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SPATIAL PROCUREMENT OF FARM PRODUCTS AND THE SUPPLY OF PROCESSED FOODS: APPLICATION TO THE TOMATO PROCESSING INDUSTRY

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ABSTRACT. Increased transportation and logistical costs in agricultural markets have affected the spatial allocation of production in the agricultural and food sectors of the economy. We develop a spatial model of farm product procurement by a food processor, designed to capture the effects of supply-chain disruptions on the spatial procurement of farm products in the processed food sector. We use detailed data on production and procurement by a large California tomato processor to estimate the key parameters of the model which allow us to calculate the price elasticity of supply for California tomato paste production and describe how changes in energy prices and transportation costs for primary agricultural products affect the supply of processed food.

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1. Introduction

Recent supply chain issues involving shocks in transportation and logistical costs in agricultural markets have played an important role in food price inflation, as rising energy costs and increased trucking rates have affected the spatial allocation of production in the agricultural and food sectors of the US economy. Agricultural products used as an input in the production of manufactured or processed food products require matching the production of primary agricultural products grown on geographically dispersed farms with the operation of food processors, who rely on the primary farm products to produce wholesale food for downstream markets. Because primary agricultural products provide the raw material inputs used by the food processing industry, farmers who produce agricultural products for the processing sector tend to co-locate with food processing plants (food processing firms typically operate several plants), raising the issue of how the allocation, pricing, and distribution of primary agricultural products across space in the upstream procurement market affects the supply of manufactured food products in downstream markets.

In this paper, we examine how the spatial delivery of primary agricultural products affects the elasticity of supply in the downstream processed food market. While the importance of spatial delivery costs for agricultural products has been recognized since at least Samuelson (1952) and Takayama and Judge (1971), it is surprising to note that there has been little development of models to understand how changes in transportation costs for primary agricultural products in upstream markets affects the supply of processed food in downstream markets.[1] This omission is notable, because agricultural products are generally homogeneous commodities traded at publicly-available and observable prices, which provides an important lens to understand the role of transportation and logistical shocks in input procurement on the supply of manufactured goods more broadly in the economy. Understanding how changes in transportation costs impact consumer prices for manufactured food is particularly important given the increased public attention on energy policies such as carbon taxes that raise fuel prices, and the potential role of such policies on food price inflation and the consumer incidence of commodity price shocks in the agriculture.

Transportation costs for primary agricultural products represent a substantial portion of overall food processing costs. As C. Durham, R. Sexton, and Song (1996) observe for the case of processed tomato

[1] A notable exception is Chavas, Cox, and Jesse (1998).

products, changes over time in the geographic location of tomato production in California caused tomatoes to be hauled longer distances, raising transportation costs for the industry to a 15%-20% share of raw product value. As a result, shocks in the transportation sector have the potential to profoundly affect the supply of manufactured food products.

Among other things, understanding how changes in transportation costs for primary agricultural products affect food processing costs is important for understanding price pass-through in vertically structured industries with an upstream input procurement market and a downstream manufactured product market. In the case of food markets, the literature on wholesale and retail price pass-through has found substantial price rigidity at the wholesale level that reduces pass-through rates and causes delayed pass-through to occur (Nakamura 2008; Nakamura and Zerom 2010; Hong and Li 2017). Bonnet et al. (2013) point to the potential role of nonlinear pricing contracts and vertical restraints in the manufacturer-retailer portion of the supply chain in explaining wholesale price pass-through in response to cost shocks in primary agricultural product markets; however, such an outcome may be driven instead by changes in transportation costs in the food processing/manufacturing sector when procurement costs rise over distance and upstream shocks in farm prices alter the spatial distribution of deliveries. This is particularly true in cases where changes in food commodity prices coincide with changes in energy prices, as in the case of grain that can be used to produce either manufactured food or biofuel.

We apply our model to examine the production of processing tomatoes in California. The processing tomato industry in California is ideal for studying these effects for several reasons. First, California food processors are responsible for the production of roughly 95 percent of all processing tomatoes in the US and have approximately 33 percent market share global market share (USDA National Agricultural Statistics Service 2022b). Second, unlike food manufacturing for highly differentiated food products, the production process for tomato processing is relatively simple, essentially involving the combination of heat and pressure to a primary agricultural input to produce processed tomato products such as tomato paste. Third, the tomato processing industry in California relies on a uniform pricing schedule, wherein all sellers of primary agricultural products receive the same posted farm price for processing tomatoes regardless of the firm they contract with or their distance from the processing plant (C. Durham, R. Sexton, and Song 1996). Unlike the case of free-on-board (FOB) or "mill" pricing under which a food processor pays a constant mill price at the plant gate and sellers are responsible for costs of shipping product to the plant, uniform pricing involves the food processor fully absorbing the shipping costs.[2]

In this paper, we develop a spatial model of primary agricultural product procurement from the California processing tomato sector and use this framework to characterize the processed food supply function for tomato paste. Because farmers and food processors co-locate in geographic space, the model results in pass-through of higher energy costs that raise transportation costs for primary agricultural products into higher prices for processed food. Predicting how changes in energy prices and transportation rates in the farm sector impact processed food supply is essential to understand how changes in farm product prices pass through to changes in wholesale prices for manufactured foods.

Our model conceives the food processing firm as relying on capital and labor inputs to operate one or more plants, where the scale of the plant then determines its capacity to process a primary agricultural product into manufactured food products. Firms of this sort must solve not only the usual neoclassical problem of choosing optimal combinations of inputs and scale to maximize profits, taking prices as given, but must also deal with the problem of sourcing the agricultural input over geographic space from dispersed farm operations to the processing plant. Because producing the primary agricultural product (processing tomatoes, milk, corn, sugar beets, etc.) necessarily occurs on agricultural land, and because different land is better or worse suited to the production of particular crops, the food processing firm solves an important co-locational problem when it decides where to construct and operate its plants. Specifically, as long as transporting the agricultural input is costly (either because of the direct costs of moving the inputs, or because of the perishability of the input) the firm has an incentive to locate its plants near productive agricultural land where the primary agricultural product is sourced. The operating scale of the plant, in turn, becomes a scarce factor that generates positive Ricardian (quasi) rents.

