More Competitive Than You Think? Pricing and Location of Processing Firms in Agricultural Markets

Marten Graubner* and Richard J. Sexton†

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 and efficiency 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 (including genetic algorithms) to study duopsony firms' joint choices of location and pricing policy. Our results differ considerably from those presented in prior literature. 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,

*Leibniz Institute of Agricultural Development in Transition Economies (IAMO), Theodor-Lieser-Strasse 2, 06120 Halle, Germany; Email: graubner@iamo.de.

†Department of Agricultural and Resource Economics, University of California, Davis, California 95616, USA; Email: rich@primal.ucdavis.edu.

1 Introduction

Perhaps the single characteristic that most distinguishes agriculture from other forms of production is its spatial dimension. 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 (Hamilton and Sunding, 2020; Jung et al., 2021) .

Although the economic importance of the spatial dimension of agricultural markets has been acknowledged and studied at least since von Thünen (1826),[1] our understanding of the implications of spatially dispersed farm production for the location of 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; Hamilton and Sunding, 2020).

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), Polopolus (1965), and Hilger et al. (1977). 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. 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. See Lucas and Chhajed (2004) for a review of this literature.

[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]

2 Background and Related Literature

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; Schuler and Hobbs, 1982; Zhang and Sexton, 2001),[5] and a multiplicity of asymmetric

[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 early 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), and d'Aspremont et al. (1979), who corrected Hotelling, demonstrated the nonexistence of pure strategy equilibrium in Hotelling's base model, and established maximum differentiation (location at the market endpoints) as the location equilibrium with FOB pricing and quadratic transport costs. More recent examples are 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, and van Leeuwen and Lijesen (2016) who used agent-based simulations to investigate Hotelling's game under quadratic transport costs and FOB-pricing. Other work has addressed seller location assuming discriminatory pricing (e.g., Lederer and Hurter, 1986 and Hamilton et al., 1989). Summaries of this literature are provided by Thisse and Norman (1994), Greenhut and Norman (1995), and Biscaia and Mota (2013).

[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; Nes et al., 2021).

[5] Nonexistence of pure-strategy equilibria is due to "market stealing," the phenomenon whereby, with linear transport costs and symmetric pricing strategies, 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 and pure-strategy equilibria fail to exist (Dasgupta and Maskin, 1986).

equilibria in others (Mérel and Sexton, 2010).[6]

We eschew the quest for analytical solutions in favor of a framework that relies upon computational economics methods. In particular, we identify firms' decisions regarding location and price policy by genetic algorithm (GA) learning of equilibrium strategies within an agent-based model (ABM). The use of ABMs in agricultural economics gained a foothold in the last 25 years, with Balmann (1997) and Berger (2001) representing prominent early applications. Kremmydas et al. (2018) and Huber et al. (2018) provide recent reviews of agent-based approaches in agricultural economics.

Although most ABMs have been based on mathematical programming or ad-hoc decision rules, some authors have employed flexible and powerful optimization techniques, including the application of artificial intelligence methods, to study decision problems of high complexity within ABMs (Zhang and Brorsen, 2010; Boyer and Brorsen, 2013; Feil et al., 2013). We follow this approach, in particular Graubner et al. (2011), and combine an ABM structure with an artificial intelligence technique (GAs), which 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. This approach leads to surprising results that stand in contrast to much of the conventional wisdom in the spatial economics literature.

Our model follows most previous studies of firm location decisions by focusing on duopsony/duopoly competition and location along Hotelling's line or street. 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 $\alpha = 1$, i.e., so-called free-on-board (FOB) pricing wherein sellers are responsible for all transport costs, departures from FOB pricing are

[6] Mérel and Sexton (2010) show that a continuum of asymmetric Nash equilibria exist with FOB pricing in market settings that they termed "weak duopoly".

common in reality, including full buyer absorption of transport costs, i.e., $\alpha = 0$, known as uniform-delivered (UD) pricing (Durham et al., 1996; Alvarez et al., 2000; Tribl et al., 2017). 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 (Ali, 2004; Meyer, 2005), operating receiving stations at intermediate locations,[7] 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 (Schipmann and Qaim, 2010; Kopp and Brummer, 2017). Such buyers are able to 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 $\alpha \in (0, 1)$.

FOB pricing is nondiscriminatory because, although all sellers obtain a differentiated net price based upon their location relative to the buyer, the price differences equate the transport cost differences between locations. Any departure from FOB pricing represents a form of third-degree price discrimination against farmers located nearby the processing or packing facility, with UD pricing representing a particularly extreme form of price discrimination.[8]

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), mixed pricing

[7] Receiving stations are especially common in the developing world for commodities such as coffee and milk (Dries and Noev, 2006; Ndahetuye et al., 2020). For example in Latin America they are known as *centro de acopio*, which translates to "collection center."

[8] 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).

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 GA optimization, Graubner et al. (2011) were able to study a richer set of spatial pricing options than just UD and FOB pricing for buying firms located at the endpoints of Hotelling's street. 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 itself be challenged by the restrictive assumption that buyers are located at the market endpoints and the fact that casual empiricism reveals frequent examples of FOB pricing in farm product procurement markets (e.g., Jung et al., 2021).

Although maximum differentiation minimizes price competition between firms, such locations are inefficient from the perspective of minimizing transport costs, and some authors have considered alternative market structures. Examples include Alvarez et al. (2000), who investigated a milk market duopsony under UD pricing and an unbounded line market, Sesmero et al. (2015), who considered a third buyer at the market center in a FOB-pricing model of a spatial market for corn stover, and Wang et al. (2020) who analyzed alternative market structures in a two-dimensional FOB pricing model of procurement markets for corn ethanol plants. In each of these contributions, however, firm locations and price policies were treated as exogenous.

Neither FOB pricing nor maximum differentiation maximize buyer profits for most spatial competition settings, raising the question of how behavior is affected if firms are able to choose both their location and pricing policy, especially if the denizens along Hotelling's street, whether they be consumers or farmers, 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 to the market boundary (Zhang and Sexton, 2001), a key consideration once firms are no longer constrained to locate at the competition-stifling endpoints of Hotelling's line.

3 Model Framework

Two buyers, denoted as A and B, are free to choose a plant 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.[9] 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

[9] 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.

product of the farm input, i.e., the marginal value prior to accounting for shipment costs.

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, p, at her location, x:

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

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.[10] 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 (consumer) 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 $|x - x_i| = 0.25$, then the transport costs would represent 25% of the gross value of the farm product. In the prototype model with maximum differentiation t represents the differentiation between the buying firms and, thus, depicts the intrinsic competitiveness of the input procurement market, 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 (e.g., Zhang and Sexton, 2001). Intermediate values of t characterize different intensities of oligopsony competition. Importantly, however, when firms are free to choose locations within the market area, the product of t and the distance between the firms, $x_B - x_A$, determines the intrinsic competitiveness of the market.

[10] 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 response to prices they encountered.

We define the price $p_i(x)$ offered by buyer i to the seller at location x as a function of the mill price m_i and the portion α_i of the transport costs between i's location x_i and the seller's location x that is borne by the 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 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 illustrates $p_i(x)$ and $b_i(x)$. Given the supply function (1), i's profit at seller 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 $p_i(x)$ in figure 1. 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:

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

The optimal price strategy for the monopsonist is $(m_M, \alpha_M) = (1/2, 1/2)$, a result that can be found analytically (see, e.g., Norman, 1981) 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" for $t = 4$, where 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 $p_A(0) = p_B(1) = p(1/2) = 0$.[11] This equilibrium is illustrated in Figure 1.

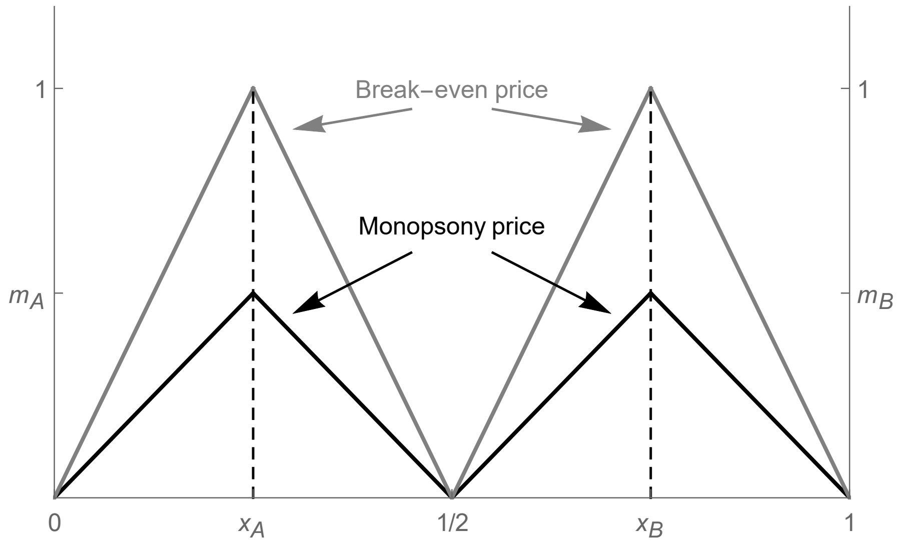

Figure 1: Touching Equilibrium ($t = 4$) with OD pricing ($m = 1/2$ and $\alpha = 1/2$) and location at the quartiles.

OD pricing maximizes both the market radius and the local profit (4). Location at the market quartiles is also efficient in the sense of minimizing the total 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).

[11] The touching equilibrium is derived for the seller case under FOB pricing by Economides (1984) and Hinloopen and van Marrewijk (1999).

4 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 (GAs) are applied to solve the decision problem of the buyers. GAs 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), Graubner et al. (2011), and Feil et al. (2013).[12]

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 iterations 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 at

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

hand, we explicitly consider the spatial dimension of a market by an array of $n = 400$ equidistant locations, each occupied by one farmer $j = \{1, \ldots, n\}$. 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 her/his own location and set quantity according to the supply function (1), given this price. The decision rule of buyers must, however, incorporate strategic interactions, and the search for Nash equilibrium strategies involves all of the aforementioned complications.

4.1 Modeling Buyer Decision Making with a GA

To illustrate how the GA operates and to demonstrate its ability to identify NE, we begin by replicating the touching equilibrium $\gamma_A = (1/2, 1/2, 1/4)$ and $\gamma_B = (1/2, 1/2, 3/4)$ with the simulation. 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 buyer'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 $\Gamma_{i,0} = \{\gamma_{i,0}^k | k = 0, \ldots, v\}$ 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:

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

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 repeatedly 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 identify 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. Because we use $\dot{v} = 0.8$ 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 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 4% and the rate of crossover is 10%. 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 1,000 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 eventually yields a variable distribution that is very close to the expected solution.

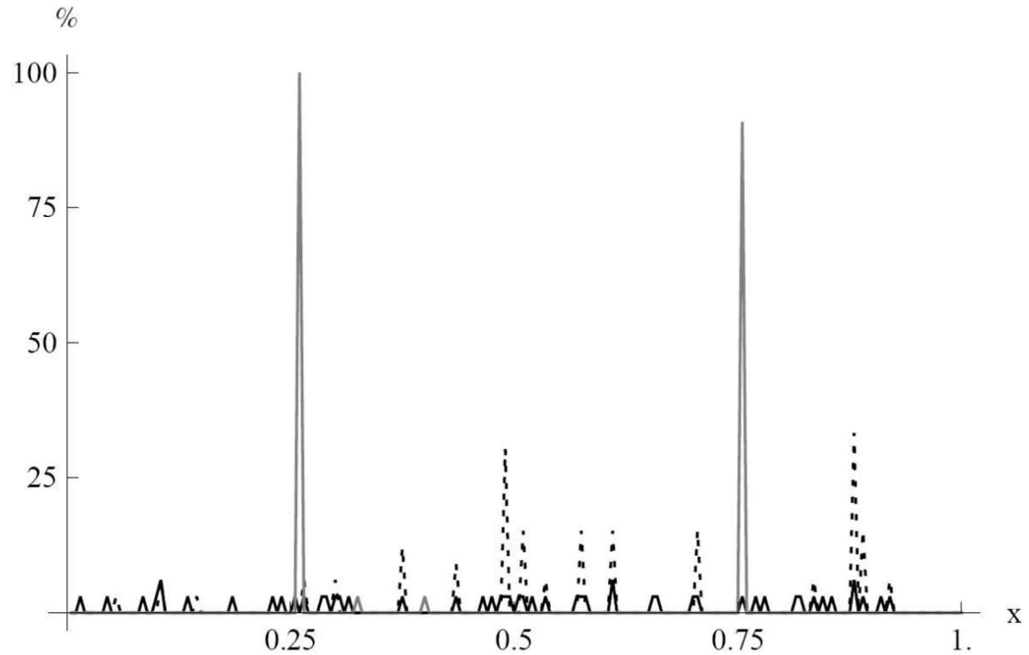

Figure 2: Distribution of the buyers' location parameter x in the initial population (solid, black), after five (dashed, black), and 1,000 generations (solid, gray), respectively.

