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Meet me halfway? Spatial Pricing and Location of Processing Firms in Agricultural Markets

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Abstract: The spatial distribution of production is a defining characteristic of agriculture, and the location choice in geographic space and the spatial pricing policies adopted by agricultural processing/packing firms are key determinants of the competitiveness of agricultural product procurement markets. Spatially distributed buying firms in the presence of costly transportation of farm products creates natural oligopsony procurement markets. Although several studies have contributed to our understanding of price and output determination and the distribution of welfare in these markets, all are limited in that they address buying firms' locations or their choices of spatial pricing strategy in isolation, holding the other factor fixed, even though both would be chosen jointly in reality to comprise a firm's product procurement strategy. Here we overcome this limitation by using computational methods (a genetic algorithm) to study duopsony firms' joint choices of location and pricing policy. Our results differ considerably from those presented by authors who have viewed either the location or pricing-policy choice in isolation. In general, we find that, when buyers have the flexibility to jointly choose their locations and pricing strategies, market outcomes are much more competitive and locations more efficient in terms of cost minimization than has been predicted by prior studies viewing location choice or pricing strategy in isolation.

Keywords: Oligopsony, Price discrimination, Spatial competition, Genetic algorithm
JEL codes: Q13, L13, R32, C63, C72,

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1 Introduction

Perhaps the single characteristic that most distinguishes agriculture from other forms of production is its spatial distribution. The spatial distribution of production is a key determinant of the structure of markets for the procurement of farm products, the competitiveness of these markets, the efficiency with which farm products are assembled, and the determination of prices, outputs and distribution of welfare in them.

Although the economic importance of the spatial dimension of agricultural markets has been acknowledged and studied at least since von Thünen (1826), our understanding of the implications of spatially dispersed farm production for the location of the processing/packing firms and the nature of competition in farm-product procurement is of much more recent vintage. Stripped to its essence, the issue is that costly transport of farm products due to their inherent bulkiness and perishability incentivizes processing/packing firms to locate in close proximity to producing areas and limits farmers' access to spatially distributed buyers, creating procurement markets that are natural oligopsonies (Faminow and Benson, 1990; Rogers and Sexton, 1994).[1]

Researchers have sought to understand two questions that are fundamental to determining prices and outputs and the competitiveness of these markets: (i) where within the producing region will buying firms choose to locate and (ii) what spatial-pricing strategies will they adopt? Despite a number of contributions in recent decades to addressing these questions, a key limitation of all prior work is that it has addressed one question or the other, while treating the unaddressed question as a given,[2] even though the two decisions are quite clearly interrelated and chosen

[1] The study of optimal processing plant locations has a rich history in agricultural economics, with key examples being Stollsteimer (1963), King and Logan (1964), and Polopolus (1965). These studies utilized programming models to derive least-cost plant locations, given plant economies of scale and shipment costs for both the farm and processed products. These studies tended to find significant economies of scale in processing, leading to few plants in the least-cost configuration. Although some authors noted the implications of number and location of processing firms for possible market power (e.g., (Stollsteimer et al., 1975), p. 113) none made any attempt to account for it in their analysis.

[2] For example, studies of firms' choice of spatial pricing policy have located buying firms exogenously at the endpoints of Hotelling's line (Zhang and Sexton, 2001; Graubner et al., 2011), while studies of firm location have typically assumed free-on-board (FOB) pricing (Fousekis, 2015).

jointly by a firm as defining elements of its product-procurement strategy.[3]

The goal of this paper is to surmount this central limitation of the literature and study firms' geographic-location and pricing-strategy decisions jointly. In so doing, we hope to contribute to understanding of the efficiency of farm-product assembly and processing and of the importance of buyer power in agricultural product procurement markets, topics of longstanding and ongoing interest in both western and developing economies.[4]

The essential reason for the failure of the prior literature to address location and pricing decisions jointly is the analytical complexity involved in introducing spatial considerations into a model of market competition. The goal of such models is to determine Nash equilibrium strategies for buying firms, but the models quickly become intractable and analytical solutions are attainable only if supported by strong and limiting assumptions. Further, these models are plagued by problems of nonexistence of equilibrium in pure strategies in some cases (d'Aspremont et al., 1979), and a multiplicity of equilibria in others (Mérel and Sexton, 2010).[5]

We eschew the quest for analytical solutions in favor of a framework that relies upon computational economics methods. This approach enables us to investigate spatial competition between buyers of an agricultural product as a non-cooperative game within a very general framework and to surmount the aforementioned analytical difficulties. We identify firms' decisions regarding

[3] The same limitation applies to a parallel set of studies that have examined location and pricing by sellers operating on Hotelling's line. Key examples include Hotelling (1929) himself, who believed erroneously that FOB-pricing firms would each locate at the market center (a result known as minimum differentiation), d'Aspremont et al. (1979), who corrected Hotelling and established maximum differentiation (location at the market endpoints) as the location equilibrium with FOB pricing and convex transport costs, and Hinloopen and van Marrewijk (1999), who established that neither maximum nor minimum differentiation prevail in general as location equilibria with FOB pricing when a finite consumer reservation price is introduced into the inelastic-demand model of Hotelling. Other work has addressed seller location assuming discriminatory pricing (e.g., Hurter and Lederer, 1985 and Lederer and Hurter, 1986). Summaries of this literature are provided by Thisse and Norman (1994), Greenhut and Norman (1995), and Biscaia and Mota (2013). van Leeuwen and Lijesen (2016) used an agent-based simulations to investigate Hotelling's game under quadratic transport costs but the authors maintained the focus on FOB-pricing.

[4] Arguably intermediaries' buyer power over farmers has become the central market structure policy issue in agricultural supply chains for most countries, supplanting in importance concerns about food manufacturers' and retailers' abilities to raise prices to consumers (Sexton and Xia, 2018).

[5] Nonexistence of pure-strategy equilibria is due to "market stealing," the phenomenon whereby, with linear transport costs, one firm, by offering a price sufficiently higher than its rival, can capture the entire market area it is willing to serve at that price, causing discontinuity in the payoff functions. Mérel and Sexton (2010) show that a continuum of asymmetric Nash equilibria exist with FOB pricing in market settings that they termed "weak duopsony."

location and price policy by genetic algorithm (GA) learning of equilibrium strategies within an agent-based model. This approach leads to surprising results that stand in contrast to key findings in the prior literature.

Our model follows most previous studies of firm location decisions by focusing on duopsony competition and location along Hotelling's line. However, instead of assuming a particular pricing policy, we allow buying firms to adopt any linear pricing strategy consisting of paying a fixed "mill" price at the processing-plant gate, plus some fraction, $\alpha \in [0, 1]$ of the costs of transporting the product from farm gate to plant gate. Although most studies of spatial agricultural markets have assumed $\alpha = 0$, i.e., so-called free-on-board (FOB) pricing, departures from FOB pricing are common in reality, including full buyer absorption of transportation costs, i.e., $\alpha = 1$, known as uniform-delivered (UD) pricing. Instances of pricing policies between the extremes of FOB and UD pricing, i.e., $\alpha \in (0, 1)$, are also common and easy for buying firms to implement through offering farmers hauling allowances, operating receiving stations at intermediate locations, or directly providing the farm-to-plant transportation and billing farmers for only a fraction, $0 < \alpha < 1$, of the cost.

Our model also conforms to important real-world settings, especially in developing countries, where buyers (e.g., traders) procure farm product at seller (e.g., village) locations and pay costs to transport the product to processing, packing, or export locations. Such buyers may offer an unique purchase price at each location, with price decreasing in distance to the processing facility or export terminal, so as to conform in practice to our pricing schedule and an $\alpha \in (0, 1)$.

Although all sellers obtain a differentiated net price based upon their location relative to the buyer under FOB pricing, it is nondiscriminatory because the price differences equate the transport cost differences between locations. Any departure from FOB pricing thus represents a form of third-degree price discrimination against farmers located nearby the processing plant, with UD pricing representing a particularly extreme form of price discrimination.[6]

[6] The nondiscriminatory character of FOB pricing has caused competition authorities to regard it (incorrectly) as competitive pricing and to view UD pricing with suspicion (Zhang and Sexton, 2001).

Although the choice between FOB and UD pricing for duopoly sellers located at the endpoints of Hotelling's line had been studied for the case of inelastic-demand consumers arrayed uniformly along the line (Kats and Thisse, 1989; Espinosa, 1992), Zhang and Sexton (2001) were the first to study the problem in a procurement market, where farmers had (unit) elastic supply functions. They found that mutual FOB pricing emerged as equilibrium strategies when spatial competition was intense (i.e., transport costs were low relative to the value of the farm product),[7] mixed pricing strategies (UD for one firm, FOB for the other) emerged under moderate competition, with mutual UD pricing emerging only when relative transport costs were high and competition was weak. Fousekis (2011) revisited the problem in a mixed duopsony setting, with competition between one invester-owned firm and one cooperative. The cooperative, operating with a zero-profit objective, is an aggressive competitor in this model, leading to results that stand in considerable contrast to Zhang and Sexton (2001)—UD (FOB) pricing emerges when relative transport costs are low (high).

Using a GA, Graubner et al. (2011) were able to study a richer set of spatial pricing options than just UD and FOB pricing. They adopted the aforementioned linear pricing schedule and showed that price discrimination in the form of either UD pricing or partial freight cost absorption emerge as equilibrium pricing strategies in the duopsony case with maximum differentiation, but FOB pricing does not.

