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Centre Interuniversitaire sur le Risque, les Politiques Économiques et l'Emploi

Cahier de recherche/Working Paper **07-40**

On the Formation of Buyer-Seller Relationships when Product Quality is Perfectly Observable

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Novembre/November 2007

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We are grateful to Jonathan Alevy, Ernst Fehr, Glenn Harrison, and Andreas Lange for excellent insights that markedly improved the study. Seminar participants at several universities also provided useful insights.

Abstract:
This study explores the formation of buyer-seller relationships in markets with observable quality. We develop a model that explains why relationships form in equilibrium within such markets. A key feature of our model is that as individuals gain experience in the marketplace, they resolve uncertainty over unobserved bargainer types. Relationships thus form as a means to reduce such transactions costs and uncertainty. We explore the usefulness of our theory by using a battery of simulations and experimental treatments. Overall, we find that our theoretical predictions are largely confirmed. Interestingly, the quantitative impact of relationship on overall market efficiency depends critically on the extent to which market structure affects the matching of buyers and sellers that could profitably transact. In certain important cases, a greater numer of buyer-seller relationships can *reduce* market efficiency.

Keywords: Field experiments, pricing, market structure

JEL Classification: C93, D4

I. Introduction

Economic theory highlights the importance of contractual arrangements to align individual interests and overcome possible market failures. Yet, there are many instances where certain dimensions of a transaction cannot be contractually specified and enforced by neutral third parties. This has spurred the development of a rich literature that examines systematically the formation and impact of long-term relations in labor and product markets as a means to alleviate such enforcement problems (see, e.g., Klein and Leffler, 1981; Shapiro and Stiglitz, 1984; Bowles, 1985; MacLeod and Malcomson, 1989; Dixit, 2003; Levin, 2003; Brown et al., 2004). Intuitively, the formation of long-term relationships fosters cooperation that is difficult to sustain in one-shot trades.

In this paper, we show that long-term relationships may emerge even *absent enforcement problems*. In our environment, standard economic models do not explain why relations form. We therefore propose a new explanation, based on *ex ante* unknown differences in individual bargaining types. As the market evolves, individuals learn about the bargaining strategies of other traders. If a good match occurs, then both parties have an incentive to interact in the future rather than search for opportunities with other participants with whom they have never transacted.

We develop our analysis in two stages. We first develop a very simple model that explains the rational emergence of buyer-seller relationships in bilateral trading markets that closely mimic Chamberlain's (1948) seminal construct.[1] A key feature of our setup is that product quality is observed and homogenous. Thus, relationships cannot emerge as an efficient means to motivate sellers to provide high quality. Individuals initially are unaware of other's types, but learning takes place as the market evolves and trades are consummated. We implement simulations based on this learning process. In a second stage, we make use of the simulation parameters to design a series of treatments in a field experiment. We closely align the design of the simulations and experiments to allow a detailed qualitative and quantitative comparison of simulated and experimental data.

[1] Such markets are not uncommon in practice. Prior to the development of modern price systems and associated financial institutions in the United States, goods exchange was based primarily upon individual bartering and bargaining. Some less-developed economies still rely upon such mechanisms for trade and the exchange of goods (e.g., Morocco). Bilateral bargaining is fundamental to the sports and entertainment industries where agents for an athlete (actor) negotiate personal service contracts on an individual basis. Similar behavior is observed in agriculture and commercial fisheries where farmers (fishermen) negotiate bilateral contracts with processors specifying prices and terms of exchange for harvested resource stock.

We study three main outcomes in the simulations: (i) the number of relationships that form, (ii) the impact of relationships on the probability that a particular buyer or seller executes a transaction, and (iii) the impact of relationships on measures of surplus at both the individual and market level. Our simulations provide a number of insights regarding the emergence and impact of buyer-seller relationships. First, the learning model generates significantly more relationships than what would be expected if agents acted randomly. Second, individuals in a relationship are more likely to trade in the learning model with this effect larger when reservation values are closer to the competitive price. Third, average surplus is lower in relationships than in one-shot trades. This leads to a fourth insight, that relationships can have a *negative* impact on overall market surplus.

We complement these simulation results with data drawn from field experiments. Overall, the experimental results replicate the qualitative nature of our simulations remarkably well. First, we find that significantly more relationships form in our experimental markets than predicted under a model of random matching. On average, buyers in our markets are approximately 40% (60%) more likely to engage in repeated transactions with their initial (any prior) trading partner than what is predicted by the random model. Second, agents in a relationship are more likely to execute a trade, with this difference greater in concentrated markets. While this second result leads to increased market efficiency, we find that surplus measures are lower in relationship trades than in single-shot transactions. In the limit, we find that a greater number of buyer-seller relationships can *reduce* market efficiency.

The remainder of our study is crafted as follows. Section II reviews the relevant literature. Section III presents our theoretical model and simulation results. Section IV outlines our experimental design. Section V describes our results. Section VI concludes.

II. Previous Literature

Our paper builds on several branches of the literature. First, there is a rich literature that examines the impact of repeated interactions in markets with enforcement problems (see, e.g., Klein and Leffler, 1981; Shapiro and Stiglitz, 1984; Bowles, 1985; MacLeod and Malcomson, 1989; Dixit, 2003; Levin, 2003; Brown et al., 2004). A fundamental insight from this literature is that repeated interactions provide a means to overcome incentive problems that are likely to emerge when parties engage in single-shot transactions. Since product quality is observed and homogenous in our markets, such incentive problems do not arise. However, uncertainty over the nature and bargaining behavior of other market participants can be viewed as a problem of transactions costs which relationships help to reduce.

Second, an important feature of our environment is that trade in each period occurs via decentralized, bilateral negotiation. There is a large theoretical literature that studies the types of conditions under which Walrasian outcomes may be approached or attained in such bilateral markets.[2] Such models do not consider multiple trading rounds and the emergence of buyer-seller relationships which is the focus of our paper. In a similar spirit, our paper builds upon a growing experimental literature that examines decentralized outcomes in both the laboratory using student subjects (see, e.g., Chamberlain, 1948; Hong and Plott, 1982; Joyce, 1983; Grether and Plott, 1984) and in the field using market professionals (see, e.g., List, 2004; List and Price, 2006). An important insight from these studies is that Walrasian outcomes are closely approximated in decentralized markets when subjects engage in multiple rounds of exchange or enter the laboratory with previous trading experience. Yet our analysis differs from these papers in that we focus on the emergence and impact of buyer-seller relationships rather than testing Walrasian predictions per se.

Third, our paper is related to the literature on buyer-seller networks. For example, Kranton and Minehart (2001) examine the formation of buyer-seller networks in a game with a unique trading round where link formation is costly and takes place before trade occurs. This differs from our setting where trade occurs over several rounds and link formation is not a separate process from trade – i.e., links in our model arise through trade. Corominas-Bosch (2004) studies trade patterns when identical buyers and identical sellers are linked through an exogenous network. This contrasts from the environment considered in our paper where relationships are endogenously formed and market participants may differ in their valuations. Further, our approach differs from the theoretical literature on networks in that we allow agents to trade with any other trading partner in the market. This is a stark contrast to the network literature where agents can only trade if they have formed a link.

Fourth, our paper is closely related to the literature on reinforcement learning which has been used to explain buyer behavior in markets for perishable goods of

[2] For models with complete information see Rubinstein and Wolinsky (1985), Gale (1986), or Jackson and Palfrey (1998). For models where valuations for the good are private information, we refer the interested reader to Samuelson (1992) or Moreno and Wooders (2002).

homogenous quality (Weisbuch et al., 2000; Kirman and Vriends, 2001). These models show that loyalty may emerge, and that we should expect a sharp distinction between loyal and non-loyal behavior. Importantly these models suggest that loyalty is more likely to arise amongst buyers who visit the market more frequently and who purchase a greater volume. Using transaction level data from the Marseille wholesale fish market, Weisbuch et al. (2000) find support for these predictions – a large number of cod buyers are loyal to a single seller and the extent of loyalty is increasing in the average volume of monthly cod purchases for a buyer.

There are a number of differences between their approach and ours. First, loyalty emerges in their model when buyers put sufficient weight on the memories of past transactions in their current decisions. As such, buyers may become loyal to a specific seller absent economic incentives. Importantly, such an outcome cannot arise in our model. Rather, loyalty only emerges in our model through a salient economic incentive – faced with uncertainty on others' behavior, transacting with a known seller may be less costly than with an unknown one. Second, the authors acknowledge that the level of complexity present in real markets prevents a direct fit of their theoretical model to data. We would argue that such complexity also makes it difficult to parse different rationales for loyalty.[3] In contrast, the controlled environment of our experimental markets dramatically simplifies this level of complexity and permits a more comprehensive qualitative and quantitative comparison of simulated and real data.

III. Theoretical Discussion and Simulation Results

We wish to develop a theory of relationship formation in the marketplace that focuses on the role of the uncertainty over the bargaining types of the market participants rather than enforcement problems and reciprocal exchange. An important feature of our theoretical model is the assumption that product quality is observed and homogeneous. However, we assume that agents are uncertain about the nature and bargaining behavior of potential trading partners.

