Competition and Lock-In in an Experimental Market with Network Effects

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Abstract

Markets with strong network effects often have multiple equilibria, including winner-take-all equilibria in which one firm has a monopoly. Lock-in to one of these equilibria—arising from individual consumer switching costs and/or the difficulty of consumer coordination—may allow the dominant firm to collect rents. Firms may therefore compete dynamically with the aim of selecting a favorable equilibrium. In this paper we create an experimental market with differentiated products and network effects. When lock-in is created by simulating naïve buyers, monopoly does arise with sellers setting high prices. However, with human buyers, we find that markets without switching costs are extremely competitive, with no support for stories of lock-in and monopoly. Markets with switching costs are inefficient, but this is overwhelmingly due to the individual switching costs rather than monopoly.[1]

1 Introduction

Stories of competition in markets with network effects often have a winner-take-all dynamic, with an inferior product sometimes winning. This story has been formalized theoretically, and applied to historical cases such as the QWERTY keyboard layout (David, 1985) and the VHS-Beta videocassette format competition (Ohashi, 2003). It has also been used to analyze possible anti-competitive practices, as in the Microsoft anti-trust case (Salop and Romaine, 1998) and the AOL/Time-Warner merger (Faulhaber, 2002). In this paper, we examine such stories in an experimental setting.

Network effects result when consumers benefit from other consumers who consume the same or similar products in many markets. Sometimes the benefit is subtle and indirect, such as the benefit to a car owner when many repair shops service a popular model (e.g. Katz and Shapiro, 1985). Other times, the benefit is obvious and intrinsic to the nature of the product, such as for a telephone. It is only useful when there are other people with telephones to talk to. There are many products, particularly in information technology, that fall in-between, where the lone consumer can derive some benefit from a

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product, but compatibility is a major concern. These demand-side economies of scale are generally called network externalities or network effects, because in the most obvious cases (such as the telephone) the benefit comes from belonging to a network.

Markets with strong network effects and competing networks do not have unique competitive equilibria. Competition over time gives rise to the possibility of lock-in: the survival of an inferior equilibrium because consumers are unable to switch to an equilibrium with a superior or lower-priced product[2].

The experiments reported in this paper create markets with strong network effects. We study the behavior of the experimental markets to see whether—and under what conditions—lock-in occurs, and the competitive and welfare implications. In particular, the experiments are designed to distinguish between *individual* lock-in and *systemic* lock-in. Individual lock-in frequently exists with or without network effects, when individual switching costs hamper the transition to a superior situation. Such switching costs may be actual monetary costs involved in the switch, such as the need to purchase media in a different format for a new type of media player, or costs in terms of time and inconvenience such as the need to retrain on a new piece of software. Systemic lock-in arises when the difficulty of coordination hampers such a transition. Systemic lock-in—if it occurs—is a product of network effects, but may be reinforced by individual lock-in. Since the experiments create a complete market, we also observe how firms respond strategically to lock-in.

The organization of this paper is as follows. Section 2 gives the background on network effects theory and an overview of previous experiments. Section 3 describes the basic design of this experiment and the three treatments.

Results are presented in section 4. Sellers respond strategically to both systemic and individual lock-in. However, neither network effects alone or combined with individual lock-in were enough to create systemic lock-in. Discussion and concluding remarks are presented in section 5.

2 Background

2.1 Models of network effects and lock-in

Lock-in, if and when it occurs, is important for both strategy and welfare. To fully understand lock-in, it is necessary to distinguish between possible sources of lock-in, and the extent to which disparate sources of lock-in act in concert. It is necessary to understand whether lock-in can arise from network effects alone, as the disputed tales of the QWERTY keyboard and VHS format adoption imply, or whether such lock-in is also driven by individual

[2]That is, an equilibrium inferior by some criterion, usually total surplus or consumer surplus.

switching costs. Furthermore, it is important to determine the extent to which lock-in is truly inefficient. If lock-in arises, it is from some dynamic process, so assumptions about the nature of that process must be explicit.

The QWERTY keyboard story is one of systemic lock-in, based on its widespread adoption. David (1985) discusses how "...the overall user costs of a typewriting system based on QWERTY... would tend to *decrease* as it gained acceptance," due to a larger pool of trained typists. This describes demand-side economies of scale, which might lead to systemic lock-in. As David describes, path-dependent phenomena can potentially select outcomes in ways sensitive to perturbations, and not always with regard to individual or social preferences. However, he simultaneously emphasizes the "quasi-irreversibility" of individual investment in touch-typing aptitude. This is an example of individual lock-in, with switching costs for each consumer.

Individual lock-in without network effects can produce some of the same dynamics as systemic lock-in from network effects. Sellers in markets with individual switching costs may pursue similar strategies to those in markets with network effects—competing fiercely for market share early, followed later by supercompetitive pricing. Klemperer (1987) modeled markets with individual switching costs and described those dynamics. However, his results lead to oligopoly, while stories of systemic lock-in from network effects lead to monopoly.

If systemic lock-in occurs, it is as a result of a path-dependent process, in which the ultimate outcome for a market depends on events in the history of that market. Liebowitz and Margolis (1995) argue that while some markets might be path-dependent, this does not meaningfully affect their efficiency. They make a distinction between insignificant ("first degree"), middling ("second-degree"), or strong ("third-degree") path-dependence. Third-degree path-dependence results in either foreseeable inefficiency or "remediable" inefficiency that both can be recognized as inferior to an alternative and allows change to the alternative with benefits outweighing switching costs. This third-degree path-dependence can only arise (and be sustained) due to coordination difficulties, and so corresponds to what we call systemic lock-in. While Liebowitz and Margolis describe first- and second-degree path-dependence as having no welfare implications, they argue that third-degree path-dependence would be a serious problem, except that it does not occur, and criticize the stories that QWERTY or VHS were inefficient standards. The switching-cost treatment described in section 3.3 is designed, in part, to test whether third-degree path-dependence can occur.

Lock-in is a dynamic process, so predictions resulting from models of network effects depend on how dynamics are handled in the model. In an early description of lock-in, Arthur (1989) implements dynamics as heterogeneous buyers arriving in random sequence. Buyers are strictly backward-looking, receiving network benefits only from the installed base at the time of purchase. The process results in a random walk in market share, but with a critical market share threshold. After the threshold is met, the market becomes locked-in, with every future buyer purchasing the dominant product.

In forward-looking models, dynamics depend on the way decision makers form expectations about the future. Miyao and Shapiro (1981) and Brock and Durlauf (2001) include dynamics in non-market models of decision making with network effects, to examine stability. The dynamics are defined by having a representative consumer best-respond to its own earlier decisions, so while consumers are forward-looking, they are myopic in their expectations. The resulting dynamics are simple[3], and are prone to lock-in. Such naïve dynamics underlie the simulated-buyers treatment described in section 3.1.

2.2 Experiments

Several experiments examining network effects support stories of lock-in. Early behavior strongly predicts later behavior, and actions taken by firms to acquire market share result in successfully retaining that market share.

