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Posted offers in exogenous networks: A theoretical application and experimental results(1)

Lisa BREGER
University of Wisconsin, River Falls, USA
lisa.breger@uwrf.edu
Andrea SORENSEN
Southern Illinois University, Carbondale, USA
sorensen@siu.edu

Abstract. *The Federal Communications Commission (FCC) allocates bands of radio frequency on the electromagnetic spectrum to agents called primary users (PUs), typically through standard auctions. We devise ways for unused channels to be sold in a secondary market to secondary users (SUs) who do not have licensing rights to access the spectrum. We propose a model in which PUs can set prices and offer unused channels to SUs, where trading takes place in small exogenous networks. Equilibrium prices depend on both the structure of the network and buyer valuation, and interestingly, "good" buyer location on the network is not always favorable. In equilibrium, buyers with many connections on the network can face high prices despite seller competition and can even face two prices in equilibrium. We test this model in an experiment, varying network structure and price possibilities across a total of four experimental sessions. Our results provide evidence that buyers in good locations often face high prices despite seller competition and that buyers in bad locations also face high prices but have the benefit of being served first in the market.*

Keywords: spectrum trading; posted offers; network experiment; network competition.

JEL Classification: C91, D40, L10.

Introduction

The Federal Communications Commission (FCC) regulates the use of radio spectrum by allocating radio frequency to licensed users, called primary users. Non-licensed, or secondary, users wish to use the spectrum but cannot do so legally without purchasing the licensing rights from primary users. Therefore, it is economically beneficial to devise ways for primaries to sell off unused radio frequency to secondaries.

In this paper, we consider a small partially linked network of primary and secondary users who can benefit from trade. Trade can occur between the two when the two are linked. Links are defined by the respective locations of primary users and secondary users, and are therefore exogenous. That is, a secondary user may be in a location that overlaps the licensing area of a primary user and can therefore gain access rights to this primary's spectrum through trade. This overlap defines a link between the two users. Since some secondary users overlap with multiple primaries, while others overlap with just one, we focus on partially linked networks.

In such networks, we let primary users set prices for unused radio frequency and make offers to the secondary users, which can be accepted or rejected. Prices are dependent on two factors. First, primary users have a belief about how secondary users value the frequency. Second, prices are dependent on the respective locations of primary and secondary users. We propose that it is possible for a buyer to face two different prices in equilibrium and that buyers with just one access point always face high prices but are given priority over buyers who have many options to trade. Further, under certain parameterizations, buyers in good locations face high prices despite their many connections in the network.

Literature Review

The problem of spectrum allocation in cognitive radio networks has been studied widely in the electrical engineering literature. Many of these studies use game theoretic concepts to describe how spectrum channels are shared and traded (Maharjan et al., 2011; Niyato and Hossain, 2007; Niyato et al., 2009). This problem continues to be of interest for economists in developing ways for spectrum to be sold in a market of multiple buyers and sellers. While several authors have used auctions to analyze spectrum trading[(2)], another avenue is to consider trading between buyers and sellers in small exogenously given networks (see Corominas-Bosch, 2004 for bargaining results in such networks). Cao and Zheng (2005) use a bargaining model that maximizes fairness in networks. There are some practical limitations to using private markets to allocate spectrum rights, namely the assumption that markets will improve the efficiency of allocation (Levin, 1970; Melody, 1980). In this analysis, we are less concerned with the efficiency of allocation and more concerned with how specific market structures influence price-setting when agents are allowed to trade over an exogenous network.

Kranton and Minehart (2003) describe the formation of a buyer-seller network that allows trade to occur between *linked* agents. This research emphasizes that a specific link pattern influences trading. While their focus is on the efficient formation of links, we consider exogenous links between primary users (PUs) and secondary users (SUs) that are given by their respective locations and show that equilibrium prices are dependent on these location restrictions.

The model that we propose extends the research of Zhang and Zhou (2014). They use simulations to predict the convergence of prices of spectrum channels that depends on the location of PUs and SUs. We study a similar environment with overlapping licensing rights between PUs and SUs and use a game theoretic approach which supports their results. Specifically, we find that location restrictions are driving prices in equilibrium. Kasbekar and Sarkar (2010; 2011) define equilibrium conditions when there is uncertainty of bandwidth availability among primary users. Our model does not account for this type of uncertainty, but can be easily extended to do so, in which case, similar results arise.

Trading Model

We propose a model of spectrum allocation that takes the form of a one-shot interaction between primary users (PUs) and secondary users (SUs). We analyze such interactions in a network setting, where a transaction between PUs and SUs only occurs when there is a link between them. Primary users have a license to use spectrum channels over a particular geographical area, and secondary users may or may not have permission to access these channels because of their location. Therefore, links can be informally thought of as location-based restrictions.

To formalize the trade network of PUs and SUs, we start by defining a partially linked network structure consistent with Kranton and Minehart (2003). We say that a PU and SU are linked if there is a possible trade that can occur between the two because they are in the same location or market. Such links break down when PUs learn they have no units of bandwidth available to sell, or when the two users are in different locations. Thus, buyers and sellers are part of an exogenously determined network. We say a secondary user is a single-linked buyer if he is linked to exactly one primary. A secondary user is a multi-linked buyer if he is linked to two or more primaries. A group of secondaries forms an outside market if each secondary in the group is a single-linked buyer. In Figure 1, SU_1 and SU_3 form an outside market because they have a link to only one primary user in the network.

Figure 1. *Partially linked network with overlap over two licensed areas (PU_1 and PU_2)*

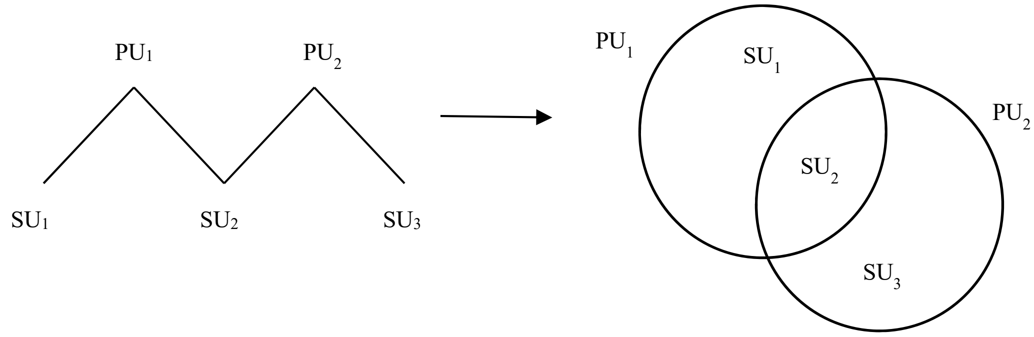


Figure 1 shows a partially linked network structure with two primary users who have an overlapping licensing area. Here, we illustrate how the location of licensing areas exogenously forms the trade links between buyers and sellers.

Consider a network of $M = \{1, 2, \ldots, j, \ldots m\}$ primary users and $N = \{1, 2, \ldots, i, \ldots n\}$ secondary users. Let each primary user j have a supply of $s_j \geq 0$ units available and each secondary user i have a demand of $d_i \geq 0$ units. Suppose that a secondary user values an additional unit of spectrum the same as any previous unit.

We assume a secondary user i values the good at

$$V_i = \begin{cases} v_H & with\ probability\ q \\ v_L & with\ probability\ 1-q \end{cases}$$

and that the expected payoff to a primary user of offering a high price is at least as good as the certain payoff of offering a low price. In other words, $qV_H \geq V_L$. After learning whether they have units available to sell, primary users offer these units strategically to buyers at a price p that maximizes their expected profits. A buyer i will accept the offer and purchase the good if the price is set such that $p \leq V_i$.

If the offer is accepted, the buyer receives a payoff of $V_i - p$. Therefore, a buyer could potentially receive a surplus if he is given a low price offer but he has a high valuation for the good. If the offer is rejected, no transaction occurs and both parties receive nothing. We assume asymmetric supply (demand) among PUs (SUs), and PUs know how many units each SU demands and how many units other PUs have to sell.

Primary users make simultaneous offers. At a certain time, all PUs realize how many unused channels they have available to sell to potential buyers. Each unused channel can be sold and used during a particular time slot, and PUs choose how to spread the time slots out over buyers to limit the amount of interference over the frequency. Each seller chooses at once how many units to offer to any buyer(s) with whom he is connected, and in which order the respective buyers can purchase and use the channel. In other words, if a seller chooses to sell 2 units to a single buyer, the seller must choose a price for each unit and the units are spread out over the first two available time slots. With this offer structure, secondary users are limited to which channels they will have access to at which time, and will accept or reject each unit as the channels become available to them.