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; we repeat the GA simulation 40 times with $g_{max} = 2,500$. The last five percent of g_{max} are reported for analysis. Thus, we investigate 5,000 games with 10,000 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.

In Appendix A.1 we present applications of the simulation to other spatial competition models in input and output markets that have been investigated in the literature, including those involving pure, mixed (Shilony, 1981; 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, whether in pure or mixed strategies, giving us confidence that we can apply the model to study behavior in a broad range of complex settings.

Given that nonexistence of pure strategy Nash equilibria is a significant phenomenon in simpler spatial markets settings than ours due to market-stealing incentives (see footnote 5), it is very reasonable to expect similar results for some values of t in our more complex model environment. Thus, the GA's ability to depict mixed-strategy equilibria is a central aspect of this paper. Unlike an analytical solution such as the touching equilibrium wherein the GA yields a definitive strategy profile, or set of strategies in the case of multiple equilibria (Mérel and Sexton, 2010), the solution for a mixed-strategy equilibrium is a probability distribution for the decision variables. The GA does not directly yield the equilibrium probability distribution in any particular simulation, but, as the results in Appendix A demonstrate, across a large number of simulations the GA does a very good job of approximating distribution functions for known mixed-strategy equilibria.

As some of the giants of noncooperative game theory have observed (e.g., Rubinstein, 1991), the idea of mixed strategies involving randomization or players executing a lottery is unappealing in economics applications, but, outside of simple games of chance, such interpretations are naive and unnecessary. An alternative interpretation, which is appropriate in the present case, is what is known as the *large population case* (Rubinstein, 1991; Oeschssler, 1997), wherein a game is viewed as an interaction involving large populations, and each occurrence of the game takes place after a draw of players from these populations. Each player implements a pure strategy, with the mixed strategy equilibrium viewed as the resultant distribution of pure strategies across the repetitions of the game.

This interpretation aptly describes the process undertaken by the GA. Each iteration within a simulation represents a draw from the population, and across a large number of draws or replications the distributions for the strategy variables are revealed. The behavior of any specific processors in a particular country or region for a particular commodity holds little interest relative to understanding the types of behavior that will and will not unfold in spatial agricultural product procurement markets generally.

5 Simulation Experiments and Results

We present results of 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. Results are reported for t in increments of 0.05, ranging from perfect (Bertrand) competition to two spatially separated monopsonies based on 5,000 games (draws from the population of processors), or 10,000 observations for each value of $t = \{0.0, 0.05, \ldots, 5.0\}$.[13] Figure 3 reports median values of the decision variables mill price, $\tilde{m}$, and share of transport costs borne by farmers, $\tilde{\alpha}$ for each

[13] Although primary interest lies in the range of t values where head-to-head competition prevails between the buying firms, we include results of interest for values of $t \in [4, 5]$ to show firm behavior under monopsony.

simulated value of t. For location, the figure presents the median distance separating the two firms, the median inter-buyer distance $\tilde{x}_{AB}$, where $x_{AB} = x_B - x_A$. Median values and standard deviation for each of the strategy variables and each value of t are reported in Appendix B.

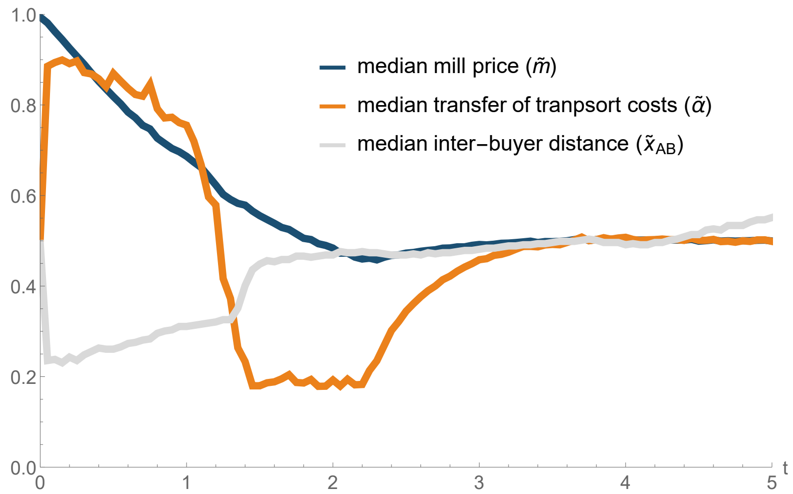

Figure 3: Simulation results for price strategy and location in the generalized Hotelling model

For high transport costs (i.e., $t \longrightarrow 4$), results are consistent with the touching equilibrium discussed previously. Firms locate at or very near the market's quartiles (i.e., at distance $|\tilde{x} - 1/2| = 1/4$ symmetrically right and left of the market center and $\tilde{x}_{AB} = 1/2$), and, given the flexibility to do so, the firms adopt pricing strategies close to optimal monopsony price discrimination, with $(m, \alpha) = (1/2, 1/2)$. For values of $t \in [3, 4)$, the pricing and location equilibrium closely resembles the touching equilibrium, where active but weak head-to-head competition exists between the firms at the market center.

At the other extreme, as $t \longrightarrow 0$, 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 is irrelevant if $t = 0$. Because all decision variables are randomly initialized according to a uniform distribution within $[0, 1]$, the expected median values of $\tilde{\alpha} = 1/2$ and $\tilde{x}_{AB} = 1/2$ (with $\tilde{x}_A = 1/4$, $\tilde{x}_B = 3/4$) are obtained.

The results depicted in Figure 3 represent the central tendency over 5,000 games for each level of 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 for each value of t is a distribution for each of the three decision variables. If there is 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 $t = 4$ and the touching equilibrium the standard deviations of α and m are 0.0151 and 0.0093, respectively (Appendix B).

Figure 4 shows the cumulative distribution functions (CDFs) for m, α, and x_{AB} for $t = \{0.5, 1.0, 1.5, 2.0, 3.0\}$ and illustrates that the distributions of the decision variables change considerably over the parameter range of t.[14] For small but positive values of t, Figures 3 and 4 highlight a rich and complex set of relationships between firms' price policies and location choices. In these settings, differentiation between firms is minor, creating the potential for intense price competition, including market stealing and nonexistence of pure strategy Nash equilibria.

The total economic surplus available in the market is highest for low values of t. A firm that locates near the center of the production region positions itself well to capture the supply available in the market, and this is a dominant incentive for low t. However, if both buyers chose to locate directly at the market center (i.e., minimum differentiation), competition between them would dissipate their profits as in a Bertrand paradox setting.

The simulation results show, however, that firms are able to avoid competing profits away completely for positive but low t by (a) each locating some distance from the market center and (b) using close-to FOB pricing, thereby limiting competition to the market boundary. Although $\tilde{\alpha}$ is consistently large for $t < 1$, reflecting near FOB pricing, $\tilde{m}$ declines monotonically in t, reflecting the lessening competitive pressure caused by higher values of t. Separation of firms $\tilde{x}_{AB}$ under low t, although critical to their profitability, is nonetheless modest and rises only

[14] The CDFs represent a smooth kernel distribution based on simulation results. The density functions that accompany the CDFs are provided in Appendix C.

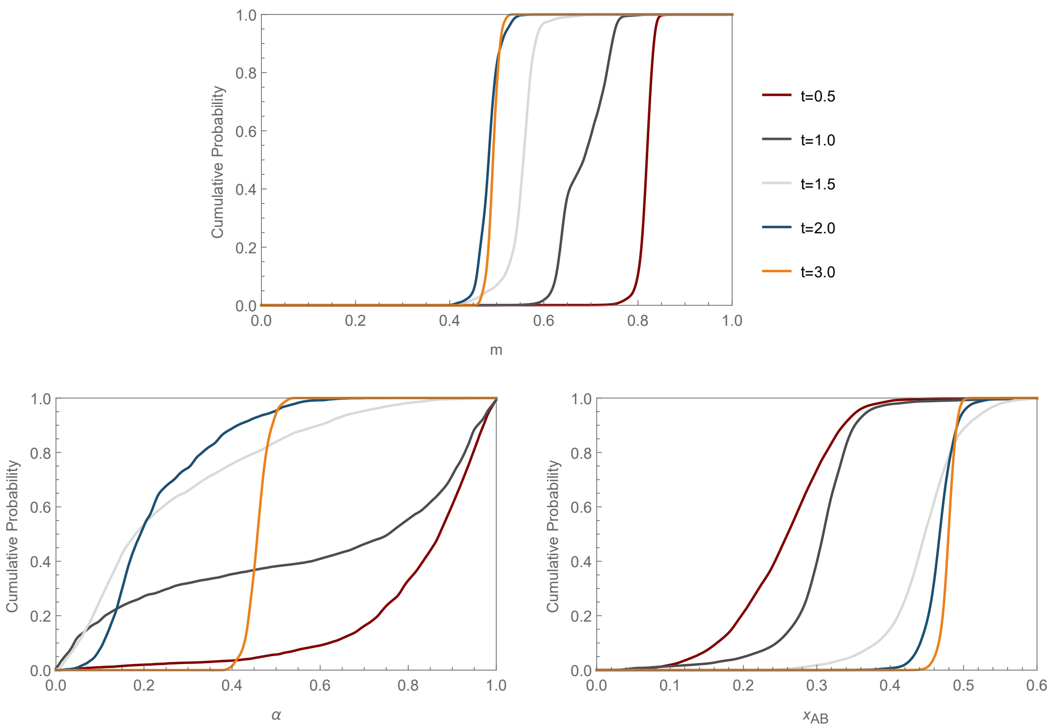

Figure 4: Cumulative distribution functions of the decision variables for selected values of the normalized transport costs t (10,000 observations).

gradually from 0.24 to 0.33 over the interval $t \in (0, 1.3]$ (see Appendix B).

A different type of result emerges for $t \in [0.80, 1.25]$. Here firms adopt asymmetric strategies. One buyer locates near the center of the market and uses FOB or near-to FOB pricing, while the other buyer locates within the first or fourth quartile of the market and uses UD or near-to UD pricing. This asymmetric pricing is illustrated in figure 5, with market boundary $\hat{x}$, and is manifest in figure 4 in the bimodal CDF for m and α (see $t = 1$). Appendix C shows the combination of the decision variables by means of density plots. Such asymmetric strategies are remindful of the Zhang and Sexton (2001) result that for moderate values of t equilibrium involved one firm choosing FOB pricing and the other choosing UD pricing. This combination of pricing strategies limits competition to the market boundary. The firms' locations under the asymmetric equilibrium also result in greater separation between them compared to lower values of t (e.g., compare the CDFs for x_{AB} for $t = 0.5$ and $t = 1$). The UD-pricing firm thus also contributes to reduced head-to-head competition by locating away from the market center. This apparent locational disadvantage is obviated by the firm utilizing UD pricing, which makes its offer competitive over a large geographic area.

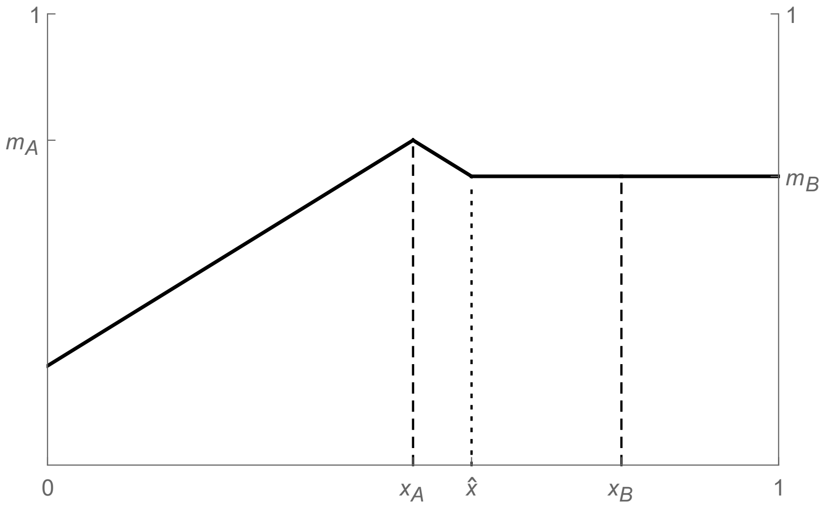

Figure 5: Pricing schedules, locations, and market areas under asymmetric strategies.