Looking at only the consumer side, Drehmann et al. (2007) conducted web-based experiments on herding, including several treatments with positive and negative externalities. In spite of there being many equilibria, in a treatment with strong positive network effects, early moves in their experiments were strong predictors of overall decisions.

Network effects can give an advantage to a dominant firm. Implementing only the seller side, with simulated buyers, Chiaravutthi (2007) conducted experiments with two sellers (one high-cost, one low-cost) in two-period markets. The low-cost firms engaged in predatory/penetration pricing in the first period, were generally successful in capturing the network effects, and partially deterred entry by the high-cost firms. The asymmetry between the firms in this experiment avoids issues of path-dependence and multiple equilibria, as the unique equilibrium gives an advantage to the dominant firm. It is also unclear how human buyers would have behaved in such a market. In Chiaravutthi's setup, buyers ignored network effects in the first period and coordinated perfectly in the second period.

In a complete market setting, there is mixed support for the lock-in story. Chakravarty (2003) explores an experimental implementation of the model in Katz and Shapiro (1986), which has multiple equilibria. In a two-period market, expectations arise from public knowledge of seller costs, which vary between sellers and over the two periods. Second-period buyers exhibit herd

[3]For example, such consumer decisions lead to only first-order difference or differential equations.

behavior, following the purchase decisions of first period buyers, and sellers act strategically to exploit this phenomenon, engaging in penetration pricing. However, Chakravarty finds mixed support for the notion that sellers with large market shares exploit their positions.

Each of these experiments supports ideas of path-dependence and lock-in. However, they also deviate from common stories of competition with network effects. Drehmann et al. (2007) and Chiaravutthi (2007) each examine only one side of the market. Studying the buyer side alone doesn't allow for strategic competition by the sellers. Studying the seller side alone imposes assumptions about buyer behavior which are at the core of the theories of lock-in. Imposing these assumptions with robot buyers makes sellers' strategic decisions too simple.

Chakravarty (2003) has a strong implementation of a complete market, but the two-period model allows for little of the dynamics commonly described in stories of network markets. The experiment also inherits from Katz and Shapiro (1986) the confounding interaction of network effects with individual lock-in. Each period's buyers make their purchase decisions in only that period, but receive network benefits from other buyers in both periods.

Our experiment approaches these problems via three treatments. All three treatments take place over 20 periods, allowing for rich dynamic competition. Only one has any individual lock-in. The first treatment uses simulated buyers, to observe sellers' behavior given the assumption of buyer systemic lock-in. The second makes a complete market by putting human buyers into the same environment, to compare actual buyer behavior to the simulated buyers, and find differences in sellers' strategic response. The third treatment keeps the complete market, but adds individual lock-in to see how it interacts with network effects and whether individual lock-in contributes to systemic lock-in.

3 Experiment Design

In three treatments, we implement markets with network effects. One experiment has human sellers and simulated buyers, while the other two are full markets with human buyers and sellers. The market takes place over 20 periods. This allows for rich competitive interaction, and observation of any sustainable lock-in. Comparing the three treatments helps identify when lock-in might occur, and the implications for competitive behavior and market outcomes whether it does or does not occur.

Experimental subjects take the roles of buyers and sellers in a posted offer market with network effects. There are three nondurable products—each having network effects—and an outside option. The three networks are incompatible in that consumption of one does not add to the value of the others. The general environment and institution is described below, followed by details of the three treatments.

On the supply side, each seller owns one of three networks. Sellers produce with zero cost, and begin each period by simultaneously setting their prices. Unlike many experimental posted-offer institutions, sellers do not limit quantity. This matches many service and software products where the quantity is only softly limited. Sellers are allowed to set either positive or negative prices for their good. It is explained to both buyers and sellers that a negative price means the seller is paying the buyer to take the good. The option for negative prices was included to allow vigorous competition for customers. Charging a negative price can be considered buyer subsidization, such as offering a service below cost. Alternatively, it can be likened to spending to affect preferences via advertising campaigns.

Sellers begin each run with an endowment of experimental dollars. They are forbidden from charging a negative price at any time that could cause the seller to have a negative balance, so any negative price offered must be small enough that the seller's balance would be at least zero if all 8 buyers purchased from them. Buyers are allowed to have negative balances.

On the demand side, buyers have differentiated induced demand. Each buyer has a "Base Value" for each of the three goods, shown in Table 1. A buyer can buy at most one good per period. The good's base value, plus network effects from other buyers choosing the same good, determines the value of any good purchased. Frequently, network-effects are modeled with concave functions, to capture the intuitive decreasing marginal value of network size. In these experiments, the network-effects function was linear to ease subject understanding. Subjects are told, "*In addition* to your base value, you will also earn 1.00 for every other buyer who chooses the same item as you." The outside option has no network effects, and gives a guaranteed payoff of zero.

Table 1: **I**nduced values ("Base Values") for idiosyncratic preferences

	Good **A**	Good **B**	Good **C**
Buyer 1	0.00	0.00	0.00
Buyer 2	4.60	0.00	0.00
Buyer 3	0.00	4.60	0.00
Buyer 4	4.60	4.60	0.00
Buyer 5	0.00	0.00	4.60
Buyer 6	4.60	0.00	4.60
Buyer 7	0.00	4.60	4.60
Buyer 8	4.60	4.60	4.60

The equilibria of markets with network effects arise from the interaction of network effects and diverse preferences. When idiosyncratic preferences are strong, they dominate network effects and there tends to be (depending on prices) a single interior equilibrium in which various products are purchased in roughly the same quantity. When idiosyncratic preferences are weak, there tend to be multiple corner equilibria in each of which only a single product is purchased. For these experiments, parameters were chosen to exhibit moderately strong network effects, having only corner equilibria in pure strategies when prices are equal[4].

Each period, after all sellers have set their prices, buyers are asked to simultaneously make purchase decisions. They can choose Good **A**, **B**, **C**, or "**None**" (the outside option). In addition to making the purchase decision, they are asked to guess how many other buyers will choose each product[5].

Guessing is not required and there is no direct financial incentive to guess correctly, but there are advantages to soliciting guesses. First, upon entering a guess, the complete payoff for selecting an option (incorporating base value, price, network effects, and switching cost) is automatically calculated for the subject. Thus, they can see, without mental computations, how much they will receive if they have guessed correctly. Second, there is some evidence that encouraging subjects to introspect on a decision problem can speed learning. Asking the question focuses the subjects' attention on the critical part that guessing others' choices has on one's best choice. Since every buyer has to make decisions this way, the act of guessing can help put each buyer in the other buyers' shoes[6].

Most information in the game is public. Every subject—buyer or seller—is able to see the values in Table 1, so that they can understand the nature of the decisions others must make. At the end of a period, buyers and sellers receive the same information on the results of that period. Everyone is told how many units were sold of which good, and at what price. The purchase decisions of each specific buyer remain private information[7].

