Costly Information Acquisition, Social Networks and Asset Prices: Experimental Evidence

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7 August 2017

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August 7, 2017

Abstract

We design an experiment to study the implications of information networks for the incentive to acquire costly information, market liquidity, investors' earnings and asset price characteristics in a financial market. Social communication crowds out information production as a result of agent's temptation to free ride on the signals purchased by their neighbors. Although information exchange among traders increases trading volume, improves liquidity and enhances the ability of asset prices to reflect the aggregate amount of information in the market, it fails to improve price accuracy. Net earnings are higher with information sharing due to reduced acquisition of costly signals.

JEL Classification Numbers: C92, D82, D83, D84, G10, G14

Keywords: Asymmetric Information, Costly Information Acquisition, Experimental Asset Markets, Social Network, Uncertainty

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*We gratefully acknowledge the financial support from the Singapore Ministry of Education Academic Research Fund (AcRF) Tier 2 grant (MOE2014-T2-1-105), Nanyang Technological University, Singapore and City University of Hong Kong, Hong Kong. The paper benefited from discussions during presentations at the AEI5 Joint Conference at the Seoul National University, ESSEC Business School (Singapore campus) and the 2017 ESA World Meeting, San Diego. We are especially thankful to Yan Chen, Syngjoo Choi, Douglas Davis, Sascha Füllbrunn and Chad Kendall for helpful comments. Lim Chang Yi, Poh Huizhen Isabella and Quah Zong You provided excellent research assistance.

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1 Introduction

Knowledge about fundamentals influences security prices. Acquisition of such costly information is one of the central topics in economics. A long line of research initiated by Grossman and Stiglitz (1980) and Verrecchia (1982) has investigated the incentives to acquire costly information and its implications for financial markets. Using the principle of rational expectations, this literature has shown that investors' diverse information is reflected in asset prices and individuals incorporate the information content of prices into their trading decisions. The information dissemination and aggregation properties of market organization have been explored at great depth in the theoretical and experimental literature. However, the important issue of the possibility of social communication via information networks among investors has been ignored to date.

Although the significance of the embeddedness of economic activity in social settings has long been recognized in sociology (Granovetter (1985)), economists have been sluggish in acknowledging the paramount role played by neighbors and friends in influencing our beliefs, decisions and behaviors. However, the last two decades have seen a flurry of studies that have demonstrated that the effects of social networks on economic activity are abundant and pervasive, including roles in transmitting information about jobs, product adoption, technologies, and political opinion (Jackson (2008, 2010)). Several research papers have shown that information sharing with peers via social networks, word-of-mouth communication among people with whom we interact on a regular basis and shared education networks play an important role for investment decision making including stock market participation and portfolio choices.[1] It is now widely recognized that there are many economic interactions where the social context is not a second-order consideration, but is actually a primary driver of behaviors and outcomes.

The objective of this paper is to examine the impact of information exchange among investors on individual trader's decisions to invest in information production and subsequently on market outcomes including trading volume and asset price characteristics. Specifically, we ask the following set of questions. How does so-

[1]The pertinent studies are briefly mentioned in the next section where we discuss the related literature.

cial communication influence the incentives to acquire costly information regarding stock fundamentals? How does information sharing via networks affect the ability of market prices to reflect investors' diverse information as well as the propensity of prices to reveal the underlying state of nature? What are the implications on trading volume and trader profits? In order to answer these questions, we design an experimental asset market with endogenous acquisition of costly information. We assume two equally likely states of nature, A and B, and a single asset, a Arrow-Debreu security that provides a payoff only in state A. Prior to trading, individuals may acquire costly and imperfect signals about the state of nature. Signals are binary, and independent and identically distributed (i.i.d), conditional on the state.

While laboratory markets are much simpler in structure than actual asset markets in the field, they provide an invaluable controlled setting that enables the causal identification of the network structure. An exogenous network of interactions could be imposed among a group of subjects, and several treatments could be implemented to isolate the effect of the structure of the network on individual behavior as well as market outcomes. The novelty of our research stems from the fact that we embed network structures within the framework of Arrow-Debreu security market. We believe that our research would complement the analysis of financial markets that uses field data.

What distinguishes our paper from previous studies on information acquisition is the existence of a network among the traders. Before trading takes place, individuals can communicate their purchased information to those connected to them in the network. The network structure is assumed to be exogenous. As emphasized in Cohen, Frazzini and Malloy (2008), a convenient aspect of social networks is that they have often been formed ex ante, sometimes years in the past, and their formation is frequently independent of the information to be transferred. We further assume that information exchange is perfect and non-strategic, such that any acquired information by one individual is automatically exchanged to her connection and vice versa. We model a society where individuals are embedded in a social network of long term relationships that took time to form, express mutual trust and are not easily undone (Granovetter (1985)). In such a society, lying or withholding information is extremely costly. As discussed in Han and Yang (2013), one can interpret networks as friendships, club memberships, and social media, or more generally, being connected through the network can also be viewed as using common information sources, such as newsletters.[2]

On the one hand social communication is envisaged to reduce the risk of the asset by enlarging each trader's information set as well as increasing the informational efficiency of prices, but on the other hand the expectation of learning from informed connections and more informative market price also gives rise to a temptation to free ride on others' acquired information. In our experiment, we find that, on an average, the likelihood of acquiring information and the amount of signals purchased are both decreasing in the number of connections of a trader. Compared to the case of no information sharing, the proportion of investors not buying any signal rises by around 55% when information exchange takes place on a complete network. This possibility of an incentive to free ride has been recently explored theoretically in Han and Yang (2013) and we complement their study by providing empirical support.

Despite lowering information disparity among investors, social communication results in more trades and improves market liquidity. With information sharing among investors, a larger fraction of the available information in the market is impounded into asset prices. While prices typically under-react to the information in the market, the extent of under-reaction decreases with the density of the information network. However, the ability of prices to correctly predict the underlying state of nature is not enhanced with information sharing. This happens due to the fact that the strong free riding incentive crowds out information production to such an extent that the information accuracy of the cumulative signals in the market remains low. Thus, contrary to conventional wisdom, we show evidence that enhanced information exchange via social communication does not improve the quality of prices as forecasting tools.

The remainder of the paper is organized as follows. Section 2 reviews the related literature and section 3 provides the hypotheses. In section 4, we describe the design and procedures of the experiment, and in section 5, we present the data. Section 6 concludes.

[2]Although our study abstracts away from the issues of endogenous formation of networks as well as strategic information revelation, we stress that these are nevertheless important topics to be investigated in future studies.

2 Literature Review

The primary contribution of this paper is in the subject of costly information acquisition in financial markets, a literature that is pioneered by the seminal theoretical papers by Grossman and Stiglitz (1980) and Verrecchia (1982). If information is costly to obtain, Grossman (1976) showed that market prices cannot be fully efficient, since fully revealing prices remove any incentive to acquire information. While the fully revealing rational expectations equilibrium predicts no information acquisition (Grossman and Stiglitz (1980)) and no trade (Milgrom and Stokey (1982)), many studies have proved the existence of noisy rational expectations equilibrium in which the amount of costly diverse information each trader acquires is endogenously determined (Grossman and Stiglitz (1980), Verrecchia (1982), Peress (2004)). Some noise, often introduced through stochastic noise trader demand or variability in supply of the risky asset, prevents the equilibrium price from fully revealing traders' private information.

The majority of the experimental asset pricing studies follow Smith, Suchanek and Williams (1988) and are devoted to the investigation of asset price bubbles and crashes. In studies based on this design, a market is created for a dividend-paying asset with a lifetime of a finite number of periods, and the asset structure is common knowledge. The key finding is that prices greatly exceed the fundamental value for a sustained temporal duration before finally crashing to prices close to fundamental values.[3] Another class of asset pricing experiments has demonstrated that markets can disseminate information efficiently (Forsythe, Palfrey and Plott (1982) and Friedman, Harrison and Salmon (1984)) as well as aggregate private information in static markets (Plott and Sunder (1982, 1988)). More recently, Bossaerts, Frydman and Ledyard (2014) examine the relationship between eventual price quality and the proportion of traders in an economy that has private information by comparing two theories, one using the Bayes Nash equilibrium, and the other using noisy rational expectations equilibrium.[4]

[3] The phenomenon of asset price bubble has been replicated in numerous studies. Palan (2013) provides a review of articles that investigate bubbles and crashes in experimental markets.

[4] For a detailed overview of the experimental asset market literature, see Sunder (1995) and Noussair and Tucker (2013).

The experimental literature on endogenous information acquisition in financial markets is, however, limited. Copeland and Friedman (1992) observe that outcomes support the fully revealing rational expectations in simple environments in which the uninformed traders can easily infer the private information of informed traders. They also find support for non-revealing rational expectations in more complex (noisy) environments. Similar results are obtained by Sunder (1992). Both these studies find that when traders submit sealed bids for perfect information, the market value of information approaches zero. Ackert, Church and Shehata (1997) investigate the effects of imperfect, private information on prices and find that imperfect information is partially disseminated and that imperfect information is in fact valued by the market participants. Huber, Angerer and Kirchler (2011) have demonstrated that it is possible for informed traders to obtain lower net profits on average compared to uninformed traders. A recent study by Page and Siemroth (2017) reports that traders are more likely to acquire costly information if they have a larger endowment in cash and assets, if their existing information is inconclusive, and if they are less risk-averse.[5]

While the above theoretical and experimental studies have significantly enhanced our understanding of the aspect of costly information acquisition in financial markets, the role of information exchange among traders themselves has been ignored so far. The vital importance of such communication, particularly word-of-mouth communication, among financial market investors has been recognized in Shiller (2000) and more recently in Shiller (2017). Contemporary theoretical studies find that social communication via networks improves market efficiency when information is exogenous (Colla and Mele (2010), Ozsoylev and Walden (2011)). Once information is endogenously acquired via purchase of costly signals, social communication can affect market outcomes in a way that is opposite to that in the exogenous information case (Han and Yang (2013)). This happens due to the fact that information exchange through social networks adversely affects the overall production of knowledge. In

[5] A related line of research has investigated the capacity of prediction markets to aggregate existing knowledge. A prediction market is a special type of contingent claims futures market that is designed with the intention of providing probabilistic predictions about future events. See Healy et al. (2010) and Page and Siemroth (2017) for recent experimental studies on such markets. Deck and Porter (2013) provide a survey of laboratory studies on prediction markets.

contrast to the existing experimental studies on costly information acquisition, we introduce information networks among investors. To the best of our knowledge, this is the first paper to study the issue of how social communication affects market outcomes with costly and endogenous information acquisition in experimental asset markets.[6]

Our paper also contributes to the large and growing literature on the effect of networks on economic and financial decision making, especially in the context of information sharing. Several empirical studies have documented that the exchange of information through social networks has important implications for investment decisions such as stock market participation and portfolio choices. See, for example, Kelly and O'Grada (2000), Duflo and Saez (2003), Hong, Kubik and Stein (2004, 2005), Ivković and Weisbenner (2007), Brown et al. (2008), and Cohen, Frazzini and Malloy (2008), among others. Social connections have also been shown to be important in spreading information about jobs (Munshi (2003), Bandiera, Barankay and Rasul (2009)), microfinance (Banerjee et al. (2013)), public health (Kremer and Miguel (2007)) and aggregating information about poverty status (Alatas et al. (2016)).[7] Our experimental investigation of the consequences of communication networks among friends and neighbors on the information acquisition incentives and asset prices complements the above mentioned studies.

3 Hypotheses

The theoretical models utilizing the framework of noisy rational expectations imply that equilibria with information acquisition exist (Grossman and Stiglitz (1980), Peress (2004)). Recently, Han and Yang (2013) analyze a rational expectations equilibrium model of a competitive market in which heterogeneous traders learn about a risky asset's payoff from three sources: market price, costly information

[6]Endogenous information acquisition is an important topic in financial economics, with several studies applying this concept to understand a wide range of issues, including portfolio choice, home bias puzzle, mutual funds behavior and large price movements. See Han and Yang (2013) for a list of references in this literature.