A secondary user, at any given time, must compare the units he has been offered for that particular time slot as he may be offered two channels by two different sellers for the same slot. A buyer accepts the unit at the lowest price and rejects any units at a high price if his valuation is low. If a buyer rejects an offer, the time expires and the seller can no longer offer the channel to another buyer. Since buyers are indifferent between radio channels, a buyer will choose at random who to purchase from when he is offered multiple units at the same price by different sellers.

A couple of results arise immediately out of the assumptions we have made about buyer valuations and the specific offer structure. First, since single-linked buyers are segregated in the link structure (by location), the PUs hold a monopoly over those buyers and have an incentive to charge a monopoly price ($p = V_H$).

Proposition 1. *A single-linked buyer will always be offered a high price in the one-shot game.*

Proof. Proposition 1 follows directly from the assumption that the expected profit of offering a high price is at least as good as the expected profit of offering the low price to any buyer ($qV_H \geq V_L$).

This result holds for a one-shot interaction between a buyer and seller. If we consider a case where the PU offers the high price in the first period and the offer is rejected, the PU quickly learns the buyer's value and offers the competitive price in future periods. A second result is that the outside market is given priority by the PUs. If the outside market demands enough units, the PUs linked to this market will try to meet that demand before they start offering units to multi-linked buyers. This leads us to Proposition 2.

Proposition 2. *A primary user sells as many units as possible to their outside market at the high price and offers the remaining units to multi-linked buyers.*

Proof. Consider any single unit offered to the outside market by a PU at the high price.

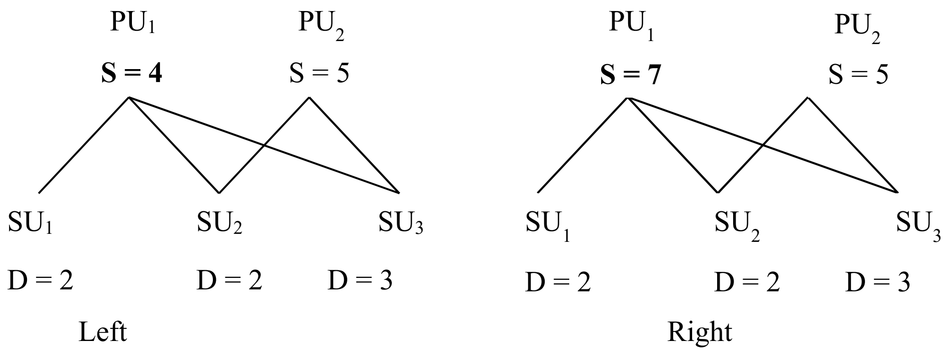
The PU's expected profit from this unit is qV_H. We wish to show that this PU could not receive a higher expected profit by instead offering this unit to a multi-linked buyer. Suppose the PU did offer this unit to a multi-linked buyer, then their payoff from a low price offer would be at most V_L (if any other offers for this time slot of this buyer are at the high price). Since $qV_H \geq V_L$, the PU is not better off. If instead the PU offered this unit to the multi-linked buyer at the high price, then their expected payoff from this unit would be at most qV_H (if no other PUs make offers to this buyer for this time slot), which is still not better than offering to the outside market. Thus, a PU will sell as many units as possible to the outside market before making offers to multi-linked buyers.

These propositions serve to illustrate the importance of the link structure and how location-based restrictions can both benefit (by giving priority) and harm (by constraining a high price offer) the single-linked buyers. They also point to the fact that there is a possibility that multi-linked buyers would be completely ignored by sellers if the demand of the outside market is high enough.

The next part of our analysis illustrates how prices are determined in equilibrium for multi-linked buyers when there is asymmetric demand and supply. In a fully linked network structure, it is possible for the price to be driven down for all buyers when $V_L > \frac{1}{2}qV_H$ and when each seller can meet the full demand of each buyer to which they are linked. When we see complete overlap of licensing areas, all buyers can benefit from competition and possibly receive a surplus if they value the good highly. However, in our model, we examine partially overlapping networks where only some buyers can benefit from competition, and even in these cases, it is likely for buyers to face high prices (i.e. when $V_L \leq \frac{1}{2}qV_H$).

Consider an example (Figure 2) where we have two sellers and three buyers with asymmetric demand and supply.

Figure 2. *Partially linked networks with asymmetric demand and supply*



Example 1

In Figure 2 the link structure is such that SU_1 forms an outside market. According to the first two propositions, PU_1 offers 2 units at the high price to SU_1 and has 2 (left) or 5 (right) units remaining to offer to the multi-linked buyers.

First looking at the scenario on the right, notice that both PU_1 and PU_2 have enough remaining units to make offers for all 5 of SU_2's and SU_3's demanded units. Thus, the only potential variability in Nash equilibria for this scenario is in the prices of the offers from PU_1 and PU_2. The simplest equilibrium is the one in which all offers to SU_2 and SU_3 are made at the low price. For any given unit offered to SU_2 or SU_3, the PU's expected payoff is $\frac{1}{2}V_L$. If either PU were to deviate to a high price offer, their offer would be rejected with certainty, so neither PU has incentive to deviate. If $V_L > \frac{1}{2}qV_H$, then this is the only pure-strategy Nash equilibrium. If $V_L \leq \frac{1}{2}qV_H$, then in addition to the above equilibrium, there are 31 additional pure-strategy Nash equilibria in which anywhere from 1 to 5 of the offers by PU_1 and PU_2 to SU_2 and SU_3 are at the high price, the rest are at the low price, and offers by PU_1 and PU_2 to a given SU for a given time slot are of the same price.

Now looking at the scenario on the left, it is no longer the case that PU_1 can make offers for all demanded time slots they are linked with. Thus, possible equilibrium strategies for PU_1 vary not only in the prices of PU_1's offers, but also in the number of offers he makes to SU_2 and SU_3. In any Nash equilibrium however, PU_1 still offers two units to SU_1 at the high price. Note that PU_2 still has enough units available to make offers for all 5 of SU_2's and SU_3's demanded units.

If $V_L \leq \frac{1}{2}qV_H$, then in any pure-strategy Nash equilibrium, all units are offered at the high price. This yields 3 pure-strategy Nash equilibria in which PU_1 offers two units to SU_1 at V_H, and two additional units at V_H either both to SU_2, both to SU_3, or one to each of them. PU_2 offers two units to SU_2 and three units to SU_3 all at V_H.

If $V_L > \frac{1}{2}qV_H$, there are no pure-strategy Nash equilibria.

This example outlines various Nash equilibria that depend on the expected benefit of making high price offers. What we find is that sellers may have an incentive to offer high prices to buyers with multiple links and that competitive prices will prevail when both $V_L > \frac{1}{2}qV_H$ and each seller can meet their entire market demand.

Remarks on Posted Offers

First, we develop a model where there is complete information between sellers. We find that it is possible for a secondary user to face two different prices in equilibrium. We also find that SUs who are linked to just one PU have a priority over those who have multiple trade links. Such SUs will be sold to first and receive a majority of the available units, but will be offered a high price due to the lack of competition. This result is consistent with other research that uses simulations to show that more spectrum channels are offered to SUs who have access to only one PU (Zhang and Zhou, 2014).

The implication of this model is that PUs and SUs trading on a small network face equilibrium prices that are dependent on the exogenous structure of the network. Thus, location is important in models of spectrum sharing as a “bad” location could adversely affect buyers who face no competition as well as those who are in a “good” location but have a high demand. The reality that certain frictions in a small network, in this case location friction, as well as the inability to negotiate prices, puts buyers at a disadvantage in trading.

Experiment

The purpose of this section is to take this model to the laboratory to observe price-setting behavior in two exogenously imposed networks. First, we test whether sellers with little or no competition in the network set high prices. Second, we test whether sellers in competition offer high prices to buyers with multiple links despite network competition. Third, we test the effect of buyer valuation on a seller’s willingness to charge high prices. Fourth, we observe convergence toward equilibrium behavior and suggest that the complexity of a network can slow the learning process and lead to more nuanced results about which price-setting strategies are favored over others.