For simplicity, we develop a model with fixed bargaining behavior and two types – "soft" and "hard" bargainers. In our model, bargaining type refers to the distinct reservation payoff an agent expects to earn from a transaction where we

[3] In particular, the authors are unable to determine whether loyalty arises as a means to overcome possible information asymmetries about product quality. To be clear, however, Kirman and Vriends (2001) provide a compelling argument that the effects of asymmetric information about quality should be minimal in the Marseille fresh fish market.

assume that hard bargainers seek to extract more surplus from every transaction than soft bargainers. Thus, if a soft and a hard bargainer realize a trade, then the hard bargainer earns a higher payoff. However, when a buyer and seller of the same type execute a trade, the available surplus is shared equally. Because hard bargainers seek to extract greater surplus per transaction, the probability that two hard bargainers execute a trade is less than the probability that two soft bargainers execute a trade.

Initially, agents are unaware of bargaining types, but individual type is revealed during the negotiation process. Thus, as the number of market rounds (repetitions) increases, there is learning in the market that potentially influences behavior. For example, a soft buyer and a soft seller who realize a trade in round t should start round $t + 1$ by commencing bargaining with one another.[4] The reason being that at the beginning of a round, the expected utility from bargaining with a known soft bargainer is strictly greater than the expected utility from bargaining with an unknown bargainer. Thus, soft bargainers who have previously traded should start every subsequent round by checking whether they can again trade. This is a key mechanism that we explore below.

To analyze a fully rational model of repeated buyer-seller interactions under bargaining type uncertainty would be prohibitively complicated.[5] We do not tackle such a comprehensive analysis here. Rather, we study a very simple model focusing on the mechanism highlighted above. We assume that market participants have a fixed bargaining behavior and distinct reservation payoffs that represent the minimum amount they expect to earn from a transaction. When a buyer and a seller bargain, they trade only if both can earn their reservation payoff and surplus allocation is determined through a simple Nash bargaining procedure. More precisely, let the reservation payoff for soft bargainers equal π_S and let the reservation payoff for hard bargainers equal $\pi_H > \pi_S$. Now suppose that buyer i with value v_B and reservation payoff π_i bargains with seller j with value v_S and reservation payoff π_j. We assume

[4] For precision we should note that this only holds if the buyer and seller have not traded with another soft bargainer in a prior period. If a buyer (seller) has previously traded with multiple soft sellers (buyers), they should start period t + 1 by bargaining with one of the known soft trading partners.

[5] In such a model, we would have to specify the expectations of each individual over the types of all the other participants. Further, we would have to describe and model how these expectations are updated after each new transaction in the market. Individuals would also have expectations on the values of all other participants within rounds, and we would need to describe how agents dynamically update these expectations. Finally, we would need to describe and model how individuals condition their strategies on the transaction histories.

that if v_B-v_S< π_i+ π_j, trade does not take place. However, if v_B-$v_S \geq \pi_i+\pi_j$, then buyer *i* and seller *j* trade at price given by $\frac{1}{2}(v_B-\pi_i+v_S+\pi_j)$.

In the next section, we use numerical simulations to study two simple models with heterogeneity in bargaining types. The two models differ only in how buyers select the sellers with whom they will bargain. In the *random model*, individuals simply choose their partners randomly. In the *learning model*, soft bargainers who know each other, i.e. who have traded together in the past, prefer to bargain together.

Simulation Design: Bilateral Negotiation Markets

Our simulations mimic the spirit of the literature as well as the manner in which participants interact in our experimental markets described below. Each session is comprised of 5 rounds. At the beginning of a session, buyers and sellers are randomly assigned a type and at the beginning of each round they are allocated round-specific values. We use the same values as those in the symmetric experimental markets, which generates the basic supply and demand array illustrated in Figure 1. The perfectly competitive outcome in these markets yields \$37 in rents per round and occurs where competitive price theory predicts a static price/quantity equilibrium of price = \$13.00 to \$14.00 and quantity = 7.

To capture the fact that buyers may approach various sellers within a round, we decompose each round into several sub-rounds, which we denote as periods. In each of these periods, the matching process follows two steps. First, each buyer chooses one seller to visit. Second, sellers choose one buyer among those visitors and the pair of matched buyers and sellers bargain. If bargaining is successful, then a trade is realized. Otherwise, the participants approach other possible trading partners in the following period. As the number of periods grows large, a greater number of opportunities for trade are exploited within each round.

Importantly, we assume that a buyer and a seller who trade learn each other's types. In the learning model, this affects behavior in subsequent rounds. We assume that if a soft buyer knows any soft seller, he always chooses to visit him (or one among them if he knows many). If he does not know any, he selects a seller at random.[6] Similarly, if a soft seller knows a soft buyer among the buyers visiting him, he always elects to bargain with him initially. Decision rules for hard bargainers are

[6]More precisely, he picks a seller at random among all the sellers he does not know. Any hard seller he may know is excluded from his choice, except, of course, if he only knows hard sellers.

more ambiguous than those for counterparts who are soft bargainers.[7] For simplicity, and without loss of generality, we thus assume that hard bargainers behave randomly.

Simulation Results: The Formation and Impact of Relationships

Our simulation model is characterized by 4 main parameters: the number of soft buyers, the number of soft sellers, the reservation payoff π_S for soft bargainers, and the reservation payoff π_H for hard bargainers. We set the number of periods within a round at 20, a value for which most opportunities for trade are exploited in every market round, and report simulation results obtained from 1000 replications of a 5 round session. We first examine the performance of the random and learning models with respect to basic market characteristics: the average price paid per transaction, the average quantity traded per round, and the efficiency of the market.

We find that in both models the average price is approximately equal to \$13.50 if the proportions of soft buyers and soft sellers are equal.[8] We thus assume this property to hold in all discussion that follows. However, while the average price is little affected by reservation payoffs, the average quantity traded is decreasing in both reservation payoffs and the proportion of participants who are hard bargainers. Thus, to guarantee that the average quantity traded lies between 6 and 8 units across all treatments, we set $\pi_S=0.5$ and $\pi_H=1.5$.

The Extent of Relationships

Having shown that competitive price theory adequately organizes the data in our simulations, we now examine the extent of relationships across our various models. Table 1 compares the extent of relationships emerging across the learning model and a model based on random matching for different proportions of soft bargainers. The table presents results for markets with symmetric rent allocation and either four (denoted PC4) or twelve (denoted PC12) sellers, with an aggregate market supply as indicated in Figure 1. Cell entries report the frequency of two different types of relationships that can form in the market - transactions with one's initial trading partner and transactions with any prior trading partner. In calculating these

[7]Consider a hard buyer who has traded with a soft seller in one round. Should he choose this seller again at the beginning of the next round? The soft seller prefers to bargain with another buyer if he can, but bargains with this hard buyer if he cannot find another potential buyer. If the hard buyer chooses this soft seller again, his probability to bargain is lower but his expected payoff conditional on bargaining is higher. In contrast, a soft buyer who has traded with a soft seller in the first round always prefers to visit him at the first period of the second round.

[8]The average price is greater than \$13.50 if the proportion of soft buyers is greater than the proportion of soft sellers and it is lower than \$13.50 if the proportion of soft sellers is greater than the proportion of soft buyers.

frequencies we consider all transactions for buyers who have already traded during a given five round session. In the random model, relationships form by chance as buyers randomly match with a particular seller in each period. The proportion of repeat purchases with the initial seller is thus approximately equal to 1/4=25% for PC4 sessions and to 1/12=8.3% for PC12 sessions in the random model.

In contrast, the extent of relationships is significantly greater in the learning model in PC4 and PC12 sessions.[9] This leads to a first result:

> *Result 1: The learning model generates significantly more relationships than the random model. The extent of relationships is increasing in the proportion of soft bargainers in the population.*

In the learning model, relations predominantly form among soft bargainers as a way to reduce transactions costs associated with bargaining with an unknown market participant. Not surprisingly, our simulation results suggest that relations are more prevalent when the proportion of soft bargainers is higher. Data from our experimental results described below are consistent with the learning model for a proportion of soft bargainers between 25% and 50%. We thus set our baseline value for this proportion at 50% in the discussion that follows.[10]

Effect of relations on the likelihood to trade

We now examine how relationships affect the likelihood an agent with a given induced value trades in both the learning and random models. Given the large amount of data generated in the simulations, we adopt a fully non-parametric approach. For example, consider a buyer with a specific buyer's value v_B. We count over all 1000 sessions the number of rounds where a buyer in a relationship has this value and obtain the realized probability to trade as the proportion of such instances where the buyer executes a transaction. Similarly, we obtain the probability to trade when a buyer is not in a relation as the number of times a buyer with this value who is not in a relationship executes a trade.[11]

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[9] The only exception to this is the case where there is only one soft seller in a PC4 session.

[10] It should be noted that we have also examined the impact of reservation payoffs on the formation of relationships and found almost no effect. This is consistent with the fact that preferential bargaining among soft bargainers is not affected by the absolute levels of the reservation payoffs.

[11] A buyer is in a relation as soon as he has traded twice with the same seller. Notice that in the round where this second trade happens, a trade is guaranteed and systematically counted as taking place within a relation. Thus, including the observations where relationships start lead to slightly overestimate their effect on the likelihood to trade. In the simulations we correct for this bias by simply removing these observations. Given data limitations, this is not feasible with our experimental observations. However, we use the simulations to estimate the magnitude of this bias. We find it to be quantitatively small.