[7]There are several excellent surveys available on networks in finance (Allen and Babus (2009)), social-network applications for economic problems (Easley and Kleinberg (2010), Jackson (2008, 2010)), and economic networks in the laboratory (Kosfeld (2004), Choi, Kariv and Gallo (2016)).

acquisition, and communications via an exogenous social network. They argue that information sharing with friends over a network has two positive effects on reducing the risk of the stock. First, it enlarges each trader's information set and hence the precision of a stock's payoff conditional on each agent's information set increases. Second, exchanging information among more friends improves the informational efficiency of the asset price by causing more information to be impounded into the asset price. This improved market efficiency further reduces the risk of the asset for everyone.

However, there is a negative effect of social communication when information acquisition is endogenous and the cost to obtain such information is sufficiently high. In anticipation of learning from informed friends and more informative market price, Han and Yang (2013) predicts that traders would have less incentive to incur a cost and acquire information on their own. This incentive to free ride on others' acquired information reduces the total amount of information produced in the society. This provides the basis for our first hypothesis.

Information Acquisition Hypothesis. *The aggregate amount of information in the market is lower with social communication.*

Next, we hypothesize that information sharing among friends would have an impact on the trading volume in the asset market. Han and Yang (2013) argue theoretically that with fewer people choosing to acquire information at a cost when they are connected to more friends, trading aggressiveness is lower with social communication which harms liquidity and volume. This is also in line with the market-level implication from the overconfidence literature (Odean (1999), Barber and Odean (2001), Scheinkman and Xiong (2003)) that there is a positive relationship between the aggregate amount of information purchased and market trading activity. Additional justification comes from the observation that communication of private information among friends lowers the information heterogeneity among traders, thereby lowering the divergence in beliefs about the state of nature.

Trading Volume Hypothesis. *Market trading volume is lower with social communication.*

A trader's private information is a critical determinant of the price at which she places bids and asks in the marketplace. Social communication leads to less divergence in the private information held by traders and thus, the asset price better reflects the aggregate information present in the market. In other words, with information sharing among investors, a larger fraction of the available information in the market is impounded into the asset price. Defining the price informativeness as the ability of prices to reflect the information available in the market, we have the following hypothesis.

Price Informativeness Hypothesis. *Price informativeness is higher with social communication.*

Finally, we argue that the accuracy of the asset price does not change with information exchange among friends. The accuracy of asset price is defined as the difference between the actual value of the asset and the market price measured by an appropriate distance metric. Social communication results in lower aggregate amount of information in the market (information acquisition hypothesis), thereby reducing the information accuracy of the composite signals in the market.[8] This will have a negative impact on the accuracy of asset price. However, at the same time, the ability of market price to aggregate information efficiently is also increasing with communication (price informativeness hypothesis). Thus, the effect of information sharing on price accuracy is ambiguous as two factors (information accuracy and price informativeness) are changing at the same time with exchange of information among connections.

Price Accuracy Hypothesis. *Social communication does not improve the accuracy of the asset price.*

4 Experimental Design

4.1 Procedures

The data for this study were gathered from eight experimental sessions conducted at the Nanyang Technological University (NTU), Singapore. We had 192 participants in total, with 24 participants in each session. They were recruited from the popu-

[8]Information accuracy measures how accurate is the information in the market and is defined as the difference between the actual value of the asset and the value implied by the available information in the entire market.

lation of undergraduate students at NTU from various majors ranging from Social Sciences, Business and Economics, Humanities, Engineering, and Sciences. No subject participated in more than one session of this experiment. The sessions lasted approximately two hours and participants earned on average S$24.40 in addition to a show-up fee of S$2.[9]

Upon arrival, subjects were seated at visually isolated computer workstations. Participants were randomly divided into groups of eight.[10] Instructions were read aloud and subjects also received a copy of the instructions.[11] Participants were prohibited from talking during the experiment and all communication took place via the experimental software. Each session consisted of two practice periods and twelve main periods.[12] Activity during the practice period did not count toward final earnings.

We employed the ball-and-urn setup of the experiments conducted by Anderson and Holt (1997) and followed Page and Siemroth (2017) in explaining the setting to the participants. At the start of each period, a virtual urn (A or B) was randomly selected by the computer, with each urn having an equal chance of being chosen. Both types of urn contained 10 balls in total. Urn A contained 6 black balls and 4 white balls, while urn B contained 4 black balls and 6 white balls. All of this information was common knowledge to the participants. The realization of the urn was revealed perfectly to subjects only at the end of a period.

Traders had the opportunity to exchange several units of an asset every period by participating in a virtual financial market. All accounting and trading were done in experimental currency units (ECU). The market was computerized and we used the continuous double auction trading rules (Smith (1962)) implemented with the z-Tree computer program (Fischbacher (2007)). At the end of each period, one unit of the asset paid a dividend of either 10 ECU if the underlying urn was A or 0 ECU if the urn was B.

[9]Payoffs, inclusive of the show-up fee, ranged from S$17 to S$36 with a standard deviation of S$3.71.

[10]Each session had three independent groups with eight subjects in each group.

[11]A sample copy of the instructions is provided in the Appendix.

[12]At the end of the instructions phase and prior to the start of the experiment, all participants had to complete a quiz to ensure that they understood the important concepts and instructions required for the experiment.

Each period, all participants started with the same initial endowment of 60 ECU and 4 assets. The endowment and earnings from one period could not be carried forward to the next period. That is, each period was independent of the other. Prior to trading, participants received initial information about the underlying urn. This information was provided in the form of two balls drawn independently and with replacement from the underlying urn. That is, each signal was independent and identically distributed (i.i.d), conditional on the underlying urn (or state of nature). These two signals were revealed without any cost to traders and were observed publicly by all participants in a market. This feature ensured that traders started with a common prior belief about the state of nature.

After observing the initial information, traders could acquire up to 5 additional draws at the cost of 3 ECU each.[13] All participants were given sixty seconds to decide on how many additional draws they would like to acquire.[14] This information gathering stage occurred at the same time for each participant and agents did not observe the results of others' information purchases at this point. Before the decision to acquire additional costly information, each participant was shown the pattern of connections in the form of an undirected graph. Each node in the graph represented the location of a subject. An edge between two nodes implied that the traders occupying the two nodes were neighbors. Each trader knew the number of neighbors that they had. Subjects were told that the information that they purchase would be shown to their neighbors at the end of the sixty seconds of the information acquisition stage. Likewise, any additional information purchased by neighbors would be revealed to the subject as well.[15] Thus, when traders decided on the number of costly signals to acquire, they most likely took into consideration the expected learning through social communication via their connections.

The ball draws revealed to participants provided them with some information about the underlying state of nature and hence, the value of the assets. For instance,

[13]Again, each signal was an i.i.d draw from the underlying urn.

[14]In this study, we focus on the setup with endogenous acquisition of costly information. We do not explore the case where information is exogenously given as we believe the implications of social communication on asset price characteristics are straightforward and less interesting in such a setting.

[15]Participants observed their direct neighbors' information but not the information purchased by neighbors' neighbors (or second-order neighbors). This is motivated by the fact that people usually know and trust their friends well, but not their friends' friends.

observing more black ball draws tend to indicate that urn A was the underlying urn. In the instructions, we briefly explained to each subject about the concept of posterior probability and the procedure for computation of the posterior. Participants were not required to compute the posterior themselves. Instead, the computer program displayed the posterior for each subject according to their individual ball draws.

After the information acquisition stage was over, participants entered the trading stage. A trading phase lasted for three minutes, within which all subjects were free to purchase and sell units of the asset at any time provided that they do not violate the short-selling (negative holdings) constraint.[16] In addition, subjects were required to maintain a positive cash balance to make any purchases. If engaging in a trade would violate either the short sale or cash balance constraint, the computer program prohibited individuals from doing so.[17] Throughout the trading stage, pertinent information such as the profile of draws revealed to them, posterior probability of the underlying urn being A given their draw profiles, as well as their ECU and asset balance available for trading were displayed on the trading window of a participant. Once trading closed, the underlying urn was revealed together with the subjects' earnings and average transaction price in the period.

Following completion of the last period, subjects were required to complete a total of ten probability-related quantitative questions designed to assess their quantitative skills. They participated in the standard risk-elicitation task (Holt and Laury (2002)) as well.[18] At the end of the experiment, the program randomly selected 3 of the 12 periods for the purpose of payment. The average of the payouts from these three periods was paid to the subjects.

[16] To buy (sell) an asset, a trader could either accept the existing sell (buy) offer or create a buy (sell) offer. Offers could be withdrawn at any time without any cost. In addition to existing buy and sell offers, participants were also shown a list containing the prices of all completed trades within the period.

[17] No borrowing or short sales are standard restrictions in asset market experiments.

[18] Participants were also asked to answer a questionnaire aimed at collecting additional information such as gender, age, prior trading experience, Business and Economics background etc.

4.2 Treatments

We implemented four treatments and conducted two sessions for each of them. This resulted in six independent groups per treatment. The treatments differed in the underlying exogenous structure of information network among traders (see Figure 1). The *non-networked* treatment resembled the markets considered in earlier studies with no information exchange between investors. Each participant only observed the information purchased by herself privately, apart from the two initial signals. Each trader was connected to the other seven traders in the *complete network* sessions. Here, participants were able to observe the additional information acquired by everyone else. In the *circle network* treatment, traders exchanged additional information with exactly two other traders. There were two traders who formed the core and the remaining six traders constituted the periphery in the *core-periphery network* treatment. Each core subject was connected to three periphery subjects as well as the other core participant. The same participants held the core position each period.[19] A periphery subject was connected to one of the two core participants. Every trader exchanged additional information with their neighbors.

All the three network structures that we study are *connected*.[20] Except the *core-periphery* treatment, participants had equal degree within each of the other treatments: the permutation of network positions does not change the total number of connections for each participant.[21] In contrast, the two core subjects were in significantly more influential positions than the periphery subjects. Furthermore, the four network structures also differ in density: 0 in *non-networked*, 1 in *complete network*, 0.29 in *circle network* and 0.25 in *core-periphery network*.[22]

Although the traders started with a common prior belief about the state of nature, the endogenous decisions to acquire information resulted in information being dispersed among participants, except in the *complete network* sessions. When each trader was connected to every other trader in the market, then regardless of

[19] This eliminates any repeated game effect on the behavior of the core subjects.

[20] A network is *connected* if every pair of nodes i and j is linked by a path and *disconnected* otherwise.

[21] The network structures where every participant has the same degree are also known as "balanced networks".

[22] The density of a network is defined as the ratio of actual connections to the total number of possible connections in the network.

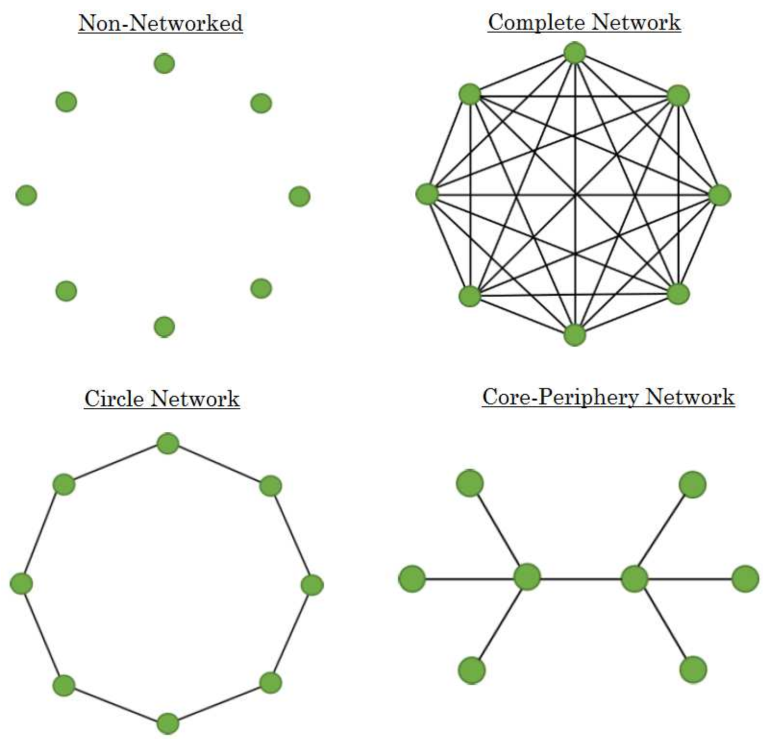

Figure 1: Treatments - information networks among investors. Each node on the undirected graph represents an investor and a link between two nodes denotes bidirectional exchange of privately acquired signals by the nodes.

the amount of information purchased, the available information in the market was observed by each participant. That is, each trader had the exact same information set.