We depart from the existing literature by modeling a production process that requires sourcing the primary agricultural product from a procurement market that involves increasing transportation costs over distance. The processor chooses plant operating capacity in the long

[2]Uniform pricing, for this reason, has been noted as a form of price discrimination in which nearby growers cross-subsidize more distant growers (C. Durham, R. Sexton, and Song 1996).

run, which requires deployment of capital and labor inputs. Then the processor procures a primary agricultural product (e.g., processing tomatoes), applying pressure and heat to inputs of raw farm material to produce a finished processed food product (e.g., tomato paste) for sale in the wholesale market. Changes in transportation costs for the primary agricultural product thereby affect the marginal cost of processed food production by altering the geographic extent of the procurement market around the processing plant, giving rise to an upward-sloping supply function for the manufactured good.

To estimate the long run elasticity of supply for processed tomato products, we combine restrictions from our simple model with proprietary data collected from a sample of California tomato processing firms to calculate the elasticity of processed tomato supply. Results from the model are as follows: (i) the spatial distribution of primary agricultural products affects the marginal cost of processed food supply; (ii) in terms of the supply elasticity of processed food, greater land productivity and/or a larger land density of farms in geographic proximity of the processing plant makes food product supply more elastic; (iii) processed food supply becomes less elastic as plant capacity increases; and (iv) higher transportation costs for the primary agricultural product, for example from changes in logistical expenses of contracting loads, make processed food supply less elastic. Perhaps surprisingly, we find that changes in the fixed cost of loading farm products has essential effects on the elasticity of processed food supply, while changes in unit transportation costs do not.

We apply the model to examine the elasticity of supply for tomato paste in California using detailed data on the spatial procurement of processing tomatoes. Our estimate of the price elasticity of tomato paste supply is 2.90, which is at the lower end of the range of residual supply elasticity estimates facing food processors calculated by C. A. Durham and R. J. Sexton (1992). The relative rigidity of tomato paste supply vis a vis processing tomato supply in the upstream farm product market indicates the important role of transportation costs in dampening price responses to output changes in markets with uniform pricing and spatial procurement. We also identify novel impacts of transportation cost shocks on the output of processed food, contributing estimates to the literature on the elasticity of processed food supply with respect to various parameters of the transportation cost function.

The remainder of the paper is organized as follows. In the next section we provide some background detail on the processing tomato market. Section 3 describes our model, focusing first on our novel description of production, and describing the firm's inverse supply function given this form of production. The critical element for determining supply and other elasticities is the cost of sourcing the primary agricultural input from across different points in space. We describe how the location of agricultural production on land around the processing plant affects transportation costs, and develop expressions describing the input cost function in the case where farm products are procured on a plane surrounding the processing plant. Section 4 describes our highly granular data on processing tomato transport costs, which we combine with additional data on processing outputs to construct an estimated transport cost function that we use to calculate various supply elasticities. Section 5 concludes.

2. Background

California processed tomato manufacturers are responsible for producing 96 percent of all processed tomato products in the U.S. (11.1 million metric tons (MT) out of 11.6 million MT in 2021) and provide nearly one-third of total world tomato supply (39.1 million MT in 2021). After California, Indiana, Ohio, and Michigan account for most of the remaining domestic production, while the dominant international producers that compete with California are in China, Italy, and Spain. Processing tomatoes are mostly processed into tomato paste, with a lesser share devoted to diced tomatoes and various tomato sauces.

During the prime processing season in late summer (July-September), tomato processing facilities seek to maximize capacity by running continuously, 24 hours a day, 7 days a week. Part of the management of this production schedule involves arranging harvest contracts with growers that specify logistics and timing of deliveries. The raw tomatoes are harvested ripe and supplied from farmers' fields to the processing facility, where they are maintained at the facility for a brief time within the season, and are not kept in cold storage. Processed tomato products such as tomato paste and canned tomatoes are shelf-stable and generally are stored at room temperature on pallets or drums at the plant for sale thoughout the year without the need for refrigeration. Thus, storage of both processing tomatoes and processed tomato output requires minimal additional energy beyond that accounted for during production within the facility. While some Californian processors produce additional specialty products, the dominant products are paste and diced tomatoes, which are either sold in bulk to downstream food manufacturers for further processing into tomato sauce, ketchup, and other food products, or else are sold in retail-ready packaging for consumers (USDA Economic Research Service 2022).

Within the State of California, the three biggest processing tomato counties are Fresno, Yolo, and San Joaquin, in order of importance, although significant production also occurs in Kings, Colusa Counties, Merced, Stanislaus, Solano, and Sutter counties. While farm production of processing tomatoes is primarily centered in the San Joaquin and Sacramento Valleys, 19 (of 58) counties in the state reported significant processing tomato production in 2021 (see Table A.2).

Tomato is a warm-season crop, either planted by sowing seeds directly into the ground during late January or early February, or grown in greenhouses until they are ready to be planted in the spring (Naeve 2015). The tomato harvest season typically lasts nineteen weeks with the major portion of the harvest occurring between July and September. The harvest period typically begins in mid-July, and operates at full capacity throughout August and September, with the harvest season generally winding down in mid-October (Trueblood, Wu, and Ganji 2013).

While some processing plants manufacture pulp-based products like stewed and diced tomatoes, most initial processing is done by firms that manufacture raw paste. Almost all processing tomato production in California is forward contracted between the grower and the processing firm, rather than sold on the open market, with prices settled contractually well before the season starts. In terms of processed food production, bulk tomato paste comprises roughly 50%-60% of processed tomato output, followed by canned tomatoes and sauces, with a small share sold as whole peeled tomatoes (USDA National Agricultural Statistics Service 2022b). Thus, tomato paste is the most important processed tomato product produced in California, which is either sold in bulk form to downstream food manufacturers or else used as an intermediate input in production of catsup and sauces. After tomato paste, various sauces including puree, diced tomatoes, chili, and pizza comprise the next largest sales category, followed by whole peeled tomatoes.

Processing tomatoes are unique in that a single bargaining association, the California Tomato Growers Association (CGTA), represents the majority of growers, negotiating prices in contracts with each of the nine tomato processors operating in the state. CGTA prices for processing tomatoes are contracted prior to the growing season to ensure the participation of growers in the market, and as a result, a given tomato processor pays all California farmers approximately the same price for tomatoes in delivery contracts each season (though this price varies slightly across processors), with transportation arranged via uniform pricing.

In our analysis of the processing tomato market, we view the decision of farmers and processing plants to produce in a given region as a co-location decision. Economic shocks that increase production costs or shift consumer demand after the growing season commences thus impact regional economic activity at both stages of production jointly. Specifically, food processing plants and the farmers that support them tend to exit the market together when the margin between the consumer price and farm price narrows in relation to margins provided elsewhere. For this reason, the transfer of processed food production out of a particular region is closely tied to the land allocation decision of farmers in the region (i.e., the long-run price elasticity of farm supply), and to the ability to trans-ship processed goods into the consumer market from other regions to meet consumer demand.

