Social Network Effects on Coordination

A Laboratory Investigation

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Does social network structure influence coordination? We examine a coordination game in which each player engages with an exogenously connected "local" subset of the player population, the pattern of links defining a social network. Players know the number of local links they possess but otherwise have incomplete information about the global network structure. All networks in our experiment have the same pooling equilibria. Each also exhibits separating equilibria in which player actions differ by the number of local social links they possess. We investigate two potential network effects on equilibrium selection: the global network effect as represented by the density of the grand network, and the local network effect as represented by the number of local links an individual has. In high-density networks, we observe coordination consistent with the payoff-dominant pooling equilibrium. In the sparser networks, more connected players exhibit higher levels of coordination than do players having fewer social links, with overall coordination levels consistent with separating equilibria. Our findings indicate that network density, individual connectivity, and economic return modulate the amount of strategic risk in coordinating and can account for the pattern of equilibrium selection we observe.

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1. Introduction and Literature Background

Economic coordination is an inherently group activity. Experimental economics finds that group *size* plays a critical role in coordination (e.g. Huyck, et al. 1990, Weber 2006). Larger groups of people find it more difficult to coordinate while small groups find it easier. There has been much less experimental work, however, on the effect of group *structure* on coordination. We conduct experimental research on coordination games in which each player engages with a connected subset of the player population. The game configuration determining "who plays with whom" defines a social network. The broad research question that guides our work is: How does the social network structure influence the coordination behaviors of individuals within the network? In this paper we investigate networked coordination in a controlled laboratory environment.

The adoption of products and technology with network effects, and associated literature, serve to illustrate the important conceptual issues related to this research. In the classical models for products with network effect (e.g. phone, fax machine), every product adoption adds value to the product itself, since more product purchases expand the network over which the product is useful (Katz and Shapiro. 1992, 1986, 1985). Therefore, customer purchase decision should depend on the size of the user network. In the above-mentioned models, it is assumed that each adoption is affected by the *entire* user network size. Sometimes, however, a customer's benefit from buying a product depends on the adoption decisions from a *subset* of people in the user network, whom she needs that product to interact. For example, suppose a customer decides whether to buy the new generation of iPhone that carries a particular video-chat unit that only works with the same type of phone. For the video-chat to function, the customer has to coordinate his buying with the people whom she intends to video-chat (e.g. her family, friends, colleagues), but obviously she does not need to coordinate this decision with everyone else. If we connect each customer with the persons she needs to interact via the product, we have obtained a network. While the Katz-Shapiro models assume a *complete* network where everyone is connected to everyone else, Sundararajan (2007) develops a model where each customer only coordinates the decisions of a subset of population. Galeotti et al (2010) models the scenario in a more general economic setting.

Coordination in network contexts has been gaining attention of laboratory research in recent years. Keser et al. (1998) compares interaction on a complete network and that on a circle. Berninghaus et al (2002) addresses the question of how interaction structure affects the evolution of coordination. Their experiment tests the models of Ellison (1993) and Berninghaus and Schwalbe (1996). Cassar (2007) extends the experiments of Berninghaus et al (2002) by introducing random networks and small-world networks as the underlying interaction structures. Corbae and Duffy (2008) investigates coordination in endogenously formed networks with subjects self-determining whom to coordinate with. Our work can be distinguished from these studies in the following ways. First, in our experiment players have incomplete information of the network configuration beyond their own direct connections, which is a common feature in individual interaction with social networks. Also, we examine equilibrium selection with respect to both the global network density and ego connectedness.

There are also several field studies on product adoption in specific industries that involve network effects: Tucker (2008) on the adoptions of video-messaging units, Ryan and Tucker (2007) dealing with videoconferencing technology diffusion with benefit-cost heterogeneity, Conley and Udry (2007) examining the diffusion of agricultural innovations in Ghana, Ackerberg and Gowrisankaran (2006) analyzing the adoptions of ACH e-payment system, Rysman (2004) addressing the competition in yellow-page market, and Saloner and Shepard (1995) studying the ATM installations of banks. Among these works, Tucker (2008) and Ryan and Tucker (2007) are closest to ours in that they consider the position of a player in the network as a factor that affects her adoption decision; in the same spirit, we look at local network effects as implied by individual connectivity. Our study complements the field empirics in that we provide laboratory observations that strictly control the social network effect aside from other noisy factors which are hard to tackle in field data.

In the social networks we study, players have incomplete information on the network structure beyond their direct connections. In theory, full-coordination and full defection are pooling equilibria, and in some cases there are also threshold-equilibria depending on the local connectedness of players. The rest of paper is organized as follows. Section 2 introduces the experimental design and hypotheses. In Section 3 we analyze the data. Section 4 concludes and discusses limitation.

2. Experimental Design and Hypotheses

Our experiment manipulates the *network density* and the *economic return* associated with coordinating. Each factor takes on two levels, *high* or *low*, in a fully crossed 2×2 factorial design, for a total of four treatments. In each treatment, 40 subjects are connected in a *grand network*. Directly connected players are *neighbors* [2], and one's number of neighbors is called her *degree*. Neighbors play with each other a binary-action coordination game described as follows. If a player chooses to *coordinate*, she incurs a cost C, and then receives a benefit of R from *each* of her neighbors who also coordinates. If the player chooses to *defect* (chooses not to coordinate), she receives a default payoff of zero. In all cases the player does not receive any benefit from defecting neighbors. This payment structure reflects strategic complementarities and positive externalities typical in social networks where coordination is the issue. For example, it applies to the problem of strategic product adoption described in the Example given in Section 1: To purchase the product the customer pays a price of C, and derives R from each of her social neighbors who also buy it.

Prior to choosing whether to coordinate, a subject is notified of her own degree. Besides that, the *only* information provided to a subject about the grand network she lives in is the degree distribution of neighbor. In fact, in all treatments subjects receive identical directions up to neighbor degree distribution and economic factors (R and C).

In all networks, each player has degree of either 2 or 3.[3] The proportion of degree-three players, denoted by q, is 0.5 in the high density network and 0.25 in the low density network.

[2] Throughout the paper, the connections are *undirected*, i.e. we do not distinguish the direction of connections.

[3] An alternative approach would be to use random networks like those developed by Bollobas (1985) and Erdos and Renyi (1960). We chose our current network design for its ease of control for degree types, and also because we found it intuitively easy for subjects to understand.

Throughout the experiment we fix $R = 80$ *but vary the cost*, thereby varying the economic return. The economic parameters and network densities used in each treatment are reported in Table 1. The instructions are provided in the Appendix.

2×2 factorial design		Network density	
		Low: *q*=¼	*High*: *q*=½
Economic return	*Low*: R/*C=80/130*	*LrcLden*	*LrcHden*
	High: R/*C=80/100*	*HrcLden*	*HrcHden*

Table 1. Summary of experimental design

To obtain statistically independent observations, we organized each grand network (with 40 subjects) as separate, anonymous network *cohort*s. Each (network) cohort has 8 subjects, and is connected to satisfy either high or low network density as described above, depending on the grand network it belongs to.

The game above is played in a repetition of 20 rounds. Repeating the play allows us to observe more experienced subject behavior. In each round subjects are randomly matched to be neighbors in the network. This randomization is intended to minimize prior updates and keep a player interacting with different people so that every round is treated as an independent one-shot game. We can also check the data for evidence of updating. As we shall see, the assumption of non-updated priors fits well with the data (Section 3).

Each cohort of eight subjects is a statistically independent observation (see foregoing paragraph). We form five cohorts (i.e. five independent observations) for each of the four treatments.[4] In total, the data was collected from 160 subjects from March through June 2010, at the Laboratory for Economics Management and Auctions (LEMA) at Penn State University. Subjects are mainly undergraduate students at Penn State, recruited from an online information system. Cash is the only motivation offered for subject participation. The software is

[4] The resulting 20 network cohorts are labeled as N1, N2…N20 respectively.

programmed in zTree (Fischbacher, 2007). Sample software screenshots are found in the Appendix.