We utilized the *circle* and *core-periphery* network structures for two reasons. First, these are the two most widely used incomplete network configurations (see Choi, Kariv and Gallo (2016)). Several theoretical models on endogenous network formation provide justification for such structures (see Bala and Goyal (2000) and Galeotti and Goyal (2010), among others). Second, while these two network configurations have similar densities in our setting, one is balanced while the other is not. This allows us to explore the impact of information exchange over a balanced versus unbalanced network on market outcomes. Another aspect is that it is socially efficient if core players acquire information while periphery players do not. This is because of the fact that any information acquired by the core player is observed by four others, while information purchased by a periphery player is seen by only one other trader. No such asymmetry exists in the *circle* network where information obtained by any player is observed by exactly two others.

5 Results

5.1 Information Acquisition

How does information exchange among neighbors affect the incentive to acquire costly information?

The period-average summary statistics for each treatment is shown in Table 1. The number of acquired signals per period per subject is highest with no information exchange and lowest under *complete network*. The proportion of traders acquiring at least one signal is also lowest in the *complete network* treatment. Figure 2 plots the distribution of information acquisition choices for each of the four treatments. The distribution in the *complete network* as well as in the *circle network* are skewed towards the left compared to the other two treatments, thereby implying that subjects in the *complete* and *circle* treatments purchase less number of signals than the other two treatments.

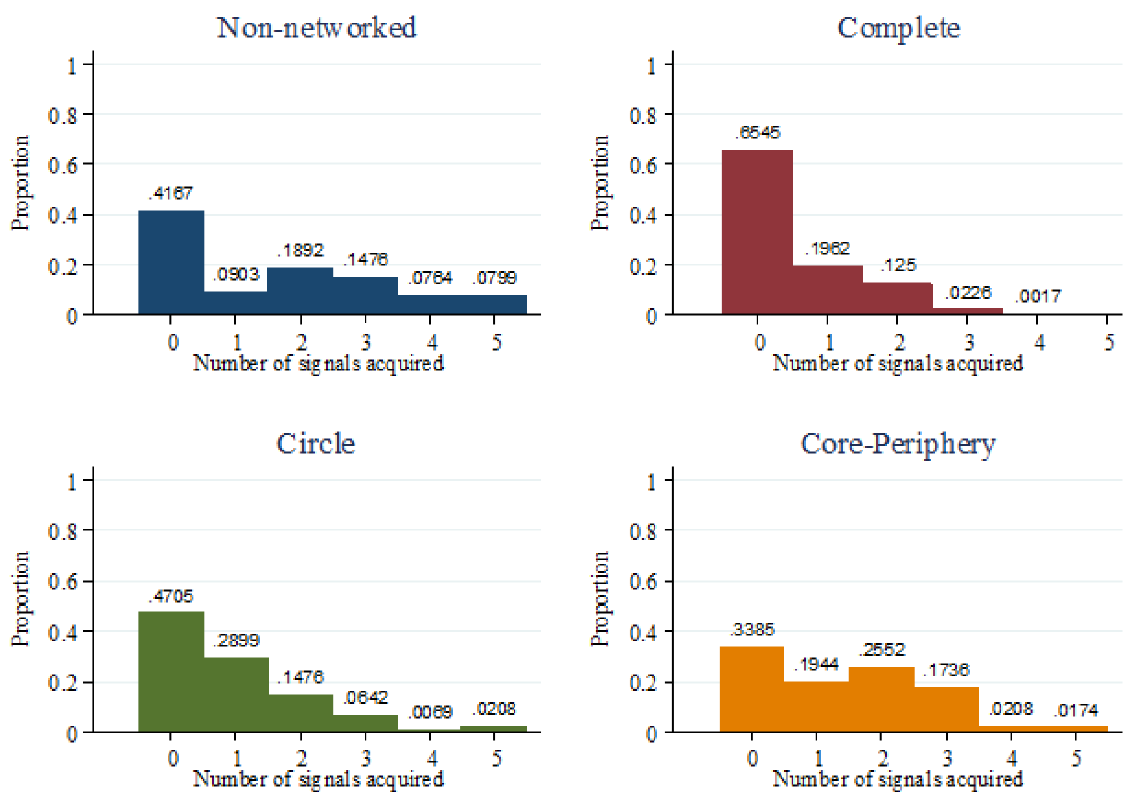

Figure 2: Distribution of information acquisition choices (number of signals acquired by a subject), by treatments. Each treatment has 576 observations.

Table 1: Period-average summary statistics across treatments. Standard deviations are in parentheses.

	Non-networked	*Complete*	*Circle*	*Core-periphery*
No. of acquired signals (s_i)	1.62	0.52	0.91	1.40
	(1.67)	(0.81)	(1.12)	(1.26)
$\mathbb{1}\{s_i > 0\}$	0.58	0.35	0.53	0.66
	(0.49)	(0.48)	(0.50)	(0.47)
Net profit	-4.85	-1.56	-2.73	-4.19
	(14.19)	(13.01)	(11.86)	(14.49)
No. of transactions	9.86	13.14	8.50	12.11
	(4.74)	(6.94)	(3.15)	(5.09)
No. of participants	48	48	48	48
No. of observations	576	576	576	576

Notes: s_i denotes the number of signals acquired by a subject in a period. $\mathbb{1}\{s_i > 0\}$ takes a value of 1 if a subject acquires at least one draw and 0 otherwise. Net profit is the difference in the value of trader portfolios at the end and at the beginning of each period. Number of transactions is calculated at the market level. There are 72 market-level observations for each treatment.

For a detailed investigation of the determinants of information acquisition behavior, we perform regression analysis with several specifications. Table 2 reports the estimated values of the regression coefficients. Using all data, specification (1) performs the ordinary least squares (OLS) regression of number of information signals acquired by a subject (s_i) and specification (2) estimates a logit model with dependent variable being the dummy variable which takes a value of 1 if a subject acquires at least one draw and 0 otherwise ($\mathbb{1}\{s_i > 0\}$). Corresponding models for only the *core-periphery* sessions are reported in (3) and (4) specifications in Table 2. While *complete* and *circle* are the treatment dummies, *core* (*periphery*) equals 1 if the participant is located at the core (periphery) position and 0 otherwise. The variable "inconclusive initial draw" equals 1 if the initial two draws provided to subjects at no cost are inconclusive, that is, results in the draw of one black and one white ball. In this case, the Bayesian posterior probability of urn A is 0.5, the same as the prior probability. "Inconclusive initial draw" equals 0 if the initial information is conclusive, that is, both drawn balls are of the same color. When the initial information is conclusive, the Bayesian posterior probability of urn A is either 0.69 (with draw of two black balls) or 0.31 (with draw of two white balls), in contrast to the prior of 0.5. We also include several demographic variables as additional regressors.[23]

The coefficients on the treatment dummies strongly indicate the negative effect of knowledge sharing on information acquisition behavior, especially in the *complete* and *circle* networks. Compared to the situation without any social communication, participants acquire less information in the anticipation of free riding on the signals acquired by their neighbors. A separate specification with number of neighbors as regressor instead of the treatment dummies show that there is a significant negative effect on both s_i and $\mathbb{1}\{s_i > 0\}$.[24]

Table 3 displays the results of regression of (a) the number of signals acquired in the market and (b) the number of participants who acquired information in the market on treatment dummies and average values of the demographic variables in the market. The possibility of sharing information among investors located on a network decreases the aggregate number of signals acquired in the market: by 2.7 draws in *core-periphery*, 6.8 draws in *circle* and by 9.9 draws in *complete* network. Thus, the temptation to free ride on information signals purchased by neighbors crowds out the production of information in the market. This provides support for the information acquisition hypothesis and certainly has implications for the informativeness of the asset price which we discuss in a later section.

Apart from the treatment dummies, several other factors significantly affect the incentives to acquire information. First, if the initial information provided to subjects is not conclusive, then they are more likely to spend money on gathering additional information. Second, the period in a session has a negative effect on the number of signals purchased as well as the likelihood to get informed. Third,

[23]These variables are risk aversion (measure of how risk averse a subject is; ranges from 1 to 11 with larger values indicating higher risk aversion), age (age of participant in years), male (equals 1 if the participant is male and 0 otherwise), economics/business major (equals 1 if the subject is pursuing major in Business or Accountancy or Economics), quantitative skill (measure of the number of correct answers to the questions in quantitative stage; ranges from 0 to 10) and trading experience (equals 1 if the subject had previous experience of trading in the stock market and 0 otherwise).

[24]For the sake of brevity, the results of this additional regression are not displayed in any of the tables.

Table 2: Regressions of number of signals acquired (s_i) and $\mathbb{1}\{s_i > 0\}$. Robust standard errors are in parentheses.

	All data			Core-periphery		
	(1) OLS	(2) Logit		(3) OLS	(4) Logit	
	s_i	$\mathbb{1}\{s_i > 0\}$	margins	s_i	$\mathbb{1}\{s_i > 0\}$	margins
Complete	-1.19***	-1.31***	-0.28***			
	(0.19)	(0.33)	(0.06)			
Circle	-0.70***	-0.17	-0.04			
	(0.21)	(0.30)	(0.06)			
Core	-0.05	1.15*	0.23**			
	(0.29)	(0.66)	(0.11)			
Periphery	-0.40*	-0.07	-0.02	-0.55*	-1.56**	-0.21*
	(0.23)	(0.33)	(0.07)	(0.29)	(0.67)	(0.11)
Inconclusive initial draw	0.21***	0.37***	0.08***	0.10	-0.03	0.14***
	(0.05)	(0.09)	(0.02)	(0.18)	(0.38)	(0.04)
Inconclusive initial draw×*Periphery*				0.45**	0.85**	
				(0.21)	(0.43)	
Risk aversion	-0.07**	-0.13**	-0.03**	0.04	-0.02	-0.01
	(0.03)	(0.06)	(0.01)	(0.07)	(0.15)	(0.03)
Age	-0.08	-0.11	-0.02	-0.06	-0.01	-0.00
	(0.06)	(0.08)	(0.02)	(0.09)	(0.21)	(0.04)
Male	-0.10	-0.19	-0.04	0.03	-0.44	-0.09
	(0.16)	(0.27)	(0.06)	0.34	0.68	0.14
Economics/Business major	-0.38***	-0.64***	-0.14***	-0.50**	-0.77	-0.16
	(0.14)	(0.23)	(0.05)	(0.23)	(0.50)	(0.10)
Quantitative skill	-0.02	-0.13**	-0.03**	0.03	0.12	0.02
	(0.03)	(0.07)	(0.01)	(0.08)	(0.17)	(0.03)
Trading experience	-0.32	-0.80	-0.17*	0.01	-0.77	-0.16
	(0.35)	(0.49)	(0.1)	(0.58)	(1.01)	(0.22)
Period	-0.04***	-0.07***	-0.02***	-0.04**	-0.07**	-0.01**
	(0.01)	(0.01)	(0.00)	(0.02)	(0.03)	(0.01)
Constant	4.54***	5.72***		2.91	2.26	
	(1.23)	(2.02)		(1.96)	(4.42)	
No. of observations	2304	2304		576	576	
R^2	0.17			0.13		
Clusters	192	192		48	48	

Notes: The baseline is the *non-networked* treatment. Apart from the treatment dummies, the variable "inconclusive initial draw" is included as an independent variable which takes a value of 1 if the initial two draws provided to participants are inconclusive (that is, if the balls are of different color) and 0 otherwise. The regressions also include the trading period as well as several demographic variables. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 3: OLS regression of market level variables. Robust standard errors are in parentheses.