Tables 2 and 3 present the probability to purchase or sell a card in the learning model. Cell entries report these estimated probabilities for both the PC4 and PC12 markets as a function of values and relationship status. In general, we find that relationships have a positive impact on the likelihood to trade for both buyers and sellers. These results are consistent with the underlying mechanism at work in the simulations. In the learning model, an individual in a relation has a higher chance to bargain at an early stage of each new round. This has two positive effects on the probability such an agent is able to trade. First, there is a reduction in potential *miscoordination problems* in the search for a partner. Thus, a buyer who is not engaged in a relation may be unlucky – i.e., unable to find a bargaining partner until late in the round when the good trading opportunities have been exploited. Second, in the PC4 setting this creates a direct *eviction* effect between buyers. By design, sellers first sell the units that potentially yield a higher surplus from trade. As bargaining behavior is fixed, trade is more likely when two individuals bargain on higher surplus units. Buyers in relations are thus favored since they tend to be the first bargaining partners selected by a seller and are thus negotiating over lower cost units that are more likely to be traded.

Intuitively, relationships have two potentially competing influences on market efficiency. First, relationships may serve to stimulate trade by infra-marginal agents, who might not otherwise find a trading partner. As buyers (sellers) in our simulations cannot trade at a price above (below) their induced value, there is a limited set of feasible trading partners for agents, making it possible that such agents forego rents purely because they cannot find a partner.[12] However, relationships can also stimulate "bad" trades: agents who should be out of the market given the equilibrium price execute trades (we denote such agents as "extra-marginal") and this potentially crowds out infra-marginal agents. As agents in a relationship are more likely to match and bargain early in a trading round, the probability that a buyer (seller) with an induced value less than (greater than) the competitive equilibrium price is able to find a viable trading partner increases.

[12] For example, there are at most only 7 units which a buyer with an induced value of \$14 could feasibly purchase. However, if this same buyer had an induced value of \$19, the number of units that he could purchase increases by approximately 71.4% (or 5 units). As such, it is important that agents with induced values along the intensive margin match with possible trading partners early in a round when the number of viable trading opportunities is greatest.

Importantly, our simulation data permit a direct comparison of the impact of relationships on infra- and extra-marginal agents. As shown in Tables 2 and 3, there is a pronounced asymmetry in the impact of relationships on the probability of trade: extra-marginal agents gain more from relationships than their infra-marginal counterparts. For example, as noted in Table 2, an infra-marginal buyer with an induced value of $14 ($15) in a PC4 market is approximately 51.9% (17.7%) more likely to trade when in a relationship. In contrast, the relative impacts are much larger for extra-marginal agents: a buyer with an induced value of $13 ($12) in this same market is approximately 81.9% (119.8%) more likely to trade when engaged in a relationship.[13]

We now examine the effect of the proportion of soft bargainers on differences in the probability of trading. Interestingly, we find that this proportion does not affect the qualitative nature of such differences – conditioned on values, agents in a relationship are always more likely to trade. When the proportion of soft bargainers is equal to 25%, however, the estimated marginal effect is significantly lower for both buyers and sellers. Given the lower prevalence of relationships in such markets, mis-coordination and eviction problems for buyers who are not in relations are less severe, which serves to attenuate the positive effects of relationships. It should be noted, however, that there is an endogenous limit to this effect: we find that the marginal effect of relationships takes quantitatively similar values when the proportion of soft bargainers is set equal to either 50% or 75%. Overall, we can summarize these findings as follows.

> *Result 2: In the learning model, market participants in relationships have a higher probability to trade. This effect is stronger for extra-marginal agents and when the proportion of soft bargainers is greater than or equal to 50%.*

Having shown that relationships impact the likelihood of trade in our learning model, it is important to evaluate whether we observe similar impacts in the random model. While we find a slight positive effect in the random model, it is quantitatively much smaller than what is observed in the learning model and driven by selection related to

[13] We observe similar differences for buyers in our PC12 markets and for sellers (see Table 3). For example, an infra-marginal seller with an induced value of $13 ($12) in a PC4 market is approximately 21.5% (8.7%) more likely to trade when in a relationship. In contrast, an extra-marginal seller with an induced value of $14 ($15) is approximately 24.4% (79.7%) more likely to trade when engaged in a relationship.

heterogeneity in bargaining types.[14] Since soft bargainers are more likely to trade than a hard counterpart for all values, they tend to be overrepresented among the set of agents that randomly form relationships.

Surplus and Efficiency

In this section, we examine the effect of relationships on individual surplus measures and overall market efficiency. Table 4 reports the average surplus measures per transaction and associated standard errors for the learning model. We observe four outcomes: (i) surplus in single-shot transactions, (ii) surplus in all relationship trades, (iii) surplus in initial relationship trades, and (iv) surplus in subsequent relationship trades. Data in the table highlight a number of insights regarding the impact of relationships on average surplus measures at the individual level. First, we find that the overall surplus in single-shot trades is significantly greater than in relationship trades in both the PC4 and PC12 markets.[15] On average, single shot trades generate surplus measures that are approximately \$0.29 to \$0.41 greater than those realized in relationship trades. Second, this pattern holds for measures of both consumer and producer surplus: buyers (sellers) earn approximately \$0.12 to \$0.16 (\$0.05 to \$0.18) more per trade in single-shot transactions than in relationship trades. Finally, and perhaps a surprising insight, within relationships surplus in the initial trade is lower than the surplus realized in subsequent transactions.

To lend insights into these simulation results, recall that relationships mainly form between soft bargainers, who have lower reservation payoffs than do hard bargainers. Conditioned on trading, we thus expect the average surplus to be lower for trades between two soft bargainers than for trades between two hard ones. In addition, recall that agents in a relationship are more likely to trade extra-marginal units. Because such transactions necessarily reduce gains from trade, one would expect a further exacerbation in the difference of average surplus between single-shot and relationship trades.[16]

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[14] For instance, the marginal effect of relationships in the random (learning) model when the value is equal to 13 is 7.11% (25.56%) for buyers in PC4, 3.83% (14.22%) for sellers in PC4. For agents in our PC12 sessions, the respective marginal effects are -0.89% (12.81%) for buyers and 3.33% (16.74%) for sellers. Data from the random model simulations are available from the authors on request.

[15] To test the significance of these differences, we use a matched pairs t-test to compare the average surplus measure for single shot trades in a session versus the average surplus measure for relationship trades in that session. As each session provides a single observation, our test statistic is thus based on a comparison of 1000 different averages.

[16] It should be noted that there is a secondary effect on surplus measures per trade related to the mis-coordination and eviction effects mentioned earlier. In the presence of relationships, hard bargainers

Alternatively, the fact that, within relations, the surplus for initial trades is lower than for subsequent trades reflects the positive impact of relations on trades – agents in a relationship are more likely to match early in a trading round and bargain over lower cost units for which available surplus is larger. Relative to initial transactions, which may occur later in a trading round, one would thus expect average surplus to be greater for subsequent relationship trades. However, this effect is partially offset by the fact that agents who match early in a trading round are more likely to bargain over extra-marginal units.

As a robustness check, we examine the impact of changing the proportion of soft bargainers in the market. Importantly, across all treatments, the results are qualitatively similar when this proportion is equal to 25%. Further, we observe similar outcomes in PC12 sessions when the proportion of soft bargainers is 75%. However, it should be noted that average surplus in single-shot trades is slightly lower than in relationship trades in PC4 sessions when the proportion of soft bargainers is set to 75%.[17] In this case, the extent of relationships is very high and secondary impacts associated with miscoordination and eviction effects dominate the direct effect. Combined these insights lead to a third result.

Result 3a: In the learning model, the average surplus in single-shot transactions is greater than in relationship trades. The sole exception is in PC4 sessions when the proportion of soft bargainers is set to 75%.

Result 3b: The average surplus in initial relationship trades is always lower than in subsequent relationship trades.

Having shown that relationships impact surplus measures at the individual level, it is important to evaluate how these differences aggregate to the market level and impact measures of overall market efficiency. While one might expect lower surplus per trade to suggest reduced market efficiency, the two measures need not work in the same direction. Intuitively, this relationship depends on the extent to which individual surplus measures reflect increased trade for infra-marginal agents versus the effects on extra-marginal agents. If the former effect dominates, then one would expect relationships to enhance market efficiency; whereas, if the latter effect dominates one would expect relationships to frustrate market efficiency.

match with possible trading partners later in a round and bargain over units for which available surplus is lower. This indirect effect serves to attenuate differences across single-shot and relationship trades.

[17] The average surplus in initial relationship trades is lower than in subsequent relationship trades in all treatments.

To examine the impacts of relationships on aggregate market outcomes in the learning model, we regress the efficiency of a session (realized trade surplus over the 5 rounds divided by the maximum available surplus) on a constant term and a proxy for the extent of relationships – the proportion of purchases from any prior partner. Table 5 reports regression results using different absolute payoff values but holding the difference in the reservation payoffs (π_H- π_S) constant. As noted in the table, the effect of relationships on overall market efficiency is negative and statistically significant. This leads to a fourth result:

Result 4. Relationships can have a negative impact on overall market efficiency.

Result 4 suggests that in the absence of enforcement problems or reciprocal exchange, the formation of relationships in the market may lead to a reduction in overall efficiency. Intuitively, this result holds because extra-marginal individuals in relationships are much more likely to execute trades, serving to frustrate market efficiency. Importantly, these simulation data highlight that the quantitative impact of relationships depends on the extent to which market structure and reservation payoffs affect the coordination and matching of buyers and sellers.