While a formal theory for our network coordination game is presented in the appendix, we here briefly outline the theoretical predictions as our experimental hypotheses. To proceed, we need more notations. Denote by N_i the set of neighbors of player i, and $k_i$the degree of player i. Let x_i be player i's (binary) decision, $x_i = 1$ if the player coordinates, and $x_i = 0$ if the player defects. Player i's objective is to maximize her expected payoff, by deciding whether to coordinate or to defect. Formally, Player i solves

$$\max_{x_i \in 0,1} x_i E(R \sum_{j \in N_i} x_j - C). \quad (1)$$

We focus on the (more interesting) situation where C is not so high that there exists any player who prefers defection even if all her neighbors coordinate.[5] We write a pure strategy for player i as a mapping from i's degree to her action: $\sigma_i: k_i \rightarrow x_i$. Throughout the paper the focus is given to symmetric strategies, so we omit the player index and write $\sigma_i \equiv \sigma$.[6] A mixed strategy for a player can be written as a mapping from the player's degree to a probability distribution over her binary actions: $\sigma: k \rightarrow (p_k, 1 - p_k)$, where p_k is the probability that the degree-k player assigns to coordination (hence $1 - p_k$ the probability of defection). The solution concept to the game is Bayesian Nash equilibrium[7], which we refer to as simply *equilibrium*. We refer to a *degree-pooling equilibrium* as an equilibrium in which all players take the same action regardless of degree. A *degree-separating equilibrium* is a (possibly) mixed strategy equilibrium in which a player's action differs by her degree. The derivations in the appendix identify sources of network effects on degree-separating equilibria: the effect of "global" network as represented by overall network density, and the effect of "local" network as reflected by the degree of individual player, and the effect of economic return (R/C).[8] Attributed to these effects, the theory implies multiple equilibria. The subsequent equilibrium selection problem implies a natural set of competing hypotheses for behavioral study. Hypothesis 1 states that the set of

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[5] Formally this requires that $C < R\underline{k}$, where $\underline{k}$ denotes the minimal degree value in the network.

[6] We restrict our attention to symmetric strategies (and equilibria) because of the *ex ante* symmetry of players.

[7] See Gibbons (1992) for a discussion of Bayesian Nash equilibrium.

[8] Empirically, the interested reader may refer to Brandts and Cooper (2006) for a comprehensive discussion on the role of economic returns on coordination outcomes.

degree-pooling equilibria is the same for all social networks considered. Hypothesis 2 establishes separating equilibria for each network.

HYPOTHESIS 1. ***Pooling Equilibria.*** *In each treatment, either all players coordinate or no one coordinates*.

HYPOTHESIS 2. ***Separating Equilibria.*** **a.** ***Pure equilibria.*** *In Treatment HrcHden, high degree players coordinate while players with low degree defect.* **b.** ***Mixed equilibria.*** *Players coordinate with positive probabilities depending on degree: HrcHden:* $p_2 = 0.25, p_3 = 1$; *or* $p_2 = 0, p_3 = \frac{5}{6}$. *HrcLden:* $p_2 = 0.5, p_3 = 1$. *LrcHden:* $p_2 = 0.625, p_3 = 1$. *LrcLden:* $p_2 = 0.75,\ p_3 = 1$.

Since subjects have no knowledge on either the structure or the size of the grand network they play in, it is reasonable to assume, from a player's view, the degree types of neighbors are independent and identically distributed (i.i.d.), and the distribution of neighbor degree is approximated by network density. To give an example, notice that half of the players have degree-two (-three) in treatment *HrcHden*. With a grand network size reasonably large (40 subjects), the degree distribution of a player's neighbor is approximately the degree distribution of a randomly selected player, or network density -- (0.5, 0.5) over supports (2, 3) as in *HrcHden*.[9] That provided, under the belief that degree-three (-two) players will (not) coordinate, a degree-three (-two) player expects the benefit from coordination being 80 *3 * ½ = 120 (80 * 2 * ½ = 80) and a cost of coordination being 100. Therefore, the player's decision reinforces her belief and leads to equilibrium. The equilibria in Hypothesis 1 and 2 can be worked out likewise.

In addition to point-wise equilibria, our experiments also test for comparative statics w.r.t. social networks. To be specific, we hypothesize that equilibria in the previous hypotheses will be selected in the following way.

[9] It might be useful to notice that the degree distribution of a neighbor has to be conditioned on the fact that the neighbor degree is at least one (attached to oneself), but this does not make a difference in our setting where everyone's degree is greater than one.

HYPOTHESIS 3 ***Comparative Statics.*** **a.** *More connected players coordinate with higher probability than do less connected ones in equilibrium.* **b.** *Equilibria in higher density networks payoff-dominate*[10] *the equilibria played in lower density networks.*

While a formal analysis is left to the appendix (Proposition 2), the intuition behind comparative statics is simple: If a player has one more neighbor who has a nonnegative probability to coordinate while other neighbors' coordination levels remain unchanged, then in equilibrium the player should raise her probability of coordination. Likewise, if the network becomes denser, then a player's neighbor will *ex ante* have more neighbors. This will lead to a rise of total coordination level in the neighborhood of the player, presuming coordination of individual neighbor does not decline in the denser network. Then the player in question will be incentivized to increase her coordination probability regardless of her degree, which reinforces the equilibrium. Since this new equilibrium has every degree type coordinating with increasing probability, the social welfare must rise and thus the equilibrium payoff-dominates the present one (Harsanyi and Selten, 1988). In the same spirit, we refer to the all-coordination equilibrium as *payoff-dominant* equilibrium.

3. Results

In this section, we report our findings from the data. We define *coordination rate* as the percentage of subjects who coordinate. The notations in Table 2 below apply to our dataset. Labels of treatments (e.g. *LrcLden*) and cohorts (e.g. *N16*) are used as their corresponding indicator variables.

[10] In the subsequent paragraph we will introduce the concept of payoff dominance; also see Harsanyi and Selten (1988).

Notation	Interpretation
action	= 1 if coordination, = 0 if defection
Idegree	= 1 if degree =3 (high), = 0 if degree =2 (low).
period	round of the game, taking values of 1,2… 20.
X_Y	the interaction between two variables *X* and *Y* (e.g. *Idegree_LrcLden*).

Table 2. Notations for our dataset

OBSERVATION 1. *High density networks achieve nearly full coordination, which corresponds closely to the payoff-dominant equilibrium. Low density networks achieve partial coordination. Holding network density fixed, economic returns have little statistically significant influence on aggregate-level coordination rates.*

When the network has high density, coordination is unambiguously successful: As shown in Figure 1, coordination rates in both high density treatments are higher than 90% in every period, and higher than 95% after period 3. In all practical terms, payoff-dominant equilibria are played in these networks. Although a strict null hypothesis that coordination rate equal to 100% is weakly rejected by an one-sample Wilcoxon signed-rank test (with cohort-level coordination rate as data unit), the same test fails to show rejection when 99% is the hypothesized rate of coordination, yielding p-value = 0.4982 for both high density treatments. In contrast, the low density networks achieve a substantially lower rate of coordination, ranging roughly between 50% and 70% each period. Pair-wise comparisons of treatment coordination rates using a rank sum test confirm the observations from Figure 1. Every pair-wise comparison of a high density network to a low density network yields a statistically significant difference ($p < 0.03$ for all four comparisons). See the details of rank sum tests in Table 3.