	(1) $S_{mkt.}$		(2) $N_{mkt.}$	
Complete	-9.92***	(0.88)	-2.42***	(0.25)
Circle	-6.84***	(0.92)	-0.11	(0.24)
Core-periphery	-2.67***	(0.74)	0.28	(0.20)
Inconclusive initial draw	1.53***	(0.42)	0.59***	(0.14)
Average risk aversion	-1.33***	(0.45)	-0.75***	(0.15)
Average age	-0.78	(0.79)	0.05	(0.20)
Male Ratio	3.51	(2.13)	-0.13	(0.68)
Economics/Business ratio	-2.85*	(1.63)	-2.54***	(0.50)
Average quantitative skill	0.91**	(0.41)	-0.09	(0.16)
Average trading experience	-13.63***	(4.26)	-3.07***	(1.16)
Period	-0.29***	(0.06)	-0.13***	(0.02)
Constant	33.99*	(18.21)	11.31**	(4.84)
No. of observations	288		288	
R^2	0.57		0.53	

Notes: Column (1) shows regression with the dependent variable being the number of signals acquired in the market ($S_{mkt.}$). In column (2), the dependent variable is the number of participants who acquired information in the market ($N_{mkt.}$). The baseline is the *non-networked* treatment. Apart from the treatment dummies, the variable "inconclusive initial draw" is included as an independent variable which takes a value of 1 if the initial two draws provided to participants in a market are inconclusive and 0 otherwise. The demographic variables include average risk aversion, average age, average quantitative skills of the traders in the market and average trading experience as well as the ratio of traders being male and the ratio of subjects with an Economics or Business major in the market. **significant at 5% level; ***significant at 1% level.

the regressions show that various demographic variables affect the propensity to gather costly signals. Consistent with the previous literature, we find that, on an average, participants who are more risk averse acquire less information. A major in economics or business studies has a significant negative effect on the incentives to purchase additional information. In general, higher quantitative skills and higher trading experience are associated with lower information acquisition.

Focusing only on the *core-periphery* sessions, the specifications (3) and (4) of Table 2 show that traders occupying the core position acquire a larger number of signals and are more likely to become informed than subjects located at the periphery. This is in contrast to our general result observed previously that the incentive to acquire information declines with the number of neighbors. Furthermore, we find that a trader located at the core position is more likely (equally likely) to acquire information than the periphery when the initial information is conclusive (inconclusive).[25] Also, only the traders located at the periphery respond to the conclusiveness of initial draws, and traders at the core site acquire additional information nevertheless.

Although counter-intuitive, our results provide evidence that participants at the core invest more in information gathering activity than the ones at periphery, even without any immediate benefits. A potential explanation is that the participants positioned at the core are aware of their influential location in the network which makes them pro-active than the ones at periphery. The positive effect on the information acquisition decision of participants at the core results from the understanding that information acquired by them has a higher social benefit than the signals purchased by the agents at the periphery. The incentive to free ride is outweighed by this positive effect.

Validating our information acquisition hypothesis, we have the following result.

Result 1: *Information exchange among neighbors gives rise to incentive to free ride on others' acquired costly signals and results in lower overall amount of infor-*

[25]When the initial information is inconclusive, to investigate if there is a difference in information acquisition between participants located at the core and periphery positions, we test the null hypothesis that the sum of coefficients of the variables *Periphery* and "Inconclusive initial draw × *Periphery*" is 0 for each specification. The p-values are 0.77 and 0.37 for s_i and $\mathbb{1}\{s_i > 0\}$, respectively.

mation in the market.

5.2 Trading Volume and Liquidity

How does social communication affect market trading volume and liquidity?

Table 1 shows that the average number of transactions in a market is not lower with social communication. In fact, on average, 13.14 trades take place in a market in the *complete* network treatment, much higher than the *non-networked* sessions. In order to understand more on the impact of social communication on trading volume, we conduct an OLS regression of market trading volume on the total number of signals in the market, treatment dummies, Bayesian posterior and trading period.[26] The results are displayed in Table 4. Information sharing has a significant positive effect on market trading activity. At the same time, larger information acquisition in the market is associated with larger trading volume. Generally, we observe that more favorable information in the market (indicated by a higher Bayesian posterior) is typically associated with less trading activity. Indeed, with a higher likelihood of occurrence of state A (and hence a payoff of 10 for each unit of the asset), traders would be reluctant to sell their assets.

We also calculate the average bid-ask spread, with the average count in one trading period taken as a single observation. The value of the average spread is 0.60 for *non-networked*, 0.19 for *complete*, 0.40 for *circle* and 0.34 for *core-periphery* sessions.[27] The denser the information network, the lower the bid-ask spread. Thus, higher transaction volume with information sharing is also accompanied by narrower bid-ask spread. This points towards lower transaction costs and higher liquidity with social communication. Rejecting the trading volume hypothesis, we have the following observation.

Result 2: *Social communication improves market liquidity and results in higher market trading volume.*

Even after controlling for the aggregate information in the market, nature of in-

[26]The Bayesian posterior probability gives the posterior probability of urn A given all draws in the market.

[27]The difference between *non-networked* and *complete* treatment is statistically significant (at 5% level) while the difference in values between *non-networked* and each incomplete network is not significant.

Table 4: OLS regression of market trading volume. Robust standard errors are in parentheses.

	(1)	(2)
$S_{mkt.}$	0.34***	0.30***
	(0.07)	(0.07)
Complete	6.60***	2.83***
	(1.12)	(0.95)
Circle	0.95	2.04**
	(0.67)	(0.95)
Core-periphery	3.10***	2.42***
	(0.72)	(0.71)
Bayesian posterior	-4.59***	-3.75***
	(0.92)	(0.87)
Period	0.09	0.07
	(0.08)	(0.07)
Constant	6.85***	43.96***
	(1.24)	(6.82)
Observations	288	288
R^2	0.23	0.41

Notes: The dependent variable is the market trading volume in a period. Column (2) includes demographic variables as additional regressors. The baseline is the *non-networked* treatment. Bayesian posterior is defined as the posterior probability of urn A given all draws in the market. **significant at 5% level; ***significant at 1% level.

formation (as captured by the Bayesian posterior) and the demographic variables of the participants, market volume increases with social communication. This is a puzzling result which suggests that trading is not primarily motivated by information disparity. If it did, we would have observed far less trading activity in our treatments with information exchange than the *non-networked* sessions. One plausible justification could be that social communication fundamentally changes the type of traders such that it leads to a surge in *irrational trades*. We define such trades as those which violates the following condition: trading is performed at a price $>$ ($<$)5 if the individual Bayesian posterior $>$ ($<$)0.5.[28] The proportion of *irrational trades* is 0.45 in *non-networked*, 0.21 in *complete*, 0.33 in *circle* and 0.36 in *core-periphery* sessions, implying that with higher volume of trading, social communication in fact lowers the incidence of trade executions in the direction opposite to the one pointed by the individual Bayesian posterior.

We argue that result 2 is mainly driven by an *adverse selection* problem faced by investors in a financial market. An agent faces this problem since another trader agreeing to trade at the agent's ask or bid price may be trading because he knows something that the agent does not. *Adverse selection* might prevent certain transactions from taking place if the investor believes that she might suffer losses by trading with someone having superior information. Social communication lowers the divergence in private information, thereby making this *adverse selection* problem less severe. With information exchange over a *complete network*, no such problem exists and market trading activity is highest. The issue of *adverse selection* is deep rooted in the financial economics literature. In a related but different context, Glosten and Milgrom (1985) identify a similar problem faced by a specialist while trading with a customer with superior information.

5.3 Price Informativeness

How does sharing information with neighbors impact the ability of asset prices to reflect the cumulative information available in the market?

In order to measure the fundamental value of the asset in our setting, for each

[28] Individual Bayesian posterior calculates the posterior probability of urn A taking into account only the information available to an individual trader.

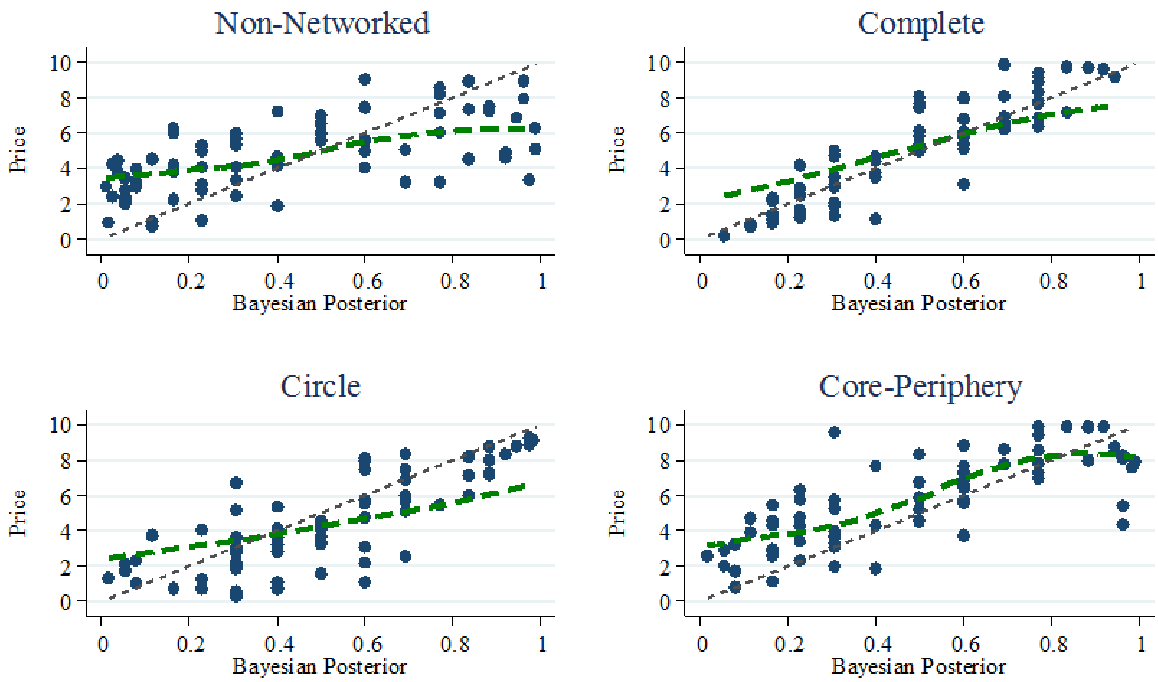

Figure 3: Average prices conditional on the Bayesian posterior ($\mathbb{E}$(Price|Bayesian posterior)) in the market, for each of the four treatments.

market, we first calculate the Bayesian posterior probability of urn A given all draws in the market. This posterior multiplied by 10 provides the risk-neutral fundamental value of the asset. Note that this value differs across markets due to the variation in the number of signals acquired as well as the difference in the information revealed by these signals. Taking the information acquisition decisions as given, this Bayesian posterior times 10 also gives the fully revealing rational expectations price. Figure 3 plots the expectation of the market price conditional on the Bayesian posterior ($\mathbb{E}$(Price|Bayesian posterior)) in each of the four treatments. Visual inspection suggests that prices follow the fundamental value more closely in the *complete network* treatment than the other treatments.

We define the linear absolute deviation (LAD) in a market as the absolute difference between the mean price and the fully revealing price, i.e, $LAD =$ |Mean price - 10(Bayesian posterior)|. In order to compare the precision of prices to track the fundamental values in the sessions with information sharing as against the *non-*

Table 5: OLS regression of linear absolute deviation (*LAD*). Robust standard errors are in parentheses.

	Coefficient	Standard error
Complete	-1.19***	(0.19)
Circle	-0.68***	(0.21)
Core-periphery	-0.42*	(0.23)
Period	-0.02	(0.02)
Constant	2.19***	(0.22)
Observations	286	
R^2	0.12	

Notes: The dependent variable is the linear absolute deviation (*LAD*) which is defined as the absolute difference between the mean price and the fully revealing price in a period. The baseline is the *non-networked* treatment. The independent variables are the treatment dummies and period. *significant at 10% level; ***significant at 1% level.

networked sessions, we perform a regression with the *LAD* as the dependent variable and the treatment dummies as the regressors. Table 5 reports the results. We find that the *LAD* is significantly lower with social communication, indicating that on average, sessions with information exchange have more precise prices. In fact, the denser the network, the lower is the *LAD*.

Figure 3 tends to indicate that prices typically under-react to the information in the market: prices are closer to 5 (which is the value corresponding to the prior of 0.5) than the fully revealing values. In other words, prices are less extreme than the fundamental values suggested by the available information in the market. Using a market as an observation, Table 6 provides the average values of under-reaction across treatments where the under-reaction is measured as (fundamental value - mean price) if posterior > 0.5, (mean price - fundamental value) if posterior is < 0.5 and 0 if posterior equals 0.5. Under-reaction is significant except in the *complete network* sessions. With each period as an observation, the last column of Table 6 displays the p-values from Wilcoxon signed-rank test of the null hypothesis that

Table 6: Average under-reaction across treatments.