Networks in the Laboratory: Relevant Literature

Observing behavior in networks is fundamental to understanding many decentralized markets. As a result, experiments involving networks have become increasingly useful in testing theoretical predictions of behavior in markets, including how networks are formed (Rong and Houser, 2015; Falk and Kosfeld, 2012), efficiency in networks (Cassar et al., 2012), and cooperation and learning in small networks (Kirchkamp and Nagel, 2006). See Kosfeld (2004) and Choi, Gallo, and Kariv (2015) for recent surveys on network games in the laboratory.

Charness et al. (2007) examine trading outcomes in a bipartite network of buyers and sellers in an experimental setting, testing the theoretical predictions of Corominas-Bosch (2004) which state that surplus depends on the structure of the network. We also use a variation of bipartite networks that are simple in structure. They find that a buyer and seller linked only to one another will split the surplus almost evenly after a period of bargaining. While our focus is not on bargaining, since buyers simply accept or reject a posted offer, their work is suggestive that we might see a division of surplus that favors sellers with single and multiple links to buyers due to lack in bargaining power of buyers.

Like these, our experiment focuses on optimal pricing strategies in bipartite networks where trade is limited by the architecture of the network itself. Our experimental methods are most closely related to that of Gale and Kariv (2009), who also use posted prices in networks, except we do not concentrate on intermediary buyers and sellers but rather on buyers and sellers in a secondary market. Although we abstract away from intermediary paths, primary users in our application are, in a sense, intermediary sellers, and buyers in the network are final destination buyers. This is because primary users receive licensing rights from the Federal Communications Commission through an auction. A second notable difference is that our trading mechanism allows sellers to make a *take-it-or-leave-it* offer to buyers, unlike Gale and Kariv, who let buyers make simultaneous bids. This subtle difference puts the focus on seller behavior rather than buyer strategies, and gives a better insight into competition among sellers in a small network that is more fitting to the application of spectrum trading.

In a similar study, Choi, Galeotti, and Goyal (2015) test the effects of market power in an experimental setting, where both the paths between intermediary traders and node criticality(3) of traders influence the amount of surplus extracted by agents in the network. Their work focuses on posted prices as well and provides persuading evidence that an individual's position in a network is crucial to their market power. Similarly, we argue that one's position can increase trading power, namely of sellers with connections to buyers with a very limited number of connections. Judd and Kearns (2008) find that players benefit from having more connections. They implement a variety of large bipartite networks in their experiment and allow players to trade two fully divisible goods with each other, and notice that trading prices vary across network treatments. Though our mechanism of trade is different from these, we too look for asymmetries in benefits to players that depend on position in the network.

Rosenkranz and Weitzel (2012) find that network structure plays a key role in determining investment in a public good and that individual contributions to the public good are decreasing in degree (or size of the network). Interestingly, they also find that individuals have a difficult time coordinating behavior in regular networks, where each individual is connected to the same number of other individuals, as opposed to irregular networks where individuals have a varying number of connections. Of the two networks we impose on players in our experiment, we might expect to find similar results in which, not the regularity in our case, but the complexity of the network influences individuals' abilities to reach a stable equilibrium.

The theory of networks is a large and growing literature, much of which focuses on the endogenous formation of links and network stability (Bala and Goyal, 2000; Watts, 2003; Jackson and Watts, 2002; Kranton and Minehart, 2003; see Jackson (2005) for a complete survey). Upon these, network experiments have become a natural step in trying to understand market behavior that would otherwise be difficult to observe in uncontrolled settings. Our work contributes to network games by allowing us to explore treatment effects across two bipartite networks characterized by varying degree distributions.

Experimental Procedures

In this experiment, we test price-setting predictions in a small exogenous network of buyers and sellers. Given a particular network structure, we allow sellers to make *take-it-or-leave-it* offers to buyers to whom they are linked. Each seller is endowed with S units, while each buyer demands D units which is public information. Since buyers in our model follow a simple decision-rule in which they only accept an offer at a reservation price of $p \leq V_i$, where V_i is the lowest possible valuation for the traded good, we let there be a computer-generated response for each buyer in the network. This allows us to focus on the price-setting strategies of sellers to find out whether their actions are consistent with profit-maximizing behavior.

Experimental Design and Procedures

We use the experimental software *z-Tree* developed by Fischbacher (2007) to conduct our network experiments. A total of 50 undergraduate students from various academic faculties at Southern Illinois University were recruited.(4)

At the beginning of each session, subjects are given an instruction packet to read privately which is also read aloud by the experimenter. Subjects are given instructions on which decisions they can make during the experiment and told that they will receive earnings based on their actions during the game. A sample of these instructions can be found in the Appendix. During the instruction phase, students are invited to ask questions to clarify any misunderstandings they might have. At the end of the session, participants are asked to fill out a short questionnaire, and are then paid privately by the experimenter. The purpose of the questionnaire is to collect information about the participants that may influence results. For example, we ask participants to rate (on a scale from 1 to 10) their desire to take risks(5) and their level of competitiveness. We also ask about gender, age, intended major, and year of undergraduate study. Payouts to the subjects include a \$10 participation fee, plus subsequent earnings that depend on the decisions made during the game.(6) Each session lasts approximately 90 minutes.

The experiment consists of each participant completing one session in which they play a total of 30 periods. In all periods, players face essentially the same game, with only their position changing. At the beginning of the session, players are randomly matched to form groups of two to replicate the network structures in Figure 3 below, where the two players act as competing sellers in a small fixed network. All paired players within a session face the same network and information. In total, we have four sessions where we vary the network structure across sessions to examine the role of network effects on individual behavior. Half the sessions face network (a) and half face network (b).

In addition to varying link structure across the four sessions, we assign a total of two treatments by changing the prices sellers can set. The treatments are designed to capture differences in price offers that are driven by the variation in buyer valuation. In other words, a large difference in valuation of buyers may result in more frequent high price offers. Across two of the four randomly selected sessions, players face the network structure shown in (a) depicted in Figure 3, while the other two sessions face the structure in (b). We randomly assign a treatment (i) or (ii) to each session such that we have half of the sessions facing a large price gap and the other half facing a low price gap. Following Example 1 from earlier, notice that a pure-strategy Nash equilibrium in treatment *(ii)* is for sellers to make high price offers across all links (since we have imposed $V_L \leq \frac{1}{2}qV_H$). In network a, treatment *(i)*, there is no pure-strategy Nash and in network b, treatment *(i)*, seller 2 will offer 2 units to Buyer D at the low price and the remaining unit at the low price given that seller 1 offers him 2 units at the low price (since $V_L > \frac{1}{2}qV_H$).