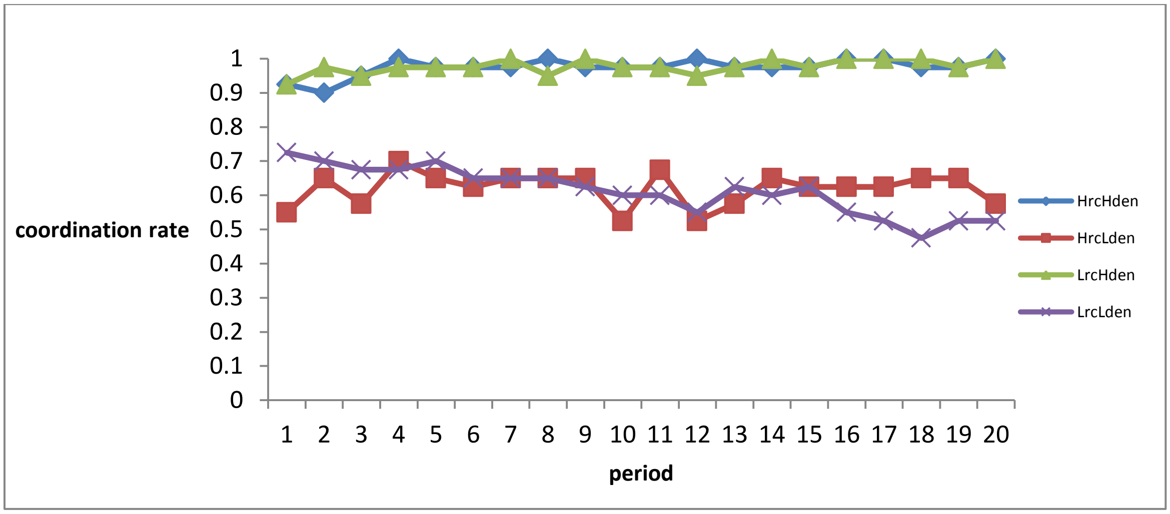


Figure 1. Treatment Effect

Whereas network density has a large impact, economic return seems to play much less a role in aggregate-level coordination. As evident from Figure 1, there is little change on coordination rates across different economic returns at each of the network density levels. In Table 3, the *p*-values yielded by pair-wise comparisons of treatment-wise coordination rates are greater than 0.46 for both comparisons involved.

Rank-sum difference in treatment-wise coordination rates**	z-value	P-value*
HrcLden - HrcHden	-2.619	0.0088
LrcHden - HrcHden	0.318	0.7503
LrcLden - HrcHden	-2.22	0.0264
LrcHden - HrcLden	2.619	0.0088
LrcLden - HrcLden	-0.731	0.4647
LrcLden - LrcHden	-2.2	0.0278

* Two-tailed

** The unit of analysis is coordination rate for each cohort in the treatment.

Table 3. Rank sum tests on coordination rates in distinct treatments

Despite an absence of effect of economic return at treatment level, we do observe remarkable influence of economic return in low density networks with data broken down by degree types (see Observation 3 and 4), for which we provide an explanation from the perspective of coordination robustness – We shall revisit this issue in later paragraphs.

OBSERVATION 2. *In high density networks, players of both degree types behave similarly towards coordination, consistent with the pooling equilibrium hypothesis.*

As implied by Figure 2, the average degree-3 player coordination rates do not appear significantly different than those for degree-2 players when network density is high. The average difference in coordination rate between two degree types is 4% (4.5%) for treatment *HrcHden* (*LrcHden*), against a base coordination rate of 95.5% for low-degree players in both treatments. Indeed, the pooling equilibria hypothesis (Hypothesis 1) is favored in high density networks, although an exact statement is weakly rejected in a paired-sample signed rank test with cohort units, yielding p-values of 0.0556 (0.0897) for *HrcHden* (*LrcHden*).

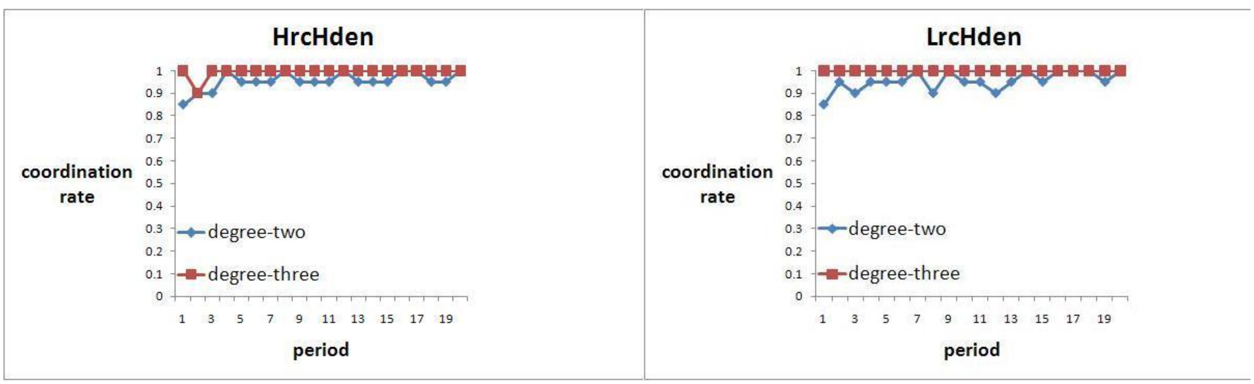


Figure 2. Pooling equilibria in high density treatments

OBSERVATION 3. *In low density networks, high-degree players play significantly higher level of coordination than do low-degree players. At treatment level this behavioral pattern supports separating equilibrium hypothesis. The overall trends of coordination differ by the economic returns attached to these treatments.*

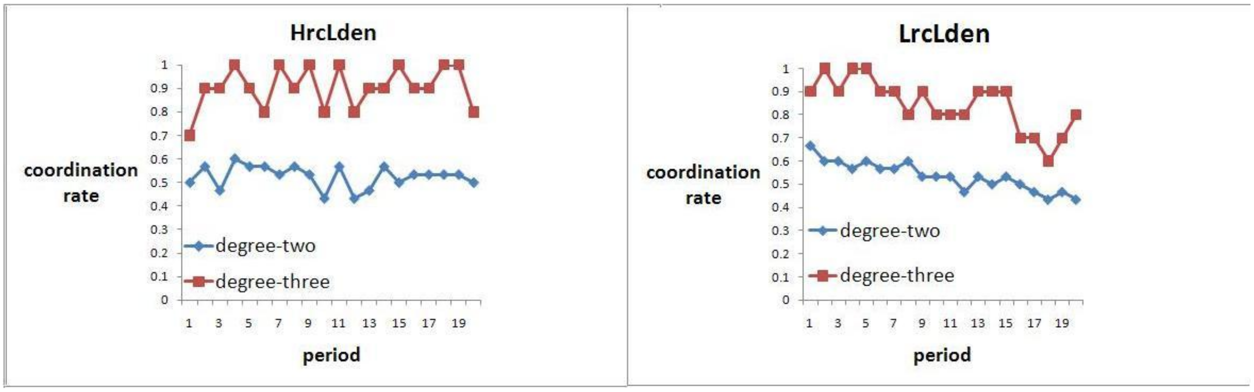


Figure 3. Separating equilibria in low density treatments

Logit regression	Dep. var. = action		
	Coef.		Odds ratio
Idegree_HrcLden	2.153975	*	8.619048
Idegree_LrcLden	1.555682	*	4.738318
HrcLden	-.0401459		.9606493
LrcLden	.1402293		1.150538

Note: a. * significance at the 1% level

b. The robust standard errors clustered on cohorts are used.

Table 4. logit regression for low density network data

Ho: coordinate rate***	*HrcLden*	z-value	P-value**
0.5	degree-2	0.135	0.8927
0.97 (1)*	degree-3	-1.219	0.2228
Ho: coordinate rate	*LrcLden*	z-value	P-value
0.75	degree-2	-1.214	0.2249
1	degree-3	-1.406	0.1599

* In practical terms we use 0.97 instead of 1. The test of coordination rate=100% gives *p*-value of 0.0422, but perfect coordination here is too strict a null hypothesis to survive.

** Two-tailed

*** The data unit is coordination rate for each degree type for each cohort in the treatment.

Table 5. One-sample Wilcoxon signed-rank tests on mixed strategy equilibria as null hypotheses

Strong patterns of degree-separating plays are present in social networks with low density. Subjects with more neighbors are more likely to coordinate (Figure 3). The logit model in Table 4 (with robust standard errors clustered on cohorts) suggests that, in both low density treatments, the effect of individual degree is a major influence on the coordination level (both significant at 1% level). In fact, one-sample signed rank tests with cohort as unit confirm that the behavioral pattern is consistent with the aggregate levels of coordination anticipated by separating equilibria in Hypothesis 2: All p-values are larger than 0.15. The observed equilibria are $p_2 = 0.5, p_3 = 1$ for $HrcLden$ and $p_2 = 0.75, p_3 = 1$ for $LrcLden$ [11] (see Table 5). We should however acknowledge that, as suggested by Shachat (2002), Walker and Wooders (2001), and Erev and Roth (1998), these aggregate-level test results are not proof that mixed equilibria are exactly executed on the individual player level.