Treatment	Mean	s.d.	min.	max.	p-value
Non-networked	1.69	1.83	-3.00	6.41	0.00
Complete	-0.14	1.02	-2.94	2.91	0.29
Circle	0.35	1.66	-3.27	4.91	0.06
Core-periphery	0.81	1.89	-2.85	6.46	0.00

Notes: For each period, under-reaction is measured as (fundamental value - mean price) if posterior > 0.5, (mean price - fundamental value) if posterior is < 0.5 and 0 if posterior equals 0.5. Columns 1-4 present the average (mean), standard deviation, maximum and minimum values. P-values from Wilcoxon signed-rank test of values being equal to zero are displayed in the last column. Each treatment has 72 observations, except the *non-networked* one which has 70.

under-reaction is zero for each treatment. Average under-reaction value is lower with information sharing than without (with Mann-Whitney p-values < 0.01 for binary comparison between *non-networked* and each of the other three treatments). In fact, the extent of under-reaction decreases as the density of the information network increases. At the very extreme, prices do not under-react when traders can share information with everyone else.

Supporting the price informativeness hypothesis, we have the following finding.

Result 3: *A larger fraction of the available information in the market is reflected in asset prices with social communication. In general, the higher the density of the communication network, the closer are prices to the fully revealing value.*

Although price informativeness is higher with information exchange, prices do not reflect the available information immediately. The large number of transactions due to improved liquidity with social communication (result 2) facilitates the information aggregation process with prices converging towards the fundamental value. Figure 4 shows the individual transaction LAD with the transaction number on the x-axis. The LAD is declining with additional trades with information exchange, especially for *complete* and *circle* treatments. Opposite is true for the *non-networked* sessions with the prices moving away from the fundamental value with subsequent trades. Statistically, Kendall's Tau is negative (-0.19) and significant (at 1% level) in the *complete* network. While the coefficients of Tau are insignificant in the other three treatments, it's value is positive only in the *non-networked* sessions.

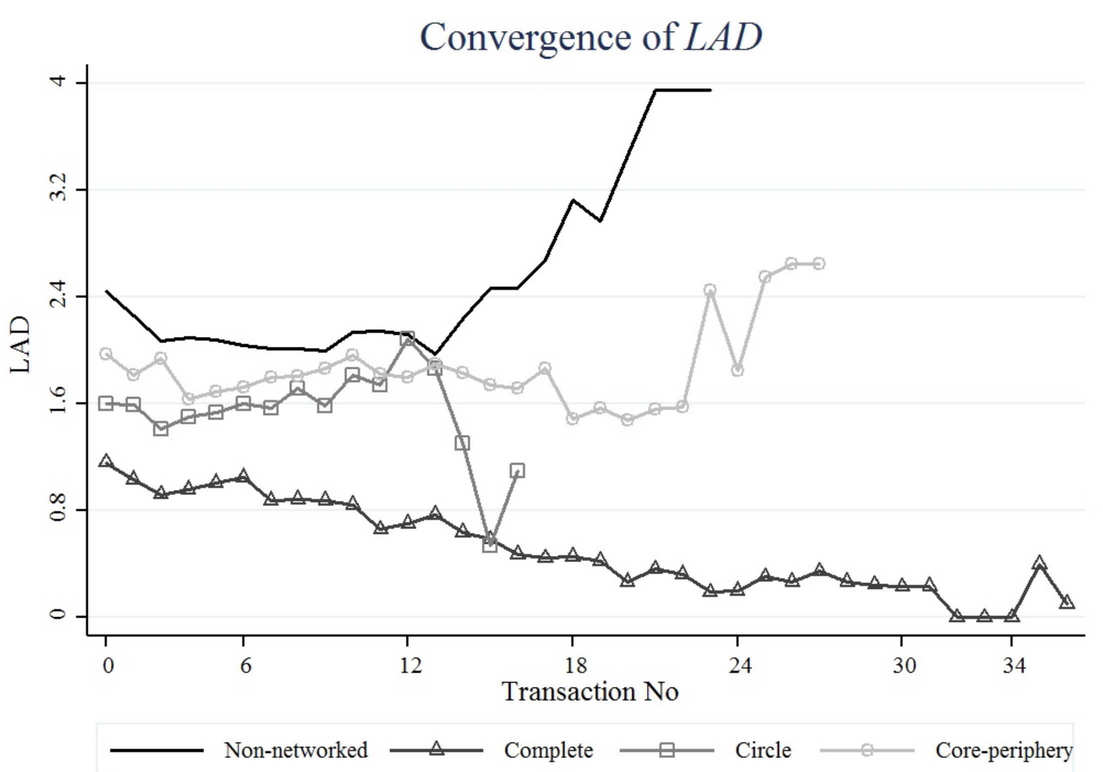

Figure 4: Individual transaction *LAD* as a function of the order of transaction, for each of the four treatments.

Result 4: *The higher volume and improved liquidity with social communication increases price informativeness.*

5.4 Price Accuracy

Is the propensity of asset prices to reveal the true state of nature affected by the exchange of information among traders?

A typical way to gauge the quality of the transaction prices as forecasting tools is to evaluate their calibration, that is, whether they are good estimates of the likelihood of the predicted event (Page and Clemen (2013), Page and Siemroth (2017)). Figure 5 shows the evidence on calibration for each of the four treatments. It displays the frequency of the outcome being urn A conditional on the value of the

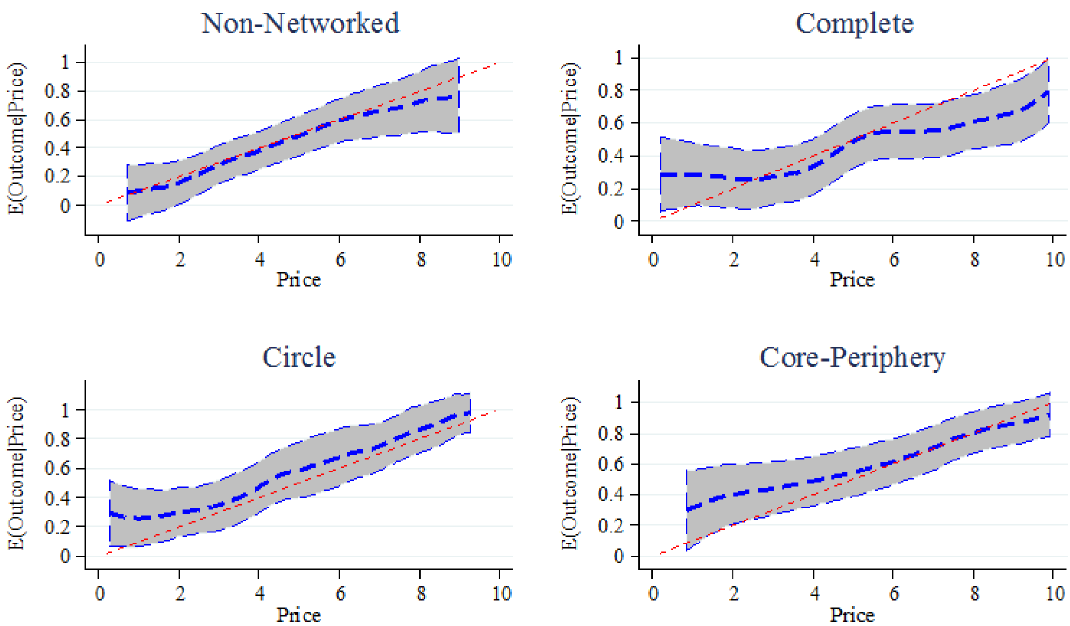

Figure 5: The frequency of outcome being urn A conditional on the observed transaction prices ($\mathbb{E}$(Outcome|Price)) in the market, for each of the four treatments. The 95% confidence intervals are displayed as well.

observed prices. Figure 5 reveals that prices are unbiased forecasts of the outcome frequencies, that is, we cannot reject the hypotheses that frequencies (times 10) are equal to prices for most of the transaction prices in each treatment, except possibly at the extreme values. However, the calibration seems to be best for the sessions with no information exchange with the frequencies being remarkably close to the $\mathbb{E}(\text{Outcome}|\text{Price}) = \frac{Price}{10}$ line. Surprisingly, the fit does not improve with information networks.

To explore further, we perform an OLS regression with the forecast error as the dependent variable and the treatment dummies as the regressors. The forecast error each period is defined as the absolute difference between the mean transaction price and the true value of the asset. If the urn is A (B), true value equals 10(0). Column (1) of Table 7 displays the results of the regression. The coefficients on the treatment dummies are all insignificant, implying that compared to the situation without any communication, none of the treatments with information exchange aid

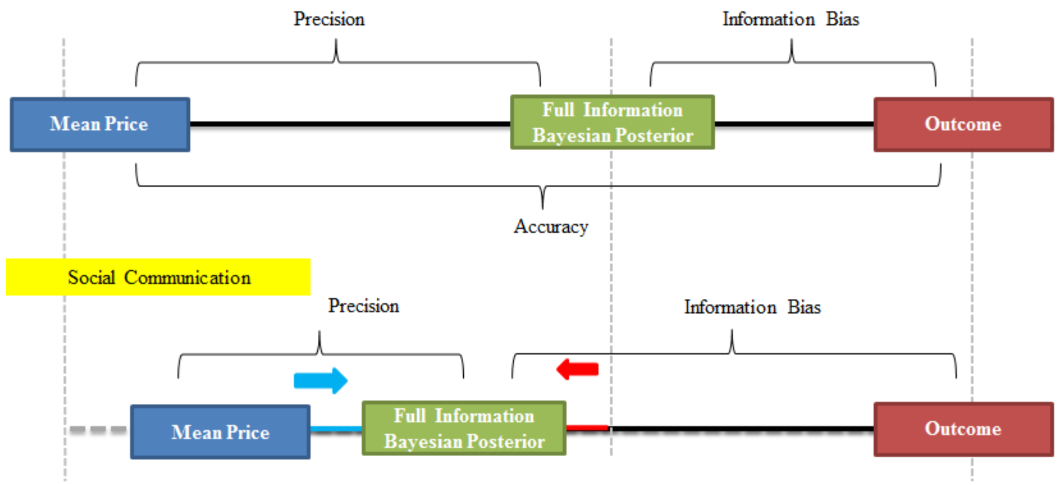

Figure 6: Effect of social communication on the precision and accuracy of asset prices.

in increasing the accuracy of the transaction prices in the market. Thus, supporting the price accuracy hypothesis, we have the following result.

Result 5: *Social communication does not improve the ability of prices to reveal the underlying state of nature.*

Results 1 and 3 together can provide an explanation for the above observation. Even though social communication aggregates information better (result 3), the total number of signals in the market is less (result 1) which results in the larger bias of the cumulative amount of information in the market. As information is imperfect in our setting, signals in the market may be systematically biased. For example, even if the underlying urn is A (that is, there is a higher probability of drawing black balls), it is still possible to end up with more white balls since these are drawn independently and with replacement. Depending on the state of the nature and the value of the Bayesian posterior, the information in the market can be categorized as accurate (posterior>0.5 and underlying urn is A or posterior<0.5 and underlying urn is B), misleading (posterior<0.5 but underlying urn is A or posterior>0.5 but underlying urn is B) or inconclusive (posterior$=0.5$).

Low information accuracy corresponds to higher cases of misleading information in the market. Indeed, the percentage of instances with cumulative information in the market being misleading increases with social communication in our data set

Table 7: OLS regression of forecast error. Robust standard errors are in parentheses.

