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The profit implications of altruistic versus egoistic orientations for business-to-business exchanges

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ABSTRACT

This study significantly expands upon previous research by Hill and Watkins [Hill, Ronald Paul and Watkins, Alison, (2007), "A Simulation of Moral Behavior within Marketing Exchange Relationships," Journal of the Academy of Marketing Science, 35 (2), 417–429] involving business-to-business exchanges through the use of a more sophisticated simulation and a different theoretical orientation. Profitability implications for sellers and firms in the context of information sharing and dynamic firm adaptation are explored using *q*-learning evolutionary models and embedded artificial trading agents in a competitive environment. This method allows buyer agents to react to complex and evolving circumstances based on historical information about seller agents. The results suggest that sellers with more cooperative strategies are more profitable in the long run, especially when firms employ multiple agents.

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1. Orientation

The strategic connection between the treatment of customers and organizational success has been discussed by marketing scholars for decades (Corfman & Lehmann, 1993). From production models to the marketing concept to relationship marketing (RM) paradigms, academics and practitioners have evolved behavioral expectations of sellers to meet the rising requirements of buyers (Morgan & Hunt, 1994). The underlying premise is that RM leads to the development of mutually-rewarding and long-term associations among trading partners. While disagreements persist, marketers concur that trust and subsequent loyalty garnered from relationship marketing results in a more profitable and stable client base (see Garbarino & Johnson, 1999). Recent evidence using simulated business-to-business (B2B) agents[2] lends additional credibility to these findings (Hill & Watkins, 2007).

Of course, such behaviors may be characterized in a number of ways, including how relationship marketing significantly overlaps with ethical business practices (Murphy, Laczniak, & Wood, 2007). Using this perspective, organizations as well as individuals seek trustworthy partners who are committed to fair transactions, i.e., dealings that are in the best interest of their firms while also serving the needs of customers (Watkins & Hill, 2005). Research in business ethics has shown the positive impact of developed moral reasoning capability, which provides employees with the skills to navigate such competing demands (Monga, 2007).

At a fundamental level, competitive and cooperative tactics exemplify business-to-business transactions. These orientations impact financial success in both positive and negative manners (Lou, Rindfleisch, & Tse, 2007; Lou, Slotegraff, & Pan, 2006). Lehmann (2001) suggests that envy and altruism are essential ingredients to these approaches, and appreciably influence the payoffs of exchange participants. Under conditions of envy, parties place little emphasis on others' transactional needs, except to the extent necessary to encourage further negotiations. On the other hand, fairness, duty, or obligation may arise among a subset of firms and individuals because of altruistic belief systems, described by Fehr and Schmidt (1999, p.819) as "self-centered inequity aversion".

The purpose of our investigation is to examine different seller-firm emphases on transactional fairness, payoff functions, and profit implications within the context of information sharing and dynamic firm adaptation. Simulation is conducted using a hybrid evolutionary model and embedded artificial trading agents in a competitive environment, as recommended by Midgley, Marks, and Cooper (1997). This method allows buyer agents to react to a complex and evolving set of marketplace circumstances based upon historical information about seller agents. A primary benefit of this technique is its capacity to look at cumulative profits over a very large number of competitive and cooperative interactions. The configuration used here is consistent with the model by Raju and Roy (2000) that examines the impact of pricing strategies and information on profitability across a limited number of firms.

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[2] Our use of the term "agent" refers to its computer-generated nature rather than independent functioning in the marketplace.

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Table 1
Summary statement of seller motivations and reinforcement schemas

Seller type	Motivation	Reinforcement
Egoists	Personal income maximization	Amount of earnings—will always seek more than previous successful exchanges.
Realists	Increase personal rating and income maximization	Average individual rating times earnings on most recent transaction.
Loyalists	Increase firm rating without concern for profitability	Average firm rating—will offer prices based on how they previously impacted firm ratings.
Altruists	Increase personal rating without concern for profits	Individual rating—will offer prices based on how they previously impacted individual ratings.

The next subsection presents details on the simulation's parameters and the nature of buyer–seller interactions, their consequences, and their potential implications. We then present the simulation results, followed by a discussion of marketing practice and theory.

1.1. Simulation model

The approach used here is common to agent-based computational economic (ACE) models, which involve computer science, cognitive science, and evolutionary economics (see Vag, 2004). Within the context of an ACE model, agents have the opportunity to learn from their actions and the actions of others and modify their behavior (Tesfatsion, 2003). For example, Kirman and Vriend (2001) created such an ACE model using two groups—buyers who learn that loyalty results in lower prices and sellers who learn that lower prices bring greater loyalty. Their research provides a starting point for our study, which concentrates on a model of reinforcement learning involving agent–environment interactions that are synchronized and occur in a discrete cycle. Langerman and Ehlers (2005) sequence these events as follows:

1. The agent senses relevant aspects of the environment.
2. Based on this understanding, the agent selects a specific action.
3. Based on both the understanding and the chosen action, the environment undergoes transition and some form of payoff is generated.
4. The payoff is allocated to the collective where the agent is embedded.