In treatments with high network density, coordination is successful and steady in all rounds of the game (Figure 2). In $HrcLden$, high-degree players persist in coordination and hence stabilize the system even with low-degree players being less willing to coordinate (Figure 3). In all the above-mentioned treatments, coordination levels are highly stable across periods. Nevertheless, some intricate trends in coordination emerge in Treatment $LrcLden$. The next observation will explore this phenomenon.

OBSERVATION 4. *In low density networks with low economic return (Treatment LrcLden), coordination evolves differently across network cohorts.*

Figure 4 plots the degree-specific coordination rates of each network cohort in the first and second half of the game. As the figure suggests, in two cohorts out of five (N16 and N20), coordination rates dramatically drop for both degree types as the game moves to later rounds (The decrements are 38.3% (35.0%) for low (high) degree of N16, and 23.3% (30.0%) for low

[11] Notice that the one-sample signed-rank tests imply that the low degree players in *LrcLden* play larger coordination rate (0.75) than those do in *HrcLden* (0.5), which may seem conflicting with the information we read from Figure 3. This happens because there are a few network cohorts in which coordination is played at rather low levels. When a nonparametric test is applied with cohort as unit of analysis, the impact of the coordination poverty of these networks has been largely cancelled. Thus, the one-sample signed-rank tests suggest a seemingly higher level of coordination than Figure 3 does. Observation 4 below decomposes the *LrcLden* data by cohorts and illustrates this point.

(high) degree of N20.). The overall coordination level of N20 (21.25%) is considerably lower than that of the N16 (43.75%). In the rest of cohorts the plays separate on degree types. High-degree subjects all perfectly coordinate in these cohorts (coordination rates being 100%), whereas low-degree players behave differently: In two cohorts (N17 and N19) their coordination level ascends as the game advances, with increments of 5.0% for N17 and 23.3% for N19. In one network cohort (N18) their coordinate rate shrinks in the later rounds, changing from 51.7% to 36.7%.

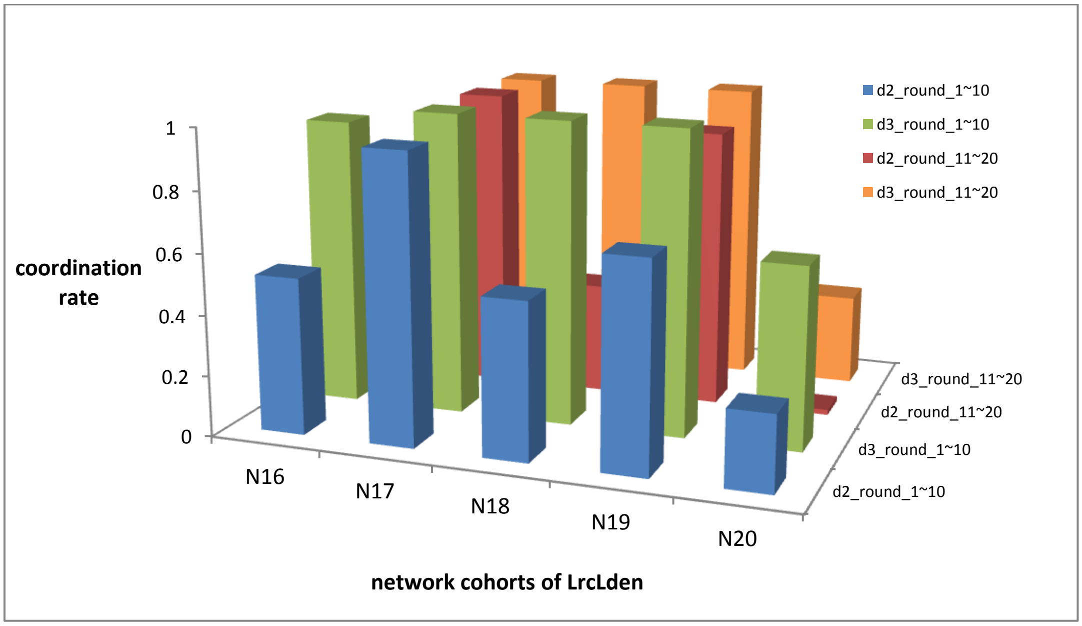


Figure 4. Coordination trends for each network cohort in Treatment *LrcLden* [12]

Further investigation on the heterogeneity of coordination in *LrcLden* treatment is found in the Appendix. We conclude that, in Treatment *LrcLden* where coordination is least attractive in all four scenarios, coordination levels begin to fluctuate across cohorts. Qualitative differences in the evolution of coordination are observed for each individual network cohorts. This instability in behavior results from lack of robustness of coordination -- as we shall illustrate later.

To summarize the results, we find strong evidence for a "density effect": Players select payoff-dominant equilibria in high density networks and perform virtually full coordination. Low

[12] In Figure 4, d2 and d3 are shorthand notations for degree-2 and degree-3, respectively.

network density reduces coordination levels, and leads to aggregate behavior consistent with separating equilibria in mixed strategies. Whenever players' actions separate on their degrees, we observe the "degree effect": Players with more neighbors show higher tendency to coordinate. The degree and density effect observed from the data respectively confirm part (a) and (b) of our Hypothesis 3 on comparative statics.

Why do we observe such equilibrium selection pattern in our game? To find an answer, we define *strategic risk* as the probability a player assigns to each of her neighbors defecting. Strategic risk is an important concept in the theories of equilibrium selection (Harsanyi and Selten 1988, Harsanyi 1995), and is central to understanding the experimental coordination results of Huyck, et al (1990). Coordination is *robust* if its optimality survives high strategic risk. As shown in Figure 5, with high economic return, coordination is better choice than defection for a high (low) degree type when the strategic risk is less than 58.33% (37.5%). With low economic returns the corresponding values are 48.53% (18.75%) for high (low) degree types. In general, if one has a larger number of neighbors, the optimality of coordinating survives higher bound on strategic risk of any single neighbor defection. Therefore, *social connections enhance the robustness of coordination*.

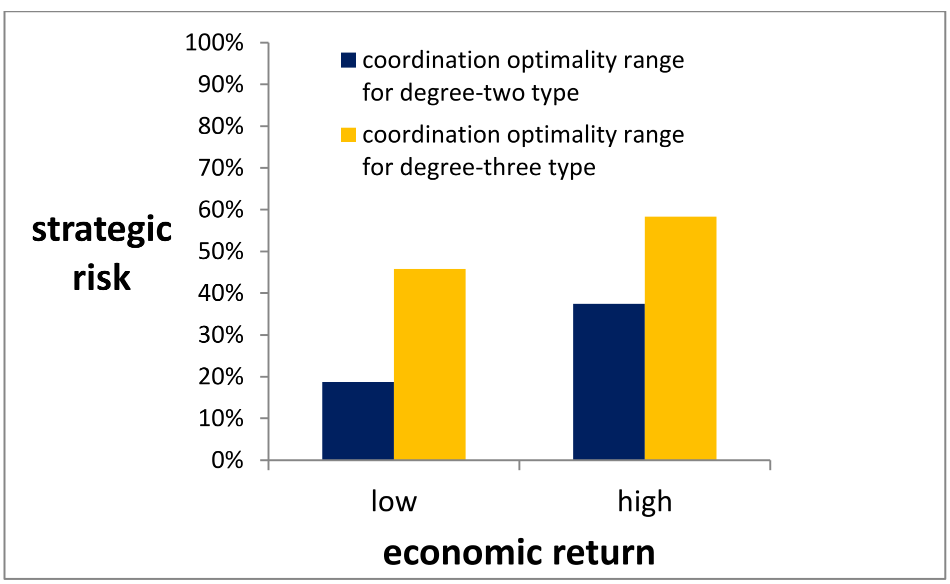


Figure 5. Ranges of strategic risk where coordination is optimal by degree types and economic return

High network density raises the proportion of high-degree players in the system, the ones for whom coordination is most robust. Furthermore, as a secondary effect, coordination becomes optimal for the low-degree players due to perceived strategic risk because, in a dense network, they are more likely to have a neighbor of high degree. This enforces the pooling equilibrium on coordination (Observation 1 and 2). In contrast to the uniform trend in high density networks, the two low-density treatments are somewhat dissimilar from one another. In treatment *HrcLden*, coordination is less optimal for the low degree players than in the high density networks because 1) their low-degree reduces the coordination robustness so that the benefit of coordinating hangs crucially on their neighbor actions, and 2) their neighbors are more likely to be low-degree also. As a result, low degree players turn to defection more often than they do in the high density networks. On the other hand, coordination from high degree players remains robust, attributed to the high economic return of the treatment. This pattern of separating is stabilized as equilibrium (Observation 3). When economic return is also low (*LrcLden*), even coordination decisions from high degree players become sensitive to neighbor actions, and are deterred by the fact that their neighbors are more probably low degree. Hence in the *LrcLden* treatment, the action of coordinating is fragile for both types of players. Consequently, behavior exhibits instability across different cohorts (Observation 4), while the overall coordination level declines (Figure 3, *LrcLden*).

