
Processed and blended oils and oilseeds (1)	69-70	15P	3.38
Sugars and confectioneries (9)	72-76	16P	11.13
Frozen and canned fruits, juices, vegetables (3, 4)	77, 79	17P	12.23
Frozen and canned specialty foods (1-6, 9-14)	78, 80	18P	16.84
Dehydrated food products (non-meat/dairy) (3, 4)	81	19P	8.08
Processed dairy products (12)	82-86	20P	33.00
Cakes, pastries, bakery, cookies, crackers, pasta, dough (1, 2)	87, 93-96	21P	34.31
Poultry and processed poultry meat products (13)	88	22P	4.19
Nonpoultry meat and processed meat products (11, 14)	89-91	23P	11.24
Processed fish and seafood products (17)	92	24P	8.38
Roasted nuts, nut butters, and snack foods (1-6, 9-14)	97-98	25P	28.84
Flavorings, dressings, sauces, spices, and extracts (1-6, 9-14)	100-102	26P	8.27
Coffee and tea, soft drinks and water beverages, ice (10)	99, 104-105	27P	24.08
Other manufactured food products (1-6, 9-14)	103	28P	24.06
Alcoholic beverages (2, 4)	106-108	29P	15.74

[a] IMPLAN sectors in parentheses are additional aggregated sectors used in second round margining of food products. Since this involves food margins of already margined food products, the degree of variation of adjusted bid prices will be minimal regardless of the aggregations chosen at this level.

[b] Mapped sectors 1F through 13F represent raw/minimally processed food products, while 14P through 29P represent processed food products.

[c] Default RPCs for New York State from IMPLAN (model year = 2019) for the aggregated food product sectors based on their gravity model (IMPLAN, 2020). Actual RPCs are used in the adjusted bid algorithm based on vendor supplied estimates.

(4) $Y_i = W_{i1}FPI_i(FPI_{i1} + NFPI_{i1} + VA_{i1}) + W_{i2}FPI_i(FPI_{i2} + NFPI_{i2} + VA_{i2}) + NFPI_i + VA_i.$

Combining the nonfood components of the spending pattern and rearranging terms, the final distribution of the spending pattern for Y_i is:

(5) $Y_i = FPI_i[W_{i1}(FPI_{i1} + NFPIVA_{i1}) + W_{i2}(FPI_{i2} + NFPIVA_{i2})] + NFPIVA_i.$

The breakdown of all processed food product category spending patterns from IMPLAN into their food and nonfood components is shown in Table 2.

Output Multipliers and Tax Coefficients.
In deriving multipliers, theoretically one can internalize any institution (i.e., households, government, and capital), but the standard practice (and the default in IMPLAN) is to internalize only households; i.e., to capture household spending out of labor income but not the spending of tax revenues by governments or returns to capital. Payroll taxes and personal income taxes are already part of the multiplier with households internalized; however, taxes on production and imports (e.g., sales taxes, property taxes, licenses, fees) represent important sources of income for local and state governments.

Internalizing local and state government spending assumes that these institutions will re-spend each dollar of local revenues collected locally for local programs. In a state model this makes sense since state budgets are required to be balanced. Internalizing local and state government also involves other property type income (OPTI), which is mostly corporate profits, as corporate taxes are an important source of government income. We internalize local and state government spending, including both non-education (i.e., hospital, health, and other services) and education sectors. Local and state government investment are not internalized since operational capital goods (e.g., trucks, computers) and large projects (e.g., highways, buildings) are often funded through bonding and are not necessarily related to the current state of the economy.

To estimate industry multipliers that also internalize local and state spending, supplemental modeling is required. Specifically, we apply the total local and state tax revenues generated per dollar of output in each food product sector to the local and state government spending pattern in IMPLAN. The additional output impacts accruing through this spending are added to the impacts with only households internalized to compute the new multipliers, M_i, (Table 3). With households and local and state government endogenized, total local and state tax revenues associated with \$1 of direct impact in each food sector i are estimated. The estimated revenues accrue from the direct, indirect, and induced effects. Total revenue is divided by the total economic impact generated by the \$1 of direct activity to compute industry-specific tax coefficients (t) as shown in Table 3.

Following from equation 5, comparable multipliers (M^*) and tax coefficients (t^*) are estimated separately for the nonfood portion of the spending pattern for each food sector (Table 3). To estimate these multipliers, we model the same direct impact as described above, but set the RPCs in the spending pattern for food product ingredients to zero. By treating that portion of spending as leakage, the resulting multipliers (M^*) represent only the effects of local nonfood intermediate input spending and value added allocations (*NFPIVA*). The tax coefficients (t^*) are computed as above but now representing tax revenues generated only from *NFPIVA* spending.

Table 2. Processed food product category spending pattern disaggregation.

Category	TAV	FPI	NFPI	VA	NFPVA
14P	0.87	0.54	0.33	0.13	0.46
15P	0.94	0.71	0.23	0.06	0.29
16P	0.83	0.38	0.45	0.17	0.62
17P	0.82	0.39	0.43	0.18	0.61
18P	0.77	0.56	0.21	0.23	0.44
19P	0.76	0.47	0.29	0.24	0.53
20P	0.86	0.59	0.27	0.14	0.41
21P	0.61	0.29	0.32	0.39	0.71
22P	0.80	0.59	0.21	0.20	0.41
23P	0.84	0.62	0.22	0.16	0.38
24P	0.74	0.52	0.22	0.26	0.48
25P	0.77	0.32	0.45	0.23	0.68
26P	0.81	0.41	0.40	0.19	0.59
27P	0.72	0.26	0.46	0.28	0.74
28P	0.79	0.43	0.36	0.21	0.57
29P	0.54	0.15	0.39	0.46	0.85

Source: IMPLAN, NYS model year = 2019.
Note: TAV + VA = 1, FP + NFPI = TAV, NFPVA = NFPI + VA.