3.1 Simulated buyers treatment (SB-NOSC)

Treatment SB-NOSC (Simulated Buyers - No Switching Costs) has simulated buyers and zero switching costs. Each market has three human sellers. The eight simulated buyers are described to the sellers as robots, and the sellers

[4]Consider the simplest case when prices are all zero. Then, if idiosyncratic preferences were stronger (with a high induced value of > 5.00 instead of 4.60), there would be 9 equilibria: the three monopoly equilibria, plus 6 fully interior equilibria in which 5, 2, and 1 buyers purchase the three products. The monopoly equilibria would disappear with a high induced value of > 7.00. The equilibria when there are switching costs depend on the game's history.

[5]Since this is a coordination problem for buyers, there may be concern about the alphabetical label order of the goods influencing decisions. In an early experiment not reported here, pains were taken to negate the order effect. However, results strongly indicated that ordering did not matter. Since the additional rigmarole required to negate order effects might have been confusing to the subjects, it was left out of the sessions reported in this essay.

[6]In practice, buyers in the switching-cost treatment entered guesses about 35% and 25% of the time in inexperienced and experienced runs, respectively. Buyers in the no switching cost treatment did so about 55% and 49% of the time. There appeared to be no particular trend over the periods during a run in the number of guesses.

[7]This makes the subjects in the market with switching costs less well-informed, since who chose what can be relevant.

are told how the robots make their decisions.

The simulated buyers are non-strategic and implement a myopic, naïve expectation-formation process. They begin the experiment with unbiased expectations. In each period the simulated buyers best-respond to the prices offered in that period, and other buyers' purchase decisions in the *previous* period[8].

Thus, the simulated buyers are (broadly) rational, and are coded to implement the dynamics in the strong lock-in story. Once one product has a monopoly (or near-monopoly), only a large price difference will induce the buyers to switch to another product. Treatment SB-NOSC is designed to identify seller behavior when systemic lock-in is guaranteed.

3.2 Market treatment (HB-NOSC)

Treatment HB-NOSC (Human Buyers - No Switching Costs) has human buyers and zero switching costs. This treatment highlights one extreme of the environmental possibilities for causing lock-in, in which coordination difficulty is the only plausible cause of lock-in.

3.3 Switching costs treatment (HB-SC)

Treatment HB-SC (Human Buyers - Switching Costs) has human buyers who are subject to switching costs. Buyers must pay a "Setup Cost" of 2.40 each time they purchase a product different from what they purchased in the previous period[9]. While coordination failure could still cause systemic lock-in, individual lock-in also contributes to such failure.

Liebowitz and Margolis' typology of path-dependence implies that it is trivial to induce lock-in with sufficiently high switching costs, but also that such lock-in may not create inefficiency. We choose a level of switching costs such that any lock-in would clearly be inefficient; any inefficiency which results in a given period is inefficient even after switching costs are taken into account.

We select the switching cost SC by considering the scenario in which buyers coordinate to purchase the lowest-priced good as a benchmark example. SC is low enough that it is *collectively and individually* in buyers' best interest to coordinate on purchasing the lowest-priced good, even after paying the switching cost. Suppose the lowest priced good is **A**. We focus on those buyers who would least like to purchase **A**, such as a buyer whose idiosyncratic value

[8]Simulated buyers behave in the first period as if they expect the same number of subjects to choose each of the three products. For the sake of having the products all appear preferable to the outside alternative, in the initial period the robots expect 2 other buyers to choose each good. This detail is not explained to the subjects.

[9]This Setup Cost is *not* paid to the seller.

for **B** is strictly higher than that for **A**[10], and who purchased **B** in the previous period, and thus could avoid the switching cost by again purchasing **B** rather than **A** in the current period.

For example, buyer 3 has a high 4.60 base value for **B** and a low 0.00 base value for **A**. If, in the current period, **A** is cheaper than **B** ($P_A < P_B$) and all the buyers other than buyer 3 purchase **A**, then buyer 3 will be better off also purchasing **A** when:

$$\begin{aligned}
(\mathbf{A}\text{ Base}) - P_A + (7.00\text{ Net}) - (\text{Setup Cost}) &> (\mathbf{B}\text{ Base}) - P_B + (0.00\text{ Net}) \\
0.00 - P_A + 7.00 - SC &> 4.60 - P_B + 0.00 \\
\Leftrightarrow SC &< 2.40 + (P_B - P_A)
\end{aligned}$$

By choosing a switching cost of SC = 2.40, coordination failure is made more costly, but it is still Pareto efficient (for the buyers) in any given period to follow the lowest-price coordination rule. Any lock-in which occurs will clearly fall into Liebowitz and Margolis' inefficient "third-degree path-dependence" category. Even higher switching costs could demonstrate inefficient lock-in. If considering efficiency as aggregate payoff rather than Pareto efficiency, buyer 3 would deny each other buyer 1.00 worth of benefit by sticking to **B** instead of purchasing **A**[11].

Table 2 shows a break-down of the types of lock-in designed into each treatment. A "?" indicates that systemic lock-in has not been imposed by design on either treatment with human buyers, but could arise out of subject behavior.

Table 2: Lock-in for the three treatments

	Systemic Lock-In	Individual Lock-In
SB-NOSC	Yes	No
HB-NOSC	?	No
HB-SC	?	Yes

3.4 Experiment Details

Experiments were conducted in the Economic Science Laboratory at the University of Arizona. Simulated buyer sessions were conducted in March, 2002; switching-cost full-market sessions were conducted in February and March, 2005; and full-market sessions without switching costs were conducted in June and July 2006. Simulated-buyer sessions were run with Java software, while

[10]Given the idiosyncratic base values, there are two buyers who strictly prefer **B** to **A**.

[11]The lowest-price coordination rule leaves the buyer indifferent between switching or not switching when the two goods have the same price. However, the rule will fail in any case when prices are exactly equal. We'll also see that maintenance of the lowest-price coordination rule grants multi-period dynamic benefits, while these welfare calculations only consider efficiency in a single game period.

all full-market sessions were run with z-Tree Fischbacher (2007). Participants were UA students[12].

Each subject took part in only one experimental session. Each session took place over one to two hours, and consisted of a total of 44 experimental periods. The first four periods were training periods[13]. Training periods allowed sellers one minute to set prices, and buyers 90 seconds to enter guesses and make choices. After the training run, subjects were given the opportunity to ask questions before proceeding to the main runs. There were two main runs of 20 periods each. In both the first and second runs, sellers were allowed 30 seconds to set prices, and buyers were allowed one minute to enter guesses and make choices.

Within a run, nothing in the environment changed from period to period, and subjects were matched in constant groups. Between runs, subjects were reordered into new groups. Although buyers remained buyers and sellers remained sellers, the buyer type (defined by their base values) changed between runs.

At the end of the experiment, each subject was asked to describe how they made their decisions on a questionnaire.

3.5 Hypotheses

Hypothesis 1: A market with network effects will exhibit systemic lock-in. A product that has more consumers in period t will have more consumers in period $t+1$, all else being equal. Using a logistic regression, we test in treatments HB-NOSC and HB-SC whether network size in period t positively effects the probability that a buyer will purchase the good in period $t+1$.