3. The Model

Our analysis of processing tomato supply is based on a spatial model of procurement in which food processors face increasing transportation costs over distance to deliver farm products to the nearest processing plant. We first describe a parametric production function for a representative food processor operating a single plant (this analysis generalizes to multiple plants), and then provide a specification of transportation costs faced by the firm given its plant's location. Finally, we combine these elements together to derive the cost function for a food processing firm under spatial procurement of the farm input and derive an expression for the inverse supply function for the case of a price-taking firm.

3.1. **The Production Function.** The production function of the food processor has two components: (i) labor and capital required to operate one or more plants, which depends on the operating capacity selected for each plant before the growing season; and (ii) energy and heat used for cooking the agricultural input, which depends on seasonal procurement of the agricultural input. Based on prevailing output prices for the processed food product, the procurement decision of each plant, and therefore the supply of processed food across all processing plants in the market, is thus determined by farm product prices and transportation costs at the individual plant level.

First consider the operating capacity of a representative food processing plant. In our interpretation of the problem, the firm uses capital and labor to operate a plant, where the size of the plant then provides the firm capacity to process the agricultural input. For a firm using energy and raw material inputs to process an agricultural input, the size of the plant then defines its capacity. We assume plant construction involves a standard Cobb-Douglas production function, with capacity equal to

$$BL^{\beta}K^{\gamma},$$

where β and γ are the usual curvature parameters in the Cobb-Douglas production function, and where B is a productivity parameter.

Next consider the cooking technology for the agricultural input. Given a plant of a particular capacity, food processing in many relevant agricultural industries is quite literally a matter of using energy to heat the agricultural input. At the individual plant level, we therefore model the food processing sector with fixed-proportions technology.

Let x denote the quantity of agricultural input. Processing a single unit of the agricultural input is assumed to require $1/\alpha$ units of energy e, so that (given a plant of sufficient capacity) output is given by

$$\min(\alpha e, x).$$

Combining the "plant operation" and "cooking" technologies described above yields an overall production function for the firm which depends on four inputs: energy (e), the agricultural input (x), labor (L), and capital (K). The production function is assumed to yield an output y, and takes the form

$$y = F(e, x, L, K) = A \min\{\min(\alpha e, x), BL^{\beta}K^{\gamma}\},$$

where, in addition to the parameters and variables defined above, A is a productivity parameter. This production function can be seen to allow for substitution between capital and labor in the operation of the plant, while the cooking process within the plant relies on Leontief technology, which we believe captures the nature of the actual production processes employed by many food processors.

3.2. **The Firm's Problem.** Now consider the problem facing a price-taking, profit-maximizing firm operating the production function described above and having to deal with the transportation costs of the agricultural input. Irrespective of the nature of the firm's profit-maximization problem, all firms that maximize profits must also solve the cost minimization problem associated with production.

Given the Leontief technology for converting energy and material inputs into processed food output, cost minimization implies that the firm will choose energy e, the agricultural input x, and labor and capital so that

$$\min(\alpha e, x) = BL^{\beta}K^{\gamma}.$$

Because energy is related to the use of the agricultural input via

$$\alpha e = x, \tag{1}$$

we have $x = BL^{\beta}K^{\gamma}$.

We are now ready to describe the firm's decision about how much labor and capital to employ. Specifically, we compute the most efficient way to process a quantity of agricultural input x, which solves:

$$\min_{L,K} wL + rK \qquad \text{such that } x = BL^{\beta}K^{\gamma}.$$

The solution to this problem is to choose

$$\begin{aligned} K &= \left(\frac{w}{r}\frac{\gamma}{\beta}\right)^{\frac{\beta}{\beta+\gamma}} \left(\frac{x}{B}\right)^{\frac{1}{\beta+\gamma}} \\ L &= \left(\frac{r}{w}\frac{\beta}{\gamma}\right)^{\frac{\gamma}{\beta+\gamma}} \left(\frac{x}{B}\right)^{\frac{1}{\beta+\gamma}}. \end{aligned} \tag{2}$$

Given the need to process a quantity x of the input, the total 'overhead' costs of capital and labor for the cost-minimizing firm can be written

$$E(x; r, w) = \left(w^{\beta}r^{\gamma}\frac{x}{B}\right)^{\frac{1}{\beta+\gamma}} \frac{\beta+\gamma}{\beta^{\frac{\beta}{\beta+\gamma}}\gamma^{\frac{\gamma}{\beta+\gamma}}}.$$

This expression provides us with the minimum overhead involved in operating a plant capable of processing x units of the agricultural input. We now turn our attention to the question of the cost minimizing way to produce y units of processed output.

Letting p denote the energy price and $q(x)$ denote the cost of sourcing x units of the agricultural input, the firm's cost function is

$$C(y; p, q, r, w) = \min_{e,x,K,L} pe + q(x) + rK + wL \qquad \text{such that } y = F(e, x, L, K).$$

Noting that this problem is necessarily the same as

$$C(y; p, q, r, w) = \min_{e,x,K,L} pe + q(x) + E(x; r, w) \qquad \text{such that } y = A\min(\alpha e, x),$$

and since (using the last constraint) $x = y/A = \alpha e$, we have

$$C(y; p, q, r, w) = \frac{py}{\alpha A} + q\left(\frac{y}{A}\right) + E\left(\frac{y}{A}; r, w\right).$$

Turning finally to the profit maximization problem, we obtain

$$\max_{y} vy - C(y; p, q, r, w),$$

where v is the price of the processed output. The solution is characterized by the first order condition

$$v = \frac{p}{\alpha A} + q'(y/A) + \left(\frac{r^{\gamma} w^{\beta}}{AB\beta^{\beta}\gamma^{\gamma}}\right)^{\frac{1}{\beta+\gamma}} y^{\frac{1-\beta-\gamma}{\beta+\gamma}}. \tag{3}$$

The right-hand side of this optimality condition represents the firm's marginal cost. Accordingly, this expression characterizes the solution to the firm's inverse supply function in the competitive case that is the focus of our attention here.

Notice that the marginal cost of processed food production depends on the marginal cost of procurement, $q'(x)$, which in turn depends on whether the pricing arrangement with growers freight on board (FOB) destination or uniform pricing (FOB origin). In the case of uniform pricing, the procurement cost for the processor depends on the spatial distribution of farms in proximity to the processing plant. Moreover, because farmers producing primary agricultural products for processed foods markets tend to co-locate with processing plants in geographic space, marginal procurement cost under a uniform pricing schedule depends on the radial distance between the processing plant and the extensive margin of farm production, which is endogenously determined by the processing plant.