The infrequent emergence of FOB pricing as equilibrium behavior in these studies might call into question the relevance of the many studies of farm-product procurement that invoke FOB pricing as a foundational assumption. However, the policy relevance of these conclusions may themselves be challenged by the restrictive assumption that buyers are located at the market endpoints. Maximum differentiation minimizes price competition between firms and, as noted, has been shown to represent equilibrium behavior under certain conditions. However, such locations are inefficient from the perspective of minimizing transport costs. Nor do they maximize

[7] FOB pricing can be a way to moderate otherwise-intense price competition because with FOB pricing firms compete directly only at their market boundaries (Zhang and Sexton, 2001).

profit at each location when consumers (farmers) have elastic demands (supplies), raising the question of how optimal behavior is affected if firms are able to choose both their location and pricing policy and if the denizens along Hotelling's street have elastic responses to price.

We seek to answer this question in the following sections, finding results at considerable variance to conventional wisdom and practice. For example, neither maximum nor minimum differentiation ever represent equilibrium behavior in the generalized setting of our model and locations and pricing strategies that are chosen tend to result in greater competition and economic efficiency than is found in prior work. Pricing strategies close to FOB pricing re-emerge as equilibrium strategies in this generalized framework in settings where competition is intense because FOB pricing limits direct price competition, a key consideration once firms are no longer constrained to locate at the competition-stifling endpoints of Hotelling' line.

2 Model Framework

Two buyers, denoted as A and B, are free to choose a location on a line market of unit length ($x = [0, 1]$), with $x_A = [0, 1/2]$ and $x_B = [1/2, 1]$ indicating the location of A and B, respectively. For example, locations $x_A = 0$ and $x_B = 1$ would represent maximum differentiation, while minimum differentiation would be represented by $x_A = x_B = 1/2$.

We assume a fixed rate of conversion from the farm input into the final product output, and without further loss of generality set that conversion rate to one through appropriate choice of measurement units so that one unit of the farm input is needed to produce one unit of the processed output. Input buyers sell the final product in a perfectly competitive market, where Φ is the constant price of the finished good.[8] Processing/packing costs are constant, c, per unit, and we set the net price $\phi = \Phi - c = 1$ via normalization. ϕ is thus the "gross" marginal value product of the farm input prior to accounting for shipment costs.

[8] The assumption of perfect competition in output sales, while allowing buyer power in farm product procurement, is realistic given that the finished product is typically much less bulky and perishable than the farm product and, thus, sold in a geographic market that is much larger and subject to more competition than the procurement market.

Farmers are uniformly distributed in the geographic space such that each location x accommodates exactly one seller of the farm product. Each has a common price-elastic supply function, and the quantity of each input seller is determined by the price at her location:

$$q(x) = \max\{p_i(x), 0\} \text{ with } i = \{A, B\}. \tag{1}$$

This supply function is unit elastic, and the absence of any slope parameter is simply a unit-of-measurement choice and achieved without any further loss of generality.[9] As Zhang and Sexton (2001) noted, including price responsiveness of farmers in a product-procurement model (consumers in a selling context) is important because otherwise pricing decisions are made primarily from a competition perspective and without regard for their impact on farmer sales (consumer purchases in the selling context), so long as the farmer participates in the market at all.

Transport costs are linear in distance with given transport rate t per unit of product and unit of distance. Given the monetary normalization $\phi = 1$, the value of t is interpreted relative to ϕ. For example, if $t = 1$ and the farm product was transported $x - x_i = 0.5$ (i.e., the maximum distance that would ever occur), then the transport costs would represent 50% of the gross value of the farm product. As has been noted by other authors, e.g., (Zhang and Sexton, 2001), t represents the differentiation between the buying firms and, thus, depicts the intrinsic competitiveness of the input procurement market in the noncooperative price-setting game between the duopsony processors, with $t = 0$ representing undifferentiated buyers and perfect competition (i.e., Bertrand's paradox) and sufficiently high values of t enabling the buyers to act as isolated monopsonists.[10] Intermediate values of t characterize different intensities of oligopsony competition.

[9] Assuming a unit elastic supply function is no more general than assuming a perfectly inelastic function, but is undoubtedly much more realistic, especially over the length of run at issue in this paper wherein we study buying firms' joint location and pricing-strategy decisions. Within this decision horizon buying firms would surely consider that farmers would have an elastic responses to prices they encountered.

[10] The specific value of t that results in monopsony depends on what pricing strategies the firms are utilizing.

We can thus define the local price $p_i(x)$ offered by buyer i as a function of the mill price m_i and some portion α_i of the transport costs between i's location x_i and the location x of the any seller. Accordingly, we denote the triple $\gamma_i = \{m_i, \alpha_i, x_i\}$ as the spatial (price and location) strategy of buyer $i = A, B$. The linear price schedule is:

$$p_i(x) = \begin{cases} m_i + \alpha_i t(x - x_i), & \text{if } x < x_i, \\ m_i + \alpha_i t(x_i - x), & \text{if } x \geq x_i. \end{cases} \tag{2}$$

The local break-even price, $b_i(x)$, is the price at each location that, if paid, yields zero profits to the buyer:

$$b_i(x) = \begin{cases} 1 + t(x - x_i), & \text{if } x < x_i, \\ 1 + t(x_i - x), & \text{if } x \geq x_i. \end{cases} \tag{3}$$

Figure 1 provides an illustration of $p_i(x)$ and $b_i(x)$. Given the supply function (1), i's profit at buyer location x is:

$$\pi_i(x) = [b_i(x) - p_i(x)]\, p_i(x). \tag{4}$$

The buyer's profit per unit at each location is represented by the vertical distance between $b_i(x)$ and $p_i(x)$. However, importantly, profit is also a function of the amount of farm product supplied, $p_i(x)$, at the location, a factor ignored in the spatial models that assume inelastic consumer demands or farmer supplies.

The profit is zero if the local price is zero, so no product is supplied, or if $b_i(x) = p_i(x)$. Accordingly, the buyer will not serve locations outside the market radius r where:

$$r = \min \left\{ \left. \frac{m_i}{\alpha_i t} \right|_{\alpha_i > 0}, \left. \frac{1 - m_i}{(1 - \alpha_i)t} \right|_{\alpha < 1} \right\}. \tag{5}$$

The optimal price strategy for the monopsonist is $(m_M, \alpha_M) = (1/2, 1/2)$, a result that can be found analytically and involves price discrimination, with partial freight absorption (Löfgren, 1986). This result is known as optimal discriminatory (OD) pricing, and under OD pricing there is a unique location equilibrium known as the “touching equilibrium” if $t = 4$; firms locate at the quartiles of the market, $x_A = 1/4$ and $x_B = 3/4$, and market areas "touch" at the market center, $x = 1/2$, with $p_A(0) = p_B(1) = p(1/2) = 0$ (Economides, 1984; Hinloopen and van Marrewijk, 1999). This equilibrium is illustrated in Figure 1.

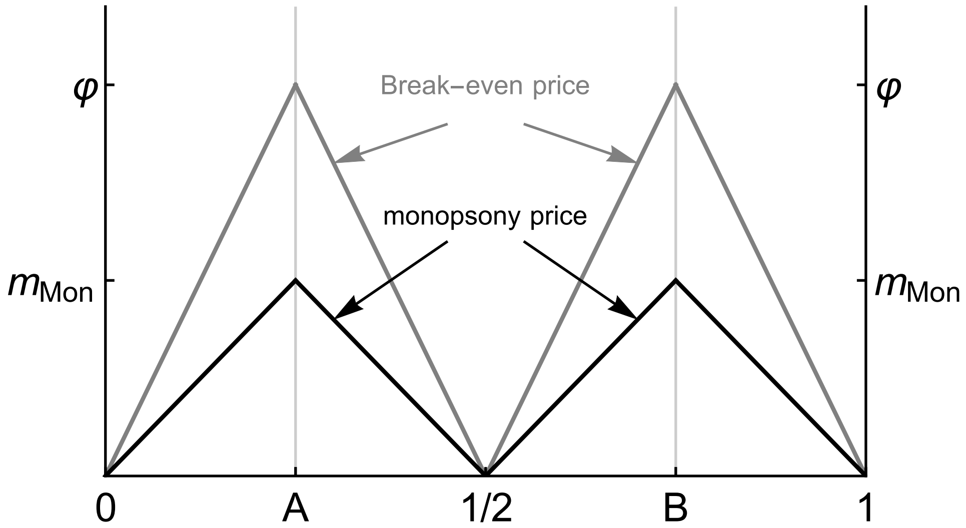

Figure 1: Touching Equilibrium ($t = 4$) with OD pricing ($m_M on = \phi/2$ and $\alpha_M on = 1/2$) and location at the quartiles.

OD pricing (m_M, α_M) maximizes both the market radius and the local profit (4). Location at the market quartiles also minimizes cost of transporting the farm product.

Complications arise, however, for lower transport costs because the potential market areas of both buyers will overlap. Without further restrictions on the price or location strategies of the buyers, there is a variety of possible competition scenarios, which may require alternative formulations of the buyers’ profit functions. This, in turn, can cause discontinuous payoff functions and non-existence of Nash equilibrium in pure strategies (d’Aspremont et al., 1979), multiple Nash equilibria with asymmetric buyer strategies, (Mérel and Sexton, 2010) or inability to obtain closed-form solutions (Osborne and Pitchik, 1987).