Hypothesis 2: Individual lock-in in a market with network effects will strengthen systemic lock-in. The relationship between market share in period t and $t+1$ will be greater when there is individual lock-in as well as network effects, and the difference will not be completely attributable to individual lock-in. Also from the logistic regression, we test whether sensitivity to network size is greater in treatment HB-SC than HB-NOSC.

Hypothesis 3: Sellers in a market with systemic lock-in set super-competitive prices. Markets with stronger systemic lock-in will have higher prices. We examine prices to see whether prices are highest in treatment SB-NOSC (built-in systemic lock-in), and lowest in HB-NOSC (with no built-in systemic or individual lock-in).

[12]The significant majority of subjects were undergraduate students. A few graduate students participated, all from non-economics fields.

[13]Subjects were paid if they earned positive amounts in the training periods. Some subjects lost money in the training periods, in which case, those losses were canceled.

Hypothesis 4: Sellers in a market with systemic lock-in compete *for the market* with penetration pricing. In early periods, sellers will set low—even negative—prices in an attempt to gain market share and benefit from lock-in.

Hypothesis 5: Greater lock-in leads to greater seller profits. The limited competition that arises from lock-in allows for profits significantly greater than zero. Markets with stronger systemic lock-in will have higher seller profits.

4 Experimental Results

By inducing systemic lock-in through simulated buyers, we find support for stories of lock-in, with consistent high market shares, and sellers pricing supercompetitively. Replacing the simulated buyers with real human buyers, lock-in vanished and the market became extremely competitive. When the human buyers also faced individual switching costs, the result was inefficient oligopoly rather than systemic lock-in to a monopoly.

Table 3 gives general statistics from experienced and inexperienced runs in all three treatments. Section 4.1 addresses buyer behavior for hypotheses **H1** and **H2**. Section 4.2 addresses seller behavior for hypotheses **H3**, **H4** and **H5**. Section 4.3 has further discussion of behavioral regularities and market efficiency.

4.1 Systemic Lock-in

One treatment (SB-NOSC) has simulated (robot) buyers built explicitly to exhibit systemic lock-in. The other two treatments (HB-NOSC and HB-SC) have similarly strong network effects, to examine whether systemic lock-in results. To discriminate between systemic and individual lock-in in these treatments, we ran a time-series multinomial logit regression on period-by-period buyer choices, given by Equation 1. The independent variables in the regression include subject (indexed by i), product (indexed by j), and time (indexed by t) characteristics. Since the goods were created to be symmetric, that symmetry is imposed in the regression coefficients. The normalizing choice is the outside option. Individual lock-in should appear as an effect of whether a particular buyer i has to switch to good j from a different product in period t (binary dummy variable $Switch_{i,j,t}$), while systemic lock-in should be an effect of the previous period's network size for that good ($Count_{i,j,t-1}$)[14].

[14] $Count_{i,j,t-1}$ is the number of buyers who purchased good j in period $t-1$, *not including* buyer i. The buyer is excluded in the count for their own regression because we want to capture individual lock-in in the $Switch_{i,j,t}$ variable. Therefore, $Count_{i,j,t-1}$ is slightly variable by buyer, but is primarily a characteristic of the network in period $t-1$.

Table 3: Descriptive Statistics

	inexperienced					
	SB-NOSC Treatment		HB-NOSC Treatment		HB-SC Treatment	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Total Buyer Profit	907.918	291.496	1031.032	157.308	812.562	199.314
Total Seller Profit	527.097	150.385	310.668	87.435	374.005	164.288
Total Surplus	1435.015	180.080	1341.700	92.184	1186.567	41.386
Buyer % Total Profit	61.825	15.534	76.557	7.738	68.113	15.215
% Negative Prices	6.282	11.729	4.722	4.002	7.778	4.554
Run Avg Price	2.315	1.140	0.849	0.575	1.269	1.131
Avg Herfindahl	0.757	0.149	0.651	0.092	0.559	0.043
LIHI	0.834	0.146	0.582	0.101	0.779	0.153
	experienced					
	SB-NOSC Treatment		HB-NOSC Treatment		HB-SC Treatment	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Total Buyer Profit	1055.037	195.417	1138.467	153.333	931.425	79.886
Total Seller Profit	429.794	178.862	288.467	89.265	288.175	71.173
Total Surplus	1484.831	120.830	1426.933	78.927	1219.600	75.299
Buyer % Total Profit	71.077	11.901	79.536	7.210	76.432	5.367
% Negative Prices	12.692	14.281	1.944	2.670	12.222	9.108
Run Avg Price	1.581	1.146	0.693	0.580	0.687	0.463
Avg Herfindahl	0.774	0.161	0.742	0.093	0.523	0.079
LIHI	0.857	0.115	0.512	0.048	0.872	0.100
N	13		6		6	

Run Avg Price is the quantity-weighted average for a run over all 20 periods.
Avg Herfindahl is averaged for a run over all 20 periods.
LIHI (Lock-in Herfindahl index) is explained in section 4.1.

The effects of a product's price work to counter both kinds of lock-in, and so can't clearly discriminate between them. Price is included in the regression in two ways—as the price level ($P_{j,t}$), and as a binary dummy variable ($PMIN_{j,t}$), which indicates if the good j has the lowest price in period t[15]. The impact of these price variables is discussed in Section 4.3.

$$P_{i,j,t} = \frac{exp\left[\beta_0 + \beta_1 Base_{i,j} + \beta_2 Switch_{i,j,t} + \beta_3 P_{j,t} + \beta_4 PMIN_{j,t} + \beta_5 Count_{i,j,t-1}\right]}{1 + \sum_{k=A,B,C} exp\left[\beta_0 + \beta_1 Base_{i,k} + \beta_2 Switch_{i,k,t} + \beta_3 P_{k,t} + \beta_4 PMIN_{k,t} + \beta_5 Count_{k,t-1}\right]} \tag{1}$$

Table 4 shows the results of the logit regression for buyer choice. We use these results to address **H1** and **H2**.

H1: A market with network effects will exhibit systemic lock-in. Network effects alone were not enough to induce systemic lock-in. Human buyers without switching costs (HB-NOSC) didn't respond to the previous period's market share—Table 4 shows that *Count* has a small and statistically insignificant negative marginal effect (-0.004). Network effects with individual switching costs did induce systemic lock-in—*Count* has a small but statistically significant positive marginal effect (0.019).

[15] $PMIN_{j,t}$ takes value 1 only for an exclusive minimum. If two or three goods share the same, minimum price, then $PMIN_{j,t}$ is zero for every good in that period.

H2: Individual lock-in in a market with network effects will strengthen systemic lock-in. When switching costs are introduced to the experimental design (HB-SC), there is strong individual lock-in, but only weak systemic lock-in. Both are statistically significant. The p-value of a K-S test on increasing the influence of $Switch_i$ is 0.002, and on increasing the influence of $Count$ is 0.016.