3.3. **Procurement Cost for the Agricultural Input.** Equation (3) gives a solution to the processor's supply conditional on the marginal cost of procurement, $q'(x)$. Sourcing the agricultural input involves using a transportation network to move the primary agricultural product from the land where it is produced to the processing plant that receives it. A processing plant that wishes to acquire greater farm product inputs must procure the agricultural product from greater distances, and it follows that the marginal cost depends on the spatial distribution of farms around the processing plant. Thus, when spatial procurement costs increase over distance from the processing plant, rising transportation costs over distance result in upwards-sloping supply for processed food even in the case of constant returns to scale in the operating capacity of a plant. This section presents a simple spatial model of procurement on an agricultural landscape around the processing plant that determines the procurement cost function, $q(x)$.

We conceive the plant as being located in an agricultural landscape, where the surrounding agricultural land can vary in its productivity for producing the raw material input. We introduce a productivity parameter μ to index land productivity. The productivity of agricultural land near the processing plant determines how much of the raw product may be transported from within a given distance to the plant, which in turn determines the rate at which the processing plant must expand procurement over distance to increase its output level.

We next need to put some structure on the space within which the firm makes its location decision. The simplest structure for farm product procurement locates agricultural land on a plane in a Hotelling-like locational space centered around the processing plant, so that plants source tomatoes from a circular area.[3]

Suppose transportation costs for delivering the raw product to the processing plant are increasing in the distance between the processing plant according to a quadratic transportation technology. In particular, the cost of hauling a single ton of tomatoes m units of distance from the farm gate to the processing plant is given by

$$\tau_0 + \frac{\tau_1}{2}m + \frac{\tau_2}{3}m^2.$$

The "fixed cost" τ_0 can be thought of as time required to load, grade, and unload the processing tomatoes at the plant, all of which are independent of the distance m. The second parameter τ_1 captures costs which are linear in the distance traveled, for instance fuel costs. The third parameter τ_2 governs the quadratic term, which we motivate by noting that travelling more miles increases the probability of encountering traffic congestion.[4] It may also be the case that the handful of tomato processors in California are sufficiently large that they face an upward-sloping supply curve for drivers of the specialized tomato gondola trailers used in the industry.

A given processor faces the cost of moving tomatoes from an entire region of production. We define this region by supposing that a given processing plant sources all the tomatoes within a distance $\bar{m}$. Then the cost of transporting *all* the tomatoes in this region is given by the expression

$$\mu \int_0^{\bar{m}} \left(\tau_0 + \frac{\tau_1}{2}m + \frac{\tau_2}{3}m^2\right) dm = \mu\left(\tau_0\bar{m} + \tau_1\bar{m}^2 + \tau_2\bar{m}^3\right).$$

The distance traveled to procure loads of the farm input is incidental to the problem facing the food processor of sourcing x units of the primary agricultural product. Instead, the distance $\bar{m}$ is endogenous to the food processor and determined by its demand for the input x;

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[3]We have also calculated solutions to the model when the input is sourced from locations on a Hotelling line, which produces qualitatively similar results.

[4]During the busy harvest season traffic on the two-lane highways of the Central Valley is often delayed by the large number of tomatoes being moved about, just as traffic in Napa Valley is delayed some months later during the grape crush.

thus, we write $\bar{m}(x)$. If the uniform price paid to growers per ton of tomatoes is q_0 then the *total* cost of sourcing and transporting x tons of tomatoes is given by

$$q(x) = q_0 x + \tau_0 \bar{m}(x) + \tau_1 \bar{m}(x)^2 + \tau_2 \bar{m}(x)^3, \tag{4}$$

while the corresponding marginal cost is given by

$$q'(x) = q_0 + \tau_0 \bar{m}'(x) + 2\tau_1 \bar{m}(x)\bar{m}'(x) + 3\tau_2 \bar{m}(x)^2 \bar{m}'(x). \tag{5}$$

3.4. **The Agricultural Space.** We consider agricultural product procurement on a plane in which a food processor sources all tomatoes within a distance $\bar{m}$ from a circle having area $\pi\bar{m}^2$. In this case we have $\bar{m}(x) = \sqrt{\frac{x}{\pi\mu}}$. Notice that food processing creates agglomeration economies, as a greater density of farmland around the processing plant devoted to growing the processed input reduces procurement cost at the plant by reducing the travel distances required to procure a given quantity of the primary agricultural product.

Substituting this relationship into our specification of transportation cost gives us the cost function and its first and second derivatives:

$$q(x) = q_0 x + \frac{\tau_0 \sqrt{x}}{\sqrt{\pi\mu}} + \tau_1 \frac{x}{\pi\mu} + \tau_2 \left(\frac{x}{\pi\mu}\right)^{3/2}, \tag{6}$$

$$q'(x) = q_0 + \frac{\tau_0}{2\sqrt{\pi\mu x}} + \tau_1 \frac{1}{\pi\mu} + \tau_2 \frac{3\sqrt{x}}{2\pi\mu\sqrt{\pi\mu}}, \tag{7}$$

while the second derivative of the cost function is

$$q''(x) = -\frac{\tau_0}{4\sqrt{\pi\mu x^3}} + \tau_2 \frac{3}{4\pi\mu\sqrt{\pi\mu x}}. \tag{8}$$

Notice that even in the case in which processing plants are competitive and operate constant-returns-to-scale production technologies, the need to source tomatoes at increasing costs over distance seen in (8) implies that supply curves are not perfectly elastic. Put differently, ownership of the scarce land factor creates rents to land owners that materialize over distance from the processing plant, while ownership of plants with capacity to process additional agricultural output is a scarce factor that generates a Ricardian (quasi) rent. In this case, the uniform pricing employed within the tomato processing industry implies that rents accrue to the owners of land within a distance $\bar{m}$ of the processing plant.

4. Empirical Analysis

In this section, we illustrate how the model and spatially indexed cost function can be used to estimate the supply elasticity for tomato processors in California. We use actual production data provided to us for three California tomato processing firms to estimate parameters of our production model and then use equation (10) to calculate the elasticity of supply at the plant level for processed tomatoes in California.