Deriving B^*

The RPCs supplied in the new bid process are applied to their respective margined components to compute total impact (*TI*), which is then multiplied by the respective tax coefficient (*t*). The sum of *tTI* across all margined components reveals the amount of the bid price adjustment. For completeness, we consider four types of food products: (*i*) processed food products produced from two processed food product ingredients, (*ii*) processed food products produced from one raw food product ingredient and one processed food product ingredient, (*iii*) processed food products produced from two raw food product ingredients, and (*iv*) raw food products.

In the first case, consider a food product *i* (e.g., pizza) bid by a producer that is primarily made from two processed food products *i1* (e.g., cheese) and *i2 (*e.g., tomato paste*)* and where those food product ingredients are mapped to *i11* (milk from farms) and *i21* (e.g., tomatoes from farms), respectively. The adjusted bid price $B^* = B - tTI$ is expressed as:

$$(6)\ B^* = B - B(FPI_i W_{i1} RPC_{i1} FPI_{i1} M_{i11} t_{i11} + FPI_i W_{i1} RPC_{i1} NFPIVA_{i1} M_{i1}^* t_{i1}^* + FPI_i W_{i2} RPC_{i2} FPI_{i2} M_{i21} t_{i21} + FPI_i W_{i2} RPC_{i2} NFPIVA_{i2} M_{i2}^* t_{i2}^* + NFPIVA_i RPC_i M_i^* t_i^*)\ ,$$

where $NFPIVA_i$ is the sum of the GAV of nonfood ingredients in product *i* and the value-added coefficient, RPC_i is the RPC for product *i*, M_i^* is the output multiplier of product *i* associated with only $NFPIVA_i$ spending, t_i^* is the local and state tax revenues generated only from $NFPVA_i$ spending per dollar of economic impact associated with \$1 of direct impact in industry *i*, FPI_i is the GAV of food product ingredients in the production of *i*, W_{i1} is the proportion of FPI_i allocated

Table 3. Output multipliers (M) and tax coefficients (t) by sector.[a]

Sector	M_h	M	t	M*	t*
W398 [b]	1.959	2.116	0.055		
W400 [b]	1.750	2.080	0.129		
T417 [b]	1.808	1.973	0.062		
1F	1.158	1.241	0.049		
2F	1.462	1.497	0.016		
3F	1.523	1.641	0.053		
4F	1.289	1.390	0.054		
5F	1.343	1.458	0.059		
6F	1.570	1.697	0.056		
7F [c]	1.000	1.000	0.000		
8F	1.649	1.749	0.042		
9F	1.573	1.696	0.054		
10F	1.879	2.013	0.049		
11F	1.868	2.023	0.058		
12F	1.265	1.375	0.060		
13F	1.656	2.028	0.154		
14P	1.580	1.641	0.026	1.481	0.027
15P	1.391	1.447	0.028	1.373	0.027
16P	1.684	1.779	0.039	1.700	0.039
17P	1.647	1.735	0.037	1.654	0.037
18P	1.533	1.607	0.033	1.461	0.033
19P	1.493	1.571	0.036	1.499	0.035
20P	2.041	2.156	0.038	1.469	0.035
21P	1.741	1.893	0.060	1.787	0.062
22P	1.522	1.603	0.037	1.443	0.035
23P	1.588	1.679	0.039	1.471	0.038
24P	1.493	1.585	0.042	1.553	0.041
25P	1.604	1.693	0.038	1.618	0.038
26P	1.605	1.693	0.037	1.579	0.037
27P	1.613	1.721	0.046	1.671	0.046
28P	1.698	1.791	0.038	1.657	0.037
29P	1.551	1.951	0.185	1.907	0.188

[a] M_h are multipliers with only households internalized, M also internalizes local and state government. t is local and state tax revenues per dollar of total impact associated with $1 of direct impact. M* and t* are multiplier and tax coefficients for only nonfood and value added portions of the spending pattern.

[c] W398 and W400 are wholesale sectors associated with food and nonalcoholic beverage products and alcoholic beverages, respectively. T417 is the truck transportation sector. The multipliers and tax coefficients are used for wholesale and transport margins of products supplied by wholesale distributors.

[b] Sector 17F represents sugarcane and sugarbeet farming, with zero economic activity in NYS, hence multipliers of one and a tax coefficient of zero.

to $i1$ (0.67 by default), M_{i11} is the full output multiplier of product $i11$, and t_{i11} is the local and state tax revenues generated from all intermediate input and value-added spending per dollar of economic impact associated with $1 of direct impact in industry $i11$ (the industry associated with commodity $i11$). Combining like terms,. equation (6) is expressed as:

$$(7)\ \ B^* = B[1 - NFPIVA_i RPC_i M_i^* t_i^* - FPI_i\{W_{i1} RPC_{i1}(FPI_{i1} M_{i11} t_{i11} + NFPIVA_{i1} M_{i1}^* t_{i1}^*) + W_{i2} RPC_{i2}(FPI_{i2} M_{i21} t_{i21} + NFPIVA_{i2} M_{i2}^* t_{i2}^*)\}]$$