Indeed it has commonly been argued that high price discrimination in the form of UD pricing is superior to FOB pricing in settings with intense spatial competition because UD pricing makes a firm's price competitive over a broad market area (Greenhut et al., 1987; Thisse and Vives, 1988; Espinosa, 1992; Graubner et al., 2011). Firms choosing close-to FOB pricing for low values of t and choosing asymmetric UD and FOB pricing strategies for moderate t is not consistent with these results and beliefs, but is consistent with the idea that firms in intensively competitive market environments will find ways to mutually forbear and mitigate the competitive pressures to some degree. With mutual UD pricing, a 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, FOB pricing restricts direct price competition to the market's boundary, making it a tool to mitigate competition. An FOB-pricing firm that increases its mill price m only captures incremental sales at the market border regardless of the pricing strategy employed by its rival, and, meanwhile, loses profits from all infra marginal sellers.[15] Choice of asymmetric pricing strategies also works

[15] The exception is the aforementioned "market stealing" case wherein a FOB-pricing firm overbids its FOB-pricing

to limit direct competition to the market boundary and to limit market-stealing opportunities.

The second strategic tool to moderate competition, which is unexplored when firms are exogenously located at the market's endpoints, is for one or both firms to forbear from operating directly at the center of the production region. For given t, separation in space increases differentiation between the firms, mitigating the pressures of pure price competition. Indeed, when a model endows firms with the full set of tools they would ordinarily possess in the real world, it becomes apparent that some of them broadly substitute for each other. Choice of location and share of freight charges to pay is a key example. Both FOB pricing (or near-to it) and location away from the market's center are tools to mute price competition with a rival. Similarly, location near the market's center and adoption of UD or close-to UD pricing are also substitute tools to access product over a broad geographic area. Thus, the combination of locating within the first or fourth quartile to limit price competition and adopting UD or close-to UD pricing to facilitate access to farm product can be roughly equivalent to a strategy of locating near the market's midpoint to facilitate access to product and implementing FOB or close-to FOB pricing to limit direct price competition. Indeed firms adopting these asymmetric strategy combinations for moderate values of t are better off compared to two buyers locating close to the market center using FOB pricing and capturing only half of the market.

Note the simulation shows that minimum differentiation does not occur. If the distance between both firms is too small, market stealing is easily possible. The potential for market stealing, however, decreases with the inter-buyer distance x_{AB} because market stealing for i requires that $m_i - \alpha_i x_{AB} \geq m_{-i}$. As long as the distance between a buyer's location and the market center $|x_i - 1/2|$ is sufficiently large (but still small relative to the market region), the competitor is better off by locating away from the market center (close to the quartiles) and using close to UD pricing.

As t rises we see a sharp increase in spatial price discrimination; $\tilde{\alpha}$ decreases rapidly in t, approximating UD pricing for both firms for a range of values in the vicinity of $t = 2$. We also

rival sufficiently to capture the entire market area that receives a positive net price.

see an increase of spatial differentiation, x_{AB}, representing a movement of both firms towards the efficient location at the market quartiles. Further increases in t have little impact on the location choice of the buyers. Spatial price discrimination, however, begins to dissipate for larger values of t, and converges upon OD pricing.

The median 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. This non-monotonic relationship between m and t corresponds to the "weak duopsony" case described by Mérel et al. (2009). For relatively large values of t, competition is weak but given $\alpha > 0$, increases in t reduce grower supplies and buyer profits for a given value of m and, if t is sufficiently large, the market would no longer be covered. Buyers rationally respond to increases in t in this range by raising price to maintain supplies of the product, including full market coverage.

All three decision variables converge eventually to the optimal values under monopsony for sufficiently large values of t. As figures 3 and 4 illustrate, this convergence occurs for $t \approx 3$, when head-to-head competition still exists but is weak. The OD price strategy prevails throughout the monopsony range of $t > 4$. As t increases above 4.0, however, x_{AB} increases again, reflecting buyers' locations at the midpoints of their shrinking market areas. These markets feature two spatially separated monopsonies, and "subsistence" regions around the market center and/or at the region's border(s) that are unserved by either buyer.

A particularly important result illustrated in both figures 3 and 4 is that neither maximum nor minimum differentiation ever appear as part of the equilibrium strategy for buyers regardless of the value of t. Even when t is low and location at the market center maximizes a buyer's access to valuable farm product, each buyer forbears by locating strictly within the second and third quartiles.

The incentive to maximally differentiate to reduce competition does not ever dominate the other incentives at work in the generalized market environment studied here. Thus, despite many studies of spatial markets exogenously locating firms on the endpoints of Hotelling's street,[16] and some analytic results supporting maximum differentiation as an equilibrium strategy in special cases (e.g., d'Aspremont et al., 1979; 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.

To understand the reasons behind this divergence in results, note that the location of the buyer within its own market area does not affect the firm's profit under FOB pricing and inelastic farm supply (or consumer demand), as in the base Hotelling model. When $\alpha = 1$ and supplies are inelastic (and normalized to 1), local 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 incentive for firms to locate at the market boundaries to minimize direct competition becomes dominant in these cases.

However, if supply is elastic, buyer profits earned at each farm location 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 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

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

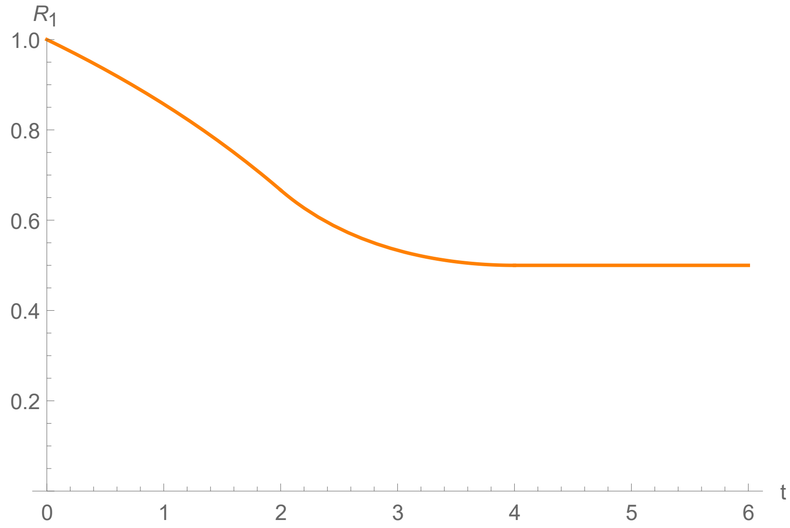

Figure 6: Ratio R_1 of total supply for buyer A using competitive FOB pricing ($m_A = 1$ and $\alpha_A = 1$) and located at the market endpoint ($x_A = 0$) relative to the same buyer located at the quartile ($x_A = 1/4$) over the relevant range of spatial competition.

supply functions. Performing the calculations yields the following:

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

Figure 6 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, $R_1(2) = \frac{2}{3}$.[17] 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, with the importance of the effect increasing in t.

Independent of the elasticity of the supply function, any price strategy that involves the buyer paying some portion of the transport costs, i.e., $0 \leq \alpha < 1$, also creates the incentive to choose

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

a central location within the procurement area because the buyer's per unit transport costs are minimized if the firm locates in the center of its own market area. This *cost effect* of firm location is also increasing in t.

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

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

Figure 7 illustrates the results for $R_2(t)$. Per-unit transport 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 one half, which reduces its unit transport costs. If $t = 4$, both buyers have identical market radii and per-unit transport costs, although the quartile buyer has twice the supply.

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, but the powerful incentives they create are missed in analyses that assume one of these polar forms of spatial pricing or locate firms exogenously. The supply effect is also missed for any analysis that assumes inelastic response to price for the residents of Hotelling's street. Both effects incentivize firms to locate at the center of their respective market areas.

Offsetting forces are the already-noted incentive to maximally differentiate in location from the rival firm to lessen price competition and an opposite incentive to locate near the center of the total production region to maximize access to farm production. Both the cost and supply

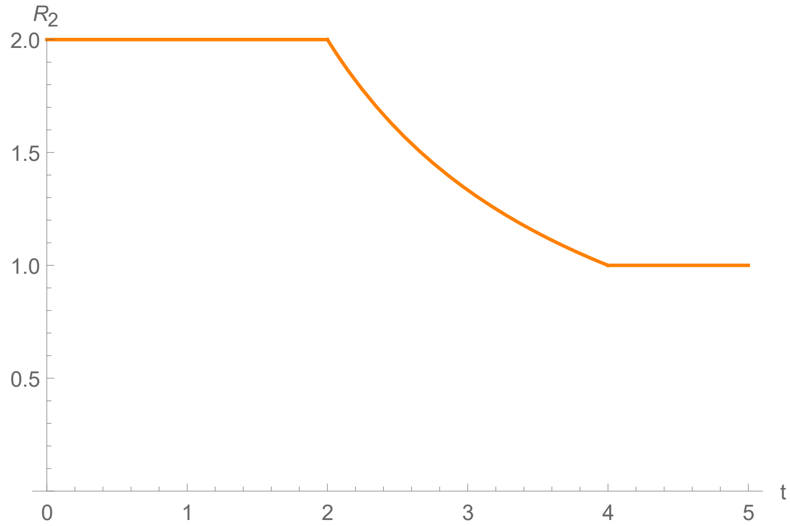

Figure 7: Ratio R_2 of per-unit transport costs paid by the OD-pricing buyer located at the endpoint ($x_A = 0$) relative to location at the quartile ($x_A = 1/4$).

effects increase in importance with t, so for low values of t they are not powerful enough relative to the incentive to choose a central location in the total production region to pull the firms to the quartiles. Firms' locations drift towards the market quartiles as t increases above 1.1, with convergence to the quartile locations for all $t \approx 1.5$ and greater (Appendix B).

5.1 Welfare Distribution

Figure 8 shows the distribution of economic surplus among producers, processors, and deadweight loss as a function of t. The outcomes of each game (i.e., m_i, α_i, and x_i) were used to calculate total buyer profit (Π) and consumer surplus (PS) in the market, based on equations (1) and (4) and with

$$\Pi = \int_0^1 (\pi_A + \pi_B)dx \text{ and } PS = \frac{1}{2}\int_0^1 q(x)^2 dx. \tag{9}$$

Deadweight loss (DWL) is computed relative to a solution PS_C where buyers operate at the quartiles and set the competitive FOB price, i.e., $(m, \alpha) = (1, 1)$, thereby eliminating surplus loss due to inefficient transportation and imperfectly competitive pricing: [18]

$$DWL = PS_C - \Pi - PS, \tag{10}$$
$$\text{with } PS_C = 2\int_{\max[0,(t-4)/4]}^{1/4} 1 - t(r - 1/4)dx.$$

Farmers capture the lion's share of the available market surplus in producer surplus (PS) for $t \in [0, 1.1]$, reflecting the competitiveness of these market structures. Whereas PS declines monotonically in t, total buyer profits increase over the range of low values of t and actually reach their maximum at approximately $t = 0.9$. Even though processors' share of profits is greater for higher values of t, the total available surplus is less in these settings. DWL is present and increasing in t because of suboptimal firm location relative to minimizing transport costs for low t and departures from competitive pricing for all $t > 0$.

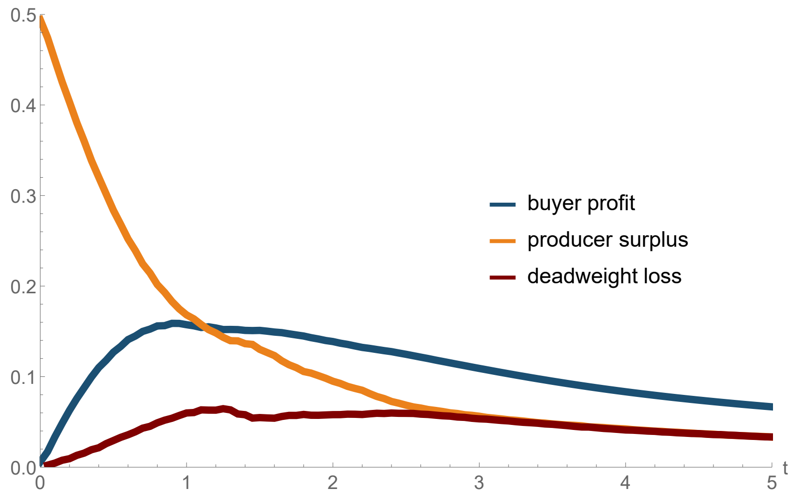

Figure 8: Buyer profit, producer surplus and deadweight loss as a function of the normalized transport cost t. The welfare measures are calculated based on the simulation results for each iteration while the graphs show median values (over 5,000 games) for each level of t.