4.1. **Data.** Our data consist of highly detailed cost information and weekly load procurement data from a sample of California tomato processors. We rely on the farm-level load data supplied by California food processors to estimate spatial material procurement relationships necessary to calculate the supply elasticity for the processing tomato industry. Our proprietary data from three tomato processing firms in California include: (i) monthly records of revenue and quantity shipped; (ii) detailed data on inventory and costs including raw material procurement costs; (iii) energy costs; (iv) transportation costs; and (v) labor costs. Our data on procurement and transportation costs comes from three processing plants operated by a single firm; it is highly granular at the level of individual loads between farmers and processing plants, including the distance shipped.

Table 1 shows summary statistics of the revenue and cost data provided by the firms. Transportation costs are converted into a basis of dollars per ton mile by dividing shipment cost by weight and distance for each load. Transportation costs for raw tomatoes, on average, are \$0.17 per ton mile. The average plant produces 724 million pounds of tomato paste from processing tomatoes that are sourced an average of 58.95 miles away.

Table 1. Summary Statistics

Variable	Parameter	Mean	Std. Dev.
Average Transport Costs (per ton per mile)	—	\$0.17	\$0.10
Average Transport Distance (per load)	$\bar{m}/2$	58.95 miles	32.26
Raw Tomato Quantity Purchased (tons)	x	1.4 million	0.8 million
Annual Labor Expenditures (\$ thousands)	wL	\$17,665	23,274
Annual Capital Expenditures (\$ thousands)	rK	\$6,917	6,079
Quantity of Output (pounds)	y	724 million	595 million
Price of Output (per pound)	v	\$0.33	0.03
Lbs of paste per ton of tomatoes	A	368.2	—

We use these data to estimate parameter values and then calculate an elasticity of supply for processed tomatoes in California. To estimate transport costs (the τ_i parameters) and the land productivity parameter (μ), we use detailed data from three processing plants (in a single firm) over three years (2010–2012) on all loads of raw tomatoes purchased from farms and transported by truck to the processing plants. Our firm data also provides the average price per ton of raw tomatoes (q_0) while we use data from USDA to calculate the parameter A.

4.2. **Returns to Scale in Plant Operation.** The expression for the long-run supply elasticity is greatly simplified if the tomato processing plants utilize a constant returns-to-scale production technology for plant operation so that $\beta + \gamma = 1$. Interpreting the plant's operation through the lens of our model makes this interpretation plausible. Recall that our model decomposes the process of "cooking" the agricultural input from the employment of capital and labor inputs for operating a plant at a given nameplate capacity, so that the production function we're immediately concerned with is just the operation (and amortized cost of construction) of a facility that can apply heat and pressure to raw material (up to this capacity) to make tomato paste.

We corroborate this intuition by estimating the Cobb-Douglas production function with no restriction on β and γ using the cost and production data provided by the firms. Our sample size is small (39 observations), because our monthly production data is limited to having observations from only 3–4 months each year at each plant.[5] Based on that regression, our estimate of $\beta + \gamma$ is 0.928 (std. error = 0.106), yielding a 95% confidence interval of $[0.71, 1.14]$.[6] Thus, we fail to reject the hypothesis that $\beta + \gamma = 1$, and we accordingly proceed under the assumption of a constant returns-to-scale production function.

4.3. **Estimating the Transportation Cost Function.** The input cost function, $q(x)$, consists of two parts: (i) the price per unit paid by the processor to procure the raw tomatoes (q_0); and (ii) the transport costs of raw tomatoes to the processing plant. We take q_0 to simply be the average price per ton paid to growers in 2012, which is \$58.95.

To estimate the parameters τ_i in the function describing the transport cost per ton of raw tomatoes as a function of distance, we utilize

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[5] The data are comprised of 2 plants that operate for 4 months of the year over the period 2010-2012 and a third plant that operates 3 months of the year over the period 2009-2013.

[6] Full results are available in the Table 1A in the Appendix.

data provided for every truckload of tomatoes transported over a three-year period (2010-2012) for three tomato processing plants operated by a single firm. This data includes the total transport cost for each load, the weight of each load, and the distance the load was transported.

Table 2 shows the results of a quadratic model regressing transport cost on distance to estimate the coefficients (τ_0, τ_1, τ_2) in our expression for the (per ton) transport costs $\tau_0 + \frac{\tau_1}{2}m + \frac{\tau_2}{3}m^2$.

TABLE 2. Regression Results on Raw Tomato Transport Costs per Ton. Standard errors in parentheses.

Variable	(1)	(2)
Intercept (τ_0)	2.300***	2.350***
	(0.003)	(0.005)
(Miles To Plant)/2 (τ_1)	0.202***	0.197***
	(0.000)	(0.000)
Miles^2/3 (τ_2)	—	5.397e-5***
		(3.84e-6)
N	387,468	387,468
R^2	0.926	0.926

$*p < 0.05, \quad **p < 0.01, \quad ***p < 0.001$

We estimate two different specifications of the transport cost function, one the general quadratic specification assumed above, and one which restricts transport costs to be linear. The quadratic term estimated in column (2) of Table 2 is highly significant and of the expected sign, but explains little additional variation in transport costs relative to the linear specification. Either specification suggests that transportation costs for raw tomato loads include a fixed cost component (τ_0) of about \$2.30 per ton, and a linear term (τ_1) of about \$0.20 per ton mile. The quadratic term indicates that transportation costs increase at a greater than linear rate with τ_3 estimated to be about 5.4e-5.[7]

Total cooking cost for the processing plant depends on the fixed cost of acquiring raw processing tomatoes basis (q_0), the transportation

[7]Because τ_1 depends on things like fuel costs one might be concerned that τ_1 is time-varying. As we are estimating a static model our τ_i estimates are based on a weighted average of fuel costs and other factors which vary over the time period analyzed. To consider the importance of variation in fuel costs over the time period analyzed, we also estimated the regression in Table 2 using interactions of year dummies with τ_1 so that we get separate estimates for each year 2010–2012. Estimates of the parameter varied by less than 3% across years (ranging from 0.195 to 0.201).

cost per ton mile (the τ_i), and the land productivity parameter (μ) to account for the spatial distribution of loads in proximity to the plant.

The remaining parameter we need is the land productivity parameter μ. In principle this can be obtained from the relationship between observed total input x and the greatest distance tomatoes are transported, $\bar{m}$. In practice, using the actual observed greatest distance may introduce error (since we're estimating this key parameter from a single observation). A better approach is to note that in our model $\bar{m}$ will simply be equal to twice the *average* miles driven. In our data the average transport distance is 58.95 miles, implying a value of $\bar{m} = 117.9$ miles.