If, instead, a product is made from one processed and one raw product ingredient, B^* simplifies. Specifically, consider a food product i (e.g., applesauce) bid by a producer that is primarily made from one raw/minimally processed food product $i1$ (e.g., apple) and one processed food product $i2$ (e.g., high fructose corn syrup) and where the processed food product is mapped to $i21$ (e.g., corn from farms), respectively. The adjust bid price (B^*) here is:

$$(8)\ \ B^* = B[1 - NFPIVA_i RPC_i M_i^* t_i^* - FPI_i\{W_{i1} RPC_{i1}(M_{i1} t_{i1}) + W_{i2} RPC_{i2}(FPI_{i2} M_{i21} t_{i21} + NFPIVA_{i2} M_{i2}^* t_{i2}^*)\}].$$

Further simplifying, consider a food product i (e.g., apple oatmeal) bid by a producer that is primarily made from two raw/minimally processed food product $i1$ (e.g., oats) and $i2$ (e.g., apples). The adjust bid price (B^*) is now:

$$(9)\ \ B^* = B[1 - NFPIVA_i RPC_i M_i^* t_i^* - FPI_i\{W_{i1} RPC_{i1}(M_{i1} t_{i1}) + W_{i2} RPC_{i2}(M_{i2} t_{i2})\}]$$

And even further simplifying, consider a food product i (e.g., apples) bid by a producer that is itself a raw/minimally processed food product. The adjust bid price (B^*) is:

$$(10)\ \ B^* = B[1 - \{RPC_i(M_i t_i)\}].$$

Finally, consider a food product sold by a wholesaler instead of directly by a producer. Considering the food product from equation (7), but now bid by a wholesaler, requires application of wholesale, producer, and transport margins.[15] The adjust bid price (B^*) is now computed as:

$$(11)\ \ B^* = B\big[1 - \big(MGN_{WH,i} RPC_{WH} M_{WH} t_{WH}\big) - \big(MGN_{TR,i} RPC_{TR} M_{TR} t_{TR}\big) - MGN_{PR,i}(NFPIVA_i RPC_i M_i^* t_i^* + FPI_i\{W_{i1} RPC_{i1}(FPI_{i1} M_{i11} t_{i11} + NFPIVA_{i1} M_{i1}^* t_{i1}^*) + W_{i2} RPC_{i2}(FPI_{i2} M_{i21} t_{i21} + NFPIVA_{i2} M_{i2}^* t_{i2}^*)\})\big],$$

where $MGN_{WH,i}$, $MGN_{PR,i}$, and $MGN_{TR,i}$ are the wholesale, producer, and tranport margins associated with food product i, respectively, and $MGN_{WH,i} + MGN_{PR,i} + MGN_{TR,i} = 1$. Other food product examples above follow similarly when incorporating wholesale and transport margins.

[15] Output for wholesale industries represent only the wholesale margin not total sales. Doing so prevents double counting of the producer value in the multiplier effects.

Vendor Input Requirements
To provide an adjusted bid price procurement process that is both scientifically defensible and practically implementable at the agency level, a limited set of information is requested of bidding vendors. Some information is already provided as part of the bidding process that can be directly applied into the bid adjustment algorithm, such as business type for margining (i.e., wholesaler or producer) and location of business establishment to populate some RPCs. Supplemental information on food product and food product ingredient categorizations and their respective RPCs denoting the percentage of them grown or produced in the state are required.

To assist vendors selecting food product categories for the bidded item(s), a template, such as provided in Appendix A, is suggested. To assist state agencies in augmenting existing bid pricing sheets for application of the algorithm, input questions are provided in Appendix B.

Empirical Application
For our empirical application, we evaluate food spending by NYS public agencies on state bid for calendar year 2022.[16] The NYS Office of General Services (OGS) manages three classes of food products put out on state bid: Fluid Milk (23239), Fresh Bread (23146), and Food (23199). Bid awards are on five year contracts, with the option to extend up to five and two additional years for the Food and Fresh Bread bids, respectively. The solicitation processes are highly structured with specific eligibility requirements for bidders and alternatively defined regions of the state by bid class.[17]

The Fluid Milk and Fresh Bread solicitations involve submitting prices for defined market baskets of goods that include estimated quantities of products needed by region based on historical usage. Bidders on the Fluid Milk solicitation must submit prices for all milk products listed in the market basket (i.e., required milk products) and are encouraged to provide prices for other products (i.e., desirable milk products) they can offer. Awards are made by region to the lowest total cost (i.e., price times estimated quantity) based on the required market basket of goods. Given existing state and federal milk marketing orders, milk prices are adjusted over the contract period by changes in market order prices. Similarly, bidders must bid on all items in the market basket for the Fresh Bread solicitation for each region bid. The market basket requirements in the Fluid Milk and Fresh Bid solicitations effectively limit feasible bidders to fluid milk and fresh bread processors, respectively.