Larger values of t dissipate the available economic surplus in the market, causing processor

[18] In the competitive setting, producers capture the market surplus and because of symmetry this surplus is identical for each market quartile. Therefore, PS_C in equation (10) is formulated for the first quartile and considers the case when the competitive buyers are not able to cover the market, i.e., $t > 4$.

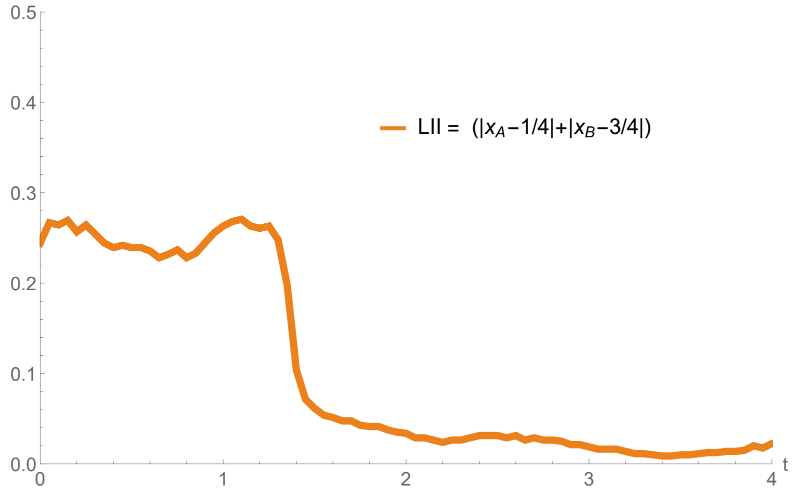

Figure 9: Location inefficiency index as a function of the normalized transport cost t.

profit to decrease in t for values of $t > 0.9$, despite processors' market power increasing as a function of t. Also notable is that DWL does not rise monotonically in t, as might be expected. Although the portion of DWL due to the exercise of oligopsony power increases in t, the inefficiency cost of suboptimal buyer locations decreases in t as firms move to the efficient locations at the market quartiles. This point is illustrated in figure 9, which displays a location inefficiency index (LII) constructed as the the sum of each firm's location relative to its efficient location at the quartile, i.e., $LII = |x_A - 0.25| + |x_B - 0.75|$. This index is roughly constant at $LII \approx 0.25$ for $t \in (0, 1.3]$, and then declines rapidly in t to converge upon zero. Inefficient locations are chosen only for low values of t when the costs of such inefficiency are low.

5.2 Market Competition

Spatial separation among buying firms in the presence of costly transportation creates differentiation between them and natural oligopsony procurement markets. This fundamental structural dimension of many farm-product procurement markets is a key reason behind concerns of buyer power in farm product markets (Faminow and Benson, 1990; Rogers and Sexton, 1994; Sexton and Xia, 2018; Hamilton and Sunding, 2020; Jung et al., 2021). Most of the theory supporting oligopsony distortions in these markets is, however, based on models with restrictive assumptions as this paper has already noted, prominent among them being locating firms at the market boundaries, using FOB pricing, and setting inelastic farm supplies.

We now ask how conclusions about market competition are impacted by the results found here for firm locations and pricing strategies. A natural basis for comparison is the analytical result of Zhang and Sexton (2001) for FOB-pricing firms located at the boundaries of Hotelling's line, given the frequency with which these assumptions are made in the literature. Their model incorporates the unit elastic supply response utilized here, which induces more competitive behavior and a higher mill price than under inelastic farm supply.

For each value of $t \in [0, 5]$ in increments of 0.05, we computed the unique value of PS for ZS's analytical result. Each iteration of the simulation yields a unique value for producer surplus, and those values were averaged across the simulation runs for each t to produce the final results. We then computed the ratio $R_3(t)$ and report the results in figure 10.

$$R_3(t) = \frac{PS_{Sim}(t)}{PS_{ZS}(t)} \tag{11}$$

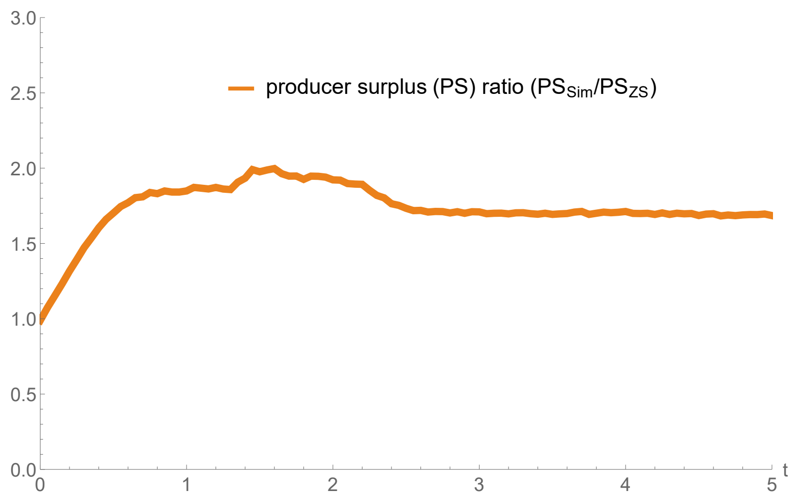

Figure 10: Ratio R_3 of median producer surplus obtained from the simulation experiments PS_{Sim} relative to the producer surplus PS_{ZS} in the model of Zhang and Sexton (2001) over the relevant range of spatial competition.

PS is higher under the simulation results for all $t > 0$. In fact, PS based on the results of the GA optimization is more than double the value from ZS, i.e., $R_3(t) > 2$, for intermediate values of t. Eventually the ratio converges to $R_3(t) \approx 1.7$ for $t \geq 2.5$. Despite the considerable importance of the spatial dimension to most farm product procurement markets, they are apparently considerably more competitive than the conventional theory would lead us to believe. The increase in producer welfare in the simulation results relative to ZS is driven by the fact that firms do not maximally differentiate, as they do by assumption in ZS, and for considerable ranges of t do not employ symmetric FOB pricing. This leads to more intense price competition and to full market coverage over a considerably larger range of t relative to ZS (i.e., $t \leq 4$ in our model relative to $t \leq 4/3$ in ZS).

6 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. 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. Nor is minimum differentiation part of equilibrium behavior, although firms locate closest to each other for low values of t, when competition is most intense. As transport costs become more important with rising t, firms gravitate to the efficient locations at the market quartiles.

We also find a rich diversity of pricing strategies depending on the importance of the spatial dimension in the market. Many of the pricing strategies involve price discrimination, with absorption of some or all freight charges by the buyer. The diversity of pricing strategies found in this paper is broadly consistent with what is observed in the real world, where firms have access to readily implementable mechanisms to absorb farm-to-plant shipping costs when it is optimal to do so.

The seemingly paradoxical result that firms locate closest to their rivals for low values of t when competition is most intense is understood in terms of firms' quest to locate accessibly to farm production in these settings when it is most valuable, their use of pricing strategies to mute the otherwise-intense competition, and the lesser importance for low t of factors that motivate firms to locate in the centers of their market areas. Firms avoid the most intense price competition by not locating in direct proximity to each other, i.e., minimum differentiation does not emerge in equilibrium, and by at least one firm choosing a pricing strategy close to FOB pricing, which limits direct price competition to the market boundaries.

Although 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. As noted, it is often optimal for firms to absorb some portion of transport costs and in that setting to locate at 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 transport costs.

In general, our results suggest farm product procurement markets are both more competitive and more efficient than is predicted based on conventional wisdom. As the possible market power exercised by buyers of agricultural products from farmers has risen to primacy among competition issues in agriculture for both western and emerging economies, we hope these results can contribute to ongoing debates regarding optimal competition policies and structure of supply chains.

References

Alemdar, N. and Sirakaya, S. (2003). On-line computation of Stackelberg equilibria with synchronous parallel genetic algorithms. *Journal of Economic Dynamics and Control*, 27(8):1503–1515.

Ali, M. B. (2004). Characteristics and production costs of U.S. sugarbeet farms. U.S. Department of Agriculture, Economic Research Service, Statistical Bulletin No. (SB-974-8).

Alvarez, A. M., Fidalgo, E. G., Sexton, R. J., and Zhang, M. X. (2000). Oligopsony power with uniform spatial pricing: Theory and application to milk processing in Spain. *European Review of Agricultural Economics*, 27(3):347–364.

Arifovic, J. (1994). Genetic algorithm learning and the cobweb model. *Journal of Economic Dynamics and Control*, 18(1):3–28.

Axelrod, R. (1997). The complexity of cooperation. In *Princeton Studies in Complexity*, Princeton (New Jersey). Princeton University Press.

Balmann, A. (1997). Farm-based modelling of regional structural change: A cellular automata approach. *European Review of Agricultural Economics*, 24(1):85–108.

Balmann, A. and Happe, K. (2001). Applying parallel genetic algorithms to economic problems: The case of agricultural land markets. In Johnston, R. and Shriver, A., editors, *Microbehavior and Macroresults: Proceedings of IIFET 2000*. International Institute of Fisheries Economics and Trade, Oregon State University, Corvallis.

Beckmann, M. (1973). Spatial oligopoly as a noncooperative game. *International Journal of Game Theory*, 2(1):263–268.

Berger, T. (2001). Agent-based spatial models applied to agriculture: A simulation tool for technology diffusion, resource use changes and policy analysis. *Agricultural Economics*, 25(2-3):245–260.

Biscaia, R. and Mota, I. (2013). Models of spatial competition: A critical review. *Papers in Regional Science*, 92(4):851–871.

Boyer, C. N. and Brorsen, B. W. (2013). Changes in beef packers' market power after the livestock mandatory price reporting act: An agent-based auction. *American Journal of Agricultural Economics*, 95(4):859–876.

Dasgupta, P. and Maskin, E. (1986). The existence of equilibrium in discontinuous economic games II: Applications. *The Review of Economic Studies*, 53(1):27–41.

d'Aspremont, C., Gabszewicz, J. J., and Thisse, J.-F. (1979). On Hotelling's "Stability in Competition". *Econometrica*, 47(5):1145–1150.

Dawid, H. (1999). *Adaptive Learning by Genetic Algorithms*. Springer, Berlin, second edition.

Dawid, H. and Kopel, M. (1998). On economic applications of the genetic algorithm: A model of the cobweb type. *Journal of Evolutionary Economics*, 8(3):297–315.

Dries, L. and Noev, N. (2006). A comparative study of vertical coordination in the dairy chains in Bulgaria, Poland, and Slovakia. In Swinnen, J. F. M., editor, *The Dynamics of Vertical Coordination in Agrifood Chains in Eastern Europe and Central Asia*, Working Paper No. 42, pages 135–165. The World Bank, Washington, DC.

Durham, C. A., Sexton, R. J., and Song, J. H. (1996). Spatial competition, uniform pricing, and transportation efficiency in the California processing tomato industry. *American Journal of Agricultural Economics*, 78(1):115–125.

Economides, N. (1984). The principle of minimum differentiation revisited. *European Economic Review*, 24(3):345–368.

Espinosa, M. P. (1992). Delivered pricing, FOB pricing and collusion in spatial markets. *Rand Journal of Economics*, 23(1):64–85.

Faminow, M. D. and Benson, B. L. (1990). Integration of spatial markets. *American Journal of Agricultural Economics*, 72(1):49–62.

Feil, J.-H., Musshoff, O., and Balmann, A. (2013). Policy impact analysis in competitive agricultural markets: A real options approach. *European Review of Agricultural Economics*, 40(4):633–658.

Foster, J. (2001). Evolutionary computation. *Nature: Reviews Genetics*, 2:428–436.

Fousekis, P. (2011). Free-on-board and uniform delivery pricing strategies in a mixed duopsony. *European Review of Agricultural Economics*, 38(1):119–139.

Fousekis, P. (2015). Location equilibria in a mixed duopsony with a cooperative. *Australian Journal of Agricultural and Resource Economics*, 59(4):518–532.

Goldberg, D. (1989). *Genetic Algorithm in Search, Optimization and Machine Learning*. Addison-Wesley, Reading (MA).

Graubner, M. (2011). *The Spatial Agent-based Competition Model (SpAbCoM)*. Number 135 in IAMO Discussion Paper. Institute of Agricultural Development in Transition Economies (IAMO).