Systemic lock-in appears in $Count$. To put the effect into perspective, a marginal effect of 0.019 amounts to a 13.3% increase in the probability of choosing a product when *every other* buyer purchased it in the previous period. This is smaller than the effect of idiosyncratic values ($Base$ has a marginal effect of 17.4%) or individual switching costs ($Switch$ has a marginal effect of -23.4%)[16]. Those two individual-level effects correctly predict 75% of purchase decisions.

Table 4: **L**ogit regressions of buyer choice

	HB-NOSC	marg	HB-SC	marg	K-S Test
constant	14.631		2.770		
	(0.000)		(0.000)		
$Base$	2.692	0.179†	3.001	0.174†	HA: HB-NOSC $\neq$ HB-SC
	(0.000)		(0.000)		(P=0.931)
$Switch$	-0.448	-0.033†	-3.133	-0.234†	HA: HB-NOSC > HB-SC
	(0.066)		(0.000)		(P=0.002)
P	-0.842	-0.062	-0.938	-0.033	HA: HB-NOSC $\neq$ HB-SC
	(0.003)		(0.000)		(P=0.113)*
$PMIN$	3.360	0.379†	0.479	0.021†	HA: HB-NOSC > HB-SC
	(0.000)		(0.014)		(P=0.002)
$Count(lag)$	-0.059	-0.004	0.598	0.019	HA: HB-NOSC < HB-SC
	(0.173)		(0.000)		(P=0.016)
Log-likelihood	-378.970		-203.801		
Observations	912		912		

Possible correlation could mean that P-values on coefficients are too small. To control for correlation, control dummies were included for each experimental market. (Tests showed these made no significant difference in treatment HB-SC, so the results shown are without the dummies.) P-values (shown in parentheses) come from bootstrapping with data clustered by period.

Reported marginal effects are the mean of marginal effects for the data. Marginal effects *at the mean* are larger, because at the mean—balanced between the different choices—decisions are unstable.

† Shows the effect of a discrete change from 0 to 1.

K-S tests are tests on marginal effects: one-sided or two-sided as noted. A data point is the estimate of that effect for a single experimental market; there are 6 points per treatment.

⋆ The p-value for the one-sided test, H0:HB-NOSC $\geq$ HB-SC, is 0.069.

One way to observe lock-in is to compare period-by-period market concentration with market concentration over the whole history of a market. If concentration over all periods is less than for individual periods, the market is dynamic, with little lock-in. Figure 1 shows the average period-by-period Herfindahl index over all sessions. The (HB-SC) treatment has the lowest av-

[16]The buyers in (HB-NOSC) exhibit minimal individual lock-in, even without a switching cost. There appears to be individual lock-in simply from psychological inertia.

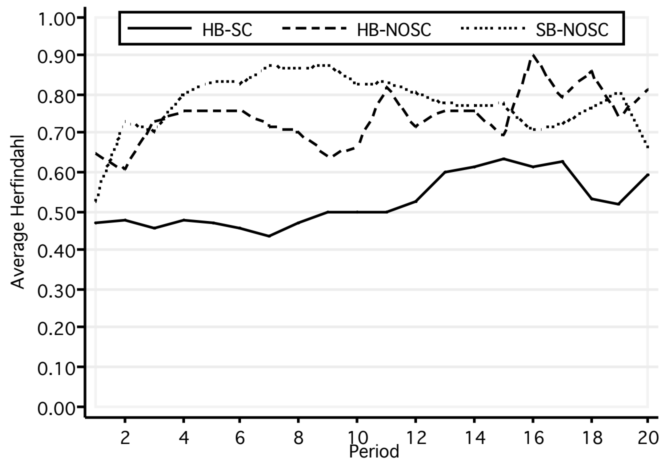

Figure 1: Average per-period Herfindahl Index, all experienced runs

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erage market concentration in every period, with a Herfindahl index mostly between 0.40 and 0.60. Switching costs decrease market concentration by making buyer coordination more difficult. Although the simulated buyers result in more *consistent* concentration than human buyers, the (SB-NOSC) treatment does not appear to have greater market concentration than (HB-NOSC). Both have average market concentration mostly between 0.70 and 0.90.

Table 5: **M**arket Concentration and Lock-In

	HB-SC	HB-NOSC	K-S Test
Avg Period Herfindahl	0.523	0.742	HA: HB-SC < HB-NOSC (P=0.016)
Lock-in Herfindahl (LIHI)	0.872	0.512	HA: HB-SC > HB-NOSC (P=0.002)
	SB-NOSC	**HB-NOSC**	**K-S Test**
Avg Period Herfindahl	0.774	0.742	HA: SB-NOSC > HB-NOSC (P=0.297)†
Lock-in Herfindahl (LIHI)	0.857	0.512	HA: SB-NOSC > HB-NOSC (P=0.000)

Numbers in parentheses are P-values from one-sided Kolmogorov-Smirnov tests.

Data is from experienced runs. Tests performed on inexperienced runs showed similar results, except for †, which had $P = 0.092$ in inexperienced sessions.

For comparison, Table 5 shows two statistics for all 20 periods of an experimental run. First, it gives the average of the period-by-period Herfindahl indices, which agrees with Figure 1, that (HB-SC) had lower period-by-period market concentration, but there was little difference between the two treatments without switching costs.

Second it gives a lock-in Herfindahl index (LIHI). Given A_t, B_t, and C_t as the number of units sold by each seller in period t, and $N_t = A_t + B_t + C_t$, the LIHI is computed as the ratio:

$$\begin{aligned} LIHI &= \frac{\text{Herfindahl for 20 periods aggregated}}{\text{Average Herfindahl over 20 periods}} \qquad (2) \\ &= \frac{\left(sum_{t=1}^{20} A_t / sum_{t=1}^{20} N_t\right)^2 + \left(sum_{t=1}^{20} B_t / sum_{t=1}^{20} N_t\right)^2 + \left(sum_{t=1}^{20} B_t / sum_{t=1}^{20} N_t\right)^2}{\frac{1}{20}\sum_{t=1}^{20}\left[(A_t/N_t)^2 + (B_t/N_t)^2 + (C_t/N_t)^2\right]} \end{aligned}$$

A high LIHI indicates lock-in by identifying stability in market shares—market shares in individual periods are similar to those for the overall experimental run. A low LIHI shows a lack of lock-in—market concentration for the overall run tends to be lower than in individual periods, showing sellers "trading" who has a high (low) market share from period to period. Table 5 shows that switching costs led to a less concentrated market—a lower Herfindahl index for (HB-SC) than (HB-NOSC). However, the market is more locked-in to the particular distribution, indicated by a higher LIHI for (HB-SC). While there's no identifiable difference in concentration between the simulated (SB-NOSC) and and human (HB-NOSC) buyers in the Herfindahl, the LIHI shows that the high concentration in (SB-NOSC) is more stable—a seller with a high market share in one period is more likely to have a high market share over all 20 periods.