Figure 3. *Partially linked network structures imposed on players*

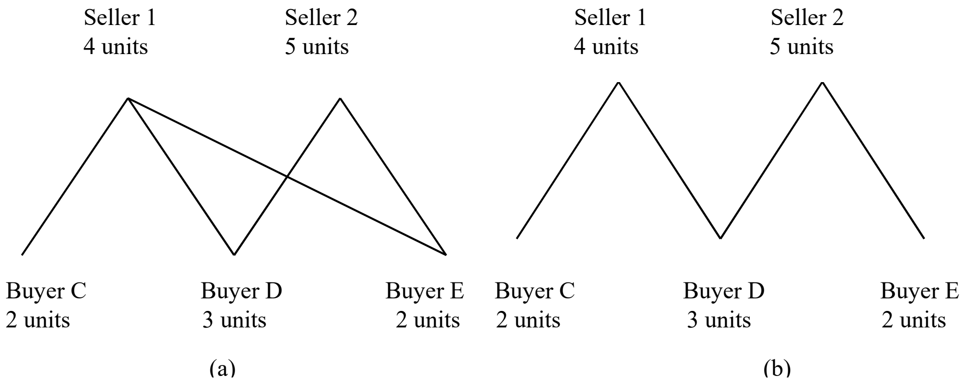


Table 1. *Four experimental treatments imposed on four sessions*

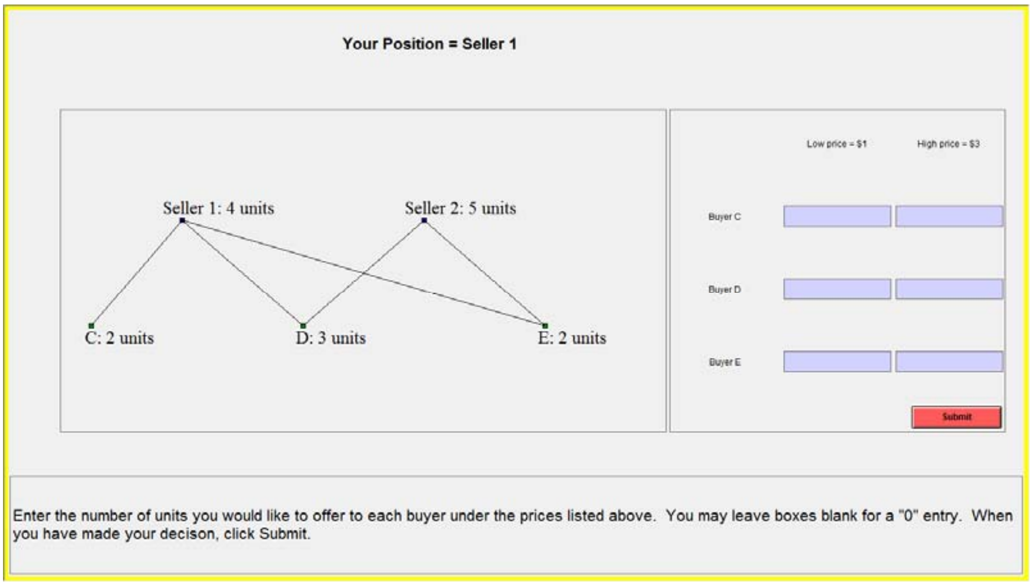
	Networks	
Treatments	*(a)*	*(b)*
(i)	Session 1, 14 subjects	Session 3, 16 subjects
(ii)	Session 2, 10 subjects	Session 4, 10 subjects

(i) = Small price gap, $p_L = 1,\ p_H = 3$ and *(ii)* = Large price gap, $p_L = 1,\ p_H = 6$
(a), (b) refer to the two network structures shown in Figure 3
We recruited a total of 50 subjects and record their offer choices over 30 rounds, giving a total of 1500 observations.

To start, players are randomly matched with an unknown partner, with whom they stay matched throughout the session. Then, each one is assigned to a node on a given network which is displayed to them on their computer screen.(7) Note that players in the session cannot see the screens of those sitting nearby and are asked not to communicate with one another. The type of all players in the network is a seller (top row of the network), but their position as a seller switches randomly each period, while the network architecture remains the same throughout the session.

Sellers are endowed with S units of the good. Sellers are also told the likelihood that the computer-generated buyer (CGB) will accept a high price offer, which is $\frac{1}{2}$. CGBs (bottom row of the network) are labeled with how many units of the good they demand. Sellers are asked to make *take-it-or-leave-it* offers to buyers with whom they are linked. They do so by first selecting one or more buyers with whom they would like to trade with, and then enter a number next to each buyer representing how many units they would like to offer him[(8)], as well as an ask price of either p_H or p_L. We have that $p_L = 1$ in all cases, but $p_H = 3 \ or \ 6$ depending on the treatment group. Once both sellers submit their offers, the results are displayed to the players, indicating their total sales for the round. After their payoffs are displayed, the next period begins and the player is assigned a new position. The game repeats.

Figure 4. *Example of screen display for network (a) and treatment (i)*



Data and Hypotheses

The data collected tells us the specific offers that each of the 50 sellers made over the course of 30 rounds. From this, we document each individual's offers to get an indication of how players' strategies evolve throughout the experiment. We expect that through the first few rounds, players will be in a state of learning, and will possibly switch strategies often. Over the course of time, we should expect players to converge toward playing an optimal strategy. Note that there are multiple possible equilibrium strategies within network play, but despite differences in actual offers, we can easily observe which ones are consistent with our theoretical predictions. While in theory the problem of multiple equilibria can pose problems, an experimental approach to testing equilibrium predictions is one way of observing which equilibria are more likely to occur (Charness et al., 2014) and, in our case, we can observe which price offers occur most frequently.

Below, we summarize group characteristics across treatments. We find that we have little variation between groups in subject characteristics (with the exception of gender), suggesting that our treatment groups are properly randomized.

Table 2. *Subject characteristics, by treatment group*

	Network (a), Low price gap	Network (a), High price gap	Network (b), Low price gap	Network (b), High price gap
Average time in decision stage	27.24	25.13	17.97	19.47
(in seconds)	(29.74)	(23.54)	(19.45)	(17.74)
Observations	420	300	480	300
Average total sales	13.74	23.5	12.79	15.05
(per person) [a]	(1.71)	(4.39)	(2.33)	(3.89)
Average age	20.64	19.6	20.25	21.40
	(3.18)	(0.70)	(2.08)	(5.60)
Average years in	2.43	2.10	2.19	2.90
college [b]	(1.16)	(0.57)	(0.91)	(0.74)
% Females	57.1	30.0	37.5	70.0
Total subjects	14	10	16	10

Standard deviations are reported in parentheses. Average time spent in the decision stage across subjects is the average over all 30 rounds. Though not reported, there is little variation in self-reported risk-seeking and competitive behavior between treatment groups.
[a] Total sales in any round for a participant is calculated as the total number of units they sold, multiplied by the selling price, and then scaled by 0.15 (0.10) in a low (high) price gap treatment, respectively. Recall that actual payouts are higher, as subjects receive a $10 participation fee.
[b] Subjects report their standing in college as such; 1 = Freshman, 2 = Sophomore, 3 = Junior, 4 = Senior.

A notable feature of our design is that we manipulate two key variables at two levels, allowing for a between-group comparison of treatments. These are network architecture and price levels. See Table 1 in the previous section for a design layout. For one, we test for network effects between groups facing the same network. We expect that a change in link structure may influence the degree to which players are willing to take risks and offer high prices. And second, we compare the price offers between groups facing the same price gap to test whether a higher price gap attracts players to charge the higher price more often. With these in mind, we state the following hypotheses. Some are directly related to theoretical predictions outlined in the first section of the paper, while others are predictions based on how we anticipate behavior to differ given the nature of the experiment.

H1. Players in any treatment group will offer single-linked buyers more units at a high price on average compared to commonly-linked buyers. (see Proposition 1)

H2. Players in any treatment group will offer the maximum number of units possible to buyers with a single link at a high price in equilibrium. (see Proposition 2)

Recall the model presented earlier where we assume a high price offer is superior to a low price offer when there is no competition. Thus, sellers will exploit single links to buyers by charging a monopoly price (H1). In all treatment groups and networks, we should observe sellers making consistent high price offers to such buyers. If we are to strictly count the number of times that sellers make strict high price offers to single-linked buyers, these statistics are quite low. For instance, players assigned as seller 1 only offer buyer C strict high prices 42 percent of the time across all networks, while buyer E is offered strict high prices 38 percent of the time in network (b). Despite the seemingly low frequency of this offer type, we compare the frequency of offer types among buyers in respective treatment groups to show that single-linked are offered more high priced units than commonly linked buyers. See the results section for a decomposed representation of offers.

H3. The number of units offered to buyers with common links at a high price will differ depending on the network structure, regardless of the price gap.

H4. Players in a group facing treatment *(ii)*, where the price gap is high, will offer more units at the high price on average to all types of buyers, regardless of network structure.

In Hypothesis 3, we predict that the degree of competition, represented in the link pattern, will influence a seller's decision to make high price offers. We find that players in network (b) – a lower competition network – offer more high priced units over common links than players in a high competition network. A possible explanation for this outcome is that lower overall competition in a network drives up prices, but as we explain later, it is more likely a result of a player's confidence that they will make money by exploiting single-links and so they may be more willing to take risks over common links by setting high prices.

In Hypothesis 4, we propose that an increased price gap will influence buyers to offer more high prices on average. Theoretically, sellers should offer the high price to a buyer when there is no competition (when there is a single link to that buyer), since the expected return is higher in both of the treatment groups. Sellers should also offer units at the high price to the extent that another seller cannot compete in prices over all of the units that a buyer demands. However, there is likely to be a difference in behavior in the group that has a higher price gap, since this group may be willing to offer high prices in earlier rounds and may be more likely to take additional risk by offering units at a high price even when they know they could be undercut by the other seller. Evidence in our data to this effect will suggest high price offers are increasing in price gap.