3 Simulation Model

We surmount these analytical complications by studying the spatial competition problem using an agent-based framework that is able to capture the interactions among many heterogeneous players (Tesfatsion, 2006). In particular, we build upon the Spatial Agent-based Competition Model (SpAbCoM) developed by Graubner (2011). Within this model, genetic algorithms (GA) are applied to solve the decision problem of the buyers. GA repeatedly have proven to be successful in identifying equilibrium strategies in complex games and have been used over a broad range of disciplines (Foster, 2001). Economic applications include Axelrod (1997), Arifovic (1994), Price (1997), Dawid and Kopel (1998), Balmann and Happe (2001), Alemdar and Sirakaya (2003), Haruvy et al. (2006), and Graubner et al. (2011).[11]

A GA is a stochastic, heuristic search method to find optimal or close-to-optimal solutions in large decision or strategy spaces. In analogy to biological evolution, the GA is based on the principle of the survival of the fittest (Dawid, 1999), i.e., good strategies are more likely to be selected within the optimization procedure, while bad strategies become extinct. During optimization, the GA enables the creation of new, potentially superior solutions, which makes the GA efficient and robust, i.e., it minimizes both the dependency on the initial conditions and makes GA optimization less vulnerable for a lock-in towards local optima than other numerical methods.

In general, a GA converges over a sufficient number of generations towards an equilibrium in evolutionary stable strategies—a NE of the game if one exists (Price, 1997; Dawid, 1999). Riechmann (2001) shows that GA optimization is a specific form of an evolutionary game, and Son and Baldick (2004) demonstrate that co-evolutionary GAs overcome the problem of iterative search algorithms, which may misidentify NE by following a local optimization path.

We use this approach and model the decision making of each buyer by the application of an individual GA within a spatial competition setting. In adapting the simulation to fit the case

[11] Introductory discussions of GAs can also be found in Mitchell (1996) and Goldberg (1989).

at hand, we explicitly consider the spatial dimension of a market by an array of n equidistant locations each occupied by one input supplier $j = \{1, \dots, n\}$. The number of sellers is specified ex ante, and we typically use $n = 400$ suppliers within the simulations. Given that the size of the market is normalized to 1.0, the distance between two neighboring farm locations is $x_{j+1} - x_j = 1/(n-1)$. Buyers can choose to locate at any of those locations. Given the normalizations of monetary and spatial units, all strategy variables $\gamma_i = \{m_i, \alpha_i, x_i\}$ are in the interval $[0, 1]$.

Each competitive farmer's strategy is to select the higher net price at their own location and set quantity according to the supply function (1), given this price. The decision rule of buyers, however, incorporates strategic interactions, and the search for Nash equilibrium strategies involves all of the aforementioned complications. We will show that our simulation model is able to accommodate them.

3.1 Modeling Buyer Decision Making with a GA

To illustrate how the GA operates and to demonstrate its abilities to identify NE, we begin by seeking to replicate the touching equilibrium of $\gamma_A = (1/2, 1/2, 1/4)$ and $\gamma_B = (1/2, 1/2, 3/4)$ with the GA. The first step to initialize a GA, is to generate a pool of possible solutions; the so-called population. In our case, such a population consists of an arbitrary number of triples. Each represents a random combination of the decision variables m, α and x within their feasible ranges to comprise a firm's strategy $\gamma = (m, \alpha, x)$. While the triples bear information in terms of real numbers (the phenotype), GA commonly work on encoded representations as binary strings (the genotype). Thereby, a single piece of information (e.g., the mill price m) is called a gene, and the chaining of genes (the strategy γ) is the chromosome. Since we consider strategic interactions among processors, we use a co-evolving simulation structure (Price, 1997; Son and Baldick, 2004), i.e., each buyer i has an individual GA with an individual population $\Gamma_{i,g}$ that is optimized over a given number g_{max} of so-called generations. Throughout the paper, we use $v = 25$ chromosomes to form the initial population $\Gamma_{i,0} = \{\gamma_{i,0}^k | k = 0, \dots, v\}$ of each buyer.

The second part of the GA is a fitness function, which measures how well a particular strategy (represented by the chromosome) solves a problem. To evaluate the performance of i's spatial competition strategy, we use the sum of local profits, i.e., Equation (4), over all seller locations x_j where firm i sets the higher local price:

$$\Pi_i(\gamma_i, \gamma_{-i}) = \sum_{j=1}^{n} \pi(x_j) \qquad \forall x_j \in [0,1] : p_i(x_j) > p_{-i}(x_j). \tag{6}$$

Because the profit to buyer A depends on the strategy chosen by buyer B, we evaluate the profit (fitness) of A for each $\gamma^k_{A,0}$ relative to a randomly selected strategy $\gamma^{k'}_{B,0}$ of firm B. Clearly, if we select a different strategy, $\gamma^{k''}_{B,0}$, for firm B the profit of $\gamma^k_{A,0}$ is likely to change. Hence, we conduct a tournament, where all of A's strategies are tested at least five times and in different combinations with the competitor's strategies to approximate the expected profits of A's strategies for the given set of B's strategies. This process yields an average profit $\bar{\Pi}^k_A(\gamma^k_{A,0}, \boldsymbol{\gamma}_{\mathbf{B,0}})$ of strategy $\gamma^k_{A,0}$, with $\boldsymbol{\gamma}_{\mathbf{B,0}} \subset \Gamma_{B,0}$ being a vector of randomly selected strategies out of buyer's B strategy pool. The repeated test of all $\gamma_{A,0} \in \Gamma_{A,0}$ assigns an average profit value ($\bar{\Pi}^k_{i,0}$) to each strategy k of buyer A as well as buyer B.

Given the evaluation of the fitness function, we know what is the best strategy $\gamma^*_{i,0}$ within $\Gamma_{A,0}$ and $\Gamma_{B,0}$. Of course, the best strategy of the initial population is not likely to be the optimal strategy overall. Therefore, the last step within a GA's generation g is to apply genetic operators. Depending on the application, the design of a GA may vary considerably, but usually there are three standard operators: selection, crossover, and mutation. The task of these operators is to generate a new pool of (potentially improved) strategies $\Gamma_{i,g+1}$ for the next generation $g+1$.

In our GA implementation, *selection* picks a predefined share $\dot{v} = [0,1]$ of $\Gamma_{i,g}$ that contains its best chromosomes according to the fitness evaluation. Typically, $\dot{v} < 1$ and to hold the population size v constant in each generation, the difference in the new population is filled up by $v - \dot{v}$ random copies of already selected strategies. The higher the fitness of a strategy, the more likely it will be duplicated to fill up $\Gamma_{i,g+1}$.

While selection reduces the variability of the population, crossover and mutation expand it. These two operators are commonly included with low probabilities such that the selection is the major operator to produce the next population in $g + 1$. Crossover (or recombination) splits up two (parent) chromosomes, e.g., $\gamma^1 = (m^1, \alpha^1, x^1)$ and $\gamma^2 = (m^2, \alpha^2, x^2)$, with given probability at a random locus. The exchange of the fragments yields two offspring, e.g., $\gamma^1 = (m^1, \alpha^1, x^2)$ and $\gamma^2 = (m^2, \alpha^2, x^1)$, representing (with high probability) new strategies. Mutation randomly alters the information carried by a chromosome and generates a mutant strategy, e.g., from $\gamma^1 = (m^1, \alpha^1, x^1)$ to $\gamma^{1'} = (m^1, \alpha^{1'}, x^1)$. In our simulations the probability of mutation is 1/25 and the rate of crossover is 1/10.

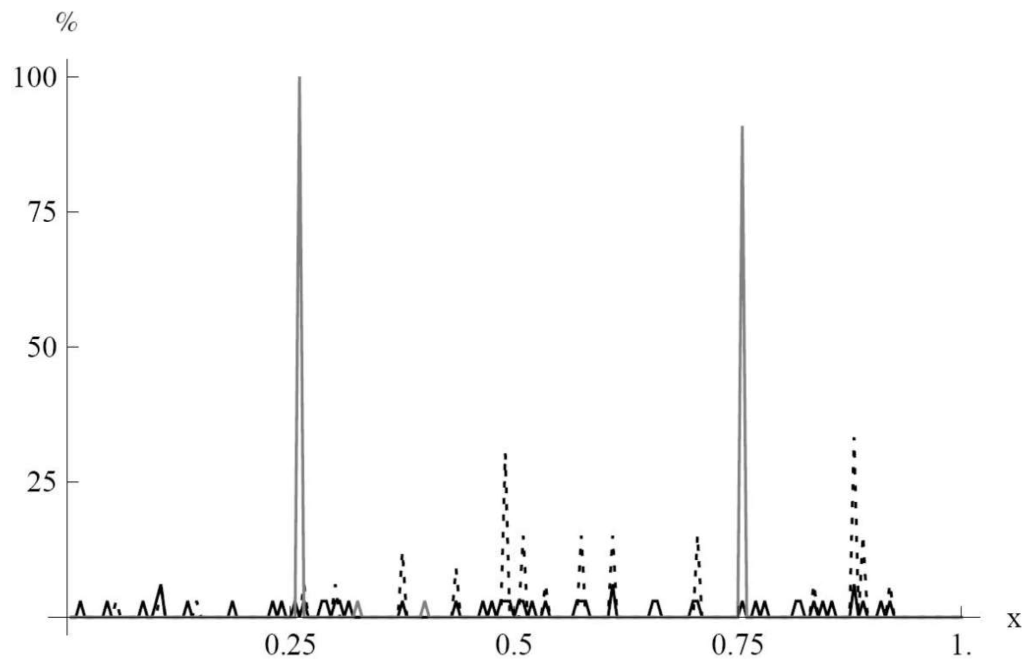

Figure 2: Distribution of the buyers' location parameter x in the initial population (solid, black), after five (dashed, black), and 1000 generations (solid, gray), respectively.