4. Conclusions and Discussion

Our laboratory experiments shed light on how the social network, which determines "who plays the game with whom", affects the outcome of strategic coordination. We find that both global networks and local networks have significant impacts on coordination behavior. Denser connections facilitate coordination and drive players' behavior towards pooling equilibria that are payoff-dominant, whereas in sparser networks, the levels of coordination are partial and consistent with separating equilibria. In the sparser networks, more highly connected individuals reveal a stronger propensity to coordinate than do the less connected. We explain the pattern of equilibrium selection by revealing that social connectivity improves the robustness of coordination.

We observed full coordination in circumstances where players had complete information about their local social links but incomplete information about the connections of the overall network. This simple pairing of global and local network effects explains reasonably well coordination at aggregate level even when coordination is partial (see Observation 2 and 3 in Section 3). This suggests the importance of local environment on subjects' coordination, and also implies the potential power of a simple measure on global network (e.g., network density) for predicting the overall coordination performance in social networks.

While previous coordination studies have achieved full coordination by manipulating population size (e.g. Van Huyck, et al 1990, Weber 2006), we fix network size and demonstrate full coordination by varying population structure (Recall that the network size is fixed in all treatments). Also worth noted is that, the player payoff in our coordination game depends on the *summation* of neighbors' actions, so the payoff from coordination weakly increases with the neighborhood size. Thus denser networks with everyone more connected eases coordination. While payoff in a summation version fits in some coordination scenarios, it is more appropriate to study a different payoff function in some other situations. In Van Huyck, et al (1990) and Weber (2006), the payoff of a player is determined from the *minimal* action played by the group that she interacts. Since in a larger population it is more probable that there exists defecting player, coordination is more difficult in their studies when more players are involved, and efficient coordination in large groups may call for external administration (Weber, 2006).[13]

Another important observation is that players with more neighbors exhibit higher tendency to coordinate (Observation 3, Section 3). This is consistent with the conventional notion that the "social hubs" act as the leading force in spreading coordinative behavior since they are exposed to more benefit from doing so. As such, it may be an important clue for a deeper understanding of the emergence of coordination patterns across networks.

[13] In Weber (2006), in order to reach efficient coordination, the author gradually increased population size during the experiment, and made new entrants to the game aware of the coordination history of the incumbent players.

Our experiment can be re-examined under various network sizes, and it is interesting to see whether / how behavior is affected by network sizes.[14] Also, in practice, individuals in social networks might also hold reasonable knowledge outside one's direct relations. Thus another extension of our experiment is to enrich the network information that players have. Third, while the data obtained in our game hues close to equilibrium, there is nevertheless a substantial amount of heterogeneity in game play in low density networks. This phenomenon is consistent with studies of mixed strategies in other settings (e.g. Shachat, 2002, Walker and Wooders, 2001), where individuals also exhibit significant diversity in strategic play. A more nuanced study of the behavioral dynamics that lead to the equilibria, including heterogeneity in low density networks, requires an assessment of subject learning (ex. Erev and Roth 1998), for which a formal investigation awaits.

[14] In fact, the theoretical results in the appendix are independent of network size, but it is certainly an interesting question whether the theory provides accurate forecasts on actual behavior when the network expands or shrinks in scale.

Appendix – Not for publication

A. Background Theory

In this section we present the theory that underlies the network coordination game studied in Section 2 of the paper. The theory is inspired by Galeotti et al. (2010) and Sundararajan (2007), but developed to fit in the context of our experiment. The network is defined by a set of players, N, and the links between players, E. Directly connected players are neighbors. Following the notation from the paper, let i be the index of players, $i \in N$, N_i be the set of player i's neighbors, k_i be the degree (number of neighbors) of player i. In our game each player is privately informed of her own degree, but outside her neighborhood she has only knowledge of the distribution of neighbor's degree, $G(\cdot)$.[15] This model specification captures a feature common to many social networks where, for example, a player has precise information of how many friends she herself has, yet has only rough estimates on the number of friends that each of her neighbors has. In our model, we assume the degrees of one's neighbors are independent and identically distributed (i.i.d.) random variables. This assumption is particularly associated with large network scenarios, where the outspread of grand network smoothes the local dependencies of players' degrees so that neighbors degrees can be approximated as independent.

The player payoff and the game played in neighborhood are as described in Section 2 of the paper. For this game, Proposition 1 establishes a general equilibrium condition, which entails both the global and local network effects (i.e. effects of network density and individual degree), and the influence of economic return (R/C).

PROPOSITION 1. *There are two degree-pooling equilibria where either 1) all players coordinate, or 2) no player coordinates. A set of degree-separating equilibria also exists where a player coordinates if having more than t neighbors, defects if having less than t neighbors, and coordinates with probability* $p_t \in (0,1)$ *if having exactly t neighbors. The degree threshold t satisfies the equation below.*

$$t = \frac{C}{R\left(1 - \Sigma_{k=1}^{t} G(k) + p_t G(t)\right)}. \tag{2}$$

Proof.

The proof on the existence of degree pooling equilibria is straightforward and omitted. Now we prove the existence of degree separating equilibria. Define a *t-strategy* as such that a player coordinates if her degree is above t, defects if her degree is below t, and coordinate with probability p_t if her degree is exactly t. We will show t-strategy can constitute an equilibrium with appropriate threshold t. Suppose all

[15] Since $G(\cdot)$ is a discrete distribution, $G(x)$ is the probability that neighbor's degree equals to x.

the players play t-strategy except for player i. Then, the expected number of player i's neighbors who coordinate is $k_i\left(1 - \Sigma_{k=1}^{t} G(k) + p_t G(t)\right)$. The expected payoff from coordination is $Rk_i\left(1 - \Sigma_{k=1}^{t} G(k) + p_t G(t)\right) - C$. For player i to have an indifferent degree type, we must have $Rk_i\left(1 - \Sigma_{k=1}^{t} G(k) + p_t G(t)\right) - C = 0$. This leads to $k_i = \frac{C}{R\left(1 - \Sigma_{k=1}^{t} G(k) + p_t G(t)\right)}$. For the equilibrium to be self-enforcing, the threshold t must satisfy $t = \frac{C}{R\left(1 - \Sigma_{k=1}^{t} G(k) + p_t G(t)\right)}$. The desired result then follows. Q.E.D.

Proposition 2 addresses the comparative statics on global / local social networks. Since global network is characterized by its density, a natural concept to evaluate the change in global network is stochastic dominance in network density. To see, suppose network density is denoted by $F(\cdot)$ (which is the degree distribution of a randomly chosen player in the network). Then a higher network density $F'(\cdot)$ implies that $F'(\cdot)$ stochastically dominates $F(\cdot)$, or $F'(k) < F(k)\ \forall k$.