Experiment Results

To formally test our hypotheses, we consider between group comparisons of high price offers, as well as estimate the likelihood that players make high price offers to buyers with whom they are linked, controlling for various subject-specific characteristics. Table 3 summarizes high price offers between treatment groups by reporting the average number of units offered at a high price to buyers C, D, and E across subjects within groups. For example, in network (a) with a low price gap, buyer C is offered on average 1.09 units at a high price across all 30 periods by a total of 14 subjects. (Recall that of the 14 subjects, only 7 can sell to buyer C in any one period, thus limiting the number of observations to 210).

We see that in all treatment groups but one, buyer C is offered more units on average at a high price than their respective commonly linked buyers, a phenomenon that is also evident when we plot offers across rounds. Likewise, in network (b) with a low price gap, the single-linked buyer E is offered more units at a high price than buyer D who is commonly linked.

Table 3. *Average number of units offered to buyers at a high price*

	Buyer C	Buyer D	Buyer E
Network (a), Low price gap	1.09	0.407	0.236
	(0.056)	(0.036)	(0.024)
	210	420	420
Network (a), High price gap	0.893	0.490	0.410
	(0.064)	(0.042)	(0.036)
	150	300	300
Network (b), Low price gap	0.95	0.577	0.796
	(0.054)	(0.041)	(0.050)
	240	480	240
Network (b), High price gap	1.03	1.17	1.04
	(0.066)	(0.061)	(0.065)
	150	300	150

Standard errors in parentheses and number of observations reported below. Means represent the average number of units offered to respective buyers at a high price in a given treatment group. Recall that in network (a), buyer C is a single-linked buyer. In network (b), buyers C and E are both single-linked buyers.

Below, we track the behavior of subjects in each treatment group across all 30 periods to summarize how price offers differ between groups and among buyers within groups. This serves to further decompose the means reported in Table 3. For simplicity, we focus on high price offers. In figures 5 – 8 below, the dependent variable represents the average number of units across subjects that were offered to a given buyer at a high price. For example, in network (a), treatment *(i)*, we have a total of 14 subjects, who on average offered buyer C a total of 1.42 units at a high price in period 1. From these graphs, it is plain to see that in all but one treatment group, buyer C (who is a single-linked buyer in each network) is offered more high priced units on average. We also note that the movement of subjects within groups across the 30 periods is quite volatile and that players do not appear to converge toward a specific strategy, but rather switch strategies often from round to round. Perhaps increasing the number of periods would result in more obvious patterns and convergence among subjects, but since we summarize averages across subjects, the depictions are not individually descriptive of subject-specific trends over time. In other words, individual players may converge toward specific strategies which are not evident in the graphs.

Figure 5. *Average number of units offered to buyers at a high price, network (a), low price gap*

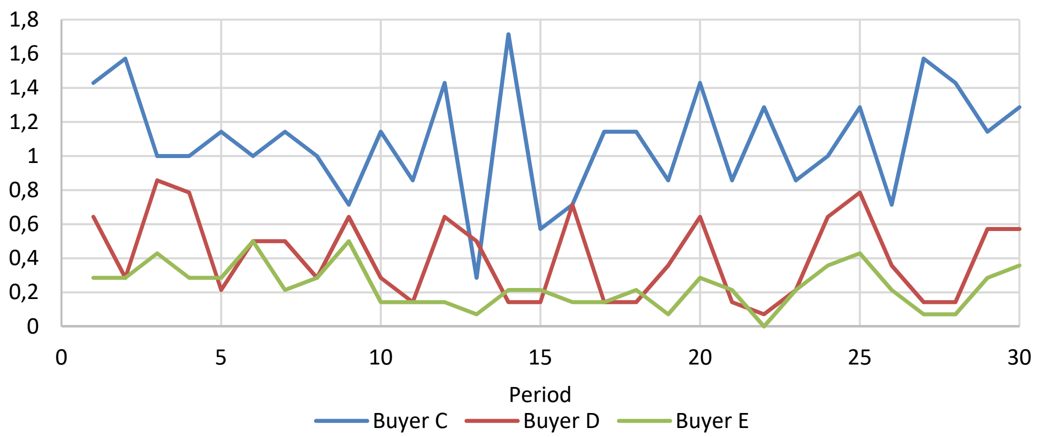


Figure 6. *Average number of units offered to buyers at a high price, network (a), high price gap*

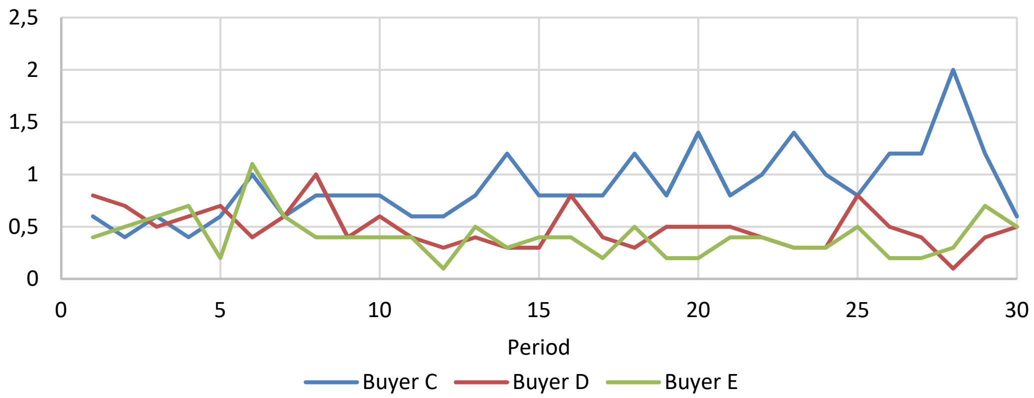


Figure 7. *Average number of units offered to buyers at a high price, network (b), low price gap*

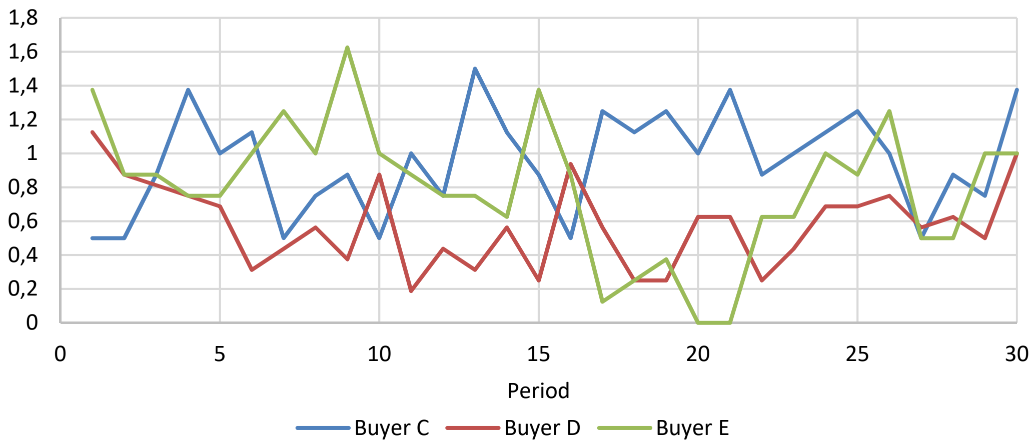


Figure 8. *Average number of units offered to buyers at a high price, network (b), high price gap*

By comparing means between buyers in each treatment group, we find that H1 is generally supported by our data – that is, single-linked buyers are given high price offers more frequently than buyers with common links. Table 4 reports two-sample test statistics to compare offers given to single-linked and commonly-linked buyers. Specifically, the test statistics provide evidence that the average number of units offered to single-linked buyers is statistically greater than the average number offered to buyers with common links. In almost all treatment groups, we find that the means are significantly different and conclude that single-linked buyers are offered more units on average at a high price. In network (a), large test statistics lead us to reject the null hypothesis that buyer C is offered the same number of units at high price on average as commonly linked buyers D and E. Similarly, in network (b) with a low price gap, large test statistics lead us to reject the null hypothesis that single-linked buyers C and E are offered the same number of units at a high price as the commonly linked buyer D. Together, these comparisons suggest that our data is supportive of H1.