In an attempt to understand the underlying structure of *Result 4*, recall that there is a pronounced asymmetry in the impact of relationships on the probability to trade – extra-marginal agents gain more from relationships than their infra-marginal counterparts. The final column of Tables 2 and 3 translate differences in the probability of trading into expected changes in overall market efficiency. The formation of relationships leads to expected efficiency gains for infra-marginal values and expected efficiency losses for extra-marginal values. Aggregating over all agents, we find that the quantitative effects are larger for extra-marginal units.[18]

Before proceeding to the experimental design and results, we wish to note two interesting features of our simulation data. First, despite the low level of assumed rationality, market participants reach a high level of efficiency in both the learning

[18] For example, in our PC4 markets, buyers along the intensive margin are approximately 2.87 – 51.9% more likely to trade when in a relationship. In terms of overall market efficiency, this corresponds to an approximate 1.77% increase in expected efficiency. However, these efficiency gains are offset by increased activity along the extensive margin where buyers in a relationship are approximately 81.9% to 11 times more likely to trade. As this corresponds to an approximate efficiency loss of 7.05%, the overall impact of relationships on market efficiency is negative.

and random models.[19] This result serves to extend recent studies of markets with "zero-intelligence" traders (see, e.g., Gode and Sunder, 1993; Gode and Sunder, 1997; Duffy and Unver, 2006). Second, efficiency is non-monotonic in payoffs: overall market efficiency is initially increasing and then decreasing in assumed reservation payoffs. This follows from the impact of reservation payoffs on quantities traded. When payoffs are low, quantities are high and there are too many trades relative to competitive predictions. If payoffs increase, then quantities decrease towards the competitive level. This initially has a positive impact on efficiency as the number of excess units traded – which necessarily reduce efficiency - declines. When payoffs increase further, however, a threshold is reached after which the volume of trade is less than the competitive benchmark and efficiency decreases as potentially profitable trades are foregone.

IV. Experimental Design

To complement the simulation results, we make use of field experiments in two distinct markets: the sportscard market and the "flea" market. As discussed elsewhere (List, 2004), both markets are characterized by consumers milling around the marketplace, higgling and bargaining with sellers who have their merchandise prominently displayed on their tables. Temporal assignment of the physical marketplace is typically done by a professional association or local seller who rents a large space, such as a coliseum, stadium, large parking area, or a fairground, and allocates tables to sellers for a nominal fee. The duration of a typical "market" is a day or weekend, and a lucrative market may provide any given dealer hundreds of exchange opportunities.

A major advantage of this particular field experimental design is that the laboratory is the marketplace: subjects would be engaged in buying, selling, and trading activities whether we ran an exchange experiment or were passive observers. An added advantage is that in the actual marketplace the natural institution matches quite well with our theory and simulations: agents engage in face-to-face continuous bilateral bargaining in a multi-lateral market context.

[19] This can be seen on the constant term, or by directly looking at the average efficiency across the 1000 sessions. When payoffs are equal to 0.5 and 1.5, average efficiency in the learning (random) model is equal to 86.64% (87.18%) in PC12 sessions and to 89.49% (90.91%) in PC4 sessions. The highest average efficiency reached is equal to 89.96% (90.33%) for PC12 sessions and to 91.15% (91.87%) for PC4 sessions.

Our identification strategy is to make use of this naturalness by observing individuals within the multilateral decentralized bargaining market. To execute the treatments, each participant's experience typically followed four steps: (1) consideration of the invitation to participate in an experiment, (2) learning the market rules, (3) actual market participation, and (4) conclusion of the experiment and exit interview.[20] The experimental instructions for the various treatments were standard and taken from Davis and Holt (1993, pp. 47-55; 1998) with the necessary adjustments.

Before proceeding to a discussion of the results, a few key aspects of the experimental design should be highlighted. First, to gather the seller subject pool, a monitor randomly approached dealers before the market opened and inquired about their interest in participating in an experiment that would take about 60 minutes. To gather the nondealer subject pool, a monitor randomly approached consumers entering the marketplace and inquired about their level of interest in participating in an experiment that would last 60 minutes. Second, all individuals were informed that they would receive a $10 participation fee upon completion of the experiment. And, following Smith (1965), a $0.05 commission for each executed trade was provided for both buyers and sellers to ensure that subjects would engage in transactions at their reservation values.

Third, buyers (nondealers) were informed that the experiment consisted of 5 rounds and that they would be consumers in the experiment. In each of 5 rounds, each buyer would be given a "buyer's card," which contained a number, known only to that buyer, representing the maximum price that he or she would be willing to pay for *one* unit of the commodity. Dealers (or vendors) were informed that they would be sellers of up to three units in each market period. In each of 5 rounds, each seller would be given a "seller's card," which contained numbers, known only to that seller, representing the minimum for which he or she would be willing to sell their units in the marketplace.

Fourth, the monitor explained how earnings (in excess of the participation and commission fees) were determined: for sellers the difference between the actual contract price and the minimum reservation value determined producer rents. Likewise, buyers' earnings were determined by the difference between the contract

[20] A portion of the experimental design discussion follows List (2004).

price and the maximum reservation value. Several examples illustrated the irrationality associated with selling (buying) the commodity below (above) induced values.

Fifth, the homogenous commodities used in the flea market (sportscard) experiments were compact discs that had been broken into two pieces (1992 Topps Cal Ripken baseball cards). Thus, the assignment given to sellers was clear, and an everyday occurrence: sell the compact disc (Ripken card) for as much as possible. Likewise, the task confronting buyers was also clear: enter the marketplace and purchase one compact disc (Ripken card) for as little as possible. The experimental commodities and participating dealers were clearly marked to ensure that buyers had no trouble finding the commodity of interest. Sixth, buyers and sellers engaged in two five-minute practice periods to gain experience with the market.

Each market session consisted of 5 market rounds that lasted 10 minutes each. After each 10-minute round, a monitor privately gathered with buyers and gave them a new buyer's card while a different monitor privately gave sellers a new seller's card.[21] The private values were determined randomly to ensure that serial correlation was not introduced. At the conclusion of the experiment subjects were paid their earnings in private.

This procedure was followed in each of five experimental treatments. Table 6 summarizes the experimental design employed in our analysis and can be read as follows: row 1, column 1 contains treatment PC12. In this baseline treatment, the market is comprised of 12 buyers (12 sellers) each with unit demand (supply). Figure 1 presents buyer and seller induced values, which are taken from Davis and Holt (1993, pp. 14-15). In figure 1, each step represents a distinct induced value that was given to buyer (demand curve) and sellers (supply curve). The perfectly competitive outcome in this treatment yields \$37 in rents per round and occurs where competitive price theory predicts a static price/quantity equilibrium of price = \$13.00 to \$14.00 and quantity = 7.

Treatment PC4 is identical to PC12 except for one important deviation: rather than having twelve sellers each providing a single unit of the good, aggregate supply is derived from four sellers each providing three units of the good. Importantly, it

[21] During the experiment, buyers mill around the marketplace and approach various dealers, who are situated at clearly marked tables located throughout the floor of the sportscard show (flea market), to bilaterally negotiate the purchase of the Ripken card (compact disc).

should be noted that in this treatment sellers are required to sell their lowest cost units first. All remaining market parameters are identical to those in the PC12 sessions, with the same competitive equilibrium predictions.

Treatment PED12 (denoting perfectly elastic demand) is identical to PC12 except for one important deviation: rather than a downward sloping aggregate demand schedule that is perfectly symmetric to the aggregate supply curve, demand is held perfectly elastic at a price of $13.50. Treatment PES12 (denoting perfectly elastic supply), holds supply perfectly elastic at a price of $13.50. In both of these asymmetric treatments, competitive price theory predicts an equilibrium price/quantity outcome of price = $13.50 and quantity = 7. This yields rents of $18.50 per round that are allocated entirely to one side of the market – sellers in PED12 and buyers in PES12.

In summary, in each treatment the monitor gives each buyer (seller) a reservation price for one (three) units of a commodity (either a broken compact disc or Cal Ripken baseball card) and allows agents to engage in bilateral haggling and bargaining until they enact a contract(s) or the trading period terminates. After each contract is completed, (i) a monitor posts the exchange price on a public board, and (ii) monitors inform all buyers and sellers of the exchange price in case they are removed from the public board. In total, the experiment includes data from thirteen unique experimental sessions (65 market periods). Since each buyer and seller competed in only a single treatment, our experiment included 208 total subjects: 120 consumers and 88 dealers.

V. Experimental Results

We begin our empirical analysis by examining the relative frequency with which agents engage in repeated transactions with a given trading partner. As with the simulation results, we are interested in two distinct types of interactions: (i) purchases from any prior trading partner and (ii) purchases from a buyer's initial trading partner.

Table 7 summarizes the frequency with which each of these types of transactions occurs in our various experimental treatments. In total, we observe 275 purchases by buyers who have already engaged in at least one prior transaction in the market. Assuming buyers were to match with a randomly determined seller, we would expect at most 38 (or 13.9%) of such purchases to be from an initial trading partner.[22] Yet, we observe a total of 54 units (or 19.6%) bought from an initial trading partner with this 5.7% difference statistically significant at the $p < 0.05$ level using a test of proportions. Importantly, the proportion of purchases from an initial trading partner is significantly greater than that expected under random behavior if we restrict attention to only the subset of asymmetric twelve seller markets, the pooled subset of twelve seller markets, or the pooled subset of four seller markets.