PROPOSITION 2. *For degree-separating equilibria:* **a.** *If the degree of a player is increased (i.e. if the player has more neighbors), then the player coordinates with higher probability in equilibrium*[16]. **b.** *If the network density is increased (in the stochastic dominance sense), there exists an equilibrium that payoff-dominates the original one.*

Proof.

a. Suppose there is one more neighbor assigned to player *i*. Because of assumed degree independence this will not affect the *ex ante* coordination level played by *i*'s incumbent neighbors. Given other neighbors' action fixed *ex ante*, with one more neighbor who has nonnegative probability to coordinate, player *i* must (weakly) increase her coordination probability.

b. Notice that increased network density in our context implies increased neighbor degree distribution (both in the sense of stochastic dominance). That said, suppose the neighbor degree distribution increases from $G(\cdot)$ to $G'(\cdot)$ (where $G'(\cdot)$ stochastically dominates $G(\cdot)$). The equilibrium changes from $\sigma(\cdot)$ to $\sigma'(\cdot)$, with the degree threshold involved changed from t to t'. We will show that there is an equilibrium with $t' < t$. For player i whose neighbors all use strategy with threshold t', her expected payoff from coordination is $Rk_i\left(1 - \Sigma_{k=1}^{t'} G'(k) + p'_{t'} G'(t')\right) - C$. To proceed, define $q(t) \coloneqq 1 - \Sigma_{k=1}^{t} G(k) + p_t G(t)$ as the coordination probability of an individual neighbor under $G(\cdot)$, and $q'(t') \coloneqq 1 - \Sigma_{k=1}^{t'} G'(k) + p'_{t'} G'(t')$ as that under $G'(\cdot)$. Assuming $t' < t$, we have that $q'(t') > q(t)$. To see, notice that

$$q(t) - q'(t') < q(t) - q(t') \leq q(t) - q(t-1) = -(1 - p_t)G(t) - p_{t-1}G(t-1) < 0.$$

[16] Notice that the probability could be possibly increased to 1, and could possibly be increased from an original level of 0.

The first "<" results from the fact that increased network density increases neighbor coordination probability under the same degree threshold. The "≤" is due to $t' \leq t-1$ and that decreased degree threshold increases neighbor coordination probability under the same network density.

Substituting $q'(t') > q(t)$ into Equation (2) yields $t' < t$. This confirms our assumption and reinforces the equilibrium. Moreover, the lowered coordination threshold together with the increased network density implies that the *ex ante* social welfare is increased, and then concludes the intended payoff-dominance relationship. Q.E.D.

B. The Heterogeneity of Coordination in Treatment *LrcLden*

To further our investigation on the behavioral heterogeneity in treatment *LrcLden* (Section 3 in the paper), we re-examine the trends of coordination by a Wald test on the significance of cohort effects. We execute a logit model on separate datasets of two degree types with explicitly posted dummy variables for cohorts. This generates the output below in Table B-1.

Logit Regression	low degree data			high degree data***		
Dep. var = action	Coef.		Odds ratio	Coef.	P-value	Odds ratio
N16	1.032802	*	2.80892543	4.509412	**	90.8683722
N17	1.887444		6.602474	/	/	/
N18	-0.64965		0.5222285	/	/	/
N19	-1.19159		0.3037395	/	/	/
N20	-0.5268		0.5904943	-3.06939		0.0464497
period_N16	-0.18604	**	0.830241	-0.25976	**	0.7712367
period_N17	0.266339	*	1.305177	/	/	/
period_N18	0.126575	*	1.134935	/	/	/
period_N19	0.360273	**	1.43372	/	/	/
period_N20	-0.14229		0.8673701	0.099604		1.104733

Note: * (**): 5% (1%) level of significance
***In logit regression on high degree data, since all actions are equal to 1 in N17, N18 and N19, we cannot obtain any legitimate estimation.

Table B-1. Logit regression for *LrcLden* data

Table B-1 reproduces the information that Figure 4 (in the paper) delivers, but on numerical scales. We see evidence of full coordination in three of the cohorts (N17, N18 and N19) with high degree players (See the note for Table B-1). The low-degree ones in each cohort display qualitatively different behaviors: The coefficients for time effects (measured by *period* interacting cohort variables) range from negative (-0.186 for *period_N16*) to positive (0.36 for *period_N19*), implying that in some cohort (N16) coordination of low-degree subjects generally deteriorates over time (*p*-value < 0.01) while in some others (N17, N18, N19) low-degree coordination level is increasing (All p-values < 0.05) as the game proceeds. The Wald test in Table B-2 evaluates the significance of cohort-related variables in the preceding logit model. It yields both of the p-values < 0.01 for data of two degree types. Therefore, we claim significant heterogeneity in game play across cohorts in *LrcLden*.

Wald test	low degree	high degree
Tested terms*	N17, N18, N19, N20, N17_period, N18_period, N19_period, N20_period	N20, N20_period
χ^2	124.34 (8**)	9.30 (2**)
p-value	0.0000	0.0095

Note: * We test whether these terms have zero coefficients in the preceding logit model.
**Degree of freedom

Table B-2. Wald test for cohort heterogeneity in *LrcLden* dataset

C. Experimental Instruction[17]

We motivate our experiments with the product adoption example as in Section 1. Coordination means purchasing the product (cell phone), defection means not buying the product. To circumvent the bankruptcy problem, in every round before decisions are made, we give each subject an endowment that equals to the price of product. If the subject chooses not to buy the product she keeps the endowment. If she buys then she pays the price, and then gains revenue that depends on the adoption decisions made by her neighbors.

****

General. Welcome and thank you for participating in this experiment. In this experiment you will earn money. The actual amount depends on your decisions and the decisions of other participants. From now on until the end of the experiment, please do not communicate with other participants. If you have any question, please raise your hand. An experimenter will come to your place and answer your question privately.

The Game. In the Experiment we use ECU (Experimental Currency Unit) as the monetary unit. The profits you make during the experiment will be added to this account in ECU. At the end of the experiment, the balance of the account will be converted from ECUs into dollars according to the conversion rate stated below, and paid out in cash after the experiment.

[17] We only present the experimental instruction for treatment *HrcHden* in this appendix. This instruction can be applied to other treatments with only adjustments of the information on network density and coordination cost.

The experiment lasts for 20 rounds. In each round, participants will be organized in a network. In this network, you are connected to either two or three people, who are your neighbors. Every round your neighbors will be different people. You know the number of neighbors whom you are connected, but you will not know their identity. Each of your neighbors has either two neighbors or three neighbors (including yourself). There is 50% of the chance that he or she has two neighbors, and a 50% of chance that he or she has three neighbors.

At the beginning of each round, each person in the network decides whether to purchase a (fictional) cell phone. Each does so without any knowledge of what any other person decides. The profit you earn depends on whether you buy a cell phone and, if so, how many of your neighbors buy a phone. Specifically:

If you don't buy the cell phone,

• Your profit is 100 ECU.

If you buy the cell phone and you have two neighbors then

• If both neighbors buy the cell phone, your profit is 160 ECU.

• If exactly one neighbor buys the cell phone your profit is 80 ECU.

• If neither neighbor buys the cell phone your profit is 0 ECU.

This is summarized in the Payoff Table as below, also shown on your computer screen during your play.

The number of My Neighbors who Buy

My Choice		Two	One	Zero
	Buy	160	80	0
	Don't Buy	100	100	100

If you buy the cell phone and have three neighbors, then

• If all three neighbors buy the cell phone your profit is 240 ECU.

• If exactly two neighbors buy the cell phone, your profit is 160 ECU.

• If exactly one neighbor buys the cell phone your profit is 80 ECU.

• If no neighbor buys the cell phone your profit is 0 ECU.

This is summarized in the Payoff Table as below, also shown on your computer screen during your play.

The number of My Neighbors who Buy

		Three	Two	One	Zero
My Choice	Buy	240	160	80	0
	Don't Buy	100	100	100	100

All the scenarios and associated profits are summarized in the Payoff Table as shown below. The payoff table is also shown on your computer screen during your play. The conversion rate is 1ECU=0.003 dollars. Before the game starts, you are required to complete a quiz, which covers the important knowledge about the game. The quiz will be shown on your computer screen. You will start to play the game only after you correctly answer all the questions in the quiz.