The authors call this method *q*-learning, which they define as a straightforward and mathematical-based learning paradigm. The first step is to create the initial agent's action-value function *Q*. If prior information is not available, values are determined arbitrarily. The first agent assesses the current state of the environment x and then chooses an action a to execute as directed by its action-value function, but will occasionally select another course for the sake of learning. The system subsequently implements the action and registers the reward r and state y that follows. The final step is to update the action-value estimate for the agent's state-action pairing. Interactions continue through multiple stages.

The orientations of our seller agents capture the extremes presented by Lehmann (2001). Specifically, agents on the selling side are described as *egoists* who seek short-term financial gain for themselves with explicit disregard for the well-being of their trading partners, or *altruists* who selflessly try to meet the desires of trading partners even if it negatively impacts short-term profitability. However, consistent with other investigations (see Hill & Watkins, 2007), two additional middle-ground orientations also are examined: *realists* who seek to maximize individual gain while at least trying to maintain relationships with buyers, and *loyalists* who operate to advance reputations of their firms among buyers even if it negatively impacts personal success (see Table 1 for details on how these descriptions are operationalized).

Agents exist within a single system or industry and each agent is affiliated with one buyer or seller firm so that a defined set of players and actions are easily identified for purposes of relationship-building. Except for the original formulation using single agents, models contain four seller firms of 100 agents each. Uniform scenario firms have an identical contingent of egoists, realists, loyalists, or altruists. In the mixed model, seller firms are dominated by one type ($n=55$) and contain an equal number of the remaining three types ($n=15$), with each orientation dominating one of the four seller firms. In firms with the capacity for adaptation, learning occurs among seller firms that allow them to modify their agent mix over time.

Each seller's personal orientation guides price-setting decisions. The product base price is $750 and a seller can add a markup of up to $250. A seller's transactional income is calculated as 1/2 the base price plus the full markup; therefore, you might expect more egoistic agents whose goal is profit-maximization to charge the highest possible amount. However, each subsequent transaction is modeled so sellers learn through reinforcement which price will give the best reward given their orientations.

For instance, Buyer B may buy from an egoist Seller S, who determines the markup by reviewing possibilities from $0 to $250 in $10 increments. If S has not exchanged before, S randomly selects a markup. At the completion of the exchange, S receives the reward, which for an egoist is a function of markup income on the transaction; the reward for charging $100 markup is the full $100. The next time S selects a price, an analysis of all possibilities will show the reward for selecting $100 is less than any higher markup (up to $250), which will cause S to consider larger amounts. Over time S builds enough knowledge about prices to find out that higher markups generally achieve greater rewards according to its payoff function. Egoistic sellers will not always select the highest amount because: (a) a small random value is added to each reward during the selection process, which means a lower markup will show a higher reward in some cases, and (b) a small percentage of markups are ignored. (Note that the other orientations are more sensitive to buyers' reactions to prices.)

Buyers move within the marketplace in search of sellers with whom they can have positive experiences. Although buyers intuitively are most satisfied when sellers make their offerings at the base price, they do have a level of tolerance for seller markups. For purposes of the simulation, buyers accept markups between $10 and $200, although markups may be as high as $250 in order to realize the full manifestation of seller tactics and buyer reactions. As a result of this variation, buyers rate transactions by calculating: (a) whether the markup was within their tolerance level, and (b) whether the new rating improves a seller's average rating. As an example, consider Seller A, who has a current average rating of 88 and hopes to exchange with Buyer B for $800, which is well within B's tolerance level of $200 above the base. B will rate A at 95 for the current transaction. The complete rating scale and system are articulated in Table 2.

The ratings are provided to sellers as feedback once exchanges are complete (only egoists ignore it). The average transactional ratings are

Table 2
Buyer rating system for seller transactions

Buyer rating	Seller action
100	Product offered at base price of $750.
95	Price within buyer's tolerance (markup between $10 and $200), and seller composite rating shows upward movement across recent model runs.
90	Price within buyer's tolerance (markup between $10 and $200), and seller composite rating shows downward movement across recent model runs.
85	Price beyond buyer's tolerance (markup above $200), and seller composite rating shows upward movement across recent model runs.
80	Price beyond buyer's tolerance (markup above $200), and seller composite rating shows downward movement across recent model runs.

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