After selection, crossover, and mutation are applied, each buyer has a new pool of strategies $\Gamma_{i,g+1}$ mostly consisting of retained strategies from the prior generation but also some newly created chromosomes. Figure 2 shows the composition of the initial strategy pool and the population after five as well as 1000 generations with respect to the location variable x. The figure highlights that the algorithm needs a number of generations to adapt to the problem but after a high number of generations, we obtain a variable distribution that is very close to the expected solution. To improve the precision of the GA's outcome and avoid effects based on the initialization, we run the simulation over a sufficient number of repetitions; usually we repeat the GA simulation at least 30 times with $g_{max} = 2500$. The last five percent of g_{max} are reported for analysis. Thus, we can investigate 3750 games with 7500 observations for the duopsony setting. In our example, the average outcome (over the last five percent of generations and all repetitions, denoted by $\bar{g}$) is $\gamma^*_{A,\bar{g}} = (0.500, 0.500, 0.248)$ and $\gamma^*_{B,\bar{g}} = (0.500, 0.500, 0.751)$, which shows that the GA is able to approximate the analytical solution with high precision. Indeed, the lower (Q_1) and upper quartile (Q_3) of 400 equidistant locations is at $x(Q_1) = 99/399 = .248$ and $x(Q_3) = 300/399 = .752$. Hence, the deviation from 1/4 and 3/4 of the location variable is due to the discrete nature of locations within the simulation. While the number of farmers is to some degree arbitrary, it is a compromise between increasing computational time and reducing small differences among these discrete locations as more farmers are added. The same type of compromise applies to the number of repetitions for the GA simulation.

In Appendix A.1 we present applications of the GA to other complex spatial competition models in input and output markets that have been investigated in the literature, including those involving pure, mixed (Zhang and Sexton, 2001), and asymmetric (Mérel and Sexton, 2010) price strategies, and games involving choice of both location and FOB price (Hinloopen and van Marrewijk, 1999). These replication exercises further demonstrate the ability of the GA to closely approximate known analytical price and location equilibria, giving us confidence that we can apply the model to study behavior in settings where analytical solutions do not exist.

4 Simulation Experiments and Results

We present simulations where two buyers choose optimal location, x_i, and pricing regime, (m_i, α_i), given the strategy $\Gamma_{-i} = (m_{-i}, \alpha_{-i}, x_{-i})$ of the competitor. Figure 3 reports median values of the decision variables mill price, $\tilde{m}$, share of transport costs borne by farmers, $\tilde{\alpha}$, and deviation from location at the market center, $|\tilde{x} - 1/2|$, for t in increments of 0.05, ranging from perfect (Bertrand) competition to two spatially separated monopsonies based on 5,000 games (10,000 observations) for each value of $t = \{0.0, 0.05, \ldots, 4.0\}$. Median values and variances for each of the strategy variables and each value of t are reported in Appendix B.

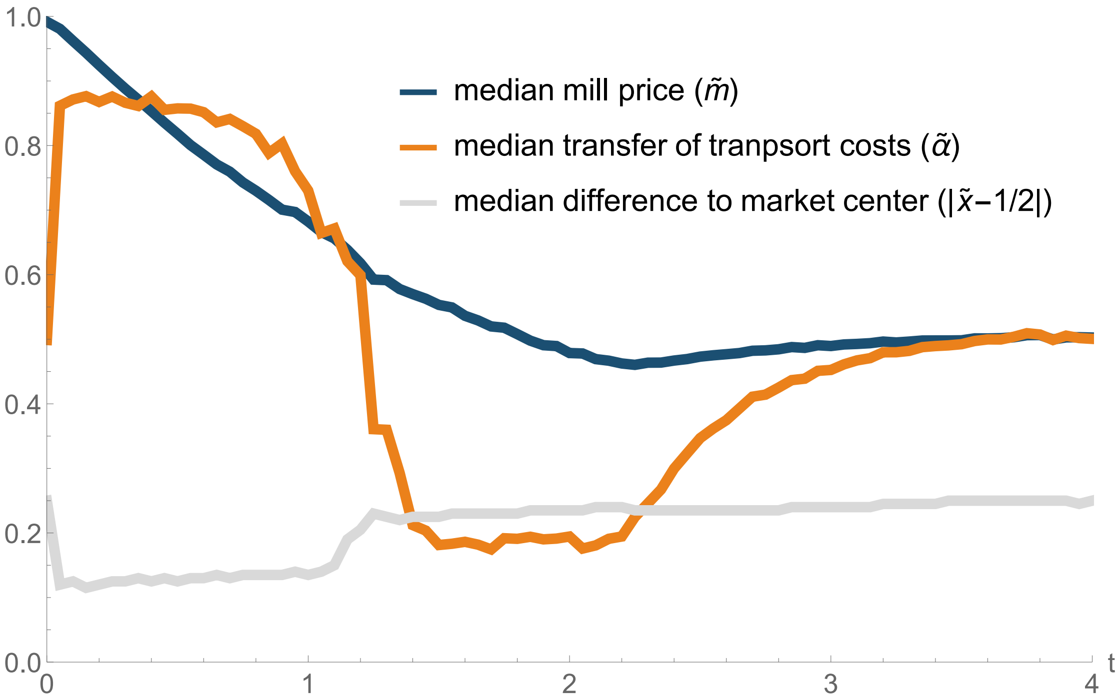

Figure 3: Simulation results for price strategy and location in the generalized Hotelling model

For high transport costs (i.e., $t \to 4$), we observe results that are consistent with the touching equilibrium discussed previously. Firms act as local monopsonies, locating at the market's quartiles ($|\tilde{x} - 1/2| = 1/4$), but, given the flexibility to do so, the firms adopt optimal monopsony price discrimination, with $(m, \alpha) = (1/2, 1/2)$.[12] At the other extreme, as $t \to 0$, we find the classic Bertrand-Nash equilibrium with mill price m converging to the marginal value product of the farm input, ($m = \phi = 1$). The choice of x and α in this setting is irrelevant. Because all decision variables are randomly initialized according to a uniform distribution within $[0, 1]$, we have the expected median values of $\tilde{\alpha} = 1/2$ and $|\tilde{x} - 1/2| = 1/4$.

Between these polar cases, Figure 3 highlights a rich and complex set of relationships between firms' price policies and location choices. If t is low, differentiation between firms is minor, creating the potential for intense price competition. In this setting we find that both price discrimination and spatial differentiation are low on average, as reflected by high $\tilde{\alpha}$ and low $|\tilde{x} - 1/2|$, outcomes approximating FOB pricing and close to minimum differentiation.

It has commonly been argued that high price discrimination in terms of UD pricing is superior to FOB pricing in this setting because it makes the firm's price competitive over a broad market area (Greenhut et al., 1987; Thisse and Vives, 1988; Espinosa, 1992; Graubner et al., 2011). Our finding of close-to FOB pricing for low values of t thus stands in sharp contrast to these results and beliefs, but is consistent with the results of Zhang and Sexton (2001), where firms were restricted to locate at the endpoints of Hotelling's line. They argued that FOB pricing, which restricts direct price competition to the market's boundary, actually represents a form of tacit collusion or "mutual forbearance" on the buyers' parts and acts to mitigate the otherwise intense price competition. For example, with UD pricing, the firm has a strong unilateral incentive to overbid its rival in order to capture the entire market within the area it is willing to serve. In contrast, the FOB-pricing firm that increases its mill price m above its rival's price only captures incremental sales at the market border.

As t rises, we see a sharp increase in spatial price discrimination ($\tilde{\alpha}$ decreases rapidly in t), approximating UD pricing for a range of values in the vicinity of $t = 2$. We also see an increase of spatial differentiation, representing a movement towards the market quartiles. Further increases

[12] This result contrasts with the assumption of prior studies of the touching equilibrium that assumed FOD pricing (Economides, 1984; Hinloopen and van Marrewijk, 1999).

in t have little impact on the locational choice of the buyers. Spatial price discrimination, however, begins to dissipate for larger values of t, and converges upon OD pricing. The average mill price $\tilde{m}$ decreases with t for low and intermediate market competitiveness before it increases under low and decreasing competitiveness to converge upon $m = 0.5$, also consistent with OD pricing.[13] All three decision variables converge eventually to the optimal values under monopsony for sufficiently large values of t.