The Food solicitation is disaggregated into three Lots: (1) Commercial, (2) Retail, and (3) Bulk Fresh Produce.[18] The Commercial Lot generally refers to products that are sold in bulk size, while the Retail Lot generally refers to products sold in grocery size packaging. Bidders may bid on any combination of lots and regions. For the Commercial and Retail Lots, no market baskets of goods are specified; however, bidders must provide supplier costs (i.e., cost of goods sold) and markup percentages for products for all seven OGS categories and be capable of supplying all categories

[16] Individual public agencies (e.g., a school district or municipality) can also administer their own bid processes as allowed by law.
[17] OGS defines eighteen multi-county regions for the Fluid Milk bid, and four identical multi-county regions for the Fresh Bread and Food Bids. Bidders may choose to bid on one or more regions.
[18] Lots 1 and 2 cover all regions of the state, while Lot 3 covers only the Food Production Center Plant of the NYS Department of Corrections and Community Supervision (ODCCS) in Rome, NY.

to all authorized users in such region.[19] For the Bulk Fresh Produce Lot, a market basked is provided and bidders must bid on all items listed within it. The requirement to bid on products that cover all seven OGS categories in the Commercial and Retail Lots and/or all bulk produce categories in the Bulk Fresh Produce Lot effectively limits feasible bidders to large wholesale vendors.[20]

Vendors
Required quarterly contract usage reports for 2022 from all awarded vendors for the Fluid Milk, Fresh Bread, and Food bids were collected from OGS. All submitting vendors for the most recent Food solicitation were found "minimally qualified" by OGS and with pricing that demonstrates the products offered will be delivered at "reasonable" prices. As such, all submitting vendors were awarded contracts, including Sysco Albany LLC (Halfmoon, NY). Sysco Long Island LLC (Central Islip, NY), Sysco Syracuse LLC (Warners, NY), Renzi Food Service (Watertown, NY), H. Schrier and Company Inc. (Brooklyn, NY), Driscoll Foods Eastern (Amsterdam, NY), and Driscoll Foods Downstate (Clifton, NJ).[21] As expected, all are relatively large wholesale food distributors.

The most recent Fresh Bread solicitation bid had only one bidder and who was awarded the state contract: Bimbo Bakeries USA Inc. (Albany, NY). The most recent Fluid Milk bid included four bidders: Cream-O-Land Dairies LLC (Florence, NJ), Derle Farms Inc. (Bethpage, NY), Hudson Valley Fresh Dairy LLC (Poughkeepsie, NY), and Upstate Niagara Cooperative Inc. (Lancaster, NY). All but Derle Farms were awarded contracts for one or more regions.[22] As expected, all bidders are food processors.

Applying the Bid Adjustment Algorithm
Our empirical application serves as a retrospective example, as in practice, the computation of B^* occurs as part of the contract awarding process. However, to assess the extent of deviation in bid (B) and adjusted bid (B^*) costs, we apply our algorithm to contract usage data for 2022. Since agencies pay B, assessing the difference in costs on local products presents an upward biased estimate of the increase in agency costs if the bidders represent new awarded contracts as a result of B^*. Specifically, we assess the change in costs as $B_L - B_L^*$ where $B_L - B_L^* \geq B_L - B_{NL}$, and where the bias goes to zero as B_L^* approaches B_{NL} (Figure 1).[23]

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[19] The product categories include (*i*) ambient/canned/dry, (*ii*) baked goods, (*iii*) dairy (nonfluid milk), (*iv*) frozen, (*v*) meat/poultry/fish, (*vi*) produce, and (*vii*) nonfood.

[20] As provided in the "Responses to Bidder Inquiries" for the latest Food solicitation, average annual historical spending on the Commercial, Retail, and Bulk Fresh Produce Lots are $65.1, $9.0, and $1.3 million, respectively.

[21] Ace Endico Inc. (Brewster, NY) was also awarded a contract but listed as canceled in May 2022. No sales reports are available for them (https://online.ogs.ny.gov/purchase/spg/awards/0245023199CAN.HTM).

[22] Specifically, Cream-O-Land was awarded contracts for eight regions (generally downstate), Hudson Valley Fresh was awarded the contract for region nine (Dutchess, Sullivan, and Ulster counties), and Upstate Niagara Cooperative was awarded contracts for seven regions (generally upstate).

[23] Arguably, a more pointed application would evaluate if contract awards would have changed based on all submitting bidders (i.e., winners and losers). However, since all bidders on the state Food and Fresh Bread solicitations were awarded contracts; and the only bidder not awarded a contract on the Fluid Milk bid had costs nearly 70% above their competitors, contract award decisions would not have changed. We leave such an application to sub-state bids to future research.

We obtain detailed quarterly food purchase contract usage data from OGS by vendor for the Food, Fresh Milk, and Fresh Bread bids. Data come in a standardized (Excel) format based on OGS's contract reporting requirements that include such things as date of purchase, state and sub-state public agency buyer, product name and description, price of the product, and, in the case of wholesale vendors, the supplier's name, supplier product number, and wholesale markup (margin). Nonfood products included in the Food contracts were excluded from our analysis.

Given our algorithm application to historical data, information on producer RPCs and detailed food product information are not available. Accordingly, we propose two applications: (*i*) utilize default IMPLAN industry spending patterns and *RPC*s (Table 1) on a product-specific basis, and (*ii*) use product category totals of B from the first application, assume all food products and food product ingredients are 100% local, and assign food product ingredient categories for each of the processed food categories (14P through 29P) based on our best judgement. In the second case, we derive B^* from equations (7) through (11). While in aggregate we expect $B_L - B_L^*$ to be higher relative to the first case (given that we assign all RPCs to 1), this may not be true for all individual categories given the food product ingredient mapping chosen and relative levels of multipliers, tax coefficients, and *FPI*/*NFPIVA* allocations across categories.