Graubner, M., Balmann, A., and Sexton, R. J. (2011). Spatial price discrimination in agricultural product procurement markets: A computational economics approach. *American Journal of Agricultural Economics*, 93(4):949–967.

Greenhut, M. L. and Norman, G. (1995). *The Economics of Location*. Edward Elgar Publishing, Aldershot.

Greenhut, M. L., Norman, G., and Hung, C.-S. (1987). *The Economics of Imperfect Competition: A Spatial Approach*. Cambridge University Press, Cambridge.

Hamilton, J. H., Thisse, J.-F., and Weskamp, A. (1989). Spatial discrimination: Bertrand vs. Cournot in a model of location choice. *Regional Science and Urban Economics*, 19(1):87–102.

Hamilton, S. and Sunding, D. (2020). Joint olipsony-oligopoly power in food processing industries: Application to the US broiler industry. *American Journal of Agricultural Economics*, 103(4):1398–1414.

Haruvy, E., Roth, A., and Ünver, M. (2006). The dynamics of law clerk matching: An experimental and computational investigation of proposals for reform of the market. *Journal of Economic Dynamics and Control*, 30(3):457–486.

Hilger, D. A., McCarl, B. A., and Uhrig, J. W. (1977). Facilities location: the case of grain subterminals. *American Journal of Agricultural Economics*, 59(4):674–682.

Hinloopen, J. and van Marrewijk, C. (1999). On the limits and possibilities of the principle of minimum differentiation. *International Journal of Industrial Organization*, 17(5):735–750.

Hotelling, H. (1929). Stability in competition. *Economic Journal*, 39(153):41–57.

Huber, R., Bakker, M., Balmann, A., Berger, T., Bithell, M., Brown, C., Grêt-Regamey, A., Xiong, H., Le, Q. B., Mack, G., Meyfroidt, P., Millington, J., Müller, B., Polhill, J. G., Sun, Z., Seidl, R., Troost, C., and Finger, R. (2018). Representation of decision-making in European agricultural agent-based models. *Agricultural Systems*, 167:143–160.

Jung, J., Sesmero, J., and Siebert, R. (2021). A structural estimation of spatial differentiation and market power in input procurement. *American Journal of Agricultural Economics*. doi http://doi:10.1111/ajae.12239.

Kats, A. (1995). More on Hotelling's stability in competition. *International Journal of Industrial Organization*, 13(1):89–93.

Kats, A. and Thisse, J.-F. (1989). Spatial oligopolies with uniform delivered pricing. *Core Discussion Paper*, 8903.

King, G. and Logan, S. (1964). Optimum location, number and size of processing plants with raw product and final product shipments. *Journal of Farm Economics*, 46(1):94–108.

Kopp, T. and Brummer, B. (2017). Traders' market power along Indonesian rubber value chains. *China Agricultural Economic Review*, 9(2):169–187.

Kremmydas, D., Athanasiadis, I. N., and Rozakis, S. (2018). A review of agent based modeling for agricultural policy evaluation. *Agricultural Systems*, 164:95–106.

Lederer, P. and Hurter, A. P. J. (1986). Competition of firms: Discriminatory pricing and location. *Econometrica*, 54(3):623–640.

Löfgren, K. G. (1986). The spatial monopsony: A theoretical analysis. *Journal of Regional Science*, 26(4):707–730.

Lucas, M. T. and Chhajed, D. (2004). Applications of location analysis in agriculture: A survey. *Journal of the Operational Research Society*, 55(6):561–578.

Mérel, P. R. and Sexton, R. J. (2010). Kinked-demand equilibria and weak duopoly in the Hotelling model of horizontal differentiation. *The BE Journal of Theoretical Economics*, 10(1):1–34.

Meyer, K. J. (2005). Current article 9 issues and agricultural credit. *Drake Journal of Agricultural Law*, 105:105–172.

Mitchell, M. (1996). *An Introduction to Genetic Algorithm*. MIT Press, Cambridge (MA).

Mérel, P. R., Sexton, R. J., and Suzuki, A. (2009). Optimal investment in transportation infrastructure when middlemen have market power: A developing-country analysis. *American Journal of Agricultural Economics*, 91(2):462–476.

Ndahetuye, J. B., Artursson, K., Båge, R., Ingabire, A., Karege, C., Djangwani, J., Nyman, A.-K., Ongol, M. P., Tukei, M., and Persson, Y. (2020). Milk symposium review: Microbiological quality and safety of milk from farm to milk collection centers in Rwanda. *Journal of Dairy Science*, 103(11):9730–9739.

Nes, K., Colen, L., and Ciaian, P. (2021). Market power in food industry in selected EU states. European Commission, JRC Technical Report.

Norman, G. (1981). Spatial competition and spatial price discrimination. *The Review of Economic Studies*, 48(1):97–111.

Oeschssler, J. (1997). An evolutionary interpretation of mixed-strategy equilibria. *Games and Economic Behavior*, 21(1-2):203–237.

Osborne, M. and Pitchik, C. (1987). Equilibrium in Hotelling's model of spatial competition. *Econometrica*, 55(4):911–922.

Polopolus, L. (1965). Optimal plant numbers and locations for multiple product processing. *Journal of Farm Economics*, 47(2):287–295.

Price, T. C. (1997). Using co-evolutionary programming to simulate strategic behaviour in markets. *Journal of Evolutionary Economics*, 7(3):219–254.

Riechmann, T. (2001). Genetic algorithm learning and evolutionary games. *Journal of Economic Dynamics and Control*, 25(6-7):1019–1037.

Rogers, R. T. and Sexton, R. J. (1994). Assessing the importance of oligopsony power in agricultural markets. *American Journal of Agricultural Economics*, 76(5):1143–1150.

Rubinstein, A. (1991). Comments on the interpretation of game theory. *Econometrica*, 59(4):909–924.

Schipmann, C. and Qaim, M. (2010). Spillovers from modern supply chains to traditional markets: Product innovation and adoption by smallholders. *Agricultural Economics*, 41(3-4):361–371.

Schuler, R. E. and Hobbs, B. F. (1982). Spatial price duopoly under uniform delivered pricing. *Journal of Industrial Economics*, 31(1-2):175–187.

Sesmero, J. P., Balagtas, J. V., and Pratt, M. (2015). The economics of spatial competition for corn stover. *Journal of Agricultural and Resource Economics*, 40(3):425–441.

Sexton, R. J. and Xia, T. (2018). Increasing concentration in the agricultural supply chain: Implications for market power and sector performance. *Annual Review of Resource Economics*, 10:229–251.

Shilony, Y. (1981). More on spatial oligopoly as a noncooperative game. *International Journal of Game Theory*, 10(3-4):117–123.

Son, Y. S. and Baldick, R. (2004). Hybrid coevolutionary programming for Nash equilibrium search in games with local optima. *IEEE Transactions on Evolutionary Computation*, 8(4):305–315.

Stollsteimer, J. (1963). A working model for plant numbers and locations. *Journal of Farm Economics*, 45(3):631 – 645.

Stollsteimer, J., Courtney, R., and Sammet, L. (1975). *Regional Efficiency in the Organization of Agricultural Processing Facilities: An Application to Pear Packing in the Lake County Pear District, California*. University of California, Giannini Foundation of Agricultural Economics, Berkeley, CA. Monograph No. 35.

Tesfatsion, L. (2006). Agent-based computational economics: A constructive approach to economic theory. In Tesfatsion, L. and Judd, K., editors, *Handbook of Computational Economics*, volume 2 of *Handbooks in Economics*. Elsevier/North Holland, Amsterdam.

Thisse, J.-F. and Norman, G. (1994). *The Economics of Product Differentiation*. Edward Elgar Publishing, New York.

Thisse, J.-F. and Vives, X. (1988). On the strategic choice of spatial price policy. *American Economic Review*, 78(1):122–137.

Tribl, C., Morawetz, U., and Salhofer, K. (2017). Spatial competition in a mixed market-the case of milk processors. Paper presented at the XV EAAE Congress: *Towards Sustainable Agri-food Systems: Balancing Between Markets and Society*, August 29 - September 1, 2017, Parma, Italy.

van Leeuwen, E. and Lijesen, M. (2016). Agents playing Hotelling's game: An agent-based approach to a game theoretic model. *The Annals of Regional Science*, 57(2-3):393–411.

von Thünen, J. H. (1826). *Der isolierte Staat in Beziehung auf Landwirtschaft und Nationalökonomie*. Gustav Fischer, Stuttgart (reprinted 1966).

Wang, Y., Delgado, M. S., Sesmero, J., and Gramig, B. M. (2020). Market structure and the local effects of ethanol expansion on land allocation: A spatially explicit analysis. *American Journal of Agricultural Economics*, 102(5):1598–1622.

Zhang, M. and Sexton, R. J. (2000). Captive supplies and the cash market price: A spatial markets approach. *Journal of Agricultural and Resource Economics*, 25(1):88–108.

Zhang, M. and Sexton, R. J. (2001). FOB or uniform delivered prices: Strategic choice and welfare effects. *Journal of Industrial Economics*, 49(2):197–221.

Zhang, T. and Brorsen, B. W. (2010). The long-run and short-run impact of captive supplies on the spot market price: An agent-based artificial market. *American Journal of Agricultural Economics*, 92(4):1181–1194.

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 Nash-equilibria (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.

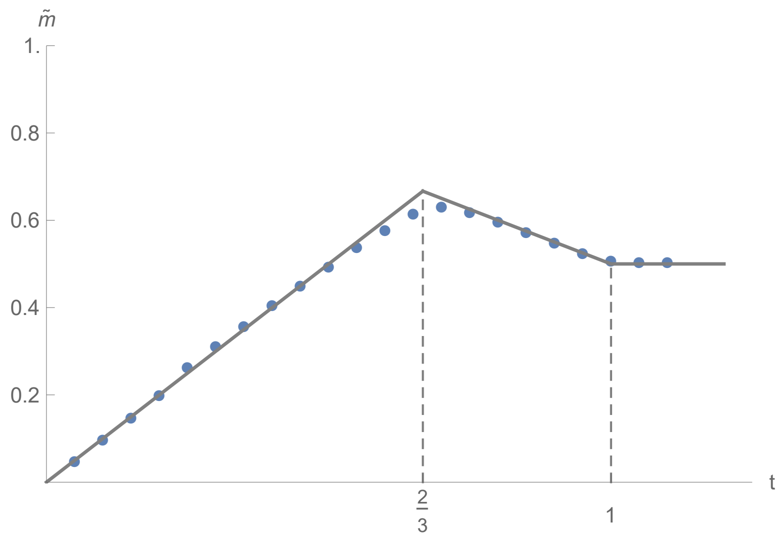

Figure A.1: The analytical equilibrium FOB price schedule (gray) due to Mérel and Sexton (2010, Figure 4) and the average FOB price for selected levels of normalized transport costs from the simulation (blue). The points represent the average mill price over 5,000 games (10,000 observations).

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

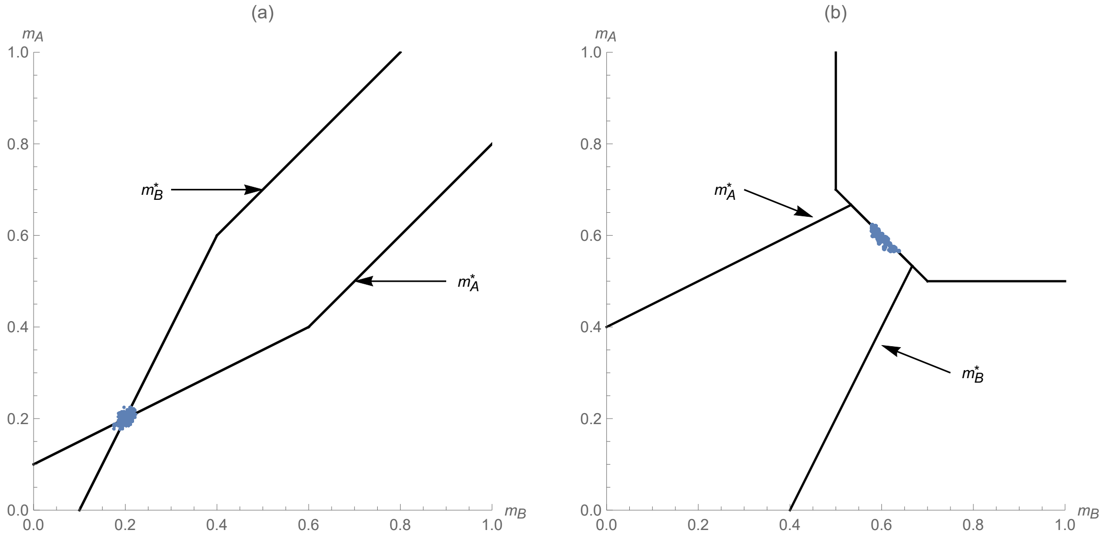

Figure A.2: FOB price equilibrium for (a) $t = 0.2$ (*duopoly*) and (b) $t = 0.8$ (*weak duopoly*) according to (Figure 6 and 7 in) Mérel and Sexton (2010) and the simulation results (blue) of 5,000 games (10,000 observations).

strategies in the range $2/3 \leq t < 1$, whereas there is a unique symmetric NE if $0 \leq t < 2/3$.[19] 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 under UD Pricing

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.[20] 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

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

[20] 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.