	(1) Forecast error	(2) Forecast error
Complete	-0.02	-0.48*
	(0.37)	(0.28)
Circle	-0.24	-0.41
	(0.36)	(0.30)
Core-periphery	-0.32	-0.52*
	(0.35)	(0.30)
Accurate information		-2.49***
		(0.33)
Misleading information		0.98**
		(0.40)
Period	-0.07*	-0.03
	(0.04)	(0.03)
Constant	4.46***	5.88***
	(0.35)	(0.42)
Observations	286	286
R^2	0.02	0.43

Notes: The dependent variable is the forecast error each period (defined as the absolute difference between the mean transaction price and the true value of the asset). The baseline is the *non-networked* treatment. The independent variables are the treatment dummies and period. Column (2) also includes "accurate information" (which takes a value of 1 if posterior>0.5 and underlying urn is A or posterior<0.5 and underlying urn is B and 0 otherwise) and "misleading information" (which takes a value of 1 if posterior<0.5 but underlying urn is A or posterior>0.5 but underlying urn is B and 0 otherwise). *significant at 10% level; **significant at 5% level; ***significant at 1% level.

with 24% in the *non-networked*, 31% each in the *circle* and *core-periphery* and 40% in the *complete network* treatment. Thus, with social communication, while prices are more precise (mean prices are closer to the full information Bayesian posterior), the posterior itself is farther away from the actual outcome due to lower aggregate number of signals (and information bias is larger). This argument is summarized in Figure 6 which depicts the trade-off in terms of precision of prices and information bias. Taken together, the quality of prices as forecasting tools remains the same with information exchange. Table 7 also shows that including the nature of information increases the fit of the model substantially, acknowledging that accurate (misleading) information is associated with lower (higher) forecast error.

5.5 Value of Information: Trader Profits

Do informed traders obtain higher returns compared to uninformed ones? Are traders better off with information exchange than without?

We calculate the net profits of a trader i in a period p as $\Delta ECU_{ip} + 10\Delta Assets_{ip}$ if the urn was A and ΔECU_{ip} if the urn was B. ΔECU_{ip} measures the final (post-trade) cash endowment minus the initial cash endowment and it accounts for the information acquisition costs as well as profits from trading. $\Delta Assets_{ip}$ denotes the stock balance at the end of the period minus the initial stock endowment. Thus, net profit is the difference in the values of trader portfolios at the end and at the start of each period.

With net profits as the dependent variable, we perform OLS regression for different specifications. We also include the dummy variable "urn" which takes a value of 1 if the underlying urn was A and 0 otherwise. The results are shown in Table 8. Column (1) results show positive and significant effect of the *complete* and *circle* dummies. This suggests that social communication tends to increase traders' net profits. However, when we further control for the number of signals acquired by a trader and signals acquired by neighbors (as in specifications (2) and (3)), the coefficients of treatment dummies become insignificant. Number of signals acquired has a significant negative effect on net profits: an increase in the purchase of one more signal lowers net profits by 2.9 units, which is almost the same as the acquisition cost of 3 ECUs. Regressions of net profits for each individual treatment show that purchase of an additional signal lowers net profits by 2.5 units in the *non-networked*, 3.3 in the *complete*, 2.5 in the *circle* and 3.4 in the *core-periphery* sessions. This implies that any positive effect of social communication on net profits is due to the savings of information cost from less purchase of costly signals. This is consistent with our finding in section 5.1.

The fourth column of Table 8 displays results for the regression when we control for the informative content of the available cumulative signals in the market as well. Accuracy of information has a positive and significant effect on net profits (increases net profits by 1.9 points) while misleading information decreases net profits significantly (by almost 3 points). This provides support that information is valuable when it is accurate. However, since there are also several instances of information being misleading, the overall value of information is not positive.

We also estimate different regression models with gross profits as the dependent variable. For the sake of brevity, we do not include the results of all these regressions in the tables. The number of signals acquired does not affect the gross profits of a trader with both informed and uninformed investors earning similar profits. Together with the observations on net profits earlier, the inability of informed traders to recover the information costs provides a possible explanation for the reduction in information acquisition over time (see the negative and significant coefficients of "period" in Tables 2 and 3). Gross profits neither differ across the four treatments nor with the number of neighbors of a subject. Within the unbalanced *core-periphery* sessions, we find that being located at an influential position does not result in higher profits than the traders on the periphery. The only variables that affect gross profits significantly are the dummies on information accuracy: accurate information has positive effect while misleading information has negative impact.

Result 6: *Informed traders fail to recuperate the costs of information acquisition, and obtain same gross returns compared to uninformed traders. Social communication increases traders' earnings via cost savings from lower information acquisition.*

Table 8: OLS regression of net profits. Robust standard errors are in parentheses.

	(1)	(2)	(3)	(4)
Urn	-0.11	0.00	-0.02	0.13
	(0.89)	(0.89)	(0.89)	(0.89)
Complete	3.29***	-0.60	-0.51	-0.41
	(1.07)	(0.98)	(1.04)	(1.03)
Circle	2.13**	-0.27	-0.27	-0.2
	(1.05)	(0.92)	(0.97)	(0.94)
Core	0.67	-0.42	-0.29	-0.51
	(1.90)	(1.86)	(1.87)	(1.85)
Periphery	0.69	-0.58	-0.58	-0.41
	(1.13)	(0.93)	(0.92)	(0.91)
s_i		-2.82***	-2.90***	-2.89***
		(0.25)	(0.27)	(0.26)
$s_i^{neighbors}$		0.22	0.19	0.22
		(0.16)	(0.16)	(0.17)
Accurate information				1.87***
				(0.65)
Misleading information				-2.94**
				(1.28)
Constant	-4.80***	-0.28	5.43	4.4
	(1.06)	(0.88)	(4.63)	(4.52)
Demographic variables included	No	No	Yes	Yes
Observations	2304	2304	2304	2304
R^2	0.01	0.08	0.08	0.10
Clusters	192	192	192	192

Notes: Column (1) shows regression on "'urn" (which takes takes a value of 1 if the underlying urn was A and 0 otherwise) and treatment dummies, while columns (2) and (3) report the results from including the number of signals purchased by the subject (s_i) and number of signals purchased by neighbors ($s_i^{neighbors}$) as independent variables as well. Last column includes "accurate information" and "misleading information" as additional regressors. The baseline is the *non-networked* treatment. **significant at 5% level; ***significant at 1% level.

6 Conclusion

We systematically investigate the effects of the possibility of social communication on incentives to acquire costly information as well as on the characteristics of security prices. We report data from a series of laboratory markets for an asset whose terminal payoff is contingent upon an unknown state of the world. Prior to trading, investors may purchase imperfect signals themselves and learn from their peers through an exogenous information network. Previous studies on experimental asset markets consider traders to be isolated which fails to take into account the aspect of social communication that is ubiquitous in today's world. When information is costly to obtain, the probability of acquiring information and amount of signals purchased decreases with the number of neighbors of an investor. We provide evidence that ignoring the investors' information networks results in overestimation of the amount of information available in the market. Due to cost savings from lower information acquisition, communication network increases traders' earnings.

While social communication results in reduced information dispersion among individuals, this lower disparity in knowledge about fundamentals does not translate into lower trading activity. To explain this apparently puzzling result, we put forth an *adverse selection* hypothesis. Certain desirable trades do not take place if an individual believes that she might suffer losses by trading with another agent with superior information. As investors exchange information among themselves, the problem of *adverse selection* weakens and this facilitates more trading and increases liquidity.

We observe that prices typically under-react to the information in the market. However, this extent of under-reaction is decreasing in the density of the information network. When information flows on a complete network, prices no longer under-react and converge to the fully revealing value. The increased trading activity with social communication aids in the ability of prices to reflect the available information in the market. However, the quality of asset prices as forecasting tools remains the same with communication, driven by the fact that social communication results in crowding out of information production. Thus, although the precision of asset prices is enhanced due to increased exchange of information among traders, price accuracy does not improve.

If the knowledge generated from costly acquisition is valuable for the society, then our results suggest that sharing of information should be discouraged. For example, if the nodes of the information network are research and development (R&D) divisions of linked financial institutions, then the information exchange among them should be regulated by the relevant authorities. Otherwise, the amount of socially beneficial information might be too slender.

The Arrow-Debreu security market design with networked information flows used here is an innovation to laboratory markets that makes it possible to address other important issues with respect to network structure, trading and asset prices. For example, instead of exchange of private information about fundamentals, a link between investors could mean the exchange of information regarding real-time portfolios among peers, or simply, word-of-mouth communication among traders. Future research could also investigate the implications of neighborhood choice on the incentives to acquire costly information, and consequently on asset price properties. In our experiments, the network structure is exogenous and remains static throughout. Recent research on endogenous formation of networks has yielded novel insights in the context of cooperation (Rand, Arbesman and Christakis (2011)) and coordination (Riedl, Rohde and Strobel (2016)). An immediate extension of our experiments would be to allow for the co-evolution of the information network. Finally, we focused on a network of trusted friends who honestly reveal their private information. It would be interesting to study strategic information transmission, including the possibility of lying and manipulation of information revealed to neighbors. More generally, the issue of voluntary disclosure of information could be studied in our framework as well.

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APPENDIX (*For Online Publication*)

Experimental Instructions[29]

GENERAL INFORMATION

Dear participant, welcome to our experiment. **Please pay attention to the information provided here and make your decisions carefully. If at any time you have questions, please raise your hand and we will attend to you in private.**

Please note that unauthorized communication is prohibited. Failure to adhere to this rule would force us to stop the simulation and you may be held liable for the cost incurred in this simulation. You have the right to withdraw from the study at any point in time, and if you decide to do so your payments earned will be forfeited.

By participating in this study, you will be able to earn a considerable amount of money. The amount depends on the decisions you make.

At the end of this session, this money will be paid to you privately and in cash. It would be contained in an envelope (indicated with your unique user ID) together with a payment receipt acknowledging that you have been given the correct payment amount.

Each of you will be given **a unique user ID** and it **will be clearly stated on your computer screen**. At the end of the study, you will be asked to fill in your user ID and other information pertaining to your earnings from this study in the consent form. **Please fill in the correct user ID to make sure that you will get the correct amount of payment**.

Your **anonymity will be preserved** for the study. You will only be identified by your user ID in our data collection. All information collected will **strictly be kept confidential** for the sole purpose of this study.

[29]These instructions are from the *circle* treatment.

PAYMENT

There are three sections in this experiment and your total payoff from the experiment will be as follows:

1. The earnings made from decisions in Section 1 & 2 will be in terms of Experimental Currency Units (ECU) and these earnings in ECU will then be converted to Singapore dollars (SGD) for your payment with the following exchange rate: **4 ECU = 1.00 SGD**.

2. The earnings made from decisions in Section 3 will be in terms of SGD.

There will also be a separate show-up fee of SGD$2, on top of the payment from your experiment.

In summary, your payment will be as follows:

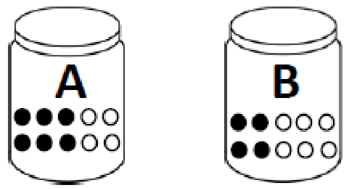
Category		Payment
Experiment	Section 1	Final ECU obtained from experiment converted with an exchange rate of **4 ECU = 1.00 SGD**
	Section 2	
	Section 3	In SGD with amount of reward depending on decisions made in this section
Show-up fee		SGD$2

SECTION 1A- EXPLANATION OF "BALL & URN" SETUP

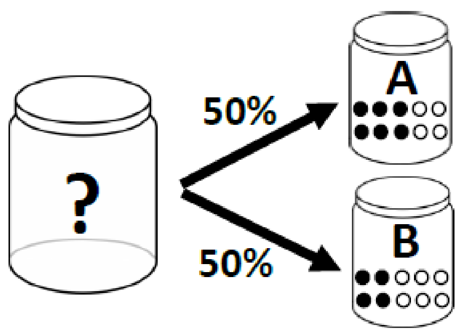
You are going to take part in a virtual financial market. In this market, you will be able to buy or sell an asset. The currency used in this market is called ECU. There will be 12 periods in this section and your final payoff for this section will be given by the average of the payouts from 3 randomly chosen periods out of the 12 periods.

In financial markets, asset dividends depend on events which are still unknown to the trader. In this experiment, we represent the uncertain market conditions through the random selection of urns with different compositions of colored balls.

There are two types of urns (A & B):



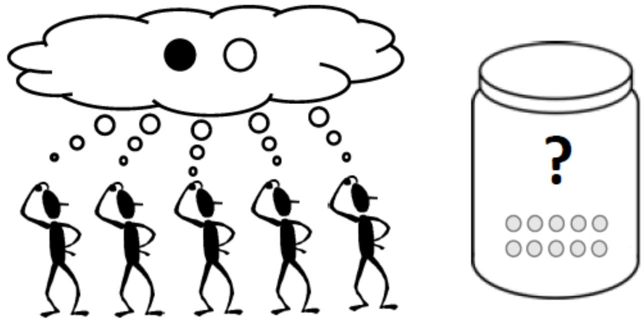
Urn A contains **6 black balls and 4 white balls**, while urn B contains **4 black balls and 6 white balls**. In every period, each urn has an equal probability of being chosen as the underlying urn. You will not be informed of the chosen urn.