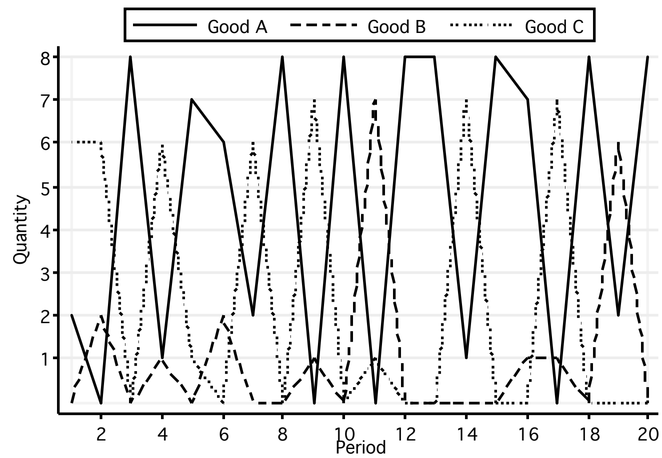
Figures 3 - 4 show example data, each from a single run with experienced subjects. The (a) plots show the period-by-period quantity sold for each seller, and the (b) plots show the period-by-period prices. With human buyers and no switching costs, Figure 2(a)[17] shows buyers switching rapidly between the three products. The seller of good **A** sells all 8 units in 8 of the 20 periods, while seller **B** approaches monopoly with 6 or 7 units sold in several periods. Seller **C** mostly has a small market share of 0-2 units sold, but is dominant in periods 11 and 19. Figure 2(b) shows, with a little jumpiness, a steady downward trend on prices until they steady at a low level[18]. While market concentration in any one period is often very high, a seller can't maintain dominance—a clear case of serial monopoly.

For the (SB-NOSC) treatment, Figure 3(a)[19] shows very high market concentration, with seller **A** having a monopoly for most of the run, and more than half the market throughout. The plot also shows that simulated buyers don't readily switch. While a seller could expand their market share from

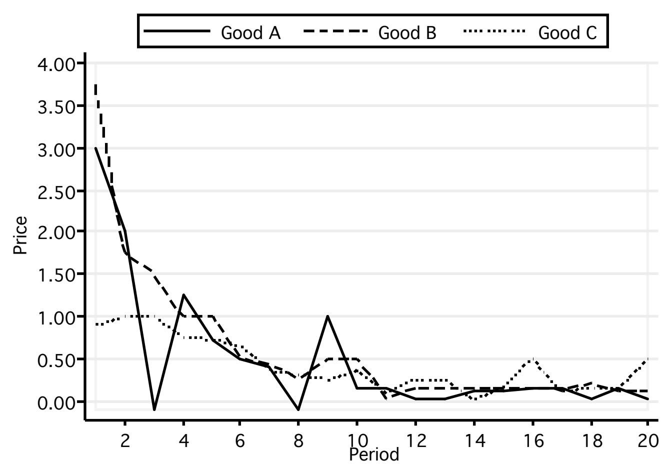
[17]The data for the session shown in Figure 2 is in Table **??** in the appendix.

[18]It was not unusual in the (HB-NOSC) treatment for some sellers to try to set higher prices in later periods, but receive little or no market share.

[19]The data for the session shown in Figure 3 is in Table **??** in the appendix.

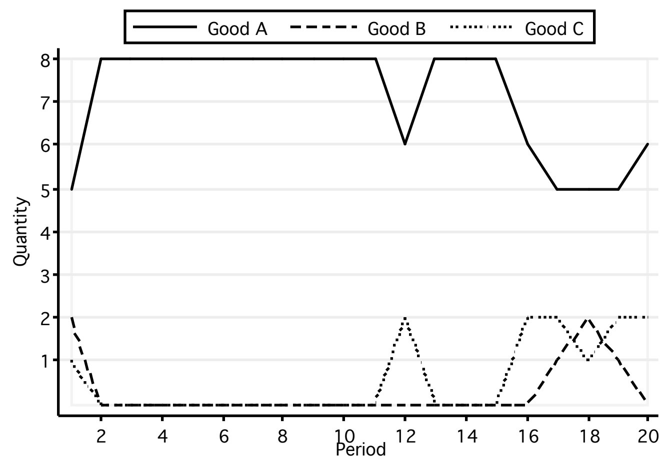


(a) Example quantities

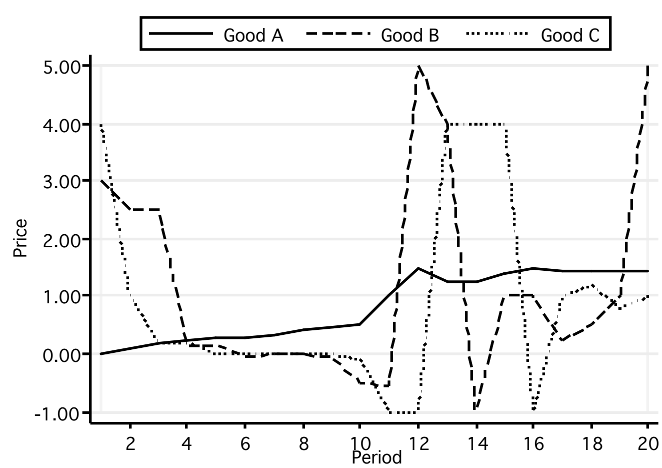


(b) Example prices

Figure 2: Period-by-period example data from one run without switching costs (HB-NOSC)

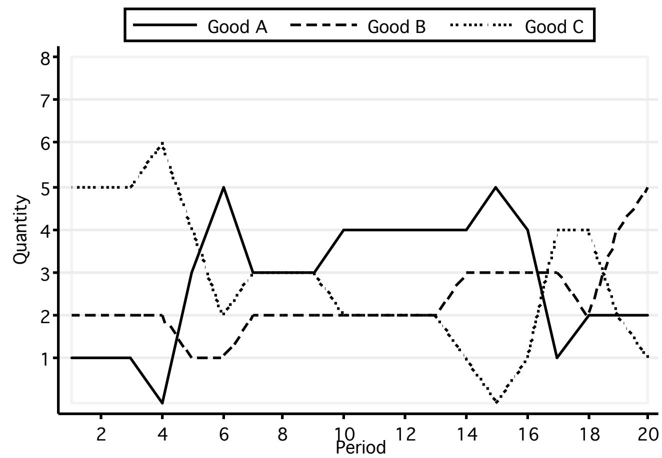


(a) Example quantities

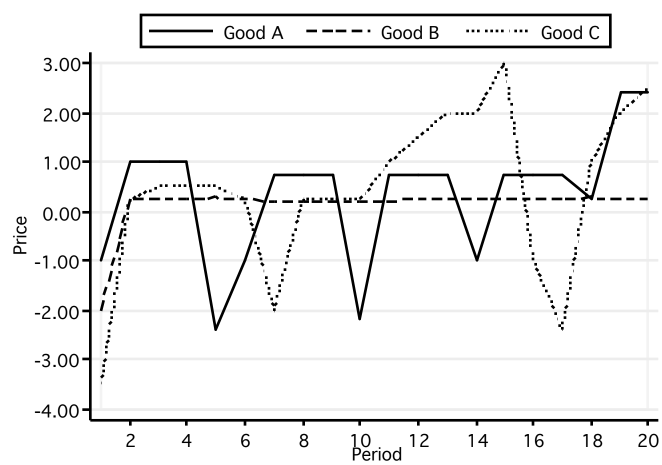


(b) Example prices

Figure 3: Period-by-period example data from one run with simulated buyers (SB-NOSC)