The results depicted in Figure 3 represent the central tendency over 7,500 games for each level of transport costs t. The initial set of strategies available to each buyer is randomly assigned and hence varies for each repetition. Because of this and the very nature of the GA simulation, which is based on stochastic processes (including the random match of strategies), the full outcome of the simulation is a distribution for each of the three decision variables. If there is a a unique NE in pure strategies, the distribution is degenerate, with the only source of variation being the numerical error which is inherent to any numerical method. For example, for $t = 4$, where there is a unique NE in pure strategies, the standard deviations of α and m are 0.0137 and 0.0086, respectively.[14]

In other cases, we need to investigate the variability within the distribution of the decision variables for the information it may provide about the potential nature of the price-location equilibria. Figure 4 shows the cumulative distribution functions (CDFs) for m, α, and $|\tilde{x} - 1/2|$ for selected values of t, illustrating that the distributions of the decision variables change considerably over the parameter range of t. In the absence of transport costs, α and x display the expected uniform distribution due to their random initialization and because both have no bearing on the buyer's profit. All three decision variables exhibit low variability for $t = 3.0$, indicating that a unique NE with close to OD pricing and location at the quartiles exists.

Distributions for intermediate values of t, however, are more complex and cannot be explained

[13] This non-monotonic relationship between m and t was also observed by Graubner (2011) and corresponds to the "weak duopsony" case described by Mérel et al. (2009). For relatively large values of t, competition is weak and profit margins are high. Given $\alpha > 0$, increases in t reduce grower supplies and buyer profits. Buyers rationally respond to increases in t in this range by raising price to maintain supplies of the product.

[14] Full simulation results are reported in Appendix B.1, Table B.1 .

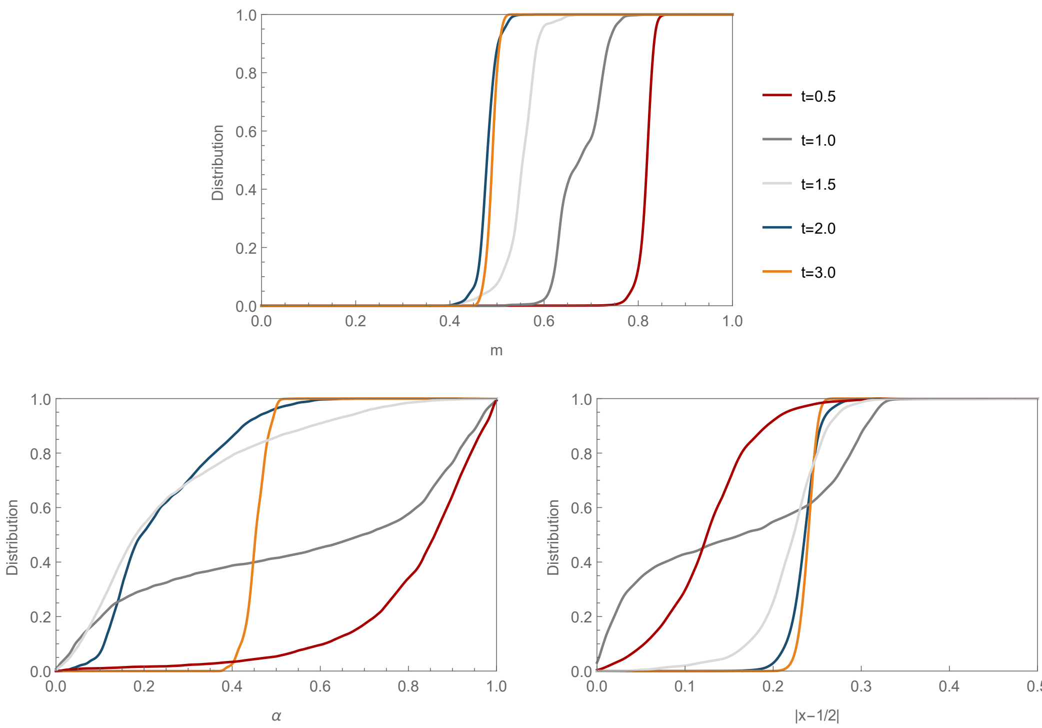

Figure 4: Cumulative distribution functions of the decision variables for selected values of the normalized transport costs t (10 000 observations).

solely by the numerical error of the algorithm. Most noteworthy is the bimodal distribution of all three decision variables for moderate transport costs. The complexity of the distributions for these ranges of t is not surprising because we know from the analytical results for special cases of our general model that Nash equilibrium may exist only in mixed strategies and that asymmetric pure-strategy equilibria may also exist (Mérel and Sexton, 2010). Despite this complexity, a number of key results, often at odds with conventional wisdom, can be deduced.

A particularly important result illustrated in both figures 3 and 4 is that maximum differentiation does not ever appear as part of the equilibrium strategy for buyers regardless of the value of t. In fact, firms on average do not locate beyond the market quartiles for any values of $t > 0$, i.e., the competition-lessening incentive to maximally differentiate does not dominate the other incentives at work in the generalized market environment studied here. Instead when t is low and spatial competition is intense, the firms adopt pricing strategies close to FOB pricing to lessen the direct price competition between them.

Thus, despite many papers on spatial markets exogenously locating firms on the endpoints of Hotelling's line,[15] and some analytic results supporting maximum differentiation as an equilibrium strategy in special cases (e.g., d'Aspremont et al. (1979) and Kats (1995)), it appears that firms do not choose those locations when confronted with elastic consumer demands or farmer supplies, costly transport of product, and the freedom to adopt flexible pricing schedules.

The location of the buyer within its own market area does not affect the firm's profit under FOB pricing and inelastic farm supply, as in the base Hotelling model. When $\alpha = 1$ and supplies are inelastic, local per unit profit in our model as defined in equation (4) reduces to $1 - m$ and is hence constant irrespective of the distance to the seller. The clear incentive then is for firms to locate at the market boundaries to minimize direct competition.

However, if supply is elastic, local profits decrease with increasing distance to the buyer's location because nearby sellers obtain a high local price and supply more, thus yielding greater local profit to the buyer compared to more distant sellers. We denote this as the *supply effect* of a location decision. As a result, elastic demand functions in the selling case (Smithies, 1941; Eaton, 1972) or input supply functions in our input-buying case create an incentive, ceteris paribus, for firms to choose central locations within the own market area when operating under a price policy with $\alpha > 0$.

To illustrate the importance of the supply effect, we computed $R_1(t)$ as the ratio of supply received by a seller located at the end point of its market area to the supply received by a seller located at the midpoint (i.e., quartile) under competitive FOB pricing ($m = 1$) and unit-elastic

[15] Examples on the farm-product procurement side include Mérel et al. (2009), Zhang and Sexton (2000), Fousekis (2011), and Sesmero et al. (2015).

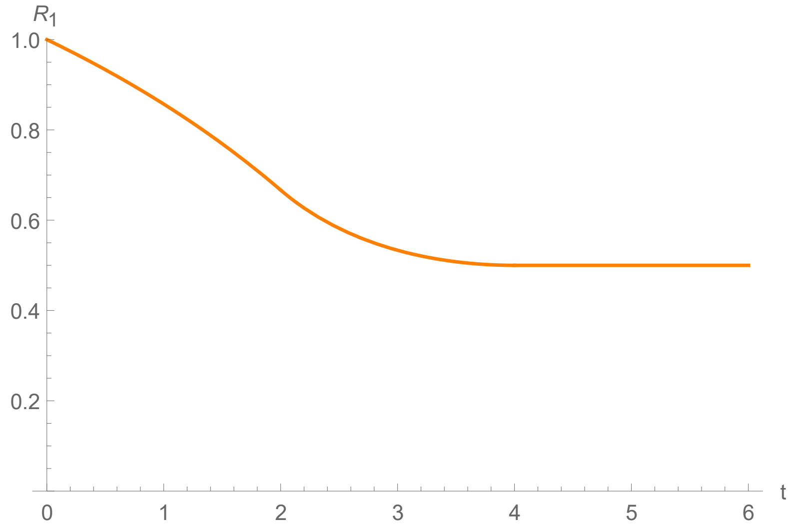

Figure 5: Ratio R_1 of total supply for buyer A using competitive FOB pricing ($m_A = 1$ and $\alpha_A = 1$) and if the buyer is located at the endpoint ($x_A = 0$) relative to the location at the quartile ($x_A = 1/4$) over the relevant range of spatial competition.

supply functions. Performing the calculations yields the following:

$$R_1(t) = \begin{cases} \frac{2t-8}{t-8} & \text{if } 0 \leq t < 2, \\ \frac{8}{(8-t)t} & \text{if } 2 \leq t < 4, \\ \frac{1}{2} & \text{if } 4 \leq t. \end{cases} \tag{7}$$

Figure 5 summarizes the results. $R_1(t) < 1$ for all $t > 0$ and declines monotonically in t, before becoming constant at $R_1(t) = 0.5$ for $t \geq 4$. For example, $R_1(2) = \frac{2}{3}$.[16] Once elastic response to price by the farmers along Hotelling's street is introduced, the supply effect creates a strong incentive for firms to locate in the center of their market area.

Independent of the elasticity of the supply function, any price strategy that involves the buyer paying some portion of the transportation costs, i.e., $0 \leq \alpha < 1$, also creates the incentive to choose a central location within the procurement area because per unit transport costs are

[16] The FOB-pricing buyer located at the market's endpoint has a market radius less than one half for $t > 2$.

minimized if the buyer locates in the center of its own market area. This *cost effect* of firm location, thus, also incentivizes firms, ceteris paribus, to locate in the center of their procurement region except for the special case of FOB pricing.