You will have the opportunity to buy or sell units of an asset which will be worth:

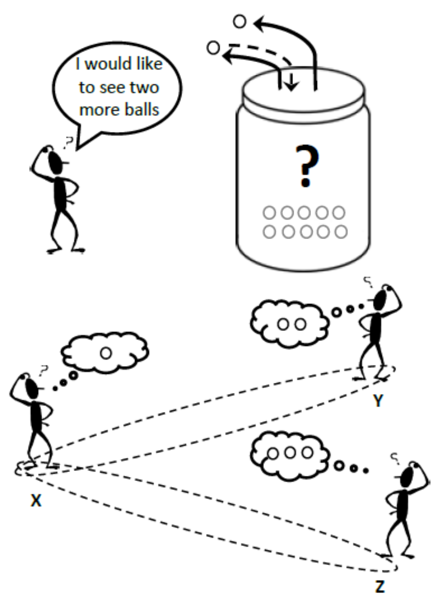
- **10 ECU** if the underlying urn is **urn A**
- **0 ECU** if the underlying urn is **urn B**

Before the trading stage begins, you will receive some information about the composition of the underlying urn. Each participant will be able to see 2 randomly drawn balls from the underlying urn. Note that each drawn ball is placed back into urn before the next ball is drawn. The initial 2 balls seen by every participant will be the same.



You will have the opportunity to acquire additional information by drawing additional balls from the underlying urn at a cost. Similarly, note that each drawn ball is placed back into urn before the next ball is drawn.

You will be connected to a number of participants whom you will exchange your acquired information with these participants are known as your neighbours. The additional information you acquired will be **revealed to you as well as your neighbours**. Likewise, additional information acquired by your neighbours will be revealed to you.[30]



Additional information will be revealed to your neighbours

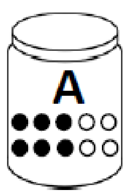
[30]For the *non-networked* sessions, participants were informed that their acquired information was only known to them.

Next, you will enter the trading stage where you will be able to buy or sell the assets. At the end of the trading stage, the underlying urn will be revealed and the value of your assets for that period will be determined. If the urn is A, each asset will be worth 10 ECU. If the urn is B, each asset will be worth 0 ECU.

<u>How can you interpret the drawn balls?</u>

The balls drawn provide an indication on whether urn A or urn B is the underlying urn.

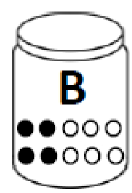
Based on the initial 2 draws, the probability that the underlying urn is A is calculated as follows:



Probability of getting:

● = 0.6
○ = 0.4

●● = 0.6 × 0.6 = **0.36**
●○ = (0.6 × 0.4) + (0.4 × 0.6) = **0.48**
○○ = 0.4 × 0.4 = **0.16**



Probability of getting:

● = 0.4
○ = 0.6

●● = 0.4 × 0.4 = **0.16**
●○ = (0.4 × 0.6) + (0.6 × 0.4) = **0.48**
○○ = 0.6 × 0.6 = **0.36**

Probability of urn A being the underlying urn given the following drawn balls:

●● $= \frac{0.36}{0.36+0.16} = \mathbf{0.69}$

●○ $= \frac{0.48}{0.48+0.48} = \mathbf{0.50}$

○○ $= \frac{0.16}{0.16+0.36} = \mathbf{0.31}$

Hence, if two black balls have been drawn, there is 69% chance of urn A being the underlying urn. If one black ball and one white ball have been drawn, there is

50% chance of urn A as the underlying urn. If two white balls have been drawn, there is 31% chance of urn A as the underlying urn.

Note that the system will compute and display the above mentioned probability. You do not need to compute this probability yourself.

In summary, having more black balls tend to indicate urn A as the underlying urn. If additional information has been acquired, the system will compute and update the corresponding probability for you.

You should make use of this computed probability to help you in assessing the expected value of the asset. If the computed probability of urn A being the underlying urn is 0.69, the expected value of each asset should be given by:

$$(0.69 \times 10ECU) + (0.31 \times 0ECU) = 6.9ECU$$

This expected value can then be used as a guide for the price at which you want to buy or sell this asset during the trading period.

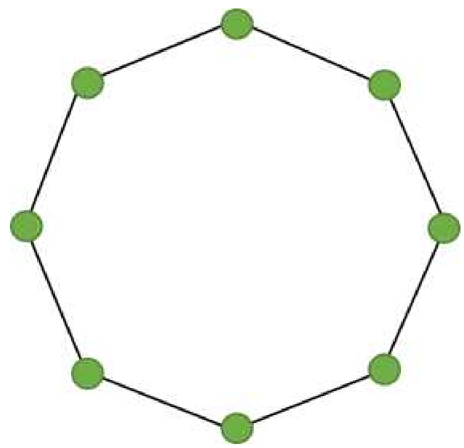
SECTION 1B- THE EXPERIMENT

We will now explain the rules of the experiment in detail. All participants in the experiment will be divided into **3 groups**. In each group, there are **8 traders** and you will be one of them. You and your group members will participate in an asset market in which you will trade units of the asset that earns dividend in each period. Each period of the experiment consists of a **two-stage decision making process**. In the first stage, you would be allowed to acquire additional information on the asset at a cost. In the second stage, you will trade units of the assets in a market setting.

There will be **12 independent periods** in the experiment. In each period, the underlying urn **may be different**. For instance, the urn may be A in the 1^{st} period with each asset being worth 10 ECU but the urn may be B in the 2^{nd} period with each asset being worth 0 ECU. In every period, each urn has an equal probability of being chosen as the underlying urn. Balls drawn from the urn will give you some hint about the value of the assets in each period. At the start of every period, all traders will see the **same two initial draws (at no cost)** and each trader will have the option of acquiring additional balls at some cost. Note that the additional balls you acquire can **only be seen by you and your neighbours**.

All traders have the same initial endowment of **60 ECU** and **4 assets**. Note that at the start of each period, the initial endowment will be reset and earnings from each period cannot be used in the next period. That is, each period is a fresh start.

Before the experiment starts, you will be provided with a figure on your screen (as shown below).[31]



This figure shows two things:

1. It shows the pattern of connections within your group. Each node represents the location of a member in a group. You are located at one of the nodes shown in the figure. A line joining two nodes together implies that the two members occupying the two nodes are neighbours. Note that in each period, you may or may not be located at the same node and may or may not have the same neighbours as in the previous period. Furthermore, do note that you will not be told who you are connected with as well as who the rest are connected with.

2. The information that you acquire will be shared with your neighbours in this

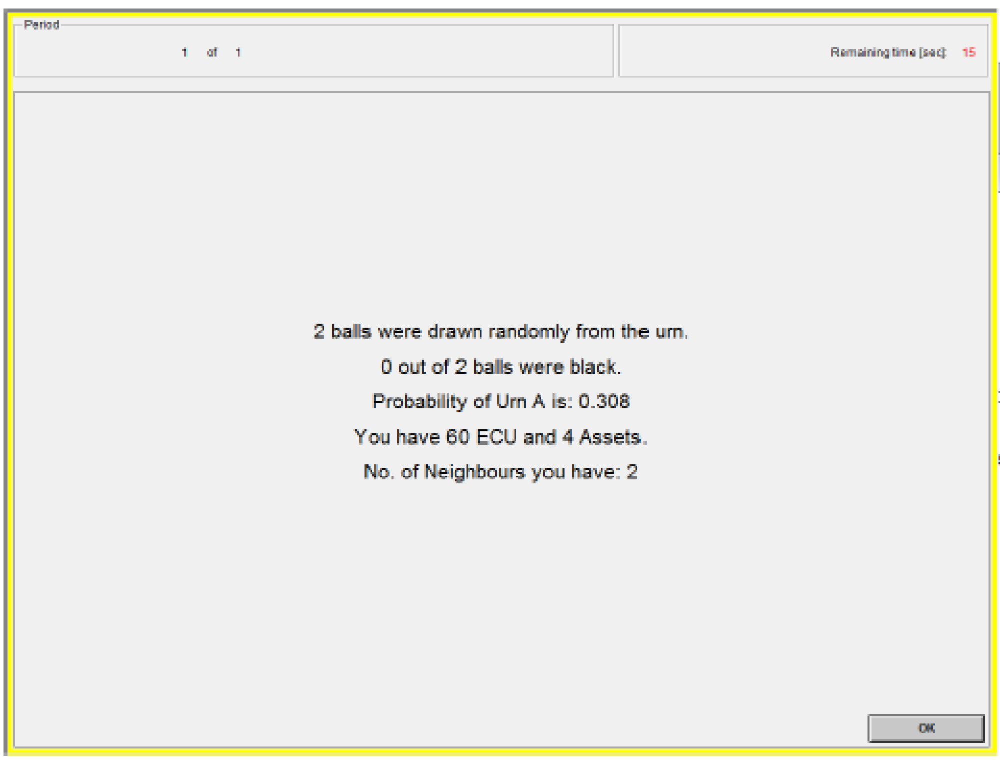
[31] The network structure shown was different for *complete* and *core-periphery* treatments. No figure was displayed for *non-networked* sessions.

structure. Likewise, additional information acquired by your neighbours will also be revealed to you.

The 1st screen of the experiment will show you a summary containing the following information:

1. Initial two draws
2. Probability that the urn is A based on the two initial draws
3. Initial endowment in money and assets
4. No. of neighbours you have

An example of the 1^{st} screen is as follows:



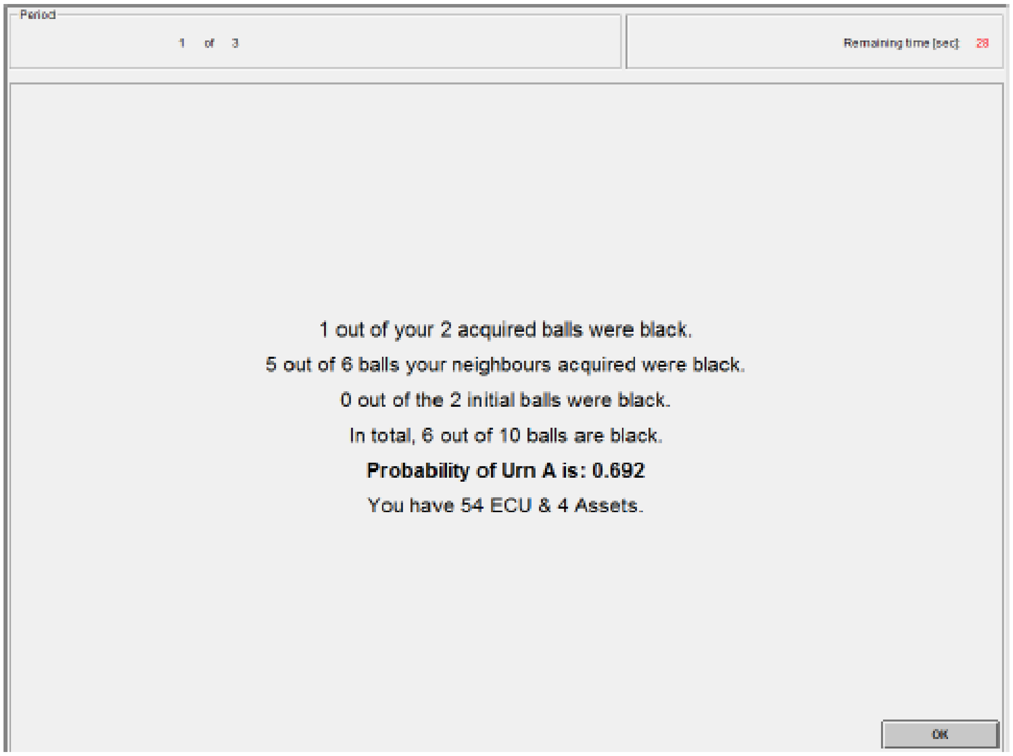
In this example, none of the 2 initial public draws were black balls. You do not have to make any decision on this screen. Just click "ok" once you have read the information.