Assuming IMPLAN default *RPC*s in the first case, distinguishing *TAV* into its *FPI* and *NFPIVA* components is unnecessary, as is the distinction of primary food product ingredients (*i1* and *i2*) and alternative multiplier (M and M^*) and tax revenue (t and t^*) coefficients. Further, since OGS contract usage data for Food vendors provides vendor- and product- specific wholesale markups, we use those stated wholesale margins and ignore the transport margin (equation 11).[24] Depending on specific product information, these restrictions could result in more or less economic impact than our detailed algorithm would suggest. Even so, default industry spending patterns and state-level RPCs provides a reasonable *ex post* analysis when evaluating spending across a range of products, producers, and vendors. The restricted computations of B^* from equation (11) for Food wholesalers and equation (7) for Fluid Milk/Fresh Bread producers are, respectively:

$$(12)\ \ B^* = B(1 - MGN_{WH,i}RPC_{WH}M_{WH}t_{WH} - MGN_{PR,i}RPC_iM_it_i) \text{ and}$$

$$(13)\ \ B^* = B(1 - RPC_iM_it_i).$$

where $MGN_{WH,i}$ is the margin reported by wholesalers for each product i and $MGN_{PR} = 1 - MGN_{WH}$. RPC_i is set to one or zero based on whether the supplier has a manufacturing location in NYS or not.[25] $RPC_{WH,i}$ is set to one or zero based on whether or not the "ship from" zip code for product i (i.e., the location of the wholesale distribution facility) in the OGS data is a NYS zip code. Each food product i was assigned to a food product category (Table 1) to which M_i and t_i are applied (Table 3).[26]

[24] The average industry transport margin for food products in IMPLAN is small, about $0.02 per dollar of output.
[25] Approximately 2,500 unique food product suppliers are included in the contract usage reports across all vendors. A Google search on each supplier determined whether they have at least one NYS manufacturing facility ($RPI_i = 1$).
[26] Approximately 21,000 unique food products are included in the contract usage reports across all vendors. Food categories for each (Table 1) were applied based on the product name, description, and supplier.

Results

Using the first empirical application approach, gross (B) and net (B^*) food costs are summarized in Table 4 by bid class and vendor. For the Food bid, all wholesalers are considered local (RPC_{WH} = 1) except for Driscoll Foods Downstate (RPC_{WH} = 0) based on their primary distribution facility location. Food costs are summed over all food products by whether they are produced outside (RPC_{PR} = 0) or inside (RPC_{PR} = 1) NYS.

Considering locally produced products (RPC_{PR} = 1) on the Food bid, the percent reduction from B to $B*$ ranges from 6.56% (Driscoll Foods Downstate) to 9.66% (Sysco Albany). The former makes sense as this vendor is the only one classified as a nonlocal wholesaler (i.e., no multiplier effects of the wholesale margin). Differences across vendors reflect differences in the distribution of products sold and the multiplier and tax coefficients associated with them. The percentage changes for RPC_{PR} = 0, reflect only the wholesale margin component of sales. Across all vendors and locally produced products on the Food bid, $B*$ drops approximately 8%.

Since all dairy products map to the same food category sector (i.e., 20P) the multiplier and tax coefficients are identical across vendors with RPC_{PR} = 1 yielding a 9.05% reduction in costs from B to B^* (Table 4) for locally produced products.[27] The higher percent reduction relative to all food in the Food bid is consistent with dairy processing's higher multiplier effect (the RPC for milk from farms in NYS is over 84%) and mid-range tax coefficient. In fact, only 21P (0.114) and 29P (0.361) have higher Mt combined influences relative to processed dairy products (0.083) (Table 3). While much of this difference is due to higher tax coefficients, the relatively strong multiplier for 21P is also a reflection of higher labor income per dollar of output required in these industries; i.e., through the induced effects (Table 2). The 12.89% change on the Fresh Bread bid is similarly a result of all products within it mapping to 21P.

Again following the first empirical application approach, Table 5 summarizes B and $B*$ by food mapping category for the Food bid where RPC_{PR} = 1. Five categories exceeded $1.0 million by dollar volume: 21P (bakery, $2.40 million), 17P (frozen and canned fruits and vegetables, $2.38 million), 20P (nonfluid dairy products, $1.71 million), 22P (poultry products, $1.06 million), and 15P (processed oilseeds, 1.03 million). Differences in percentages are defined by the respective multiplier (M) and tax coefficients (t) in Table 3. As expected, the highest <u>percentage</u> changes from B to $B*$ are in categories with the highest tax coefficients, although fresh fish (13F) and alcoholic beverages (29P) have limited local availability and are procured in small volumes on state bid.

Those categories with the highest <u>cost</u> changes (B - $B*$) represent priority industries for increasing state tax revenues as they reflect both the level of demand in these products and the multiplier effects that accrue to their local procurement; e.g., bread and bakery products (21P, $270 thousand), canned and frozen fruits and vegetables (17P, $153 thousand), and nonfluid milk dairy products (20P, $142 thousand). Combining B - $B*$ for the Fluid Milk (20P) and Fresh Bread (21P) state bids (Table 4) increases their category totals to $827 thousand and $633 thousand, respectively.

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[27] Cream-O-Land Dairies is a milk processor located in New Jersey that sources milk from farms in multiple states. Likely some is from NYS farms but since the origins of the raw milk supplied are unknown, we assume all is nonlocal.