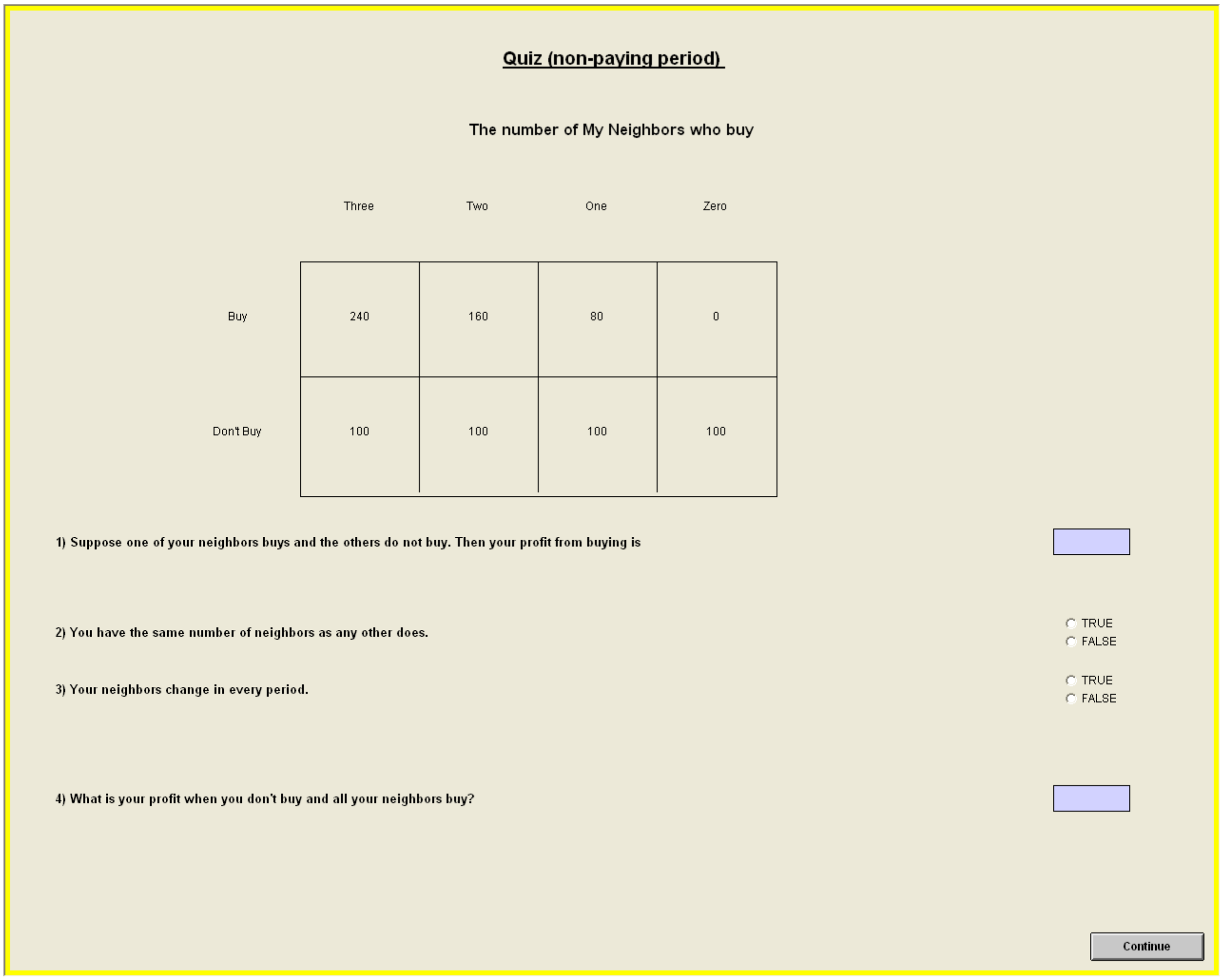
Consent Forms. Please read the consent form that is delivered to you before the start of the experiment.
****

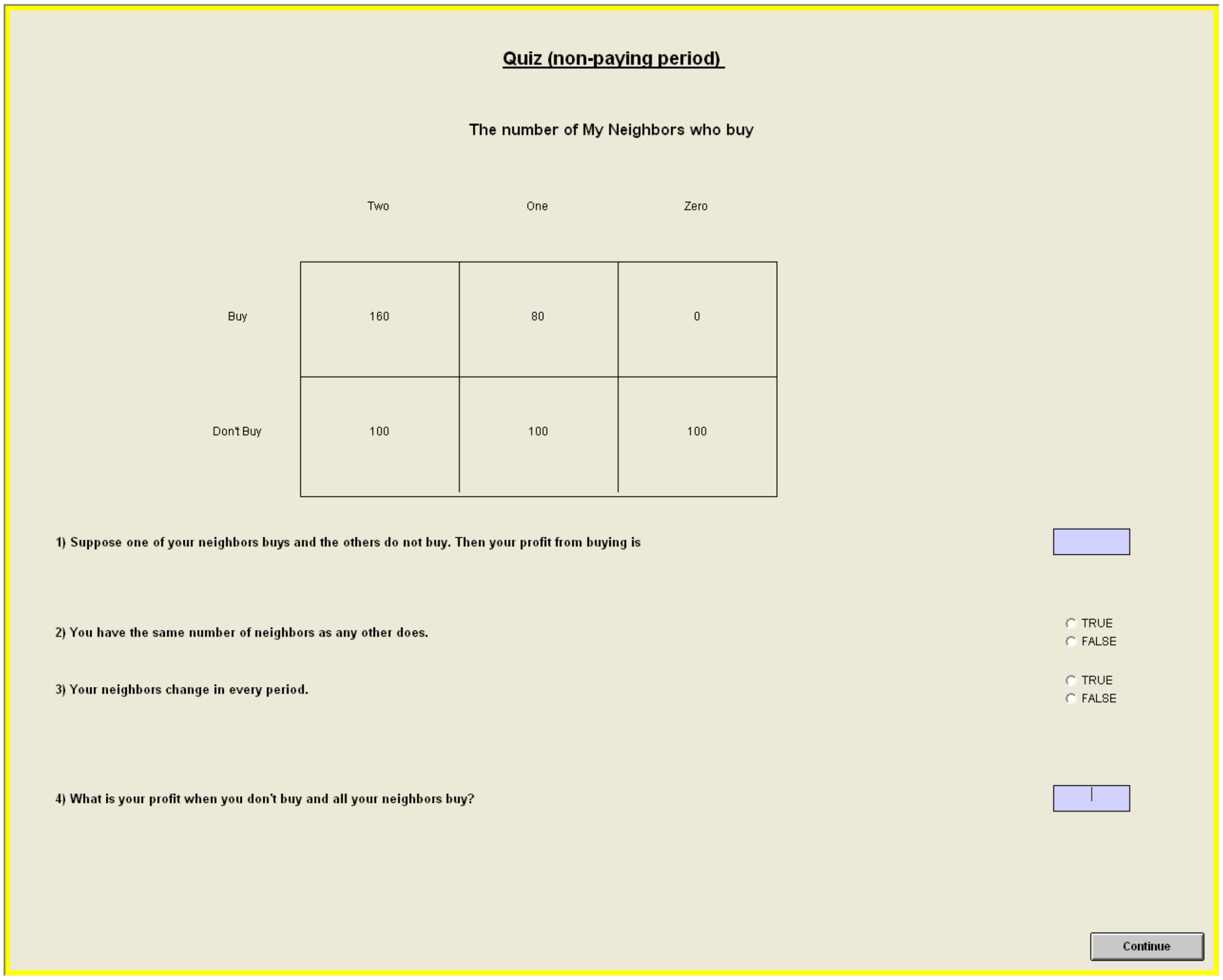
D. The Experimental Software Interface

This section provides snapshots for the experimental software. The software is programmed with zTree (Fischbacher, 2007).

All the relevant snapshots are contained in Figure D1. Subjects begin with a quiz testing their understanding of the game, with no earning accumulated to the game. The quiz screens are shown in

Figure D1-a. The actual decision making interfaces are found in Figure D1-b. For better references, the interfaces for high-degree players and low-degree players are separately presented.