SECTION 1C- ACQUIRING INFORMATION

The second screen of each round of the experiment provides you with the opportunity to pay to obtain additional draws from the urn. The **cost of acquiring one additional ball is 3 ECU**. The more additional balls you decide to obtain, the more information you will have about the underlying urn as well as the value of asset. You will be given a duration of 1 minute to decide on how many more balls you would like to draw. In the screen, you will be required to enter a number between **0 (do not want to obtain additional draws) and 5 (purchase 5 additional draws)** and click “ok”. **Failure to click “ok” within the stipulated time will result in 0 draws obtained**.

Below is an example of this screen:

The third screen gives you the results of the additional draws if you or your neighbours have decided to obtain any:



In this example, you have decided to obtain 2 additional balls and 1 out of the 2 balls was black. Your neighbours have also obtained 6 additional balls, of which 5 of them were black. Adding all draws together (including the initial 2 draws), 6 out of 10 balls are black. Now, you have some idea on the value of assets. Trading starts once all traders click "ok".

SECTION 1D- TRADING STAGE

In this stage, we have a market in which you can buy or sell units of an asset from/to other traders.

Rules of the Experimental Market

During the trading period, you may buy or sell units of the asset.

To buy an asset:

1. You can **accept a sell offer** from other traders under the list of sell offers. Note that a sell offer always offers **one asset** available for purchase and it specifies the price at which you can buy the asset. For example, if you accept

another traders sell offer of 7 ECU, your ECU balance will be reduced by 7 and you will have one more asset.
OR

2. You can **create a buy offer**, which specifies a price at which other traders can sell one asset to you. Note that you successfully buy an asset only if your buy offer is accepted. If nobody accepts your buy offer, then you do not gain more assets.

Note that if you want to **buy more than one asset**, you will have to **accept more sell offers**, or **create more buy offers**.

To sell an asset:
Selling assets is similar to buying:

1. You can **accept a buy offer** from other traders under the list of buy offers. For example, if you accept a buy offer at a price of 5 ECU, then your ECU balance will be increased by 5 and you will have one less asset. Similarly, each buy offer only **involves one asset**.
OR

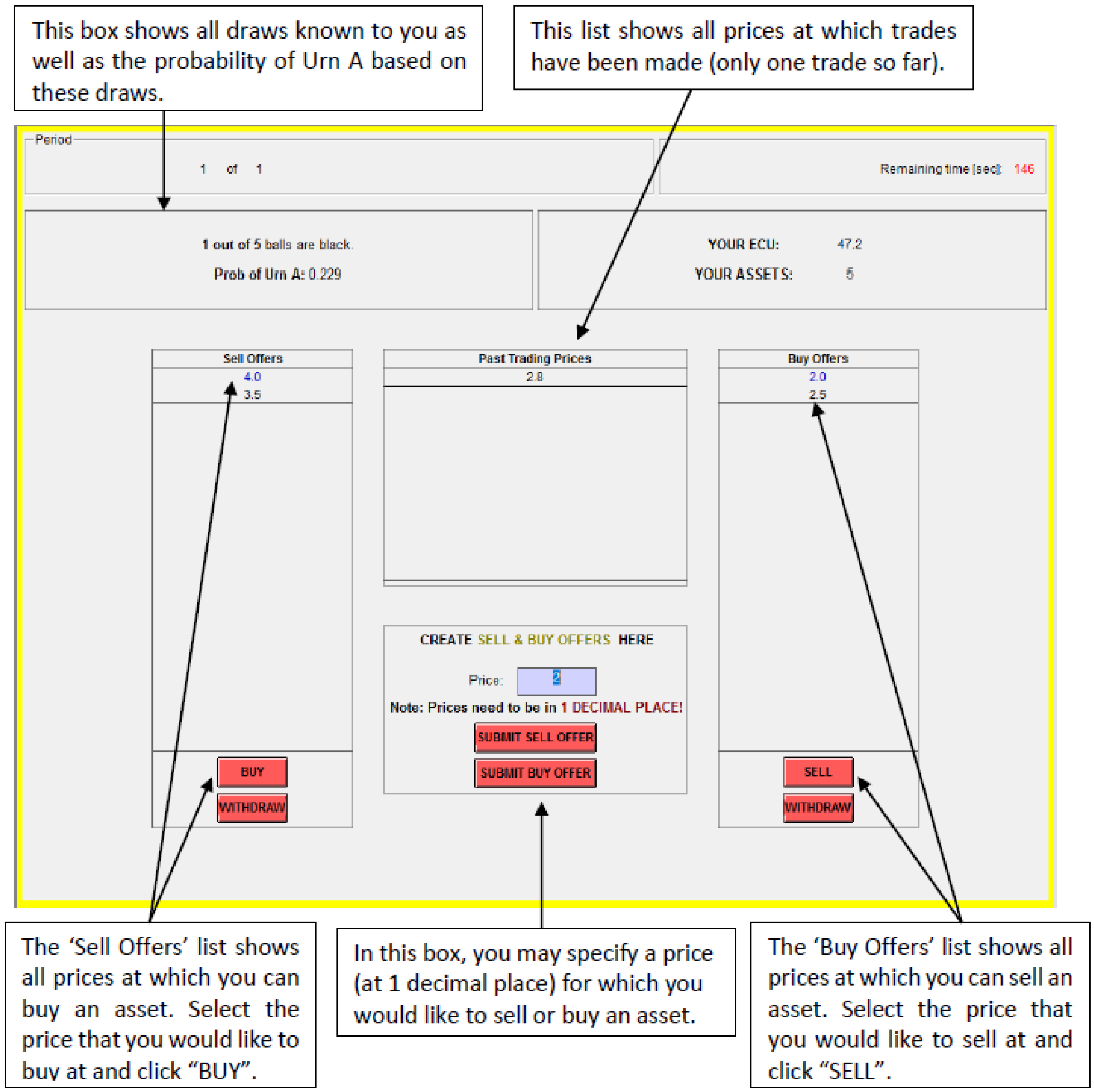
2. You can **create a sell offer**, which specifies a price at which other traders can buy one asset from you. Note that you successfully sell an asset only if your sell offer is accepted. If nobody accepts your sell offer, then you do not have less assets.

Similarly, if you want to **sell more than one asset**, you will have to **accept more buy offers**, or **create more sell offers**.

At all times during trading, you will be able to see all active offers and their respective trading prices. To create an offer, you simply enter a buy/sell price and click either the "Submit Sell Offer" or "Submit Buy Offer" button to create a sell or buy offer respectively. Note that your specified buy/sell price **needs to at least equal or better the best current buy/sell price**. If you want to make a sell offer, it must be $\leq$ **lowest current sell offer**. If you want to make a **buy offer**, it must be $\geq$ **highest current buy offer**.

Do also note that your offers must be rounded up to **1 decimal place**. For instance, you may key in a price of 4.5 or 5 but NOT a price of 4.55.

The following figure shows the trading window:



Note that your own buy/sell offers are also displayed in the list of offers in blue instead of black. You cannot accept your own offers, but you can select them and click "WITHDRAW" if you decide to withdraw your own offers.

Offers are removed from the offer lists when someone accepts or withdraws them.

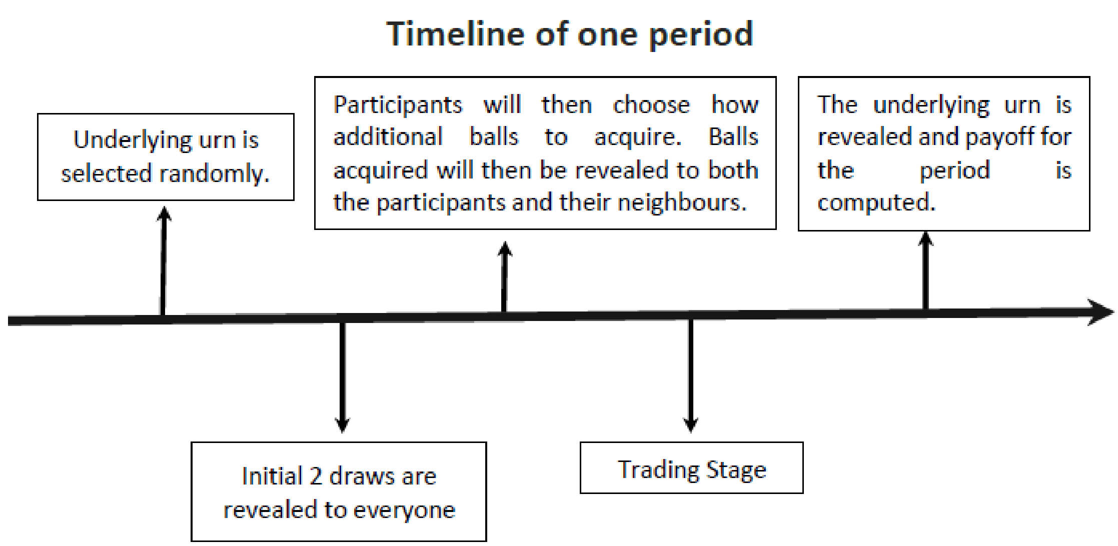
Note also that if there are any buy/sell offer that you are no longer able to fulfill (either because you **do not have any asset left for your sell offer** or you **do not have enough ECU for your buy offer**), it will also be removed.

After you have successfully made a trade, your ECU and asset balances will be updated accordingly. In general, you should accept the **highest buy offers** and the **lowest sell offers**. For your easier viewing, the offer lists will be sorted such that the **highest buy offer at the bottom of the list of buy offers** and the **lowest sell offer at the bottom of the list of sell offers**. (i.e, best offers are at the bottom of each list)

In each period, you will have **3 minutes for trading**. The remaining time (in seconds) will be displayed at the **top right hand corner** of the screen.

The last screen concludes the period. It will show the average trading price during trading and also reveal the value of the assets in this period: either 0 or 10 ECU. Your payoff for each period is the **sum of ECU you have at the end of the period and the total dividends from the assets**. A new period begins once every trader clicks "OK" on this screen.

A timeline summarizing the flow of events in each period is shown below:



Overall, you will be acquiring information and trading for **12 independent periods**. There will be **2 practice rounds** for you to get used to the experiment before the actual 12 periods of the experiment begin. Note that the **practice rounds will not be selected as payment rounds**.

If you have any questions that have not been fully answered by the instructions, please raise your hand and ask for assistance before proceeding.

SECTION 2- QUANTITATIVE STAGE

In this part of the experiment, you will have to answer 10 quantitative questions. These questions are designed to assess quantitative ability. You may write your workings on the instruction paper for your convenience but your workings will not be reviewed. For each question that is correctly answered, you will receive 2 ECU. **You will not be penalized for any wrong answer. You may also choose to leave the questions blank if you do not want to answer**. The maximum you may obtain from this section is 20 ECU and the minimum is 0 ECU.
Do note that if you do not key in your answers before the time is up, the computer will assume that you have left all questions blank. A warning message will start flashing when you have 20 seconds remaining.
The payoff from this section will be added to your total earnings.

SECTION 3- DECISION PROBLEM STAGE

In this part of the experiment, you will be asked to make a series of choices. How much you receive will depend partly on chance and partly on the choices you make. The decision problems are not designed to test you. What we want to know is what choices you would make in them. The only right answer is what you really would choose.
For each line in the table in this stage, there are two options:

- Option A: 1 SGD

- Option B: 0 SGD or 3 SGD with varying chances stated for each line

Please select the option which you prefer for each line. Notice that there are a total of 10 lines in the table but **just one line will be randomly selected for payment**. You do not know which line will be paid when you make your choices. Hence, you should pay attention to the choice you make in every line.
After you have completed all your choices, the computer will randomly determine which line is going to be paid. Your earnings for the selected line depend on which option you chose. If you chose option A in that line, you will receive **1 SGD with certainty**. If you chose option B in that line, the computer will randomly determine if your payoff is **3 SGD or 0 SGD** based on the chances stated in option B of the selected line.

QUESTIONNAIRE

In this final part of the experiment, you will be required to answer a questionnaire. When you are done, we will prepare your earnings and ask you to sign a receipt, and the experiment will be over. Thank you again for your participation!

If you have any questions that have not been fully answered by the instructions, please raise your hand and ask for assistance before proceeding.