Table 4. *Single-linked buyers face high prices more often than buyers with common links (H1)*

Network (a), Low price gap				
Buyer C	Buyer D	t-stat	Buyer E	t-stat
1.09	0.407	10.252***	0.236	13.999***
(0.056)	(0.036)		(0.024)	
210	420		420	
Network (a), High price gap				
Buyer C	Buyer D	t-stat	Buyer E	t-stat
0.893	0.49	5.290***	0.41	6.614***
(0.064)	(0.042)		(0.036)	
150	300		300	
Network (b), Low price gap				
Buyer C	Buyer D	t-stat	Buyer E	t-stat
0.950	0.577	5.528***	0.796	3.378***
(0.054)	(0.041)		(0.050)	
240	480		240	
Network (b), High price gap				
Buyer C	Buyer D	t-stat	Buyer E	t-stat
1.03	1.17	-1.512	1.04	-1.45
(0.066)	(0.061)		(0.065)	
150	300		150	
Notes: In each panel, we report the average number of units offered to single-linked buyers at a high price to the average number offered to commonly-linked buyers. Recall that in network (b), both buyer C and E are single-linked buyers. Standard errors are in parentheses, and number of observations are also given. Reported test statistics are two-sample t-tests (with unequal variances) for comparing means. In all but one treatment group, we find that single-linked buyers are offered more units at a high price on average.				

We find that, although single-linked buyers are offered more high price units on average, it is not necessarily the case that they face high prices across their full demand. Recall that in each network, single-linked buyers demand two units each. We observe the frequency at which single-linked buyers are offered two units at a high price, as well as the frequency that they are in fact offered the full two units they demand. Refer to Table 5. As expected, we see that sellers in all treatment groups exploit the single-link by frequently offering these buyers the full number of units they demand—a minimum of 68.67% of the time in network (b) with a high price gap and as frequently as 92.38% of the time in network (a) with a low price gap. However, we notice that it is not so evident that sellers prefer to offer both units to single-linked buyers at the high price. In fact, it is apparent in our data that players just as frequently split their offer (1 unit at a high price and 1 at a low). Despite players' tendencies to mix up their strategies, we can be confident that they exploit the single-link in every environment by always offering the maximum number of units to such buyers.

Table 5. Frequency that single-linked buyers are offered strictly high prices and their full demand

Network (a), Low price gap			Network (a), High price gap		
	Seller 1			Seller 1	
Two units at	0.3762		Two units at	0.2533	
high price	(0.486)		high price	(0.436)	
Full demand	0.9238		Full demand	0.8133	
	(0.266)			(0.391)	
Obs.	210		Obs.	150	
Network (b), Low price gap			Network (b), High price gap		
	Seller 1	Seller 2		Seller 1	Seller 2
Two units at	0.3208	0.2208	Two units at	0.3467	0.3400
high price	(0.468)	(0.416)	high price	(0.478)	(0.475)
Full demand	0.9000	0.7000	Full demand	0.6867	0.6933
	(0.461)	(0.461)		(0.465)	(0.463)
Obs.	240	240	Obs.	150	150
Notes: Reported are the frequencies of which single-linked buyers are offered two units at a high price by a seller. We also report the frequency at which these buyers are offered their full demand (two units). Standard deviations are in parentheses.					

We are also interested in testing for differences in means between networks to see whether high price offers to buyers with common links are dependent on network structure (H3). In Table 6 we compare the average number of units offered to buyer D (who is commonly linked in all networks) at a high price across networks for both price treatments. For example, buyer D is offered an average of 0.407 units at a high price in network (a) with a low price gap, which is statistically different than the 0.577 units he is offered in network (b) with a low price gap. The same is true in comparing networks (a) and (b) at a high price gap. Thus, our data suggests that commonly linked buyers receive more high price offers in network (b), supporting our hypothesis that network structure can play an important role in price determination. A likely explanation for this difference in our particular experiment is that, in network (b), seller 2 holds a monopoly link over buyer E. So, seller 2 can be confident that he will make profits over this link. Thus, seller 2 may be more likely to offer risky high prices to buyer D who is commonly linked, since any risk of doing so is offset by the fact that he has a stream of certain income coming from buyer E.

We also test for price gap effects (H4) to see whether high price offers are increasing in price gap for all buyers. These results are reported in Table 7. Here, we compare the average number of units offered to buyers at a high price between price treatments, fixing the network. In most cases, we find that high price offers to buyers D and E are significantly different (and increasing) in price gap in both types of networks. Buyer C is offered more units at a high price in network (b) with a high price gap treatment – but not significantly so – and he is offered less units at a high price in network (a) with a high price gap treatment. This could partly be explained by the fact that subjects facing network (a) in the low price gap group offered buyer C his full demand much more frequently (92% of the time) than subjects in the high price gap group who only did so 60% of the time. It is perhaps the case that if subjects in the high price gap group were to make full offers to buyer C, the result could be reversed. Later, we find that controlling for subject characteristics sheds no further light on this result.

These network and price gap effects are summarized in the tables below, where large test statistics represent a statistical difference in the frequency of offers given to buyers when we fix either the price treatment or the network treatment.(9) In Table 6, the test statistics confirm that buyer D was offered more units at a high price on average in network (b) than in network (a), in both a low and high price gap treatment. In Table 7, the test statistics report that in almost all cases, buyers are offered more units at the high price under a high price gap treatment. The exception is network (a), where buyer C was offered 0.197 less units at a high price on average in the higher price gap treatment.

Table 6. *High price offers to commonly-linked buyers differ among network structure (H3)*

Low price gap			High price gap		
Network (a)	Network (b)	t-stat	Network (a)	Network (b)	t-stat
0.407	0.577	-1.917*	0.49	1.17	-9.151***
(0.036)	(0.041)		(0.042)	(0.061)	
420	480		300	300	
Notes: Buyer D is the only commonly-linked buyer across all networks. We report the average number of units offered to buyer D at a high price in each treatment group and compare across network to find that buyer D is offered significantly more high price units on average in network (b). Reported test statistics are two-sample t-tests (with unequal variances) for comparing means. Standard errors are in parentheses, and observations are also given.					

Table 7. *Buyers are offered more high price units in a high price gap treatment (H4)*

Network (a)								
Buyer C			Buyer D			Buyer E		
Low	High	t-stat	Low	High	t-stat	Low	High	t-stat
1.09	0.893	[a] 2.329***	0.407	0.49	-1.491	0.236	0.41	-3.998***
(0.06)	(0.06)		(0.04)	(0.04)		(0.02)	(0.04)	
210	150		420	300		420	300	
Network (b)								
Buyer C			Buyer D			Buyer E		
Low	High	t-stat	Low	High	t-stat	Low	High	t-stat
0.950	1.03	-0.975	0.577	1.17	-8.057***	0.796	1.04	-2.958***
(0.05)	(0.07)		(0.04)	(0.06)		(0.05)	(0.07)	
240	150		480	300		240	150	

Notes: For each buyer, we report the average number of units offered to him at a high price and compare across price treatments using two-sample mean comparison test statistics. Standard errors are in parentheses, and number of observations are also given. [a] Buyer C is offered 0.197 less units at a high price on average in the higher price gap treatment, which is inconsistent with our expectations.

Conclusion

Our experiment has aimed to show how price offers may differ in small fixed networks with asymmetric demand and supply. We find that buyers with single-links are often exploited and tend to face higher prices on average than buyers in better locations (that is, with multiple links to sellers). However, due to the offer structure, we find that buyers in good locations also face high prices frequently. These findings confirm predictions of our theoretical model of spectrum trading. With a total of 1500 observations across four treatment groups we have identified how average price offers differ in networks and price treatments. Specifically, we find that network effects are present and that players in our smaller network offered more high priced units on average than in our larger network. Also, we find that players in a high price gap treatment offer more high-priced units in most cases.

The main implications of our findings are that network architecture plays a key role in determining pricing outcomes and that our particular experiment design allows us to identify differences in price offers that occur as a result of varying buyer valuation.

Notes

(1) Financial support from the NSF under grant SES-1343380 is gratefully acknowledged. Special thanks to Alison Watts for guidance and support in conducting this research.

(2) See Cramton (1997), Gandhi et al. (2007), Watts (2015), Zhou and Zheng (2009), and Zhou et al. (2008).

(3) Node criticality refers to nodes, or vertices, on a graph type network that is located on a path from a source to a final destination. These nodes are critical in the sense that a traded good, for example, must pass through this node at some point along the path if it is to reach its final destination.

(4) Traditionally, it is ideal to have roughly 100 participants in experimental studies. However, both the capacity of the computer lab and the constraint of funds to pay participants limits our recruiting ability. Despite these limitations, each of the 50 participants generate data over 30 periods, giving a total of 1500 observations.