Table 4. Actual (B) and adjusted (B^*) bid costs by OGS bid class and vendor.[a]

State Bid Type/Vendor	RPC_{PR}	B	B*	B -B*	%Change
Food (2319)					
Driscoll Foods Eastern (RPC_{WH} = 1)	0	9,356,182	9,293,271	62,911	0.68
	1	3,778,787	3,504,960	273,827	7.81
	Total	13,134,969	12,798,231	336,738	2.63
Driscoll Foods Downstate (RPC_{WH} = 0)	0	6,990,890	6,990,890	0	0.00
	1	2,653,453	2,490,169	163,284	6.56
	Total	9,644,342	9,481,059	163,284	1.72
Sysco Albany (RPC_{WH} = 1)	0	3,453,886	3,430,496	23,390	0.68
	1	663,025	604,626	58,399	9.66
	Total	4,116,911	4,035,122	81,789	2.03
Sysco Long Island (RPC_{WH} = 1)	0	3,720,649	3,695,444	25,205	0.68
	1	548,387	504,528	43,859	8.69
	Total	4,269,036	4,199,972	69,064	1.64
Sysco Syracuse (RPC_{WH} = 1)	0	24,015,164	23,852,539	162,625	0.68
	1	6,168,844	5,695,889	472,955	8.30
	Total	30,184,008	29,548,428	635,580	2.15
Renzi Food Service (RPC_{WH} = 1) [b]	0	1,969,226	1,953,108	16,118	0.83
	1	1,246,858	1,154,291	92,566	8.02
	Total	3,216,084	3,107,399	108,684	3.50
Schrier and Company (RPC_{WH} = 1)	0	6,175,604	6,119,423	56,182	0.92
	1	554,599	511,715	42,884	8.38
	Total	6,730,203	6,631,137	99,066	1.49
All Food (23199)	0	55,681,602	55,335,171	346,431	0.63
	1	15,613,951	14,466,178	1,147,773	7.93
	Total	71,295,553	69,801,349	1,494,204	2.14
Fluid Milk (23239)					
Upstate Niagara Cooperative	1	7,129,389	6,537,817	591,572	9.05
Hudson Valley Fresh	1	1,131,174	1,037,313	93,861	9.05
Cream-O-Land [c]	0	4,925,232	4,925,232	0	0.00
All Fluid Milk (23239)	0	4,925,232	4,925,232	0	0.00
	1	8,260,564	7,575,131	685,433	9.05
	Total	13,185,796	12,500,363	685,433	5.48
Fresh Bread (23146)					
Bimbo Bakery	1	3,176,944	2,814,216	362,727	12.89

[a] For vendors on Food contracts(23199), B and B^* are the sum of all products classified as produced (RPC_{PR} = 1) and not produced (RPC_{PR} = 0) in NYS, respectively. B^* estimated from equations (12) and (13)

[b] Renzi Food Service includes contract usage for only the first three quarters of 2022.

[c] Cream-O-Land Dairies is a milk processor located in New Jersey who sources milk from farmers in multiple states in the Northeast U.S. While some milk from farms likely originates from NYS farms, since the origins of the raw milk supplied are unknown, we assume all is nonlocal for our application.

Table 5. Actual (B) and adjusted (B^*) bid costs for locally produced foods across all vendors in the Food bid, by mapping category.[a]

Category	***B***	***B****	***B - B****	**%Change**
2F	199,331	193,472	5,858	2.94
3F	938,622	859,417	79,205	8.44
4F	274,902	255,337	19,566	7.12
5F	817	755	61	7.51
6F	7,523	6,853	671	8.92
8F	1,461	1,380	81	5.55
13F	10,712	7,779	2,934	27.39
14P	469,028	448,222	20,805	4.44
15P	1,032,582	986,849	45,733	4.43
16P	249,410	232,151	17,259	6.92
17P	2,380,084	2,227,246	152,838	6.42
18P	419,569	396,880	22,689	5.41
19P	179,932	165,816	14,116	7.85
20P	1,708,632	1,566,704	141,929	8.31
21P	2,404,747	2,134,891	269,856	11.22
22P	1,063,557	1,001,274	62,282	5.86
23P	824,188	771,171	53,017	6.43
24P	157,661	147,942	9,718	6.16
25P	1,025,209	955,166	70,043	6.83
26P	982,409	918,462	63,947	6.51
27P	719,144	662,472	56,673	7.88
28P	564,274	525,837	38,437	6.81
29P	158	102	56	35.55
Total	15,613,951	14,466,178	1,147,773	7.35

[a] Locally produced products only (RPC_{PR} = 1) for the Food state bid. Food categories include products sold by nonlocal (RPC_{WH} = 0) and local (RPC_{WH} = 1) wholesalers. B^* estimated from equation (12).

Utilizing the total product category costs (B) from Table 5, results from the second empirical application are shown in Table 6. As expected, changes in aggregate are higher ($1.33 million versus $1.15 million) with an overall percentage change increasing from 7.35% to 8.55%.[28] Most percentage changes are similar however, some processed food categories with low RPCs on food ingredients (e.g., processed fish, and other manufactured foods) demonstrate high increases with RPCs turned to unity. The decrease on 29P (alcoholic beverages) is simply due to margining of raw product input allocations to lower tax coefficient categories (2F, 4F) relative to the default processed category that includes within category input purchases in its production function that holds a higher tax coefficient. In any event, expected overall changes in food budget costs using the adjusted bid algorithm are expected to be around 9%.

[28] The 8.55% result uses food product ingredient weights of W_{i1} = 0.67 and W_{i2} = 0.33 (i.e., 0.67/0.33). Overall percentage changes are resilient to the weights attached. For example, percentage changes for weights defined as 1/0, 0.5/0.5, and 0/1 are 8.58%, 8.53%, and 8.48%, respectively.