To gain a sense of the importance of the cost effect in firm location decisions, we computed the $R_2(t)$ as the ratio of per-unit transportation cost paid by a buyer located at the endpoint and engaging in OD monopsony pricing to per-unit transportation cost paid by a buyer located at the quartile and also engaging in OD pricing as in the touching equilibrium. Performing the calculations yields the following:

$$R_2(t) = \begin{cases} 2 & \text{if } 0 < t \leq 2, \\ \dfrac{4}{t} & \text{if } 2 < t \leq 4, \\ 1 & \text{if } t > 4. \end{cases} \tag{8}$$

We find that per-unit transportation costs are twice as high for a buyer at the endpoint compared to a buyer at the quartile for $0 < t \leq 2$, i.e., as long as the end-point buyer can profitably buy at all locations up to the market's midpoint. $R_2(t)$ decreases with t for $t > 2$ because the buyer at the endpoint serves a market area less than than $1/2$, which reduces its unit transport costrs. If $t > 4$, both buyers have identical market radii and per-unit transportation costs, although the quartile buyer has twice the supply. Figure 6 illustrates the results for $R_2(t)$.

Both the supply and cost effects of the location choice apply to any pricing strategy outside of the polar cases of UD and FOB pricing, and they incentivize firms to locate at the center of their market areas. Offsetting forces are the already-noted incentive to differentiate in location from the rival firm to lessen price competition and an opposite incentive to locate near the center of the production region to maximize access to farm production. This latter effect is a strong force when t is low. The total economic surplus available in the market is highest when t is low, and firms have unilateral incentive to operate near the market's midpoint to capture as much of the available supply as possible. This incentive is a dominant factor in the simulation results for low values of t. For $t \in [0.05, 1.10]$, the median values of $|x - 1/2|$ are in the range of

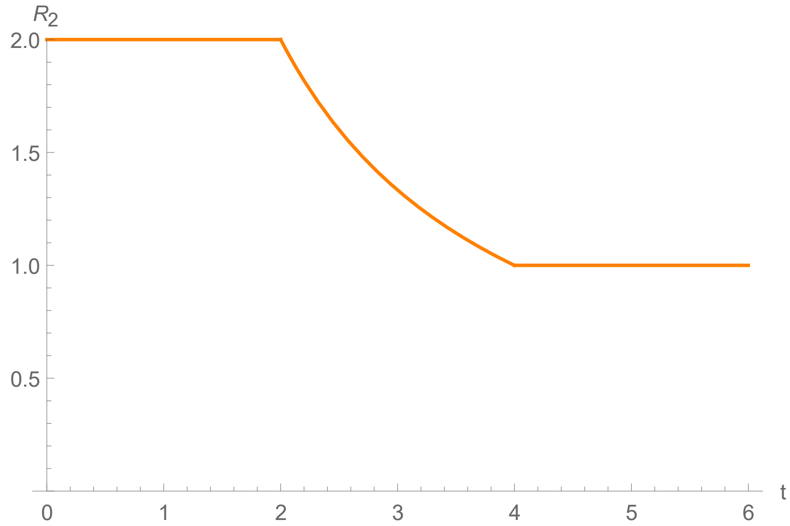

Figure 6: Ratio R_2 of per-unit transportation costs paid by the OD-pricing buyer located at the endpoint ($x_A = 0$) relative to location at the quartile ($x_A = 1/4$).

0.12—0.15, with low variance. The incentive to capture additional supplies in these settings dominates the cost and supply effects, causing firms to locate beyond the center of their market areas in equilibrium. However, minimum differentiation itself (Hotelling, 1929), is never part of an equilibrium strategy. Indeed, the most intense price competition that would emerge from minimum differentiation is avoided by firms choosing locations that, while not in the center of either firm's market area, are also not directly at the market center. Price competition is further muted in these settings by choosing pricing strategies near to FOB pricing.

5 Conclusion

Locations of agricultural processing/packing firms and the pricing strategies they adopt are critical determinants of the efficiency of farm-product assembly and the competitiveness of farm-product procurement markets. Although significant contributions to addressing these issues have been made, studies have encountered severe challenges due to the analytical complexities created by introducing the spatial dimension into models of farm-product procurement, including inability to obtain analytical solutions, nonexistence of equilibrium, presence of mixed-strategy equilibria, and existence of multiple equilibria in asymmetric strategies. Studies to date have been able to move forward only by imposing strong assumptions on economic models, with corresponding limitations on the generality of results derived from them.

This paper has eschewed the quest for analytical solutions, relying instead on a computational economics framework and the use of genetic algorithms to study processing/packing firms' decisions on location and pricing strategy. Our results stand in considerable contrast to received wisdom regarding these decisions. Specifically, we find that maximum differentiation, i.e., location on the endpoints of Hotelling's line, although often assumed as the starting point in models of spatial pricing, is never part of an equilibrium location and pricing strategy. Indeed, firms generally do not locate beyond the market quartiles.

In settings with low values of transportation costs and potentially intense price competition, firms tend to locate near to the market center in their quest to obtain farm product supplies that are especially valuable when transport costs are low. In these market settings firms avoid the most intense price competition by not choosing locations directly in the market center, i.e., minimum differentiation and Bertrand's paradox does not emerge in equilibrium, and by choosing pricing strategies close to FOB pricing, which limits direct price competition to the market boundaries.

Whereas maximum differentiation has the desirable property from a buyer's perspective of minimizing price competition with its rival, it is a poor strategy in a generalized market environment that enables farmers to have an elastic response to price and that enables flexible pricing strategies such that buyers can absorb any portion of the costs of transporting product from farm gate to plant gate. Indeed, it is equilibrium behavior for firms in general to absorb some portion of these transportation costs (i.e., to price discriminate) and in that setting to locate near the midpoint of their market areas to minimize those costs–what we termed the cost effect. Similarly, with elastic farm supplies a supply effect creates the same incentive–supplies are maximized when firms locate at the midpoint of their market areas whenever the pricing strategy involves farmers bearing some portion of the transportation costs.

In general, our results suggest farm product procurement markets are both more competitive and more efficient than is predicted based on conventional wisdom. Maximum differentiation minimizes price competition between buyers, creating significant buyer power depending upon the importance of transportation costs relative to the farm product. Maximum differentiation also is inefficient in terms of costs of transporting the farm product. We find a significant tendency for firms to locate in the center of their market areas, i.e., at or near the market quartiles. Such locations are efficient in terms of minimizing transport costs, and they increase the intensity of price competition relative to maximum differentiation, causing higher prices to be paid on net to farmers.

As the possible market power exercised by buyers of agricultural products from farmers as risen to primacy among competition issues in agriculture for both western and emerging economies, we hope these results can contribute to ongoing debates regarding competition policies and optimal structure of supply chains.

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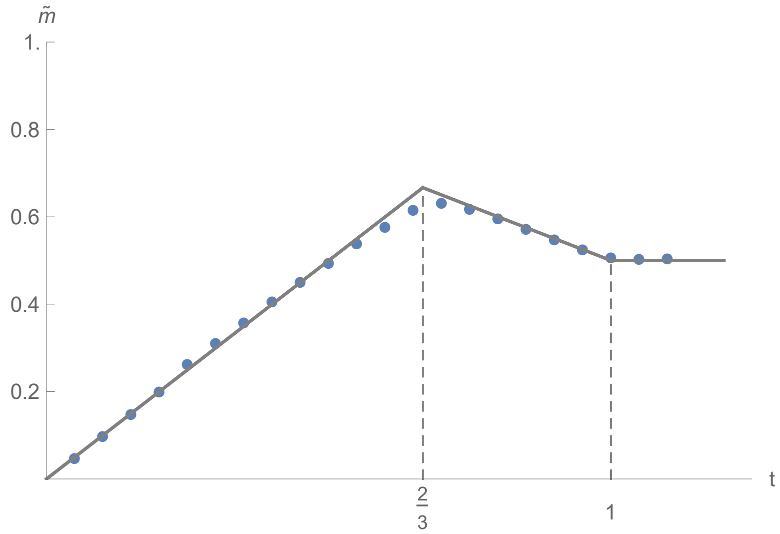

Figure A.1: The analytical equilibrium FOB price schedule (gray) due to Mérel and Sexton (2010, Figure 4) and the average FOB price for selected levels of normalized transport costs from the simulation (blue). The points represent the average mill price over 3750 games (7500 observations).

Appendix A

A.1 Validation of the Simulation Model

Here we provide further validation of the simulation framework by seeking to replicate known analytical solutions for NE in asymmetric and mixed strategies. For the sake of brevity and illustrative purposes, we borrow findings from the literature and contrast these analytical results with outcomes of the simulation.

A.1.1 Asymmetric Strategies under FOB Pricing

The first application of the simulation model concerns the full characterization of price equilibria in Hotelling's model of horizontal product differentiation provided by Mérel and Sexton (2010). The authors derive the duopolist's equilibrium price schedule under FOB pricing, fixed locations (maximum differentiation) and perfectly inelastic consumer demand functions. To replicate their result, we implemented the GA simulation as a duopoly game with $\alpha_A = \alpha_B = 1$, $x_A = 0$, and $x_B = 1$, i.e., m is the buyers' only decision variable. Simulations are conducted over the range of normalized transport costs of $t = [0, 5/4]$ with t incremented by $1/20$. The outcome is shown in Figure A.1, where the theoretical result of Mérel and Sexton (2010) and the average FOB price as reported from the simulations are depicted.