Similar data patterns emerge if we examine the proportion of trades from any prior trading partner. In total, we observe 81 units (or 29.5%) purchased from any previous trading partner. Under a model of random behavior, we would only expect 51 units (or 18.43%) purchased from a previous trading partner.[23] This 11.07% difference in proportions is statistically significant at the $p < 0.05$ level using a test of proportions. Examining outcomes at the individual level yields similar insights. For example, buyers are 10.28% (7.08%) more likely to purchase from a prior trading partner in our four (twelve) seller markets than what is predicted under a random match. Both of these differences are statistically significant at the $p < 0.05$ level.

Recall that induced values in our experimental markets are privately known and independent of the actions taken by a potential trading partner. *Ceteris paribus*, we would thus expect agents to be indifferent amongst a set of potential trading partners: our markets are devoid of lemons problems and reciprocal exchange is unlikely as agents do not observe the payoffs received by trading partners. Combined with insights garnered from raw data presented in Table 7, this suggests a fifth result:

> *Result 5: Relationships form in experimental markets absent enforcement problems and known reciprocal exchange when agents bilaterally negotiate terms of trade.*

Consistent with our simulation results, we find evidence that the extent of relationship trades in the market is significantly greater than what is predicted by a model of random behavior. This result extends insights from the literature that relationships form as a means to alleviate incentive problems or induce reciprocal exchange, and

[22] This 13.9% probability is constructed using a weighted average of the probability a buyer randomly matches with the first seller with whom they traded in our four seller (25%) and twelve seller (8.3%) sessions, respectively. We use the observed proportion of total trades in each session as our weights.

[23] To calculate the baseline probability for a model of random matching, we use a weighted average of probability of purchasing a given unit from a prior partner. For our four seller markets, the respective probabilities are 25%, 43.75%, 57.81%, and 68.36% for second, third, fourth, and fifth unit purchases. For our twelve seller markets, these associated probabilities range from 8.33% for purchases of a second unit to 29.39% for purchases of a fifth unit. Details for these computations are available from the authors upon request.

importantly suggests an alternate reason for the formation of relationships in the marketplace: uncertainty over the bargaining type of a potential trading partner.

Effect of Relationships on the Likelihood to Trade

Having found that agents in our experimental market engage in repeated trade, we now examine the impact of such relationships on the likelihood an agent with a given induced value executes a transaction. To examine this likelihood we estimate models of the probability a buyer (seller) with a reservation value (marginal cost) in the range $9-15 ($10-17) executes a transaction in our experimental sessions that explicitly control for observable and unobservable differences across agents.[24] We make use of Butler and Moffit's (1982) random effects probit model to estimate separately the decision to buy (sell) for each buyer (seller) to gain insights on factors that influence these probabilities. Specifically, we estimate:

$$T_{ij} = \beta`X_{ij} + e_{ij}, \qquad e_{ij} \sim N[0,1],$$

where T_{ij} equals unity if agent i purchased/sold a unit in period j, and equals zero otherwise; X_{ij} includes the treatment effect dichotomous variables, a treatment specific dichotomous indicator for agents in a relationship, and other controls.[25] We specify $e_{ij} = u_{ij} + \alpha_i$, where the two components are independent and normally distributed with mean zero. It follows that the variance of the disturbance term e_{ij} is $Var(e_{ij}) = \sigma_u^2 + \sigma_\alpha^2$. By construction, the individual random effects α_i will capture important heterogeneity across solicitors that would be left uncontrolled in a standard cross-sectional model.

Empirical estimates are presented in Table 8. In estimating the empirical model, we restrict attention to our symmetric sessions as, by design, agents on the extensive margin cannot execute transactions in our asymmetric sessions. As indicated in column 1 of the table, a buyer in a relationship is more likely to execute a trade than one who is not in a relationship across all market types. However, these differences are only statistically significant for the PC4 and PC12 sessions in the sportscard market. Furthermore, extra-marginal buyers – i.e., buyers with an induced value of $13 or less – are significantly less likely to execute a trade than their infra-

[24] We concentrate on these data ranges since buyers with induced value greater than $15 always purchase. Similarly, sellers with marginal costs less than $10 always sell their given unit, and no seller with a marginal cost greater than $17 ever executes a trade.

[25] We use a time variant indicator of relationship status that equals one once a buyer (seller) has purchased (sold) a unit to a previous trading partner and zero in all previous periods. We code our indicator variable as one in the period in which such transactions occur.

marginal counterparts. We observe similar results in columns 2 and 3 which augment the regressor vector to include controls for the dollar difference between buyer's induced value and the mid-point of the CE price tube ($13.50) and the interaction of this difference with the indicator for a buyer in a relationship.

Exploring this result in greater detail, we find that the impact of relationships is larger for extra-marginal buyers. For example, as indicated in Table 9, a relationship buyer with an induced value of $13 in the PC12 treatment in the sports card market is approximately 40.7% more likely to purchase a card than would a similar buyer who engages solely in single-shot interactions with different sellers. We observe similar differences in our PC4 sessions where a relationship buyer with an induced value of $13 in the flea (sports card) market is approximately 50.2% (31.8%) more like to trade.

If we consider induced values further from the margin, similar data patterns emerge. For example, in our PC12 treatment buyers with an induced value of $11 are approximately 27.7% more likely to trade when in a relationship. For buyers with an induced value of $12, there is an approximate 57.1% increase in the probability of trading when in a relationship. Insights from our experimental data are thus qualitatively similar to those observed in our simulations: agents in a relationship are significantly more likely to trade.

Interestingly, the impact of relationships on the probability of purchasing an extra-marginal unit is greater in our PC12 markets: the marginal effect of a relationship is approximately 3.04 – 18.9% greater in our PC12 sessions.[26] In terms of overall market efficiency, this translates into an approximate 1.1 – 4.6% increase in expected efficiency loss in our PC12 markets as opposed to an approximate 0.8 – 1.7% increase in efficiency loss in the PC4 markets.[27] However, this difference in the effect of relationships is balanced by a greater tendency for repeat purchases in PC4 markets (47.3% versus 16.1%). We thus observe much lower levels of relative efficiency loss across our four seller markets compared to the twelve seller markets.

Relationships and Infra-Marginal Purchases

[26] This finding contradicts results from our simulation models if the proportion of soft bargainers across the PC12 and PC4 markets is held constant. However, if there are more soft bargainers in our PC12 markets than in our PC4 markets, such a result arises in our simulations. Future work should examine this issue in greater detail by attempting to control for the proportion of a given bargaining types.

[27] If a buyer with an induced value of $13 executes a trade there is a reduction of at least $1 in total surplus (2.7% of the total available surplus). When a buyer with an induced value of $12 ($11) executes a trade the surplus loss is approximately 5.4% (8.1%) of total available rents.

Having found that the formation of buyer-seller relationships lowers efficiency by increasing the likelihood that an extra-marginal buyer executes a transaction, we now examine whether there is a compensating positive effect on overall market efficiency through the stimulation of otherwise foregone infra-marginal trades. Evaluating these predicted probabilities in Table 9, we find that an infra-marginal buyer who has formed a relationship in our PC12 treatment is approximately 3.05 – 18.63% less likely to forego trades. Given that foregone trades by a buyer with an induced value of \$14 (\$15) generates a \$1 (\$2) loss in total surplus, the formation of relationships enhances expected efficiency by 0.5 – 1.6% through the stimulation of otherwise foregone purchases. In our four seller market treatments, expected efficiency is enhanced by approximately 0.01 – 0.1% through the stimulation of otherwise foregone infra-marginal purchases.

Combined with insights presented above, these data suggest that we should observe lower measures of surplus in relationship trades than single-shot interactions in our experimental markets: relationships have a relatively larger impact on extra-marginal agents. Interestingly, however, the impacts on both margins are less pronounced in concentrated markets – i.e., those with four rather than twelve sellers. We thus observe lower efficiency levels in our twelve seller markets. These insights suggest a sixth result:

> *Result 6a: There is an asymmetry in the impact of relationship for infra- and extra-marginal agents. As the quantitative effects are larger for extra-marginal agents, partner formation reduces market efficiency.*
>
> *Result 6b: Efficiency loss due to partnership formation is attenuated by increased market concentration.*

For buyers, the formation of relationships generates both expected efficiency gains for infra-marginal agents through a reduction in the probability of a foregone purchase and expected efficiency losses for extra-marginal agents through an increased probability of executing trades. However, the negative impacts of extra-marginal agents crowding out infra-marginal agents who have not formed partnerships generates an overall reduction in expected buyer surplus and overall market efficiency.

Relationships and Extra-Marginal Sales

Empirical estimates from a model that examines the probability that a seller executes a trade are presented in Table 10. In estimating the empirical model, we restrict attention to those sellers in our three symmetric market treatments with induced values in the range \$10.00 – \$17.00.[28] As indicated in column 1 of Table 10, a seller that has formed a relationship in a PC12 or flea market session is significantly more likely to sell a unit than an otherwise identical seller who does not form a relationship.[29] Furthermore, sellers are significantly less likely to sell an extra-marginal unit with this impact greater in our four seller treatments.