(a) Example quantities



(b) Example prices

Figure 4: Period-by-period example data from one run with switching costs (HB-SC)

one period to the next by significantly under-pricing the dominant seller, this is challenging and could even lead to losses—as occurred in periods 12 and 16 when seller **C** was able to sell 2 units at a negative price. Figure 3(b) shows that seller **A** acquired a monopoly by having the lowest price in the first two periods, thereafter being able to raise their price to over 1.00 while remaining dominant.

When human buyers are faced with switching costs in the (SB-NOSC) treatment, Figure 4(a)[20] shows that there is also quite a bit of stability, but at lower concentration. The highest market share is 6 units sold by seller **C** in period 4. Figure 4(b) shows all three sellers starting with negative prices, which were also used occasionally in the middle of the experiment. Large price differences had a small impact on market share, however, being unable to overcome the inertia induced by switching costs.

4.2 Seller Pricing

H3: Sellers in a market with systemic lock-in set supercompetitive prices. Strong systemic lock-in in (SB-NOSC) motivated sellers to set high prices. Sellers facing individual lock-in and weak systemic lock-in in (HB-SC) tried to set higher prices, but overall prices were higher in the (SB-NOSC) treatment than in the (HB-NOSC) treatment without any systemic lock-in.

Table 3 shows that (SB-NOSC) had an average price of 1.581—much higher than either of the treatments with human buyers (0.693 without switching costs and 0.687 with switching costs). Figure 5 shows the quantity-weighted mean purchase price period-by-period, and shows that the prices tend to be higher in every period after the first few periods. Kalmogorov-Smirnov tests on average price show that, in experienced runs, (SB-NOSC) had higher average prices than (HB-NOSC) and (HB-SC) ($P = 0.045$ for both).

We fail to reject the hypothesis that (HB-NOSC) and (HB-SC) have the same average price ($P = 0.474$). Because of poor coordination in the market with switching costs, the buyers were paying similar prices but receiving less benefit from network effects.

H4: Sellers in a market with systemic lock-in compete *for the market* with penetration pricing. Penetration pricing is weakly indicated by the data, but not in a statistically significant manner.

Figure 5 shows (HB-NOSC) and (SB-NOSC) prices diverging at the beginning of a run, with (SB-NOSC) showing lower prices in the first few periods. Statistical tests fail to reject the hypothesis that (SB-NOSC) and

[20] The data for the session shown in Figure 4 is in Table **??** in the appendix.

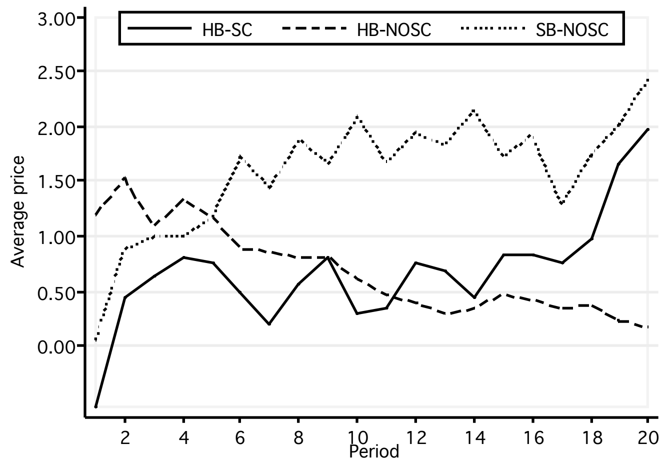


Figure 5: Quantity-weighted average purchase price, all experienced runs

(HB-NOSC) treatments had similar early prices[21]. (HB-SC) prices are also lower than (HB-NOSC) in the early periods ($P = 0.069$ for first 1, 2, or 3 periods). The figure gives some evidence that in environments with lock-in, sellers tried to use penetration pricing to create lock-in in the early periods.

Tables 6 and 7 show the prevalence of sellers' negative pricing. Negative pricing is more frequent in (SB-NOSC) and (HB-SC). It also appears that sellers in these treatments learned to price negatively to exploit lock-in by the experienced run. Since there is little lock-in in the (HB-NOSC) treatment, sellers make little attempt at penetration pricing, and appear to have learned that negative pricing was futile by the experienced run[22].

Table 6: **P**ercentage of periods with negative prices

	HB-NOSC	SB-NOSC	HB-SC
inexperienced	14.2%	15.4%	23.3%
experienced	5.8%	31.9%	30.0%

H5: Greater lock-in leads to greater seller profits. Strong systemic lock-in gives sellers greater profit in (SB-NOSC). As with setting prices, it

[21]Statistical significance ($P = 0.045$) is achieved when considering the first two periods. However, it is sensitive to the interval chosen with $P = 0.174$ for one period, and $P = 0.297$ for three periods.

[22]In spite of the large differences in overall percentages, the variance is so large (as seen in Table 3) that most differences are not statistically significant. Kolmogorov-Smirnov tests find that the only statistically significant difference is between (HB-NOSC) and (HB-SC) for experienced subjects ($P = 0.069$ for the test that (HB-SC) has a higher overall percentage of negative prices).

Table 7: **O**verall percentage of negative prices

	HB-NOSC	SB-NOSC	HB-SC
inexperienced	4.7%	6.3%	7.8%
experienced	1.9%	12.7%	12.2%

appears that the individual lock-in and weak systemic lock-in resulting from switching costs in (HB-SC) gives limited market power.

Table 8 compares profits for experienced runs. Seller profits are greatest when selling to the simulated buyers. The averages may indicate that sellers have greater profits (or a greater share of profits) when there are switching costs, but this result is not statistically significant.

Table 8: **C**omparing total seller profits

	HB-SC	HB-NOSC	K-S Test
Seller Profit	288.175	288.467	HA: HB-SC > HB-NOSC (P=0.513)
	SB-NOSC	HB-NOSC	
Seller Profit	429.794	288.467	HA: SB-NOSC > HB-NOSC (P=0.045)

Values and tests are for the experienced runs.
Numbers in parentheses are P-values from a one-sided Kolmogorov-Smirnov test.
Tests performed on inexperienced runs showed essentially the same results.