The figure illustrates that the GA is able to approximate the analytical result with high precision ($R^2 = 0.997$). However, Mérel and Sexton (2010) also identify NE in asymmetric

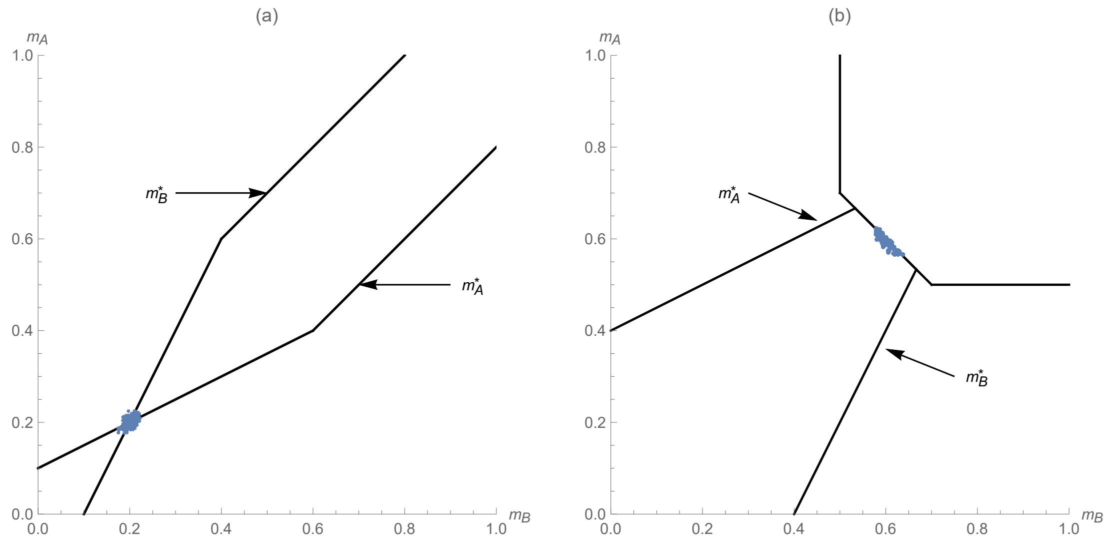

Figure A.2: FOB price equilibrium for (a) $t = 0.2$ (*duopoly*) and (b) $t = 0.8$ (*weak duopoly*) according to (Figure 6 and 7 in) Mérel and Sexton (2010) and the simulation results (blue) of 3750 games.

strategies in the range $2/3 \leq t < 1$, whereas there is a unique symmetric NE if $0 \leq t < 2/3$.[17] If we investigate the simulation outcome for each level of t in more detail, i.e., on a disaggregated level, we observe that the GA again closely approximates the unique NE (e.g., in the case of $t = .2$), but it also identifies strategies that constitute a subset of the continuum of NE in asymmetric strategies (e.g., when $t = .8$). This is illustrated in Figure A.2 where one example for each of the two situations is presented; in the case of low transport costs, the price reaction functions (m_i^*) of both firms intersect once, which constitutes a unique and symmetric NE while – in the case of moderate transport costs (b) – these reaction functions partially overlap.

A.1.2 Mixed Strategy NE in a UD Pricing Model

The second application concerns the duopsony framework of maximum differentiation investigated by Zhang and Sexton (2001) where buyers of an (agricultural) input use UD pricing, sellers have a price elastic supply function and spatial arbitrage is possible.[18] In this setting, a NE in pure strategies fails to exist as long as transport costs are not so high as to allow both buyers to act as locally separated monopsonies. Following Beckmann (1973), the authors derive the optimal mixed strategy in terms of a cumulative distribution function (CDF) with support between an upper (m_i^+) and lower (m_i^-) limit of UD prices. Figure A.3 shows the CDF and the

[17] Both firms act as local monopolies if $t \geq 1$ and set $m = 1/2$.

[18] In this setting, spatial arbitrage means that sellers can take advantage of local price differences among locations served by different buyers and transport the input to the closest location of the competitor if the price differences make this profitable.

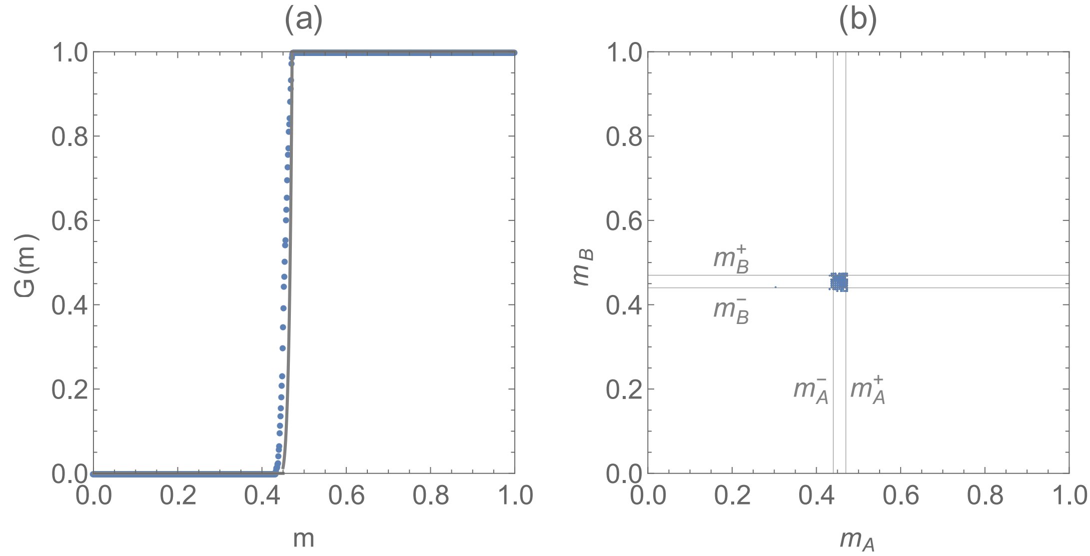

Figure A.3: The UD pricing duopsony due to Zhang and Sexton (2001): (a) Mixed strategy (expressed as cumulative distribution function) $G(m)$ and (b) upper and lower price limits of both buyers under $G(m)$. Simulation results are colored in blue based on 3750 games.

price limits for both firms in the case of $t = 1$. The results of the simulation are pictured in blue: The GAs are initialized with $\alpha_A = \alpha_B = 0$ (for UD pricing) and $x_A = x_B - 1 = 0$ (for maximum differentiation). As can be seen, the mixed strategy is closely approximated by the GA (Figure A.3a) and the selected strategies are almost never out of equilibrium (Figure A.3b).[19] The result needs to be interpreted with some caution though. The only variable that the GA considers for optimization is the (UD) price m (separately for each buyer). Accordingly, there is no information about the optimal weights (i.e., the probability assigned to a certain price) and given the implemented selection operator, the simulation result is a linear approximation of the non-linear CDF. However, the GA identifies strategies that are in support of the mixed strategy and we therefore can approximate the domain of the NE in mixed strategies with high precision. However, a full characterization of the equilibrium is not feasible in cases where we do not obtain analytical results.

A.1.3 Hotelling's Model of Horizontal Product Differentiation

While the previous applications concerned spatial price competition, the third combines price and location decision in a duopoly framework as studied by Hinloopen and van Marrewijk (1999).[20] This model is a two-stage game where players first select location and the optimal (subgame

[19] We obtained similar results for the closely related problem investigated by Shilony (1981): the UD pricing duopoly without spatial arbitrage by consumers.

[20] Another location model against the simulation was validated is the outcome of maximum differentiation in the Hotelling model for a circular market and sufficiently low consumer reservation prices derived by Kats (1995).

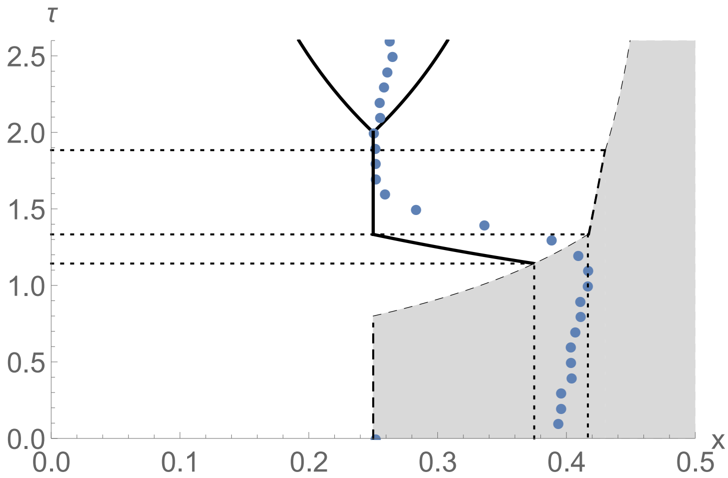

Figure A.4: The Firm's location in the half market depending on the effective reservation price τ due to Hinloopen and van Marrewijk (1999) and the outcome of the simulations (in blue). Each dot represents the average over 3750 games.

perfect) FOB price in the second stage. The authors introduce a finite consumer reservation price into the Hotelling-model and investigate firm location depending on the intensity of competition, τ, which relates the consumer reservation price to the market size.[21] The authors show that there is a unique pure or a continuum of pure (monopolistic) location equilibria if τ is intermediate or high, respectively. If τ is low, there is no pure strategy location equilibria. These results together with the simulation outcome are depicted in Figure A.4.[22] The bold black lines indicate location equilibria in the intermediate range or the limits of the continuum of equilibria in pure strategies for high τ, while the shaded area indicates that there are no second-stage pure strategy price equilibria. First, we note that the simulation produces consistent results in the upper part of the figure where τ is high and there is a unique location equilibrium or a continuum of monopolistic location equilibria. If $\tau > 2$, the figure depicts the theoretical limits. On the one hand, the simulation results (blue) are averages over simulation runs. On the other hand, these averages approximates the theoretical mean outcome within the expected range.