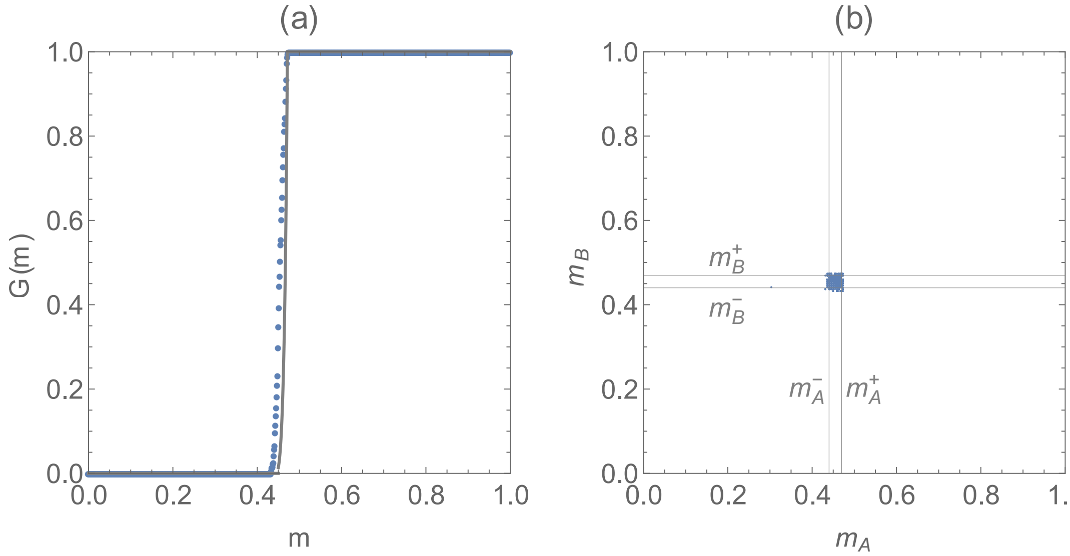

Figure A.3: The UD pricing duopsony due to Zhang and Sexton (2001) for $t = 1.0$: (a) Mixed strategy (expressed as cumulative distribution function) $G(m)$ and (b) upper and lower price limits of both buyers under $G(m)$. Simulation results are colored in blue based on 5,000 games (10,000 observations).

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). 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. This becomes apparent for the closely related problem investigated by Shilony (1981): the UD pricing duopoly without spatial arbitrage by consumers. These results are illustrated in Figure A.4.

In both examples shown in figures A.3 and A.4, 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. A full characterization of the equilibrium, however, is not feasible in cases where we do not obtain analytical results.

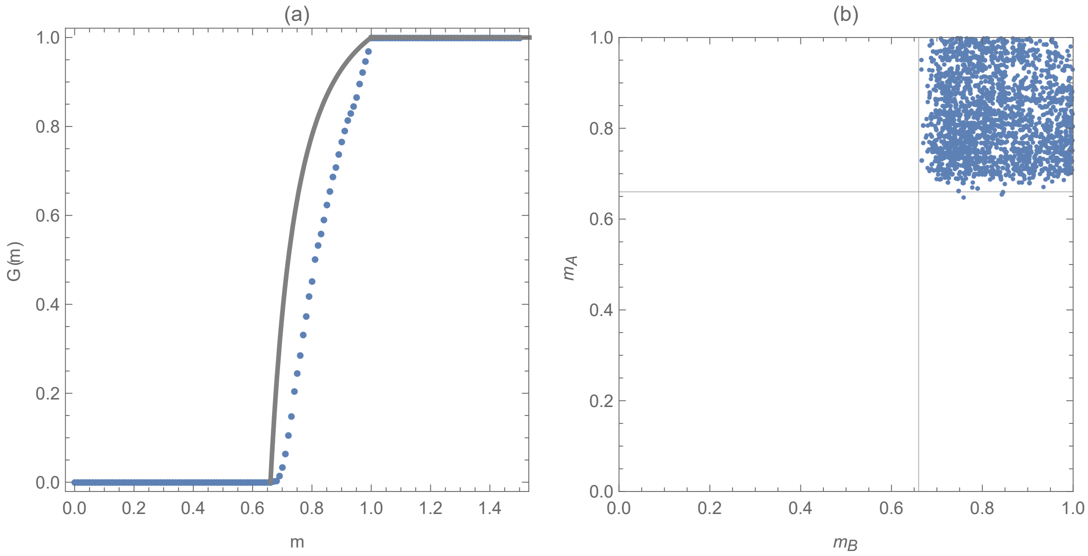

Figure A.4: The UD pricing duopoly due to Shilony (1981) for $t = 1.0$: (a) Mixed strategy (expressed as cumulative distribution function) $G(m)$ and (b) upper ($m = 1$) and lower price limits of both buyers under $G(m)$. Simulation results are colored in blue based on 5,000 games (10,000 observations).

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).[21] This model is a two-stage game where players first select location and the optimal (subgame 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.[22] 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.5.[23] 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

[21] 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).
[22] 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)).
[23] This figure replicates Figure 7 in Hinloopen and van Marrewijk (1999).

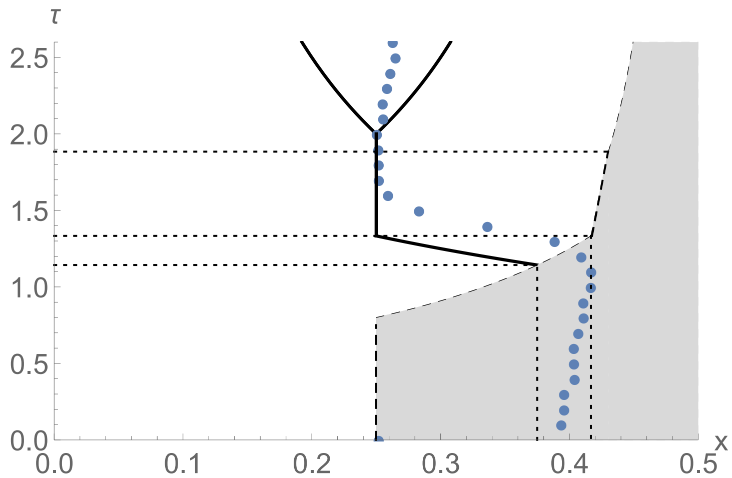

Figure A.5: The Firm's location in the half market depending on the effective reservation price τ due to Hinloopen and van Marrewijk (1999) and the outcome of the simulations (in blue). Each dot represents the average over 5,000 games (10,000 observations).

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 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: Median values and standard deviation of the decision variables.

t	$\tilde{m}$	SD(m)	$\tilde{\alpha}$	SD(α)	$\tilde{x}_{AB}$	SD(x_{AB})
0.00	0.9894	0.0767	0.5054	0.2850	0.4937	0.2030
0.05	0.9811	0.0501	0.8833	0.1693	0.2356	0.0832
0.10	0.9622	0.0433	0.8929	0.1918	0.2381	0.0877
0.15	0.9445	0.0123	0.8989	0.1355	0.2306	0.0713
0.20	0.9256	0.0207	0.8913	0.1823	0.2431	0.0745
0.25	0.9077	0.0125	0.8972	0.1531	0.2356	0.0720
0.30	0.8900	0.0163	0.8714	0.1630	0.2481	0.0741
0.35	0.8706	0.0146	0.8685	0.1626	0.2556	0.0720
0.40	0.8521	0.0154	0.8577	0.1625	0.2632	0.0668
0.45	0.8353	0.0153	0.8402	0.1712	0.2607	0.0697
0.50	0.8185	0.0174	0.8696	0.1738	0.2607	0.0690
0.55	0.8026	0.0183	0.8530	0.1997	0.2657	0.0679
0.60	0.7841	0.0196	0.8367	0.2086	0.2732	0.0658
0.65	0.7718	0.0209	0.8227	0.1917	0.2757	0.0646
0.70	0.7550	0.0260	0.8197	0.2408	0.2807	0.0663
0.75	0.7472	0.0297	0.8452	0.2470	0.2832	0.0689
0.80	0.7267	0.0312	0.7916	0.2796	0.2957	0.0655
0.85	0.7152	0.0351	0.7715	0.3121	0.3008	0.0575
0.90	0.7039	0.0377	0.7728	0.3275	0.3033	0.0583
0.95	0.6966	0.0460	0.7613	0.3487	0.3108	0.0604
1.00	0.6868	0.0481	0.7554	0.3639	0.3108	0.0592
1.05	0.6737	0.0531	0.7229	0.3715	0.3133	0.0548
1.10	0.6618	0.0546	0.6717	0.3697	0.3158	0.0561
1.15	0.6429	0.0567	0.5967	0.3613	0.3183	0.0597
1.20	0.6232	0.0603	0.5849	0.3603	0.3208	0.0658
1.25	0.6025	0.0629	0.4207	0.3544	0.3258	0.0731
1.30	0.5913	0.0607	0.3726	0.3260	0.3258	0.0777
1.35	0.5827	0.0562	0.2638	0.3006	0.3509	0.0798
1.40	0.5788	0.0531	0.2332	0.2779	0.4010	0.0751
1.45	0.5657	0.0375	0.1798	0.2208	0.4361	0.0615
1.50	0.5555	0.0338	0.1798	0.2119	0.4486	0.0532

Continued on next page.

Table B.1 – continued from previous page

t	$\tilde{m}$	SD(m)	$\tilde{\alpha}$	SD(α)	$\tilde{x}_{AB}$	SD(x_{AB})
1.55	0.5470	0.0308	0.1864	0.2008	0.4561	0.0448
1.60	0.5386	0.0275	0.1885	0.1838	0.4536	0.0419
1.65	0.5295	0.0291	0.1952	0.1842	0.4586	0.0397
1.70	0.5251	0.0261	0.2042	0.1815	0.4586	0.0366
1.75	0.5152	0.0251	0.1871	0.1725	0.4662	0.0328
1.80	0.5055	0.0233	0.1859	0.1581	0.4662	0.0314
1.85	0.5028	0.0223	0.1936	0.1440	0.4637	0.0294
1.90	0.4935	0.0230	0.1785	0.1372	0.4662	0.0258
1.95	0.4899	0.0203	0.1789	0.1393	0.4687	0.0234
2.00	0.4839	0.0217	0.1926	0.1233	0.4687	0.0214
2.05	0.4727	0.0196	0.1792	0.1280	0.4762	0.0202
2.10	0.4730	0.0190	0.1943	0.1156	0.4737	0.0201
2.15	0.4639	0.0164	0.1819	0.0949	0.4737	0.0173
2.20	0.4598	0.0142	0.1827	0.0908	0.4762	0.0140
2.25	0.4616	0.0154	0.2136	0.0653	0.4737	0.0130
2.30	0.4578	0.0145	0.2349	0.0564	0.4737	0.0118
2.35	0.4637	0.0151	0.2685	0.0496	0.4712	0.0120
2.40	0.4678	0.0135	0.3020	0.0418	0.4687	0.0113
2.45	0.4691	0.0117	0.3218	0.0368	0.4687	0.0119
2.50	0.4728	0.0123	0.3445	0.0354	0.4687	0.0114
2.55	0.4742	0.0115	0.3610	0.0327	0.4712	0.0121
2.60	0.4769	0.0121	0.3764	0.0335	0.4687	0.0112
2.65	0.4788	0.0101	0.3898	0.0264	0.4737	0.0115
2.70	0.4801	0.0112	0.4003	0.0290	0.4712	0.0116
2.75	0.4837	0.0108	0.4139	0.0254	0.4737	0.0108
2.80	0.4842	0.0109	0.4219	0.0253	0.4737	0.0099
2.85	0.4866	0.0097	0.4329	0.0230	0.4762	0.0100
2.90	0.4866	0.0094	0.4420	0.0223	0.4787	0.0102
2.95	0.4899	0.0107	0.4495	0.0243	0.4787	0.0095
3.00	0.4918	0.0112	0.4582	0.0250	0.4812	0.0087
3.05	0.4909	0.0094	0.4604	0.0202	0.4837	0.0093
3.10	0.4923	0.0110	0.4679	0.0232	0.4837	0.0093
3.15	0.4945	0.0113	0.4701	0.0221	0.4862	0.0095
3.20	0.4949	0.0117	0.4748	0.0247	0.4887	0.0096
3.25	0.4961	0.0112	0.4814	0.0224	0.4887	0.0091
3.30	0.4976	0.0111	0.4875	0.0223	0.4912	0.0090
3.35	0.4992	0.0129	0.4877	0.0238	0.4912	0.0104

Continued on next page.