Table 6. Actual (B) and adjusted (B^*) bid costs for locally produced foods across vendors in the Food bid with food product ingredient mapping and all RPCs = 1.[a]

Category	***FPI***	***B***	***B******	***B - B******	**%Change**
2F		199,331	191,760	7,570	3.80
3F		938,622	848,277	90,345	9.63
4F		274,902	251,207	23,696	8.62
5F		817	740	77	9.43
6F		7,523	6,773	751	9.98
8F		1,461	1,343	117	8.04
13F		10,712	7,530	3,182	29.71
14P	2F	469,028	446,767	22,261	4.75
15P	1F	1,032,582	966,433	66,149	6.41
16P	7F	249,410	236,433	12,977	5.20
17P	3F, 4F	2,380,084	2,197,309	182,775	7.68
18P	3F, 23P	419,569	387,595	31,974	7.62
19P	3F, 4F	179,932	166,408	13,524	7.52
20P	10F	1,708,632	1,565,967	142,665	8.35
21P	14P, 15P	2,404,747	2,179,060	225,687	9.39
22P	11F	1,063,557	966,622	96,935	9.11
23P	9F, 12F	824,188	758,590	65,598	7.96
24P	13F	157,661	128,438	29,223	18.54
25P	5F, 15P	1,025,209	950,362	74,846	7.30
26P	15P, 16P	982,409	919,463	62,946	6.41
27P	8F	719,144	660,021	59,123	8.22
28P	8F, 12F	564,274	442,136	122,138	21.65
29P	2F, 4F	158	145	13	8.34
Total		15,613,951	14,279,378	1,334,573	8.55

[a] B by category from Table 5. Assumes locally produced products (RPC_{PR} = 1), all local wholesalers (RPC_{WH} = 1), transport (RPC_{TR} = 1) and food product ingredients ($RPC_{i1} = RPC_{i2}$= 1). FPI = primary food product ingredients mapped by authors for processed food categories. FPI weights are W_{i1} = 0.67 and W_{i2} = 0.33. For single FPIs, W_{i1} = 1. B^* estimated from equation (11).

Conclusions

We propose an innovative algorithm that adjusts bid prices in public food procurement processes by incorporating economic multiplier effects. Based on recent contract usage for NYS) food bids, our algorithm demonstrates average impacts on the state and public agencies when considering local economic activity generated through direct, indirect, and induced effects. For locally produced products, net food costs (B^*) are between 7% and 13% lower than gross costs to the state across vendors. Combining all bid estimates reveals an overall reduction of nearly 9%. These reductions highlight the economic benefits of considering ripple effects when making procurement decisions. We also show that bakery products, frozen and canned fruits and vegetables, and dairy products have the highest cost changes, indicating priority industries for increasing state tax revenues. Overall, the results emphasize the importance of incorporating economic externalities in public food procurement processes to promote local competitiveness and sustainable food systems.

Our algorithm serves as a theoretical foundation of geographic preference policies by directly calculating the economic impact of local purchasing. The algorithm is also pragmatically implementable at the agency and/or state level and an improvement on current ad hoc approaches prioritizing local procurement through quotas and/or pricing preferences. An online agency dashboard tool is in development that will extract the applicable information from the submitted bid documents and the author-constructed multiplier database for automated calculation of B^*.

Since we quantify the externality effect of buying locally, computed differences between B and B^* also present upward bounds of additional subsidization the state could provide for local food procurement and be just as well off in terms of net state spending. The supplemental state revenue could be used (in whole or in part) to further incentivize local food procurement and support local agriculture and food systems growth. Furthermore, as implementation of the algorithm continues over time, public agencies can evaluate specific differences in B and B^* by food product, industry, and/or vendor to inform subsequent local food procurement choices that have the most benefit to the state.

Our algorithm provides a conceptual framework for analyzing externalities in local purchasing decisions. The algorithm can be replicated and adapted for any geographic area with sufficient baseline industry information (like that available in IMPLAN) and for which similar customizations are applied to compute local multiplier and tax coefficients by product category (i.e., M, t, M^*, t^*). Understanding spatial differences in cost savings in local public procurement; i.e., accounting for differences in local farm and food production, is a compelling area for future research study that further informs state and federal food procurement policy.

Our algorithm considers one externality associated with including multiplier effects for public food procurement decisions. Other externalities related to food procurement include environmental and health impacts of foods based on their location or mode of production, processing, and transport considered in ongoing values-based food procurement debates. Modifying procurement practices can be a cost-effective policy proposition to reduce fiscal expenditures on curative health care, environmental remediation, and social safety nets. Recent literature estimates that the current food costs omit two-thirds of costs arising from the health and environmental costs (Hendriks et al. 2023; Rockefeller Foundation 2021).

Externalities arising from greenhouse gas emissions in transport are a function of distance and thus are commonly greater for external vendors. Other externalities relate to differences among jurisdictions in environmental, food security, occupational safety, and other relevant laws and regulations affecting firms' employment, production, processing, manufacturing, storage, and transport practices. A bid adjustment mechanism that incorporates these additional externalities further levels the playing field for local producers, processors, and manufacturers and to fully reflect the full true costs states face from food procurement. In so doing, bid adjustment can create incentives for improved practices – a ‘race to the top’ – among in-state suppliers, obviating the current ‘race to the bottom’ incentives in which vendors face incentives to reduce private costs, potentially shifting those costs to the state through environmental, health and social justice externalities. Enumerating such spillover costs requires further study to understand which externalities have a strong scientific basis to support price adjustments, are manageable to include, and would not impose unreasonable data demands on prospective bidders or state agencies. A careful examination of these issues is a top priority for our continuing research.