We observe similar results for the PC12 sessions in columns 2 and 3 of the table, which augment the regressor vector to control for i) the difference between a seller's induced marginal cost and the \$13.50 midpoint for the competitive equilibrium price tube and ii) the interaction of this difference with our indicator for a seller that has formed a relationship. Interestingly, upon conditioning on induced marginal costs, there is no significant impact of relationships on the probability to trade in our four seller markets. However, there remains a significant impact of relationships on the likelihood of extra-marginal trades in our twelve seller markets once we condition on induced marginal cost.

Exploring this result in greater detail in Table 11, we observe that a seller in a relationship in a PC12 session is approximately 3.49 – 37.46% more likely to sell an extra-marginal unit than an otherwise identical seller who has not entered a relationship. In contrast, the marginal impact of relationships on extra-marginal trades in a PC4 session in the sportscard market is significantly lower: such sellers are approximately 0.91 – 5.78% more likely to trade. In terms of overall market efficiency, these differences in probability translate into increases in expected efficiency loss of 0.1 – 0.2% in the PC4 sportscard sessions and 0.4 – 2.1% in the PC12 sessions.[30]

Relationships and Infra-Marginal Sales

Examining the probability of a foregone sale in Table 11, we find that such outcomes are independent of relationship status in the four seller sportscard markets: the marginal effect of a relationship on infra-marginal sales ranges from 0.18 – 2.4 percent in these sessions. Thus, the formation of relationships in these markets has no

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[28] We restrict attention to sellers with induced values in this range as a seller with an induced marginal cost of \$18 never executes a transaction and every seller with marginal cost less than \$10 always trade.

[29] It should be noted that while sellers in a PC4 session in the sports card market are more likely to realize a transaction when in a relationship, this difference is not significant at any meaningful level.

[30] If a seller with an induced value of \$17 executes a trade there is a reduction in overall market surplus of at least \$4 (10.8% of total available surplus). When a seller with an induced value of \$14 executes a trade, the reduction in overall market surplus is at least \$1 or 2.7% of total available rents.

discernable positive impact on expected market efficiency. However, relationships have a greater impact on infra-marginal sales in PC12 and the flea market sessions. The marginal effect of relationships in these sessions range from 3.59 – 30.6% depending upon the seller's induced marginal cost. This generates an approximate 0.2 – 1.1% increase in expected seller surplus and overall market efficiency.

Combined with insights garnered from empirical models of buyer behavior, these data highlight an interesting asymmetry in the effect of relationships on surplus measures. For buyers, the formation of relationships generates both expected efficiency gains through a reduction in the probability of a foregone purchase for infra-marginal buyers and expected efficiency losses through an increased probability of executing trades among extra-marginal buyers. Yet, for infra-marginal sellers, relationships have a negligible impact on the probability of stimulating otherwise foregone sales. However, relationships do impact the probability of extra-marginal sales, generating a loss in expected market efficiency on the seller side of the market. Thus, efficiency loss among sellers is qualitatively consonant with losses found among buyers.

Surplus and Its Division in Long-Term Relationships

Having shown that agents in our experimental markets who have formed a relationship with a particular trading partner are more likely to execute trades, we now examine the impact of such increased trade volume on overall surplus and the division of rents between buyers and sellers. Table 12 provides a comparison of the average surplus per transaction for trades that occur between a buyer and seller that trade together on a single occasion with that for all trades that occur between a buyer and seller in a relationship. As noted in the first two columns of the table, average surplus per transaction in one-shot interactions is approximately 1% to 22.9% (or \$0.05 - \$0.97) greater in four of our five treatments – treatment A12 provides the lone exception. However, this difference is only statistically significant for the PC4 sessions in the sportscard market. If we exclude from the analysis initial relationship trades, we observe qualitatively similar results. In all but the PC4 session in the flea market, average surplus in one-shot interactions is greater than that for repeat trades in a relationship with these differences significant at the $p < 0.10$ level in the PC12, PED12, and PES12 treatments.

Comparing differences in consumer surplus across single-shot and relationship trade, we observe data patterns that mirror those noted for total surplus. Considering all transactions, average consumer surplus in single-shot transactions is significantly greater than that for relationship trades in three of our five market types. Similar differences emerge if we exclude initial relationship trades: consumer surplus for single-shot trades in greater in the PED12, PES12, and PC12 treatments.

Comparing the effect of relationships on measures of producer rents, we observe a more variable data pattern. Averaging over all transactions, producer rents in symmetric markets are greater in single-shot than in relationship transactions with this difference significant at the $p < 0.10$ level for the PC4 treatment in the sportscard market. In asymmetric markets, we observe an opposite result: producer rents are greater at the $p < 0.10$ level in relationships than in a one-shot interaction. However, if we exclude initial relationship trades, producer surplus is greater in one-shot interactions in four of our five treatments with the 14.3% and 52.2% respective differences for the PED12 and PC12 markets significant at the $p < .10$ level. Combined, these data suggest a final result:

Result 7: Surplus per transaction is potentially compromised by relationships.

Importantly, these data suggest that the quantitative impact of relationships depends upon the extent to which market structure affects the coordination and matching of buyers and sellers that could profitable transact.

Recall that in our theoretical model, relationships serve to stimulate trade by reducing the costs of searching for a "soft" trading partner. Given that there are two distinct sources of potential inefficiency in our experimental markets – foregone trades among infra-marginal agents and executed trades among extra-marginal agents – the overall impact of relationships on efficiency will depend on the relative impact on each margin. In markets where infra-marginal agents are unlikely to meet and trade, relationships may stimulate such trades and enhance overall market efficiency. In markets with no such coordination failure, relationships will likely have a greater impact among extra-marginal consumers, leading to a reduction in overall market performance.

VI. Conclusions

This study explores behavior in multilateral decentralized bargaining markets and finds that buyer-seller relationships emerge in the absence of enforcement problems and known reciprocal exchange possibilities. We develop a model that assumes that agents are uncertain about the nature and bargaining behavior of potential trading partners. This uncertainty motivates agents to form relationships. The key feature of our model is that once individuals have acquired experience in the marketplace, bargaining with a new trading partner is risky. The new partner may turn out to demand a greater payoff than previous trading partners. Relationships thus form as a means to reduce such transactions costs and uncertainty.

We evaluate our theory by executing simulations and designing a series of field experiments to investigate whether such relationships emerge in naturally occurring environments. Empirical results from the field are in line with our theoretical model and simulations: the extent of relationship trades is significantly greater than what is predicted by a model of random behavior. Further, agents that form relationships are more likely to execute a trade. However, as the effects are typically stronger for extra-marginal consumers, this leads to a reduction in average surplus per trade for relationship trades. Importantly, our data suggest that the quantitative impact of relationships on overall market efficiency depends upon the extent to which market structure affects the coordination and matching of buyers and sellers that could profitable transact. In a standard Chamberlain (1948) construct, such relationships potentially frustrate market efficiency.

Undoubtedly our research has raised more questions than it has answered. For example, would similar patterns of behavior arise in markets that employ more centralized trading institutions such as posted-offer pricing and double-auctions? In addition, the impact of relationships in collusive markets and markets that are highly inefficient remains an important question that is largely unanswered in the literature. We suspect that research in these areas will likely lead to insights hitherto uncovered.

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Table 1: Proportion of Relationship Trades – Simulation Results

Proportion of soft bargainers	25%		50%		75%	
	% with initial seller	% with any prior partner	% with initial seller	% with any prior partner	% with initial seller	% with any prior partner
PC4 – Learning Model	25.6%	39.0%	42.2%	57.1%	64.3%	76.6%
PC4 – Random Model	25.2%	36.1%	25.4%	38.0%	25.6%	39.3%
PC12 – Learning Model	12.3%	18.6%	24.0%	33.8%	41.1%	52.6%
PC12 – Random Model	8.3%	13.2%	8.5%	13.9%	8.5%	14.4%

Note: Cell entries provide the frequency with which a buyer purchases a second or subsequent unit from a seller with whom they have previously traded.

Table 2: Probability of Buying a Card – Simulations, Learning Model

	Buyer in a Relationship	Buyer Not in a Relationship	Marginal Effect of a Relationship	Marginal Effect on Market Surplus
PC4 Markets				
Value = 9	8.43%	0.72%	7.71%	-1.04%
Value = 10	22.04%	4.15%	17.89%	-1.93%
Value = 11	36.73%	10.71%	26.02%	-2.11%
Value = 12	43.52%	19.80%	23.72%	-1.28%
Value = 13	56.76%	31.20%	25.56%	-0.69%
Value = 14	80.67%	53.08%	27.59%	0.74%
Value = 15	94.96%	80.66%	14.30%	0.77%
Value = 16	99.70%	96.91%	2.79%	0.22%
Value = 17	100.00%	99.66%	0.34%	0.04%
Value = 18	100.00%	99.97%	0.03%	0.004%
Value = 19	100.00%	100.00%	0.00%	0.00%
PC12 Markets				
Value = 9	8.98%	1.40%	7.58%	-1.02%
Value = 10	12.38%	8.28%	4.10%	-0.44%
Value = 11	31.85%	18.38%	13.47%	-1.09%
Value = 12	48.03%	33.38%	14.65%	-0.79%
Value = 13	60.79%	47.98%	12.81%	-0.35%
Value = 14	86.26%	66.12%	20.14%	0.54%
Value = 15	97.70%	87.62%	10.08%	0.54%
Value = 16	99.72%	98.22%	1.50%	0.12%
Value = 17	100.00%	99.34%	0.66%	0.07%
Value = 18	100.00%	100.00%	0.00%	0.00%
Value = 19	100.00%	100.00%	0.00%	0.00%

Note: Cell entries provide the probability a buyer with a given induced value will execute a trade. The final column provides the lower bound on the change in market surplus associated with the increased propensity for a buyer with a given induced value to execute a trade.