Table B.1 – continued from previous page

t	$\tilde{m}$	SD(m)	$\tilde{\alpha}$	SD(α)	$\tilde{x}_{AB}$	SD(x_{AB})
3.40	0.4961	0.0115	0.4867	0.0224	0.4937	0.0091
3.45	0.4983	0.0102	0.4909	0.0190	0.4937	0.0096
3.50	0.4981	0.0124	0.4921	0.0243	0.4962	0.0100
3.55	0.4989	0.0115	0.4913	0.0219	0.4987	0.0096
3.60	0.5000	0.0117	0.4964	0.0206	0.4987	0.0113
3.65	0.5026	0.0117	0.5016	0.0212	0.4987	0.0109
3.70	0.5058	0.0103	0.5082	0.0184	0.5013	0.0117
3.75	0.5005	0.0120	0.5002	0.0195	0.5038	0.0112
3.80	0.5026	0.0114	0.5027	0.0191	0.5013	0.0115
3.85	0.5035	0.0118	0.5068	0.0198	0.4962	0.0115
3.90	0.5034	0.0102	0.5036	0.0168	0.4962	0.0134
3.95	0.5050	0.0103	0.5062	0.0165	0.4962	0.0136
4.00	0.5047	0.0093	0.5077	0.0151	0.4912	0.0171
4.05	0.5017	0.0107	0.5030	0.0178	0.4937	0.0190
4.10	0.5016	0.0107	0.5006	0.0169	0.4912	0.0207
4.15	0.5019	0.0088	0.5022	0.0137	0.4912	0.0235
4.20	0.5021	0.0101	0.5026	0.0166	0.4962	0.0259
4.25	0.5030	0.0094	0.5039	0.0144	0.4962	0.0279
4.30	0.5020	0.0099	0.5026	0.0158	0.5013	0.0310
4.35	0.5017	0.0106	0.5026	0.0173	0.5038	0.0327
4.40	0.5014	0.0082	0.5010	0.0135	0.5088	0.0354
4.45	0.5032	0.0089	0.5056	0.0147	0.5138	0.0345
4.50	0.4992	0.0089	0.5010	0.0158	0.5138	0.0382
4.55	0.5003	0.0095	0.5011	0.0162	0.5238	0.0389
4.60	0.5021	0.0081	0.5031	0.0139	0.5263	0.0386
4.65	0.4994	0.0094	0.4982	0.0158	0.5238	0.0410
4.70	0.5001	0.0085	0.4990	0.0141	0.5338	0.0406
4.75	0.4993	0.0082	0.4968	0.0134	0.5338	0.0405
4.80	0.5001	0.0086	0.5000	0.0148	0.5338	0.0436
4.85	0.5002	0.0099	0.4986	0.0167	0.5414	0.0408
4.90	0.5011	0.0084	0.5020	0.0140	0.5464	0.0427
4.95	0.5015	0.0082	0.5021	0.0141	0.5464	0.0428
5.00	0.4995	0.0082	0.4987	0.0142	0.5514	0.0425

Appendix C

C.1 Distribution of the decision variables and their combination for selected levels of the normalized transport costs

Each of the following graph reports results for the last 5% of 2500 generations of a GA run. For each level of t, 40 runs were conducted. Accordingly, we obtain 10,000 observations (5,000 for each buyer). While the density plots in the third row of each figure represent the combination of decision variables selected by each buyer in each of these repetition of the game, the histograms and the density plots in the second row show aggregated data for both buyers. The darker the color in the density plots, the more often this combination was observed in the simulations.

C.1.1 Distribution of the decision variables for *t=0.5*

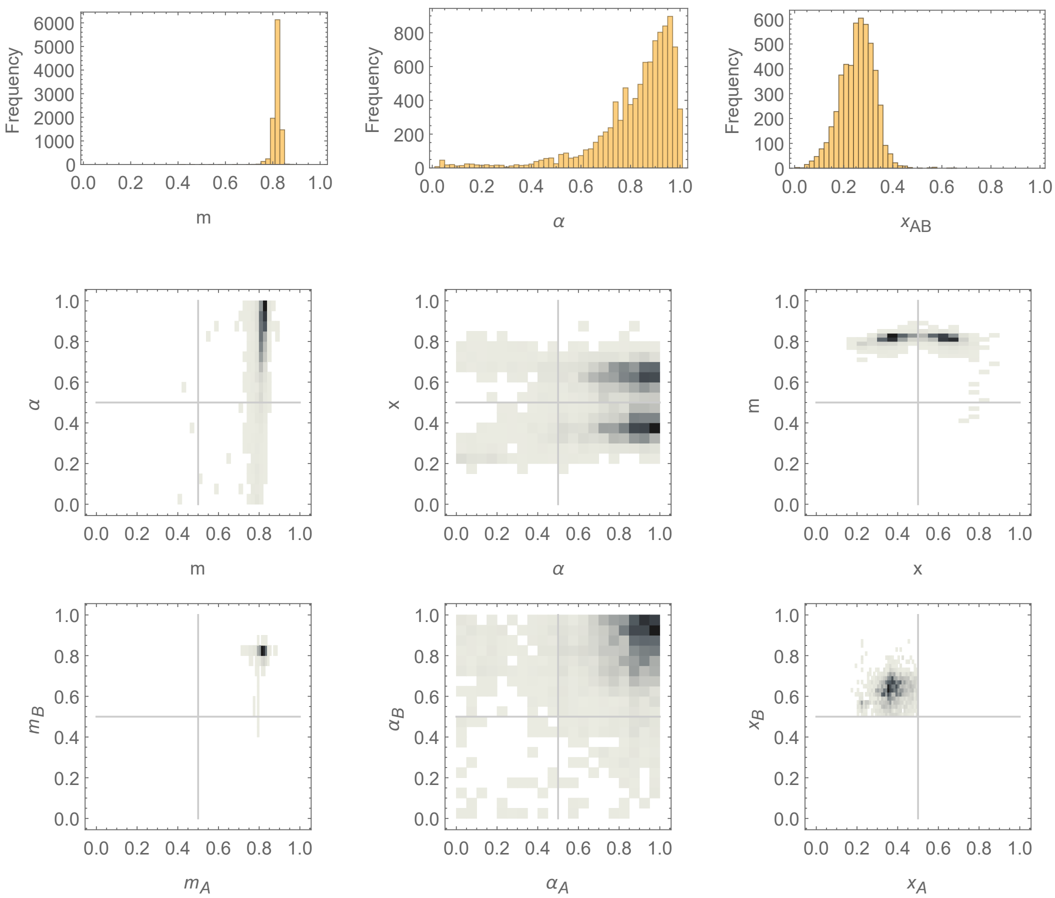

Figure C.1: Distribution and combination of the decision variables (m_i, α_i, x_i) and the distribution of the inter-buyer distance x_{AB}.

C.1.2 Distribution of the decision variables for *t=1.0*

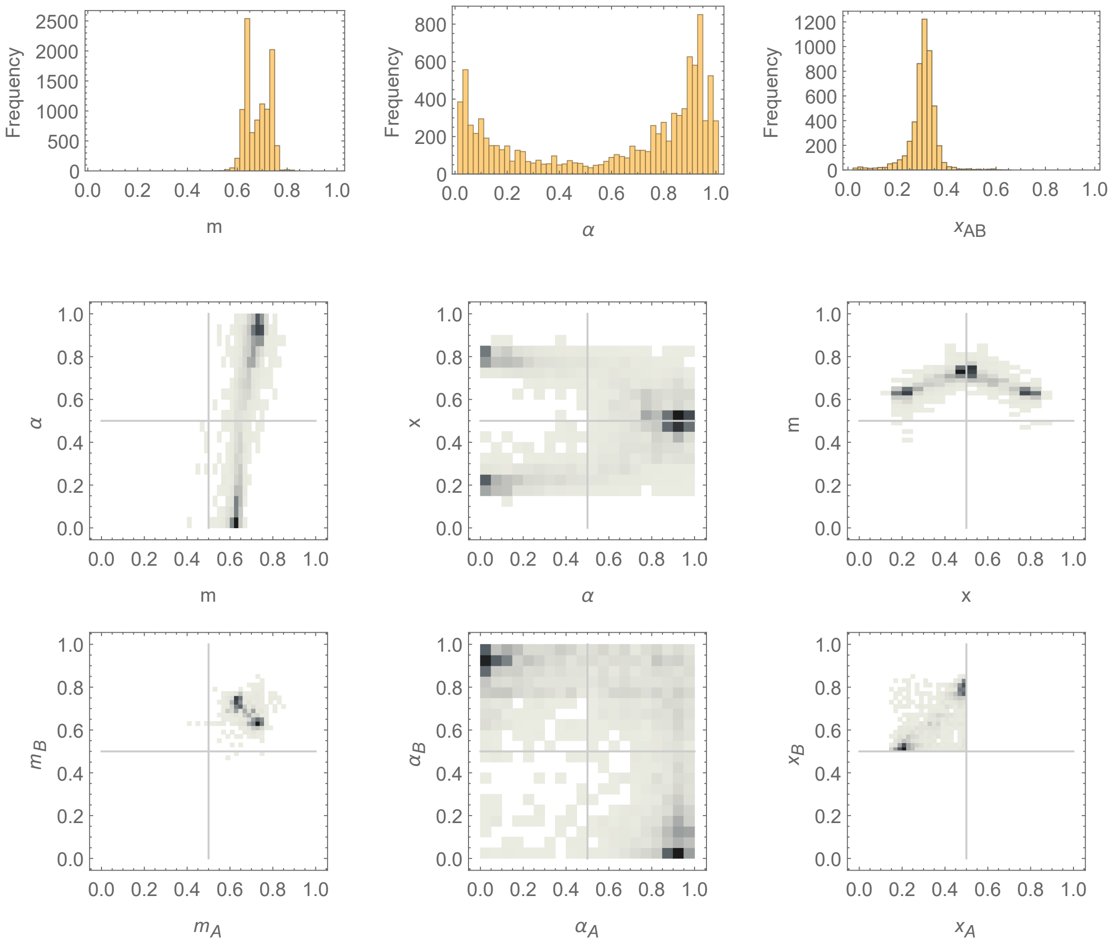

Figure C.2: Distribution and combination of the decision variables (m_i, α_i, x_i) and the distribution of the inter-buyer distance x_{AB}.