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Appendix A: Example food products for category mapping based on NYS state agency purchased products on state bid.

Code	Food Product Category	Example food products
1F	Oilseeds (without processing)	Oilseeds
2F	Grains (without processing)	Lentils, pea, quinoa, rice
3F	Vegetables & melons (without processing)	Cabbage, carrot, cauliflower, celery, cucumber, green bean, kale, lettuce, lettuce, onion, pepper, potato, radish, spinach, squash, tomato, fresh salads
4F	Fruit (without processing)	Apple, banana, grape, grapefruit, kiwi, lemon, mandarin, cantaloupe, honeydew, watermelon, nectarine, orange, peach, pear, pineapple, plum, strawberry
5F	Tree nuts (without processing)	Pecans, almonds
6F	Greenhouse/nursery products	Herbs, basil, bay leaf, cilantro, oregano, parsley, mushroom
7F	Sugar cane/sugar farming	Sugar cane, sugar beets
8F	Other crops	Tea, maple syrup, honey
9F	Beef cattle	Cattle from farms
10F	Milk from farms	Raw milk from farms
11F	Poultry & eggs	Eggs, chickens from farms
12F	Other animal products	Hogs, sheep from farms
13F	Fresh fish	Fish from commercial fishing
14P	Flour, rice, malt, wet corn, breakfast cereals	Corn starch, cornmeal, cereal bar, granola bar, cereal, grits, oatmeal
15P	Processed and blended oils and oilseeds	Margarine, cooking oils
16P	Sugars and confectioneries	Syrups, candies, chocolates
17P	Frozen and canned fruits, juices, and vegetables	Applesauce, beans, carrots, pickles, pimento, relish, corn, breaded eggplant, french fries, fruit cocktail, fruit cup, fruits, garlic, vegetarian gravy, green beans, juice cup, juices, onion rings, potatoes, pumpkin, salsa, barbecue sauce, tomato sauce, spinach, hummus, jelly, tomato sauce, paste, frozen sliced plantain, fruit ice slush
18P	Frozen and canned specialty foods	Baby food, egg rolls, pizza, canned beef ravioli, soups, waffles, tv dinners
19P	Dehydrated food products (non-meat/dairy)	Raisins, craisins, prunes
20P	Processed dairy products	Butter, cheese, cream cheese, whipping cream, creamers, ice cream, fluid milk, plant-based milk, yogurt

21P	Cakes, pastries, bakery products, cookies, pastas, doughs, tortillas	Bagel, biscuit, bread, bun, cookie, cracker, cake, flatbread, French toast, loaf, muffin, croissant, roll, pasta bowl, pancake, pasta, tortilla, taco shell
22P	Poultry & processed poultry meat products	Whole chicken, chicken dumpling, chicken leg, chicken patty, roasted chicken, chicken tender, chicken bite, goose bottom, omelet, chicken slider, turkey
23P	Meat & processed meat products (nonpoultry)	Ground meat, beef, lamb, pork, veal, meatball, beef patty
24P	Processed fish and seafood products	Fish patties, salmon, sardine, tilapia, tuna
25P	Roasted nuts, nut butters, and snack foods	Potato chip, tortilla chip, peanut butter, roasted sunflower, pretzel snack
26P	Flavorings, dressings, sauces, spices, and extracts	Baking soda, ketchup, mayonnaise, mustard, balsamic vinegar, salad dressings, salt, browning sauce, duck sauce, soy sauce, sweet and sour sauce, tartar sauce, teriyaki sauce, Worcestershire sauce, seasonings, spices, vinegar
27P	Coffee, tea, soft drinks, and water beverages, ice	Coffee, electrolyte drink, nutritional drink, soda, iced tea, bottled water, ice
28P	Other manufactured foods	Burrito, macaroni, meal kits, sandwich, sugar substitute, tofu
29P	Alcoholic beverages	distilled spirits, beer, wine

Appendix B – Vendor Input Questions
Supplemental information on food product and food product ingredient categorizations and their respective RPCs denoting the percentage of them grown or produced in NYS are required. To assist state agencies in augmenting existing bid pricing sheet for application of the algorithm, we propose the format of the food product questions below for incorporation into existing bid pricing sheets (Excel files). The questions proposed represent the set of questions for a processed food product made from two processed food products. Depending on the answers to the first question, the remaining questions may not be relevant.

1. Select the food product category from the list that most closely matches the bidded product (select one from drop down list):
   - Fresh/minimally processed food product category (1F - 13F): ___ OR
   - Processed food product category (14P - 29P): ___

2. What percent of the bidded product was made or grown in New York State? Enter a number between 0 and 100.
   - ___% Enter number 0 to 100

3. If a processed food product category in #1, select two food product categories from the list that most closely matches the top two food product ingredients in the bidded product (choose two):
   - First ingredient (select one from the drop down list)
     - Fresh/minimally processed food product category (1F - 13F): ___ OR
     - Processed food product category (14P - 29P): ___
   - Second ingredient (select one from the drop down list)
     - Fresh/minimally processed food product category (1F - 13F): ___ OR
     - Processed food product category (14P - 29P): ___

4. What percent of the of the first food product ingredient was made or grown in New York State? Enter a number between 0 and 100.
   - ___% Enter number 0 to 100

5. What percent of the of the second food product ingredient was made or grown in New York State? Enter a number between 0 and 100.
   - ___% Enter number 0 to 100

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