(5) This is perhaps an over-simplified way to capture risk attitude. Commonly, experimental papers dealing heavily with risk and behavior use Zuckerman's (1994) Sensation Seeking Scale V, a scale built on a series of 40 questions that aim to measure an individual's inherent risk attitudes, independent of situational factors. Because of the exhaustive nature of such a scale and limited time, we opt for a simple method in hopes to gain at least some information about the attitudes of our subject pool.

(6) Participants facing a low price gap treatment receive a payout of $\$10 + 0.15 * Total\ Sales$, while participants in high price gap groups receive $\$10 + 0.10 * Total\ Sales$. We scale Total Sales differently to balance earnings across groups, since players in high price gap groups will naturally earn more.

(7) See Figure 4 for an example of the screen display. Entire screen displays for each session can be found in the Appendix. Keep in mind that players will only see screens that are specific to their randomly assigned position on the network to design an environment where sellers A and B enter two similar decision stages simultaneously.

(8) Sellers choose who to trade with, how much, and the price of each unit; but they do not choose the order in which the units will be available to buyers. This aspect of the game is built into the CGB decision process, and players are instructed as to how CGBs make their purchasing decisions.

(9) These results are robust to a logistic regression analysis, where we are able to control for subject-specific characteristics such as risk, gender, and age.

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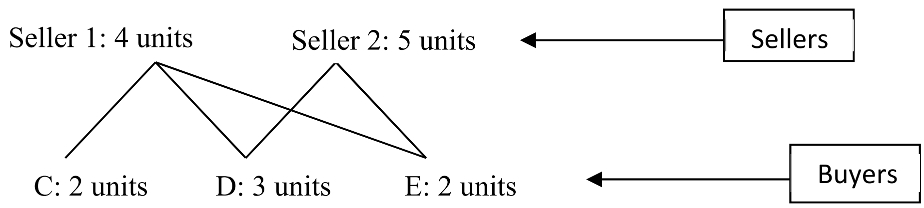
Appendix

A1. Sample Instructions

Thank you for your participation in this research study. Your decisions and the decisions of others during this experiment, as well as an element of chance, will determine your monetary payout. You will be paid privately at the end of the session; funds have been provided through a research grant. To ensure the best payout, please pay careful attention to the instructions and make your decisions carefully. This session will take approximately 90 minutes to complete.

During this session, you will complete a total of 30 periods. At the beginning, you will be randomly matched with another person in the room, but you will not know who they are. You will stay paired throughout the experiment. Please do not look at others' computer screens.

In each period, the two of you will act as sellers and will be able to sell to buyers with whom you are connected to on a network (shown below). There are no buyers in the room—all buyers are computer-generated. Here is an example:



- In each period, you will be assigned a position as **seller 1** or **seller 2** (if you are seller 1, then your matched partner is seller 2 and vice versa).
- You may sell to a buyer if there is a line connecting you and the buyer.
- The numbers represent how many units sellers have to sell and buyers want to buy (example: seller 1 has 4 units to sell, buyer D wants to buy 3 units).

At the beginning of each period, carefully take note of your position on the network and the number of units next to each person. **Your position will switch randomly** throughout the session.

You will be able to choose a Low price or a High price for each unit that you try to sell to a buyer, which will be shown to you on the screen. Some buyers are willing to pay the higher price for a unit, but others will only pay the lower price. You don't know which buyers are which. **For each buyer, there is a 50% chance that they would never buy at the higher price.** Also, even if a buyer is willing to pay the higher price, if your partner offers him a unit at the lower price, he will buy the unit at the lower price. Each period, the willingness of a buyer to pay the higher price **switches randomly**. If a buyer is indifferent between two offers, and is willing to pay the price of either offer, then he randomly decides which offer to take.

At this time, **you will choose how many units you will offer to each buyer and at which price**. You may choose any combination of units/prices you wish. You will enter this information in boxes on the right side of the screen.

Here is an example of what you might see:

	Low price = $X	High price = $Y
Buyer C		
Buyer D		
Buyer E		

In each of the boxes, **enter the number of units you would like to offer to each buyer at which price**. In total, you cannot offer more units than what you have available to sell. When you are done, click Submit.

When you and your partner have submitted your offers, your total sales during this period will be displayed.

This completes one period. In total, you will complete 30 periods. Keep in mind that each period, your position on the network will change at random but you will be matched with the same partner each time, although you do not know who this person is.

When all 30 periods have been completed, your payoff will be calculated as follows:

$$Payout = (\$10\ show\ up\ fee) + (Subsequent\ earnings)$$

Subsequent earnings depend on your sales throughout the game, an element of chance, and your partner's decisions. Sales in any one period are calculated as the number of units you are able to sell, multiplied by the price you sell them at.

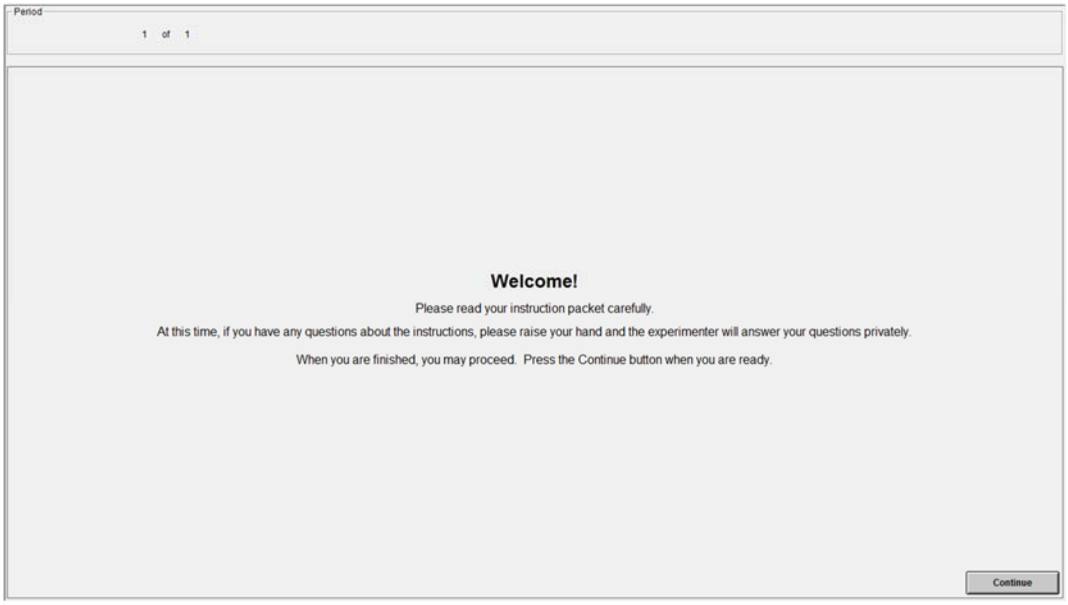
At the end, you will also be asked to answer a short questionnaire to complete the session. When you have done so, you will be paid privately by the experimenter.

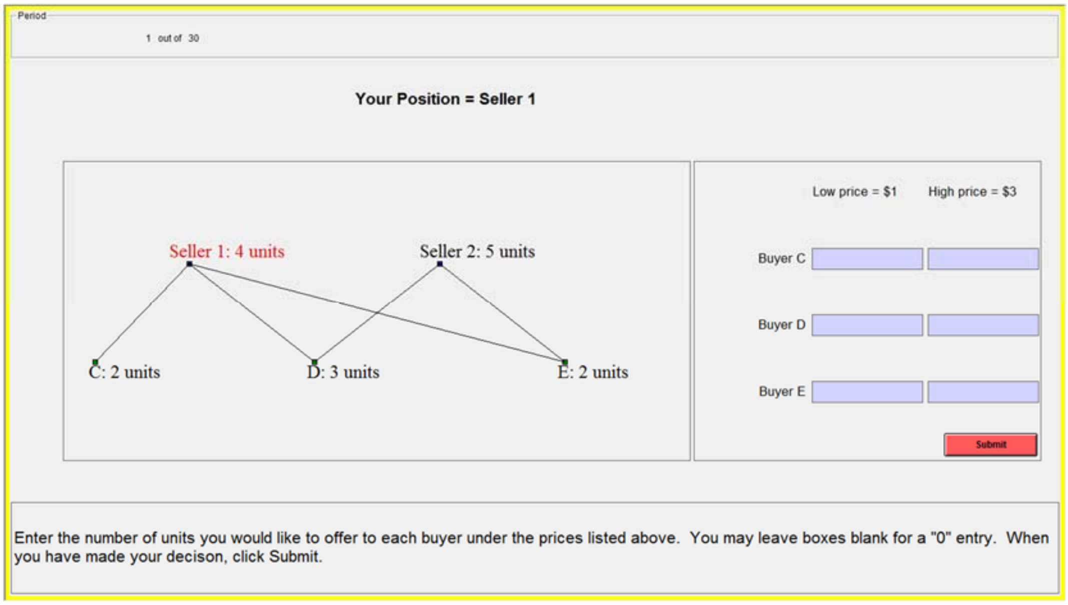
This completes the instructions. At this time, the instructions will be read out loud and you will have a chance to ask questions.