Table 3: Probability of Selling a Card – Simulations, Learning Model

	Seller in a Relationship	Seller Not in a Relationship	Marginal Effect of a Relationship	Marginal Effect on Market Surplus
PC4 Markets				
Value = 8	100.00%	100.00%	0.00%	0.00%
Value = 9	100.00%	100.00%	0.00%	0.00%
Value = 10	100.00%	100.00%	0.00%	0.00%
Value = 11	99.90%	99.73%	0.17%	0.01%
Value = 12	90.74%	83.49%	7.25%	0.39%
Value = 13	80.42%	66.20%	14.22%	0.38%
Value = 14	64.69%	52.01%	12.68%	-0.34%
Value = 15	19.78%	11.01%	8.77%	-0.47%
Value = 16	12.07%	4.43%	7.64%	-0.62%
Value = 17	6.87%	2.65%	4.22%	-0.46%
Value = 18	1.41%	0.30%	1.11%	-0.15%
PC12 Markets				
Value = 8	100.00%	100.00%	0.00%	0.00%
Value = 9	100.00%	100.00%	0.00%	0.00%
Value = 10	100.00%	99.62%	0.38%	0.04%
Value = 11	99.60%	97.57%	2.03%	0.16%
Value = 12	97.87%	85.98%	11.89%	0.64%
Value = 13	82.10%	65.36%	16.74%	0.45%
Value = 14	71.28%	46.84%	24.44%	-0.66%
Value = 15	50.57%	31.78%	18.79%	-1.01%
Value = 16	33.63%	18.37%	15.26%	-1.24%
Value = 17	24.59%	6.67%	17.92%	-1.94%
Value = 18	8.52%	1.55%	6.97%	-0.94%

Note: Cell entries provide the probability a seller with a given induced value will execute a trade. The final column provides the lower bound on the change in market surplus associated with the increased propensity for a seller with a given induced value to execute a transaction.

Table 4: Average Surplus Measures per Transaction – Simulation results

	Single Trade with Partner	Relationship Trade		
		All Trades	Initial Trade	Subsequent Trades
PC12				
Consumer	\$2.17 (0.01)	\$2.01 (0.01)	\$1.94 (0.01)	\$2.06 (0.01)
Producer	\$2.20 (0.011)	\$1.95 (0.01)	\$1.87 (0.01)	\$2.01 (0.01)
All	\$4.37 (0.02)	\$3.96 (0.02)	\$3.80 (0.02)	\$4.07 (0.02)
PC4				
Consumer	\$2.35 (0.01)	\$2.24 (0,012)	\$2.11 (0.01)	\$2.31 (0.01)
Producer	\$2.40 (0.01)	\$2.22 (0.01)	\$2.09 (0.01)	\$2.30 (0.013)
All	\$4.75 (0.02)	\$4.46 (0.03)	\$4.20 (0.02)	\$4.61 (0.03)

Note: The difference between the mean values in columns 1 and 2 is significant at the $p < 0.01$ level for all rows except for consumer surplus in PC4 where it is significant at the $p < 0.05$ level. The difference between the mean values in columns 3 and 4 is significant at the $p < 0.01$ level for all rows.

Table 5: Effect of Relations on Overall Market Efficiency – Simulation results

	$\pi_S = 0$ $\pi_H = 1$	$\pi_S = 0.5$ $\pi_H = 1.5$	$\pi_S = 1$ $\pi_H = 2$	$\pi_S = 1.5$ $\pi_H = 2.5$	$\pi_S = 2$ $\pi_H = 3$
PC12					
Constant term	83.12 (0.66)	87.74 (0.41)	90.89 (0.29)	91.19 (0.23)	88.99 (0.21)
# of relationships	-5.93** (1.79)	-2.81* (1.19)	-3.75** (0.91)	-4.57** (0.77)	-4.23** (0.80)
PC4					
Constant term	89.20 (0.75)	91.43 (0.58)	92.16 (0.44)	92.28 (0.44)	91.64 (0.41)
# of relationships	-5.13** (1.27)	-2.98** (1.01)	-2.00* (0.80)	-3.80** (0.84)	-8.78** (0.81)

** Denotes statistical significance at $p < 0.01$ level
* Denotes statistical significance at $p < 0.05$ level

Table 6: Experimental Design

Demand/Supply Structure	Sports Card Market (1)	Flea Market (2)
Symmetric		
	PC12: 12 Buyers – Unit Demand 12 Sellers – Unit Supply 3 Sessions N = 72	
	PC4: 12 Buyers – Unit Demand 4 Sellers – 3 Units Supply 3 Sessions, N = 48	PC4: 12 Buyers – Unit Demand 4 Sellers – 3 Units Supply 1 Session, N = 16
Asymmetric		
Perfectly Elastic Demand	PED12: 12 Buyers – Unit Demand 12 Sellers – Unit Supply 3 Sessions, N = 72	
Perfectly Elastic Supply	PES12: 12 Buyers – Unit Demand 12 Sellers – Unit Supply 3 Sessions, N = 72	

Note: Each cell represents one unique treatment. For example, PC12 in row 1 of col 1 denotes that one treatment (three sessions) had 12 buyers and 12 sellers competing in markets in which the demand and supply curves were symmetric. Data for treatments PC12, PED12, and PES12 come from List (2004). Data for the PC4 treatments in both the card and flea markets come from List and Price (2006). No subject participated in more than one treatment.

Table 7: Proportion of Purchases made from Prior Trading Partner

	# with Initial Seller	# with Any Prior Partner	Total # of Trades	% with Initial Seller	% with Any Prior Partner
PC4 Sessions Flea Market	13	13	18	72.2%**	72.2%**
PC4 Sessions Card Market	18	31	75	24.0%	41.3%**
PC4 Sessions Pooled	31	44	93	33.3%**	47.3%**
PC12 in Card Market	6	12	74	8.1%	16.2%
PED12 in Card Market	5	13	61	8.2%	21.3%*
PES12 in Card Market	12	12	47	25.5%**	25.5%**
All Asym Sessions	17	25	108	15.7%**	23.1%**
All 12 Seller Sessions	23	37	182	12.6%**	20.3%**
Pooled Sample	54	81	275	19.6%**	29.5%**

** Denotes statistical significance at $p < 0.05$ level
* Denotes statistical significance at $p < 0.10$ level

Note: Cell entries provide the frequency with which a buyer purchases a second or subsequent unit from a seller with whom they have previously traded. The probability that a buyer randomly trades with the first seller in a PC4 session is 25.0% and for the PC12, A12, and AS12 sessions this probability is 8.3%. The probabilities of trading with any prior partner are available from the authors upon request.

Table 8: Probability of Purchasing a Card with Induced Value $9 – 15

	Model A	Model B	Model C
Constant – PC4 in Flea Market is Baseline	0.09 (0.38)	-0.74* (0.46)	-0.88* (0.49)
Indicator for PC12 Session	0.78* (0.41)	1.02** (0.46)	1.09** (0.47)
Indicator for PC4 Session in Card Market	1.64** (0.59)	1.87** (0.64)	1.98** (0.65)
Indicator for Extra Marginal Unit	-2.00** (0.29)	0.01 (0.47)	0.24 (0.52)
Indicator for Extra Marginal Unit in Card Market PC4	-1.07* (0.59)	-1.12* (0.66)	-1.18* (0.65)
Indicator for Buyer in Relationship in PC12	1.02** (0.48)	1.49** (0.56)	1.08* (0.62)
Indicator for Buyer in Relationship in PC4	0.88** (0.41)	0.96* (0.51)	0.67 (0.54)
Indicator for Buyer in Relationship in Flea Market	1.10 (0.69)	1.28* (0.73)	1.33* (0.70)
Difference of Value and CE Price ($13.50)		0.85** (0.18)	1.02** (0.26)
Difference of Value and CE Price in Relationship			-0.31 (0.28)
Buyer Random Effects	Yes	Yes	Yes
Total # of Buyers	84	84	84
Total # of Observations	224	224	224
Log Likelihood	-78.63	-58.97	-58.38

** Denotes statistical significance at $p < 0.05$ level
* Denotes statistical significance at $p < 0.10$ level

Note: Cell entries provide parameter estimates from a random effects probit model examining the probability that a buyer with an induced value in the range $9-15 execute a trade in a given period. The associated standard errors for the parameter estimates are in parentheses. Since a buyer with an induced value greater than $15.00 never fails to execute a trade, we limit the analysis to buyers with induced values of $15.00 and less. To control for unobserved heterogeneities at the individual buyer level, we include buyer specific random effects.