4.3 General analysis

While myopic simulated buyers in (SB-NOSC) clearly experienced lock-in, human buyers in the same circumstances in (HB-NOSC) clearly did not. It appears as though the human buyers were able to achieve two things simultaneously. They had a highly competitive market, avoiding lock-in, while simultaneously coordinating to enjoy large network effects. This coordination occurs period by period in spite of the lack of a unique Pareto dominant equilibrium for the consumer choice subgame. Heterogeneous preferences cause the different equilibria to be strictly preferred to each other by different buyers, but this heterogeneity takes a back seat to the common gains from coordination[23].

Buyers achieved coordination by a tacit "choose the good with the lowest price" rule. This can be seen in the buyer choice regressions in Table 4. While the price effects can't discriminate between individual and systemic lock-in, they can give clues about how lock-in does or doesn't occur. Without

[23]It is possible that the regular rotation of equilibrium mitigates the conflicting preferences by leading to an overall "fair" aggregate outcome.

switching costs in (HB-NOSC), buyers respond strongly to a price being the lowest offered in a period ($PMIN$ flag). The price level for a product (P) was statistically significant, but less important than the price *rank*[24]. Without switching costs, buyers felt free to coordinate via a rule to purchase the lowest-priced good. There was no communication allowing them to arrange this coordination, but the lowest-price rule has obvious salience.

Lock-in occurred in the treatment with switching costs (HB-SC), but it was almost entirely due to individual switching costs. This lock-in was inefficient—a counterfactual analysis of the data shows that if the buyers had followed the lowest-price coordination rule, given the same prices, buyers' overall profit would have been significantly higher—on average 1288.427 vs. 931.425 for the actual data. There would also have been a likely dynamic benefit to the buyers of forcing sellers to compete more rigorously in prices. Recall that the switching cost was chosen to be small enough that it was efficient (optimal individually and collectively) for buyers to follow such a rule.

Table 4 shows that with switching costs in (HB-SC), the price level P_i and $PMIN_i$ were much closer in their effects[25]. The effect of price level was considerably smaller than in (HB-NOSC), and the effect of a price being the lowest offered was an order of magnitude smaller (2.1% vs. 37.9%). With switching costs, buyers were somewhat insensitive to prices at both an absolute and relative level. Sellers do not receive greater profits when there are switching costs (see Table 8), and market power is clearly much smaller than that for the naïve simulated buyers.

5 Conclusions

We found that sellers in these experimental markets behaved as predicted in most stories of competition with network effects, but real buyer behavior didn't allow the creation of a locked-in monopoly. During an introductory stage, sellers will accept losses to (they hope) generate lock-in in their favor, and exploit that lock-in once established. On the other hand, systemic lock-in due to coordination failure never arose as a significant effect. Sellers recognized this—between the inexperienced and experienced runs, they learned that there was systemic lock-in with simulated buyers and some individual lock-in with switching costs, but no lock-in in the market without switching costs. Sellers became more willing to accept losses for penetration pricing in

[24]In comparing the apples of price level to the oranges of a binary flag variable, keep in mind that the average price range between the lowest and highest prices (with some outliers censored) was 1.95 in (HB-NOSC), and 1.59 in (HB-SC).

[25]Again, it isn't completely clear how to compare these effects, but at a price difference of 1.59, the combined effect would be 1 X 2.1% + 1.59 X 3.3% $\approx$ 7.3%. Both effects combined would somewhat increase (by 7.3%) the probability that a buyer would choose the lowest-priced good.

the first two treatments, and less willing for the last.

Without the individual lock-in of switching costs, buyers were largely successful in coordinating on the focal equilibrium of everyone purchasing the lowest-priced product. This was in spite of heterogeneous buyer preferences, which did not allow Pareto ranking of equilibria. Network effects acted to *decrease* market power. One way to think about it is that strong network effects overwhelmed individual heterogeneity in preferences, reducing the market power which comes from differentiated products. The result was serial monopoly, without systemic lock-in. Such circumstances were very competitive, with sellers charging significantly lower prices than in the simulated-buyers treatment. It seems clear that in such an environment, inefficiency could not arise from cost differences, as a higher-cost seller would be unable to compete. It is less clear whether inefficiency could arise from quality differences, since this might complicate buyer coordination.

Adding individual lock-in *via* moderate buyer switching costs created inefficiency, but only induced a small amount of systemic lock-in. Individual lock-in was more directly inefficient, leading to oligopoly with unrealized network benefits that would have come from monopoly. This raises further doubts about the conflation of individual with systemic lock-in commonly found in network-effects literature. If the two went hand-in-hand, speaking of them together could be a useful shortcut. Since they don't, speaking of them together carelessly is a source of confusion.

In these experiments, simple variations radically affected market lock-in. Many other expected complications arise in real-world markets: fixed development costs and low marginal costs create supply-side increasing returns to scale; product features and quality change over time; firms create adapters for compatibility between networks. Since the competitive results were due to the way buyers coordinated on low price, any complication which hinders such coordination could have significant effects. These experiments can't identify the results of such complications. However, the results do show that in one of the most basic environments for which systemic lock-in is predicted, it clearly does not occur.

References

Arthur, W. B. (1989). Competing technologies, increasing returns, and lock-in by historical events. *The Economic Journal 99*, 116–131.

Brock, W. and S. Durlauf (2001). Discrete choice with social interactions. *Review of Economic Studies 68*(2), 235–260.

Chakravarty, S. (2003). Experimental evidence on product adoption in the presence of network externalities. *Review of Industrial Organization 23*, 233–254.

Chiaravutthi, Y. (2007). Predatory pricing with the existence of network externalities in the laboratory. *Information Economics and Policy 19*(2), 151–170.

David, P. A. (1985). Clio and the economics of qwerty. *American Economic Review 75*(2), 332–337.

Drehmann, M., J. Oechssler, and A. Roider (2007). Herding with and without payoff externalities—an internet experiment. *International Journal of Industrial Organization 25*(2), 391–415.

Faulhaber, G. (2002). Network effects and merger analysis: instant messaging and the aol–time warner case. *Telecommunications Policy 26*(5-6), 311–333.

Fischbacher, U. (2007). z-tree - zurich toolbox for readymade economic experiments. *Experimental Economics 10*(2), 171–178.

Katz, M. and C. Shapiro (1985). Network externalities, competition, and compatibility. *American Economic Review 75*, 424–440.

Katz, M. and C. Shapiro (1986). Technology adoption in the presence of network externalities. *Journal of Political Economy 94*, 822–841.

Klemperer, P. (1987). Markets with consumer switching costs. *The Quarterly Journal of Economics 102*(2), 375–394.

Liebowitz, S. J. and S. E. Margolis (1995). Path dependence, lock-in, and history. *Journal of Law, Economics, and Organization 11*(1), 205–226.

Miyao, T. and P. Shapiro (1981). Discrete choice and variable returns to scale. *International Economic Review 22*(2), 257–273.

Ohashi, H. (2003). The role of network effects in the us vcr market, 1978-1986. *Journal of Economics & Management Strategy 12*(4), 447–494.

Salop, S. C. and R. C. Romaine (1998). Preserving monopoly: Economic analysis, legal standards, and microsoft. *George Mason Law Review 7*, 617.