From the relationship $\bar{m} = \sqrt{\frac{x}{\pi\mu}}$ we have $\mu = \frac{x}{\pi\bar{m}^2}$, which corresponds with the total input sourced divided by the area of a circle of radius $\bar{m}$. This gives a value of approximately 128.24 tons per square mile, or 0.20 tons per acre. In interpreting this figure one should recall that μ will depend both on yields (e.g., tons per planted acre) as well as the proportion of acres planted. With processing tomato yields somewhat less than 50 tons per acre in California, this implies that about half a percent of land within the stylized circular catchment area would be planted to processing tomatoes.[8]

Finally, we calculate the parameter A (pounds of output per ton of input) by using the conversion ratio from fresh (farm) weight using a factor of 5.432 for pounds of tomatoes to make one pound of tomato paste (USDA-NASS). This implies a value of A equal to 368.2 when converting tons of processing tomatoes into pounds of tomato paste. Putting together our estimates of q_0, μ, and the τ_i parameters of the transportation cost function allows us to specify the input cost function as (using (6))

$$q(x) = \$58.95x + \$2.965\sqrt{x} + \$0.321x + \$0.000108x^{3/2}.$$

4.4. **Estimated Supply Elasticities.** A central goal of this paper is to express the elasticity of the supply curve for processed tomato products in a form that allows us to consider the impact of changes in the costs of transportation (i.e., the parameters of the transportation cost function) on the supply of tomato paste. Noting that the processor's technology is consistent with constant returns to scale, then the first-order conditions from the processor's problem (3) equating marginal

[8]The total area of the 19 counties with harvests reported by NASS for 2021 was 37,415 square miles, while the total harvested area was 356 square miles, so this is the right order of magnitude.

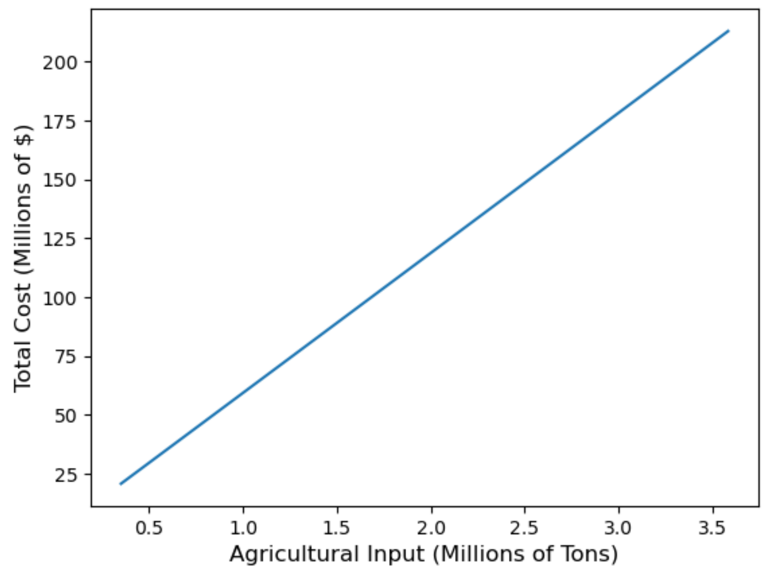

FIGURE 1. Input Cost Function. A shaded area (too small to be visible) indicates pointwise 95% confidence intervals.

cost to price define the firm's inverse supply curve,

$$v = \frac{p}{\alpha A} + q'(y/A).$$

Differentiating this expression with respect to y and exploiting the inverse function theorem allows us to assert that $\partial y/\partial v = A/q''(y/A)$, so that the price elasticity of the supply function takes the form

$$\varepsilon_v = \frac{vA}{q''(y/A)y}. \tag{9}$$

Now we can make use of q'' calculated above for the case of farm product procurement on a plane. Doing so, we obtain an expression for the elasticity

$$\varepsilon_v = \frac{v4(\pi\mu)^{3/2}\sqrt{y/A}}{3\tau_2 y/A - \tau_0\pi\mu}. \tag{10}$$

Notice that the fixed costs of transport involving τ_0 play an important role in the elasticity of processed food supply. When these fixed costs are high (approaching $3\tau_2 y/A$), supply approaches being perfectly elastic. [9] Fixed costs of loading and unloading farm products can thus profoundly impact pass through rates in the food sector, resulting in higher consumer incidence of commodity price shocks on food prices when fixed costs of transport rise in upstream farm product markets. Quadratric transportation costs have the opposite effect, as higher values of τ_2 make processed food supply less elastic, reducing pass through rates of commodity price shocks into consumer food prices. For example, if quadratic transportation costs arise through road congestion or due to capacity constraints on specialized trailers used to haul agricultural products, then relaxing these constraints through public road improvement projects and private investment would increase the elasticity of processed food supply, raising pass through rates in consumer food markets.

Perhaps surprisingly, the *linear* costs of transportation have no effect on the supply elasticity, which implies, among other things, that the supply elasticity of processed food does not depend on diesel fuel prices in the transportation sector. Changes in the linear transportation cost parameter thus shift the level of processed food supply but have no impact on the supply elasticity. This outcome has important implications for energy policy, as policies such as carbon taxes that raise fuel prices result in level effects on the supply of processed foods without changing pass through rates of increased farm prices into consumer food prices.

4.4.1. *Elasticity Estimates.* Collecting values of the estimated parameters in the Tables above and incorporating them in equation (10) provides our estimate of the long-run supply elasticity for processed tomato paste.

Our results have several implications for the effect of agricultural commodity price shocks on consumer prices for manufactured foods. First, empirical models of price pass through in food markets that fail to account for changes in the transportation sector that occur concurrently with changes in agricultural commodity prices may be misspecified. Second, because our estimated supply elasticity of tomato paste is considerably less elastic than previous estimates of the residual supply elasticity of processing tomatoes in the farm sector, our results suggest that food processors play an important role in dampening food price inflation, as the incidence of food price shocks in the farm sector on consumer food prices falls with inelastic supply. Third, because changes in transportation costs that are linear in distance have no affect on the elasticity of procesed food supply, the tax incidence of

[9]The case in which the elasticity actually flips to being negative can be ruled out so long as the processor can exit.