C.1.3 Distribution of the decision variables for *t=1.5*

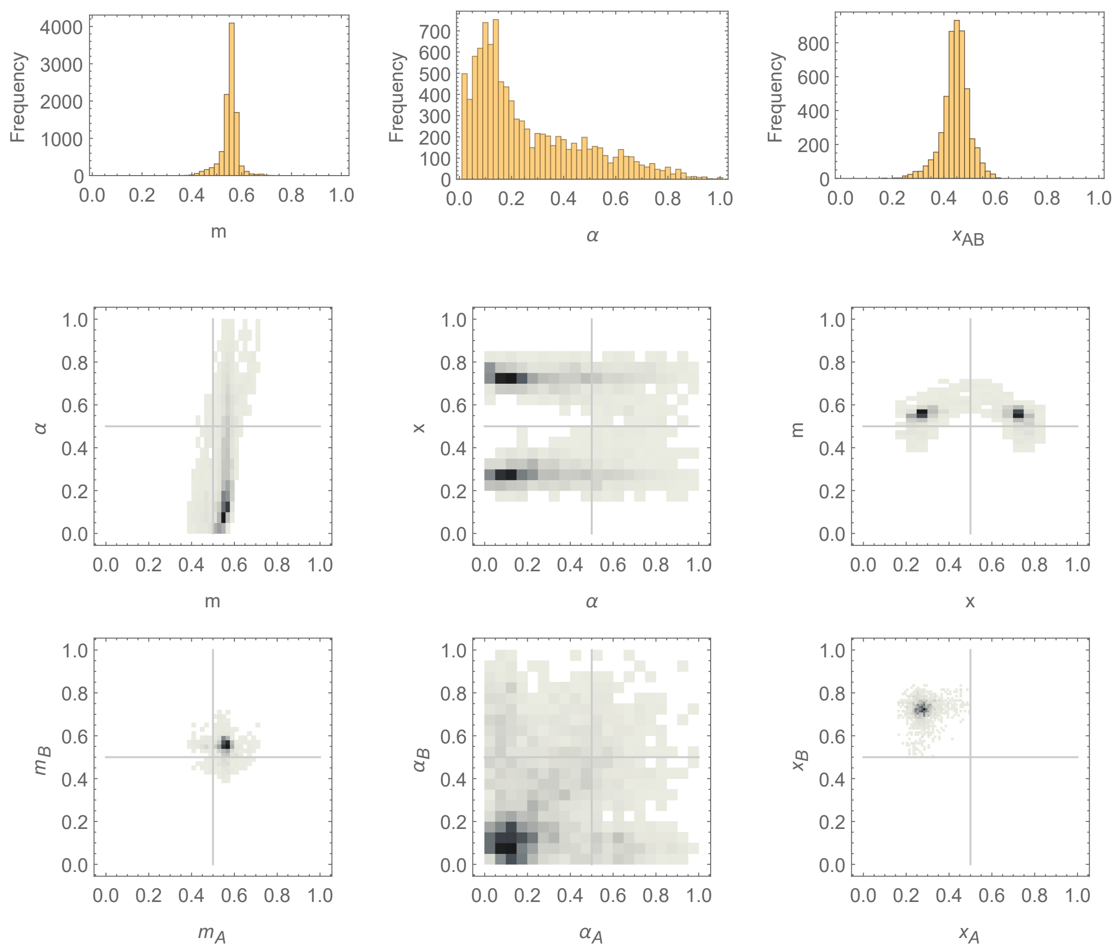

Figure C.3: Distribution and combination of the decision variables (m_i, α_i, x_i) and the distribution of the inter-buyer distance x_{AB}.

C.1.4 Distribution of the decision variables for *t=2.0*

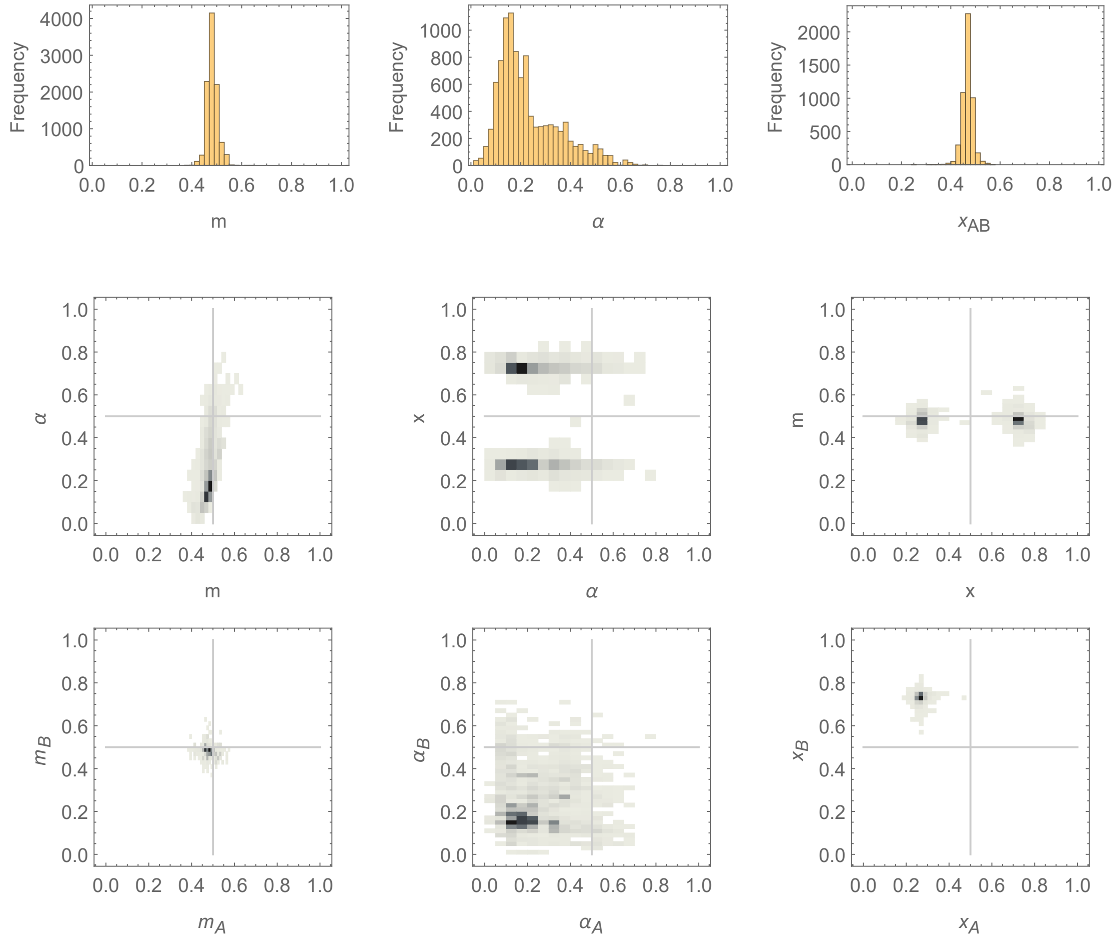

Figure C.4: Distribution and combination of the decision variables (m_i, α_i, x_i) and the distribution of the inter-buyer distance x_{AB}.

C.1.5 Distribution of the decision variables for *t=3.0*

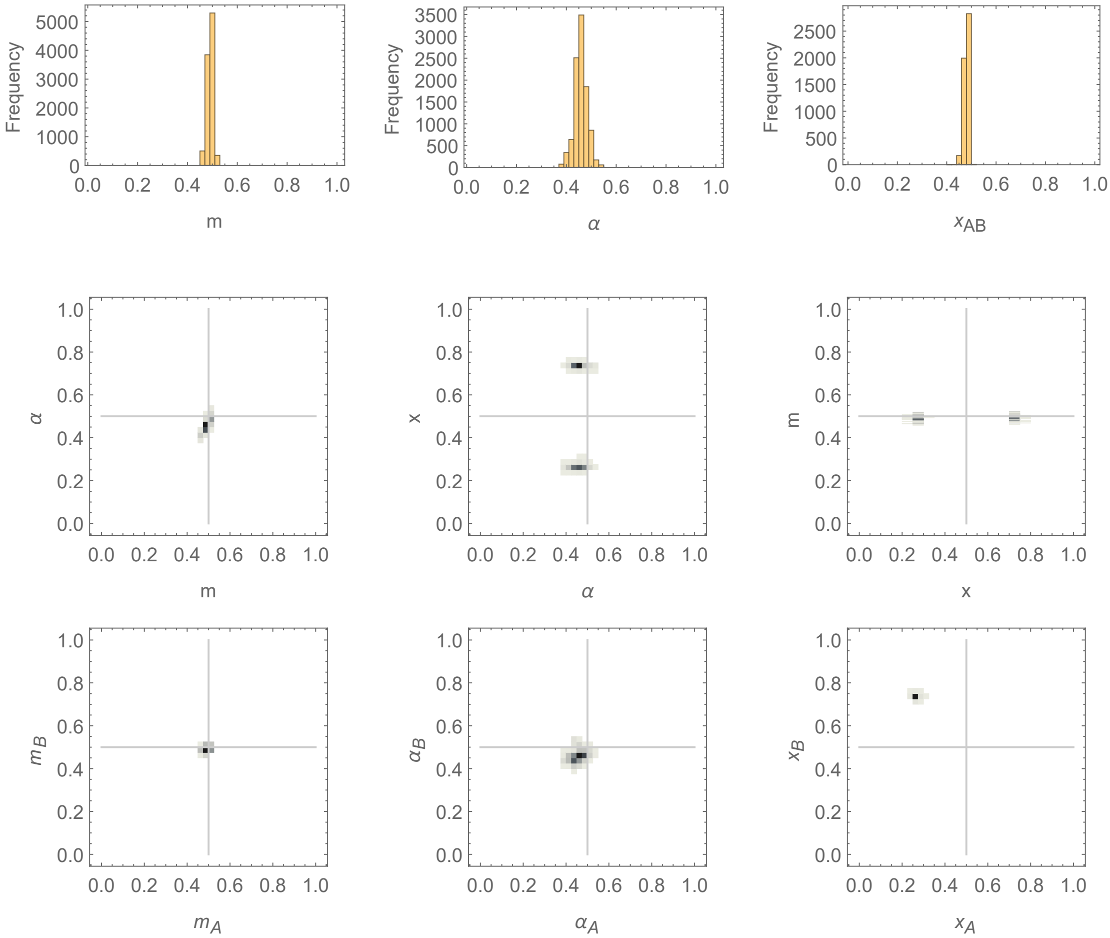

Figure C.5: Distribution and combination of the decision variables (m_i, α_i, x_i) and the distribution of the inter-buyer distance x_{AB}.

C.1.6 Distribution of the decision variables for *t=4.0*

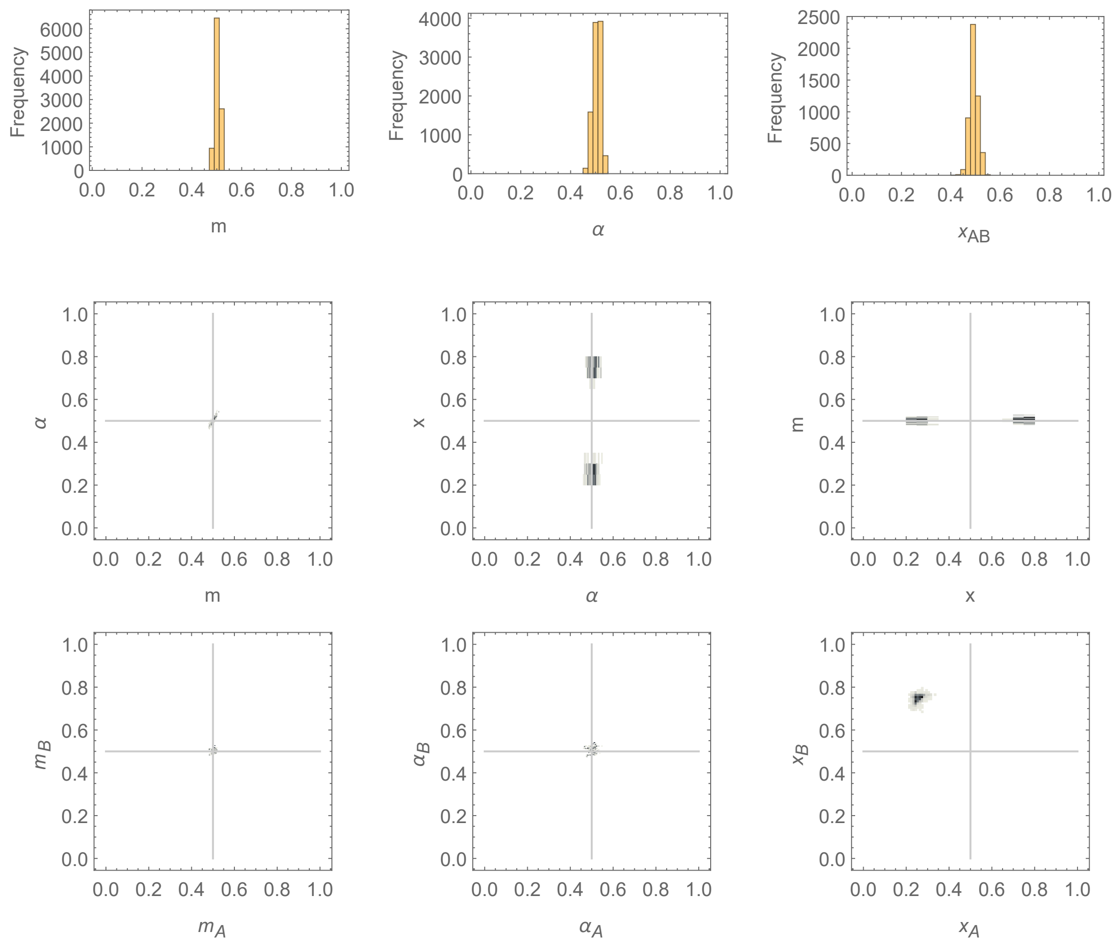

Figure C.6: Distribution and combination of the decision variables (m_i, α_i, x_i) and the distribution of the inter-buyer distance x_{AB}.