Quiz (non-paying period)

The number of My Neighbors who buy

	Two	One	Zero
Buy	160	80	0
Don't Buy	100	100	100

1) Suppose one of your neighbors buys and the others do not buy. Then your profit from buying is

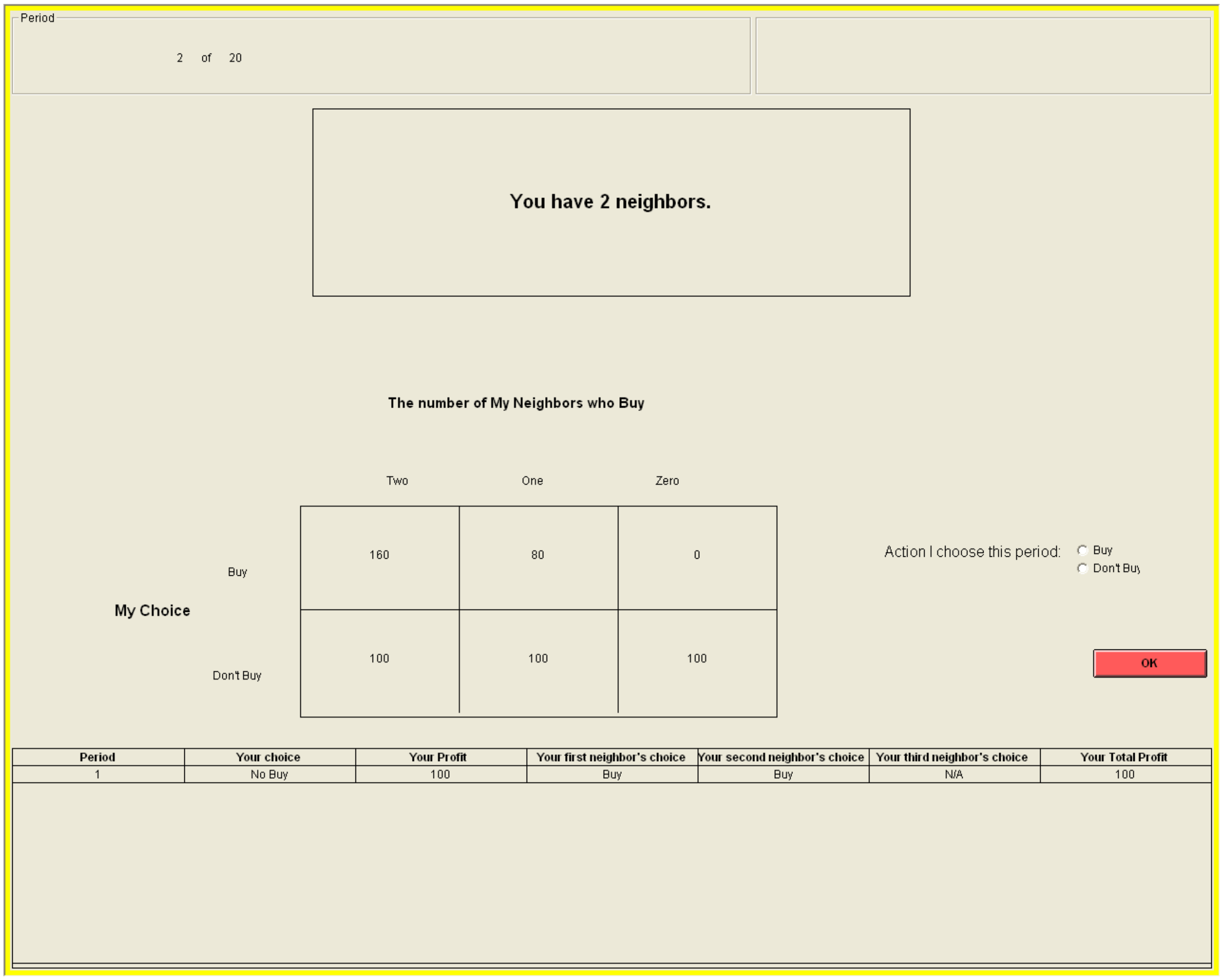
2) You have the same number of neighbors as any other does. TRUE FALSE

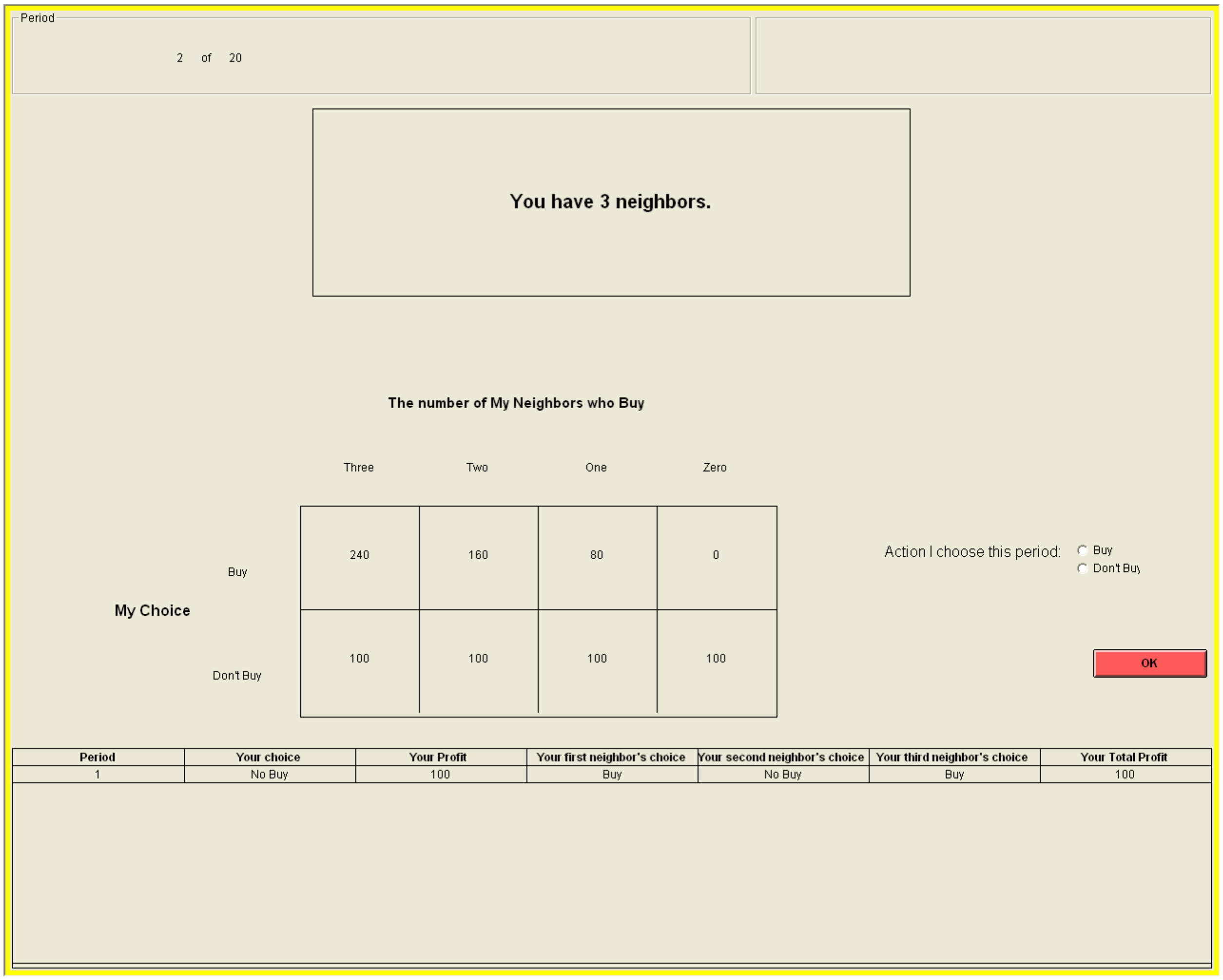
3) Your neighbors change in every period. TRUE FALSE

4) What is your profit when you don't buy and all your neighbors buy?

Continue

D1-a. Quiz


Period
2 of 20
You have 2 neighbors.
The number of My Neighbors who Buy
Two
One
Zero
My Choice
Buy
160
80
0
Don't Buy
100
100
100
Action I choose this period:
Buy
Don't Buy
OK
Period
Your choice
Your Profit
Your first neighbor's choice
Your second neighbor's choice
Your third neighbor's choice
Your Total Profit
1
No Buy
100
Buy
Buy
N/A
100



D1-b. Decision Making

Figure D1. The snapshots for the experimental software interface

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