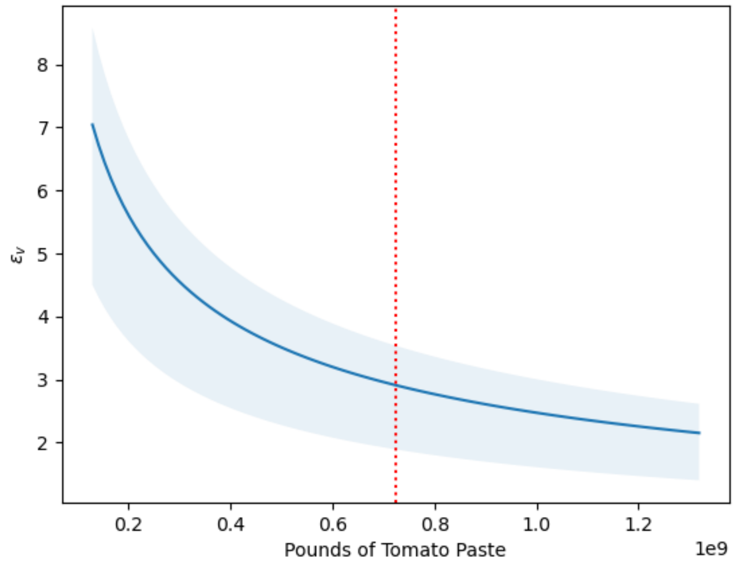

FIGURE 2. Supply Elasticity. The dotted line indicates average output. At this level of output elasticity is equal to 2.91. The shaded area provides a pointwise 95% confidence interval.

energy policy such as carbon taxes that raise fuel prices does not have corrollary effects on changing the incidence of commodity price shocks on manufactured food prices. Finally, disruptions in the food supply chain caused by pandemics and natural disasters have the potential to alter fixed and quadratic transportation cost components of raw product procurement for food processors, resulting in essential implications for the consumer incidence of commodity price shocks in agricultural markets that have the potential to exacerbate food price inflation.

For non-competitive market structures, inverse supply can be interpreted instead as the marginal cost function for the processing firm, generating implications for backwards pass through as well. Backwards pass-through, which can occur when processing plants have bargaining power in setting the annual contract price to growers, depends on curvature of the marginal cost function. Our estmated marginal cost function is concave, which suggests the potential for greater than one-to-one pass-through of tomato paste prices into processing tomato prices in the upstream farm product market. Moreover, while farm-gate prices do not impact the supply elasticity in the case we consider here, one could relax the assumption of perfectly elastic supply of the raw farm output (tomatoes), which would allow the farm price to vary with the procurement level to reflect varying opportunity costs of land. We suppress this consideration here to focus the model on the effect of changes in transportation cost on processed tomato supply. On their own, these transportation costs suffice to make competitive firms' supply curves upward sloping, a result that stands in sharp contrast to the textbook case in which a competitive firm with a constant returns to scale production technology has perfectly elastic supply. Here, because the marginal cost of sourcing tomatoes across space is increasing over distance, "nearby tomatoes" available for procurement will always be a scarce factor.

4.5. **Transportation Cost Elasticities.** So far, we have constructed estimates of the supply elasticity with respect to the price of output v, and we can see how this elasticity depends on parameters of the transport cost function. This relationship is interesting because it sheds some light on ways in which we might expect the supply of tomato paste (and related products) to be affected by disruptions to transport or logistical issues that affect raw material procurement. However, a more direct question involves the elasticity of supply with respect to the transportation cost parameters. We explore this in this section, constructing expressions for elasticities with respect to each of the three transport-cost parameters.

We obtain these elasticities by recalling that the first order conditions for the firm imply that $v = \frac{p}{\alpha A} + q'(y/A)$. Then by the envelope theorem we have $0 = (\partial q'(y/A)/\partial \tau_i)(\partial y/\partial \tau_i)/A$ for $i = 1, 2, 3$, which allows us to solve for the partial derivatives $\partial y \partial \tau_i$ via implicit differentiation. Further, note that the elasticity $(\partial y/\partial \tau_i)(\tau_i/y) = (\partial x/\partial \tau_i)(\tau_i/x)$. Then calculation of the relevant elasticities simply involves substituting the expression for q' into the first order conditions, and differentiating with respect to the parameter of interest.

These elasticities are given by:

τ_0: $\varepsilon_{\tau_0} = \frac{2\pi\mu}{\pi\mu - 3(\tau_2/\tau_0)y/A}$.

τ_1: $\varepsilon_{\tau_1} = \frac{4(\tau_1/\tau_0)\sqrt{\pi\mu y/A}}{\pi\mu - 3(\tau_2/\tau_0)y/A}$

τ_2: $\varepsilon_{\tau_2} = \frac{6(\tau_2/\tau_0)(y/A)}{\pi\mu - 3(\tau_2/\tau_0)(y/A)}$

Figure 3 shows the value of these elasticities for variation in output. The shaded areas are pointwise 95% confidence intervals (all three elasticity curves have these, but the intervals are too small to be easily visible in two cases). Changes in fixed costs have a negligible effect on supply at all output levels, while the negative impact of unit transportation charges on supply is larger when processing plants operate at relatively low output levels.

The transportation cost elasticities have important implications for the effect of energy policy on consumer food prices. While these effects are expressed in terms of the output effects of changes in transportation costs on manufactured food supply, the implication of energy policy on consumer food prices is clear. Changes in fixed costs of transportation τ_0 have virtually no effect on the supply of processed food products apart from changing the elasticity of processed food supply. Thus policies that affect fixed loading and unloading costs of agricultural products have no independent effect of food price inflation. In contrast, policies such as carbon taxes that raise fuel prices can result in large reductions in the supply of processed food, particularly in cases where processing plants operate at low capacity. In cases of relatively inelastic demand for manufactured food products in the consumer market, an elastic response of food supply to changes in fuel prices can result in sharp output reductions for processed foods, potentially increasing food price inflation in ways not accounted for in models of tax incidence that focus exclusively on fuel markets.

An interesting feature of these elasticities is that they depend on the transport cost function only via the ratios of parameters τ_1/τ_0 and τ_2/τ_0. The ratio τ_1/τ_0 can be thought of as the ratio of the linear costs of transporting a load of tomatoes per mile to the fixed cost of hauling the load. Those fixed costs, in turn, are more dependent on labor costs than costs related to actual travel (e.g., gasoline). The value of the ratio (just plugging in estimates from Table 2) is about 0.84. The second ratio τ_2/τ_0 can be thought of as the ratio of *quadratic* cost elements to fixed costs, an effect that can be driven by road congestion costs. But while this ratio is significantly greater than zero, it is still rather small, adding only about 7 cents to the cost of transporting a ton the average distance of about 59 miles, and adding only about 32 cents to the per-ton cost of transporting the farthest distances.