Table 9: Estimated Probability of Buying a Card – By Value and Treatment

	Buyer in a Relationship	Buyer Not in a Relationship	Marginal Effect of a Relationship
PC4 – Card Market			
Value = 9	0.82%	0.01%	0.81%
Value = 10	4.55%	0.01%	4.54%
Value = 11	16.60%	0.80%	15.8%
Value = 12	40.13%	8.23%	31.90%
Value = 13	67.72%	35.94%	31.78%
Value = 14	98.34%	94.63%	3.71%
Value = 15	99.78%	99.59%	0.19%
PC12 – Card Market			
Value = 9	4.46%	0.01%	4.45%
Value = 10	16.11%	0.01%	16.10%
Value = 11	39.36%	11.70%	27.66%
Value = 12	70.88%	13.79%	57.09%
Value = 13	87.90%	47.21%	40.69%
Value = 14	95.05%	76.42%	18.63%
Value = 15	99.04%	95.99%	3.05%
PC4 – Flea Market			
Value = 9	0.55%	0.01%	0.54%
Value = 10	3.36%	0.01%	3.35%
Value = 11	13.35%	0.01%	13.34%
Value = 12	34.83%	1.43%	33.40%
Value = 13	62.55%	12.31%	50.23%
Value = 14	79.10%	35.57%	43.53%
Value = 15	93.57%	74.36%	19.21%

Note: Cell entries provide the predicted probability a buyer with a given induced value will execute a trade. The predicted probabilities are evaluated using Model C in Table 4.

Table 10: Probability of Selling a Unit with Marginal Cost $10-17

	Model A	Model B	Model C
Constant – PC4 in Flea Market is Baseline	0.51 (0.36)	0.08 (0.37)	0.08 (0.37)
Indicator for PC12 Session	0.37 (0.41)	0.11 (0.42)	0.11 (0.42)
Indicator for PC4 Session in Card Market	1.07** (0.42)	1.05** (0.43)	1.05** (0.44)
Indicator for Extra Marginal Unit	-2.49** (0.32)	-1.25** (0.43)	-1.24** (0.44)
Indicator for Extra Marginal Unit in PC12	0.94** (0.43)	1.22** (0.46)	1.22 (0.47)
Indicator for Seller in Relationship in PC12	1.10** (0.52)	0.99** (0.49)	1.00* (0.51)
Indicator for Seller in Relationship in PC4	0.37 (0.39)	0.16 (0.42)	0.16 (0.42)
Indicator for Seller in Relationship in Flea Market	1.52* (0.86)	1.13 (0.96)	1.12 (0.98)
Difference between MC and CE Price ($13.50)		-0.45** (0.11)	-0.45** (0.11)
Difference between MC and CE Price in Relationship			-0.02 (0.24)
Seller Random Effects	Yes	Yes	Yes
Total # of Sellers	52	52	52
Total # of Observations	252	252	252
Log Likelihood	-96.6	-86.54	-86.53

** Denotes statistical significance at $p < 0.05$ level
* Denotes statistical significance at $p < 0.10$ level

Note: Cell entries provide parameter estimates from a random effects probit model examining the probability that a seller with an induced marginal cost in the range $10-17 execute a trade in a given period. The associated standard errors for the parameter estimates are in parentheses. Since a seller with a marginal cost less than $10.00 always executes a trade, we limit the analysis to all sellers with induced value of $10.00 and more. To control for unobserved heterogeneities at the individual seller level, we include seller specific random effects.

Table 11: Estimated Probability of Selling a Card – By Value and Treatment

	Seller in a Relationship	Seller Not in a Relationship	Marginal Effect of a Relationship
PC 4 – Card Market			
Value = 10	99.84%	99.66%	0.18%
Value = 11	99.33%	98.81%	0.52%
Value = 12	97.72%	96.45%	1.27%
Value = 13	93.63%	91.23%	2.4%
Value = 14	42.47%	36.69%	5.78%
Value = 15	25.3%	21.32%	3.98%
Value = 16	12.71%	10.66%	2.05%
Value = 17	5.37%	4.46%	0.91%
PC 12 Sessions			
Value = 10	99.78%	96.19%	3.59%
Value = 11	99.12%	90.68%	8.44%
Value = 12	97.14%	80.76%	16.38%
Value = 13	92.34%	66.11%	26.23%
Value = 14	82.36%	47.61%	34.75%
Value = 15	67.84%	30.38%	37.46%
Value = 16	42.47%	16.7%	25.77%
Value = 17	11.17%	7.68%	3.49%
PC 4 – Flea Market			
Value = 10	99.78%	95.15%	4.63%
Value = 11	99.13%	88.63%	10.5%
Value = 12	97.17%	77.52%	19.65%
Value = 13	92.44%	61.84%	30.6%
Value = 14	38.82%	8.38%	30.44%
Value = 15	22.42%	3.26%	19.16%
Value = 16	10.87%	1.08%	9.79%
Value = 17	4.36%	0.31%	4.05%

Note: Cell entries provide the predicted probability a seller with a given induced marginal cost will execute a trade. The predicted probabilities are evaluated using Model C in Table 6.

Table 12: Average Surplus Measures per Transaction

	Single Trade with Partner	Relationship Trade		
		All Trades	Initial Trade	Subsequent Trades
PC12				
Consumer	\$2.25[c] (0.18)	\$1.97 (0.27)	\$2.17 (0.49)	\$1.78 (0.27)
Producer	\$2.36[c] (0.17)	\$1.92 (0.38)	\$2.28 (0.67)	\$1.55 (0.37)
Total	\$4.61[c] (0.30)	\$3.89 (0.52)	\$4.44 (0.91)	\$3.33 (0.5)
PC4 – Card				
Consumer	\$2.29[a,b] (0.20)	\$1.92 (0.22)	\$1.67 (0.24)	\$2.14 (0.36)
Producer	\$2.92[a,b] (0.25)	\$2.32 (0.26	\$2.23 (0.40)	\$2.40 (0.34)
All	\$5.21[a,b] (0.35)	\$4.24 (0.39)	\$3.90 (0.55)	\$4.54 (0.56)
PC4 – Flea				
Consumer	\$2.75 (0.59)	\$2.78 (0.47)	\$1.50 (0.52)	\$3.46 (0.60)
Producer	\$2.95 (0.73)	\$2.88 (0.46)	\$2.93 (0.97)	\$2.95 (0.73)
Total	\$5.70 (0.71)	\$5.65 (0.59)	\$4.43 (1.29)	\$6.31 (0.55)
PED12				
Consumer	\$0.71[a,c] (0.11)	\$0.50 (0.10)	\$0.67[d] (0.17)	\$0.33 (0.10)
Producer	\$1.93[a,c] (0.19)	\$2.67 (0.42)	\$3.61[d] (0.53)	\$1.72 (0.49)
Total	\$2.64[c] (0.21)	\$3.17 (0.44)	\$4.28[d] (0.49)	\$2.05 (0.53)
PES12				
Consumer	\$2.16[a,b,c] (0.24)	\$1.24 (0.27)	\$0.98 (0.37)	\$1.48 (0.40)
Producer	\$0.88[a,b] (0.14)	\$1.56 (0.33)	\$2.43[d] (0.53)	\$0.77 (0.26)
Total	\$3.05[c] (0.23)	\$2.80 (0.39)	\$3.41[d] (0.61)	\$2.25 (0.46)

a – Denotes that the difference between the mean values in columns 1 and 2 is significant at the $p < 0.10$ level
b – Denotes that the difference between the mean values in columns 1 and 3 is significant at the $p < 0.10$ level
c – Denotes that the difference between the mean values in columns 1 and 4 is significant at the $p < 0.10$ level
d – Denotes that the difference between the mean values in columns 3 and 4 is significant at the $p < 0.10$ level

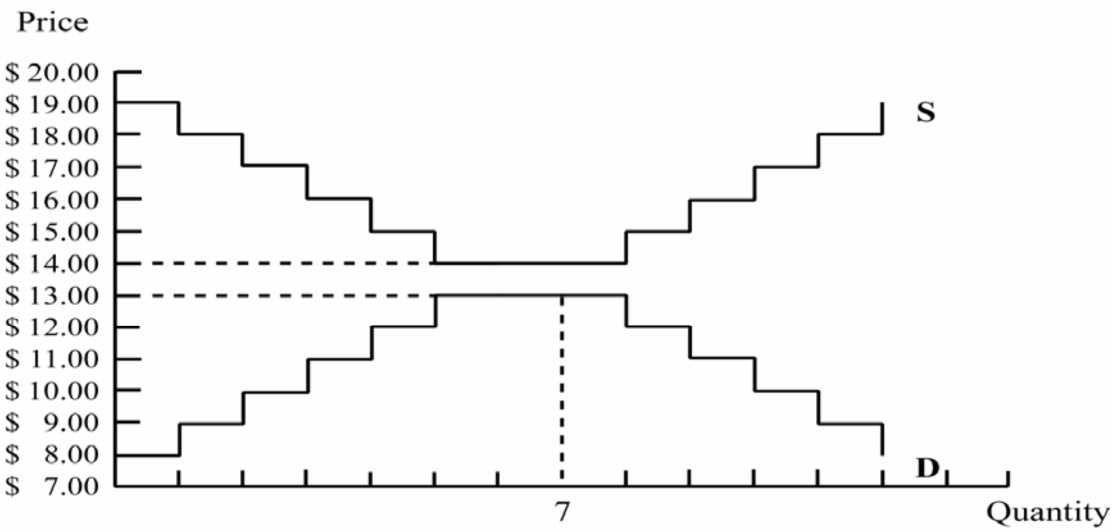

Figure 1. Supply and Demand Structure

Note: The figure provides the induced supply and demand structure for our simulations and symmetric experimental markets. Each step on the supply (demand) function represents a unique induced marginal cost (reservation value) for a respective seller (buyer). The dashed lines provide the competitive benchmarks for this market with an equilibrium quantity of 7 units sold and an equilibrium price somewhere in the $13 – 14