Second, the results from the simulation and the theoretical model deviate for moderate levels of τ. We can ascribe these differences to the different structure of the game in our simulation and the theoretical template of Hinloopen and van Marrewijk (1999). There, players can condition their pricing choice in stage two on the location choice in stage one. In our simulations, players have to choose location and price simultaneously. Despite these structural difference, however, we discover the same general price and location behavior as Hinloopen and van Marrewijk (1999) only that our thresholds (in terms of τ) for the existence of a unique and pure location equilibrium is higher compared to Hinloopen and van Marrewijk (1999). For low values of τ, a NE in pure

[21] Hinloopen and van Marrewijk (1999) denote this parameter α. We use τ to avoid confusion with α in our paper, which measures the share of transport costs that is reflected in the local prices of different locations (cf. Equation (2)).

[22] This figure replicates Figure 7 in Hinloopen and van Marrewijk (1999).

strategies does not exist (cf. gray shaded area in the figure) and again, the simulation results represent average values for x over strategies in support of the mixed strategy equilibrium.

Appendix B

B.1 Full Simulation Results

Table B.1: Descriptive statistics of the simulation results.

t	$\tilde{m}$	Var(m)	$\tilde{\alpha}$	Var(α)	$\lvert\tilde{x} - 1/2\rvert$	Var($\lvert x - 1/2\rvert$)
0.00	0.9917	0.0006	0.4989	0.0796	0.250	0.0213
0.05	0.9807	0.0013	0.8616	0.0304	0.120	0.0038
0.10	0.9620	0.0006	0.8714	0.0294	0.125	0.0031
0.15	0.9438	0.0004	0.8765	0.0276	0.115	0.0033
0.20	0.9247	0.0004	0.8675	0.0325	0.120	0.0036
0.25	0.9061	0.0001	0.8758	0.0284	0.125	0.0031
0.30	0.8881	0.0002	0.8663	0.0257	0.125	0.0029
0.35	0.8710	0.0001	0.8612	0.0241	0.130	0.0028
0.40	0.8532	0.0006	0.8759	0.0352	0.125	0.0035
0.45	0.8354	0.0004	0.8553	0.0423	0.130	0.0038
0.50	0.8182	0.0003	0.8575	0.0323	0.125	0.0031
0.55	0.8006	0.0003	0.8571	0.0296	0.130	0.0029
0.60	0.7858	0.0004	0.8517	0.0372	0.130	0.0034
0.65	0.7707	0.0005	0.8359	0.0480	0.135	0.0046
0.70	0.7595	0.0006	0.8412	0.0486	0.130	0.0042
0.75	0.7429	0.0007	0.8299	0.0594	0.135	0.0045
0.80	0.7300	0.0010	0.8181	0.0759	0.135	0.0072
0.85	0.7157	0.0011	0.7884	0.0822	0.135	0.0070
0.90	0.7007	0.0014	0.8031	0.0980	0.135	0.0096
0.95	0.6971	0.0019	0.7601	0.1166	0.140	0.0123
1.00	0.6823	0.0023	0.7302	0.1301	0.135	0.0146
1.05	0.6661	0.0027	0.6646	0.1344	0.140	0.0155
1.10	0.6562	0.0030	0.6715	0.1367	0.150	0.0157
1.15	0.6384	0.0034	0.6208	0.1389	0.190	0.0172
1.20	0.6176	0.0037	0.5992	0.1307	0.205	0.0170
1.25	0.5924	0.0041	0.3607	0.1213	0.230	0.0155
1.30	0.5915	0.0038	0.3598	0.1076	0.225	0.0135
1.35	0.5778	0.0033	0.2928	0.0924	0.220	0.0100
1.40	0.5699	0.0025	0.2122	0.0706	0.225	0.0061
1.45	0.5627	0.0017	0.2037	0.0545	0.225	0.0028
1.50	0.5532	0.0013	0.1813	0.0413	0.225	0.0018

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Table B.1 – continued from previous page

t	$\tilde{m}$	Var(m)	$\tilde{\alpha}$	Var(α)	$\lvert\tilde{x} - 1/2\rvert$	Var($\lvert x - 1/2\rvert$)
1.55	0.5493	0.0010	0.1833	0.0446	0.230	0.0010
1.60	0.5363	0.0010	0.1863	0.0362	0.230	0.0011
1.65	0.5291	0.0008	0.1819	0.0328	0.230	0.0008
1.70	0.5198	0.0006	0.1745	0.0267	0.230	0.0007
1.75	0.5179	0.0006	0.1918	0.0268	0.230	0.0005
1.80	0.5080	0.0006	0.1909	0.0236	0.230	0.0005
1.85	0.4978	0.0005	0.1941	0.0233	0.235	0.0005
1.90	0.4908	0.0006	0.1901	0.0191	0.235	0.0004
1.95	0.4894	0.0004	0.1913	0.0187	0.235	0.0003
2.00	0.4786	0.0004	0.1945	0.0161	0.235	0.0003
2.05	0.4779	0.0003	0.1758	0.0144	0.235	0.0002
2.10	0.4692	0.0003	0.1808	0.0125	0.240	0.0002
2.15	0.4668	0.0002	0.1910	0.0081	0.240	0.0001
2.20	0.4625	0.0002	0.1945	0.0070	0.240	0.0001
2.25	0.4604	0.0002	0.2247	0.0055	0.235	0.0001
2.30	0.4637	0.0002	0.2459	0.0023	0.235	0.0001
2.35	0.4638	0.0002	0.2673	0.0020	0.235	0.0001
2.40	0.4670	0.0002	0.2997	0.0017	0.235	0.0001
2.45	0.4693	0.0002	0.3234	0.0017	0.235	0.0001
2.50	0.4731	0.0002	0.3469	0.0014	0.235	0.0001
2.55	0.4751	0.0001	0.3618	0.0011	0.235	0.0001
2.60	0.4768	0.0002	0.3747	0.0012	0.235	0.0001
2.65	0.4786	0.0001	0.3928	0.0009	0.235	0.0001
2.70	0.4822	0.0001	0.4110	0.0005	0.235	0.0001
2.75	0.4828	0.0001	0.4142	0.0006	0.235	0.0001
2.80	0.4844	0.0001	0.4251	0.0006	0.235	0.0001
2.85	0.4879	0.0001	0.4367	0.0005	0.240	0.0001
2.90	0.4866	0.0001	0.4389	0.0005	0.240	0.0001
2.95	0.4907	0.0001	0.4511	0.0005	0.240	0.0001
3.00	0.4895	0.0001	0.4524	0.0006	0.240	0.0001
3.05	0.4919	0.0001	0.4611	0.0004	0.240	0.0001
3.10	0.4928	0.0001	0.4673	0.0004	0.240	0.0001
3.15	0.4939	0.0001	0.4707	0.0004	0.240	0.0001
3.20	0.4964	0.0001	0.4798	0.0004	0.245	0.0001
3.25	0.4950	0.0002	0.4799	0.0006	0.245	0.0001
3.30	0.4964	0.0001	0.4820	0.0003	0.245	0.0001
3.35	0.4980	0.0001	0.4878	0.0005	0.245	0.0001

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Table B.1 – continued from previous page

t	$\tilde{m}$	Var(m)	$\tilde{\alpha}$	Var(α)	$\lvert\tilde{x} - 1/2\rvert$	Var($\lvert x - 1/2\rvert$)
3.40	0.4981	0.0001	0.4894	0.0004	0.245	0.0001
3.45	0.4981	0.0001	0.4905	0.0003	0.250	0.0001
3.50	0.4983	0.0001	0.4923	0.0003	0.250	0.0001
3.55	0.5014	0.0001	0.4973	0.0005	0.250	0.0001
3.60	0.5013	0.0001	0.4998	0.0002	0.250	0.0001
3.65	0.5016	0.0001	0.4996	0.0003	0.250	0.0001
3.70	0.5031	0.0001	0.5038	0.0002	0.250	0.0002
3.75	0.5063	0.0001	0.5093	0.0004	0.250	0.0001
3.80	0.5065	0.0001	0.5073	0.0004	0.250	0.0001
3.85	0.4996	0.0001	0.4988	0.0002	0.250	0.0001
3.90	0.5029	0.0001	0.5056	0.0003	0.250	0.0002
3.95	0.5031	0.0001	0.5018	0.0003	0.245	0.0003
4.00	0.5027	0.0001	0.5006	0.0002	0.250	0.0003