5. Conclusion

In this paper we have constructed a model to estimate changes in food processing supply that accounts for spatial procurement costs. Processing plants are conceived to be located in an agricultural landscape in which the surrounding agricultural land produces a primary agricultural product for the processing sector by farmers who are spatially located around each processing plant. Higher processing costs

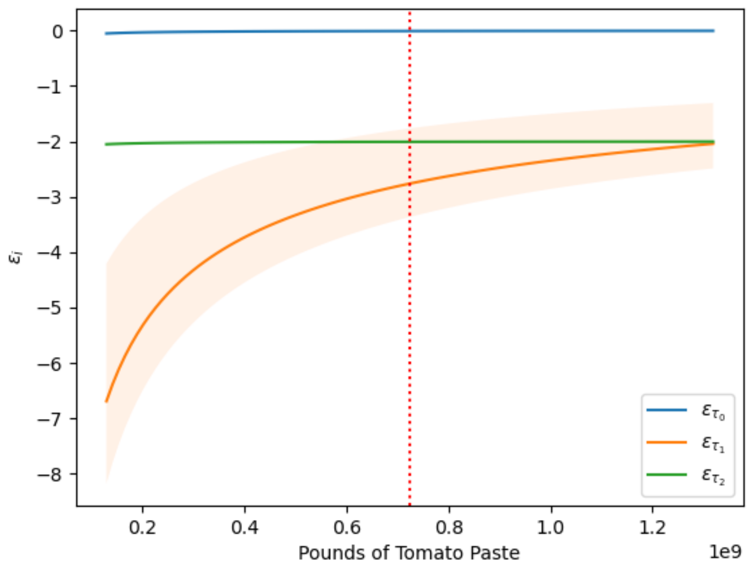

FIGURE 3. Supply elasticities with respect to parameters of transport cost function. At the average level of output (742 million lbs) these elasticities are respectively -0.001, -2.834, and -2.009. Shaded areas indicate 95% confidence intervals.

result in lower farm prices for the input, contracting the radius of deliveries to the processing plant, and we characterize how the change in spatial procurement alters the marginal cost of food processing.

We find that the spatial distribution of primary agricultural products affects the price elasticity of processed food supply, with greater land productivity and greater plant capacity making processed food product supply more elastic. Higher transportation costs for the primary agricultural product also alter the supply elasticity of processed foods, with higher fixed costs of delivering loads resulting in more elastic processed food supply, and greater road congestion resulting in less elasticity processed food supply. Perhaps surprisingly, changes in unit transportation costs over distance, for instance due to changes in diesel fuel prices, have no impact on the supply elasticity of processed foods, though they do have a direct negative effect on both purchases of the agricultural input and processed outputs such as tomato paste by changing the level of supply.

Using detailed production and procurement data from the processing tomato industry in California, we estimate the long-run price elasticity of tomato paste supply to be 2.91. We also derive elasticities with respect to the various transportation cost parameters representing changes in fixed (loading) cost, unit and quadratic cost components. These results demonstrate the important role of the transportation sector in determining output and price effects of in a food processing sector that relies on the spatial procurement of farm products as a material input for production. Further research is needed to identify how shocks in the transportation sector affect the price of manufactured food products in vertical food markets that have the potential for imperfectly competitive price adjustment.

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Appendix A. Appendix

A.1. **Estimation of Production Function.** In this appendix, we provide results from estimating a production function based on monthly production data (production occurs seasonally from July to October) from three firms over several years. The monthly firm-level data includes output, labor expenditures, and capital expenditures. Production from two of the three firms runs from July to October, and our data includes years 2010-2012 for each firm. The third firm operates from July to September and provided data from 2009-2013. We therefore have 39 monthly observations across the three firms. Because capital expenditures occur in advance of production, we aggregate all capital expenditures from the end of the previous season to the beginning of the new season to create the baseline level of capital for the year. Then we adjust this baseline each month during the production season based on additional expenditures.

We assume that the parameters of the Cobb-Douglas production function are the same across all tomato processing firms and that w and r are constant across the time period in the sample. Therefore, we use labor expenditures and capital expenditures in a regression to find the best fit production function:

$$\log(y) = \log\left(\frac{B}{w^\beta r^\gamma}\right) + \beta \log(wL) + \gamma \log(rK) + \epsilon.$$

This regression yields values for β, γ, and $\widehat{B} = \frac{B}{w^\beta r^\gamma}$.

The estimate of $\beta + \gamma$ is 0.928 (std. error = 0.106), yielding a 95% confidence interval of [0.71, 1.14]. Thus, we fail to reject the hypothesis that $\beta + \gamma = 1$, a constant returns-to-scale production function. These outcomes are shown in Table A1.

Table A.1. Production Function Estimation

Variable	Coefficient (Std. Error)
$\log\left(\frac{B}{w^\beta r^\gamma}\right)$	11.13^{***}
	(0.875)
β	0.680^{***}
	(0.139)
γ	0.248^{*}
	(0.109)
N	39
R^2	0.681

$*p < 0.05, \quad **p < 0.01, \quad ***p < 0.001$

A.2. **County-level Production Statistics for 2021.** The following table reproduces production statistics from USDA National Agricultural Statistics Service (2022a), adding information on the area (in square miles) of the corresponding counties. "Other counties" in the table are San Benito and Santa Clara counties.

TABLE A.2. Processing tomato production by county in 2021

County	Planted Acres	Harvested Acres	Yield	Production	Area (sq. Miles)	%Area
Imperial	300	300	26.2	7870	4175	0.01
Tulare	700	700	71.3	49900	4824	0.02
Other Counties	700	700	49.7	34811	2680	0.04
Butte	700	700	26.0	18200	1640	0.07
Glenn	1100	1100	46.4	51000	1315	0.13
Kern	8000	8000	56.4	451000	8142	0.15
Madera	3700	3700	47.2	174600	2138	0.27
Contra Costa	2600	2600	64.7	168200	720	0.56
Sacramento	4500	4500	36.4	163900	966	0.73
Stanislaus	7200	7000	48.2	337700	1495	0.73
San Joaquin	16100	14900	43.7	650700	1399	1.66
Colusa	13400	13200	49.5	652900	1151	1.79
Solano	9500	9500	54.1	513700	828	1.79
Merced	24900	24900	46.5	1157000	1929	2.02
Sutter	12000	12000	45.0	539400	603	3.11
Kings	29900	29800	46.9	1396000	1390	3.35
Yolo	31800	31700	49.7	1576000	1012	4.89
Fresno	62900	62700	45.2	2832000	1008	9.72
Total	230000	228000	47.3	10774881	37415	0.95