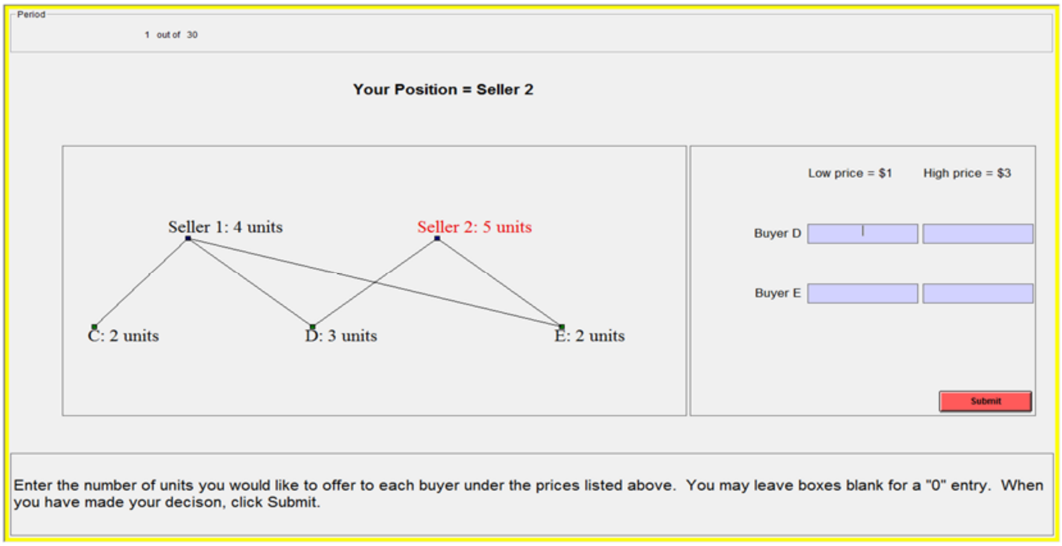
Thank you for your participation in this study. If you would like to participate in further research studies within the Department of Economics, please provide your name and contact information on the sign-up sheet before you leave.

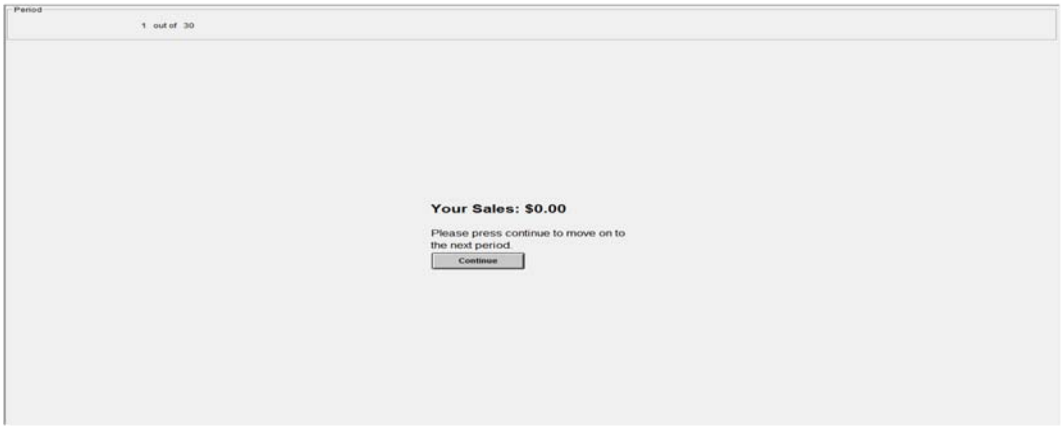
A2. Screens displayed to a subject in network (a), given treatment (i)

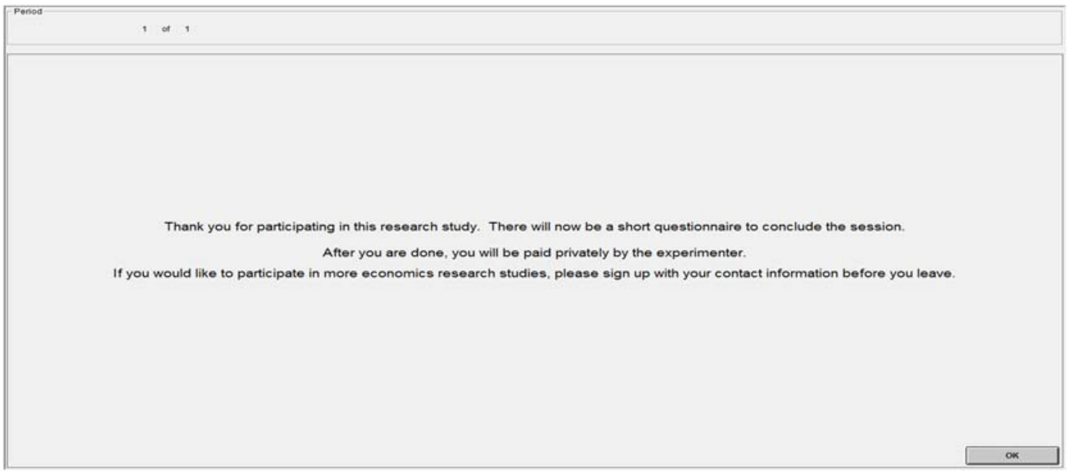
Note that the players enter one of two decision stages depending on their randomly assigned position, and they enter the stage simultaneously.


Period
1 of 1
Welcome!
Please read your instruction packet carefully.
At this time, if you have any questions about the instructions, please raise your hand and the experimenter will answer your questions privately.
When you are finished, you may proceed. Press the Continue button when you are ready.
Continue


Period
1 out of 30
Your Position = Seller 1
Seller 1: 4 units
Seller 2: 5 units
C: 2 units
D: 3 units
E: 2 units
Low price = $1
High price = $3
Buyer C
Buyer D
Buyer E
Submit
Enter the number of units you would like to offer to each buyer under the prices listed above. You may leave boxes blank for a "0" entry. When you have made your decison, click Submit.


Period
1 out of 30
Your Position = Seller 2
Seller 1: 4 units
Seller 2: 5 units
C: 2 units
D: 3 units
E: 2 units
Low price = $1
High price = $3
Buyer D
Buyer E
Submit
Enter the number of units you would like to offer to each buyer under the prices listed above. You may leave boxes blank for a "0" entry. When you have made your decison, click Submit.


Period
1 out of 30
Your Sales: $0.00
Please press continue to move on to the next period.
Continue


Period
1 of 1
Thank you for participating in this research study. There will now be a short questionnaire to conclude the session.
After you are done, you will be paid privately by the experimenter.
If you would like to participate in more economics research studies, please sign up with your contact information before you leave.
OK

Additional questions (optional):

(Please scroll down and click Finish when you are done.)

1. What is your intended major?

2. Select one of the following regarding your status as a student:
- Freshman
- Sophomore
- Junior
- Senior
- 5th Year Undergraduate
- Graduate Student

3. What is your Gender?
- Male
- Female

4. What is your Age?

5. On a scale of 1-10, where 1 is the **lowest** and 10 is the **highest**, rate your desire to take risks?
1 — 10

6. On a scale of 1-10, where 1 is the **lowest** and 10 is the **highest**, rate how competitive you are?
1 — 10

7. During this session, how likely were you to change your strategy after playing a period where you had low sales? 1 **(not likely)** to 10 **(very likely)**
1 — 10

End of Session

You have now completed the session. Please wait silently until asked by the experimenter to collect your earnings. All payments will be made in cash.
Thank you for participating!