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

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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

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purchased by their neighbors. Although information exchange among traders increases trading volume, improves liquidity and enhances the ability of asset prices to reflect the available information in the market, it fails to improve price informativeness. Net earnings and social welfare are higher with information sharing due to reduced acquisition of costly signals.

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

JEL Codes: C92, D82, D83, G10, G14

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), Jackson (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,

[1]See, for example, Shiller (2000), Kelly and Ó Gráda (2000), Duflo and Saez (2003), Hong, Kubik and Stein (2004), Hong, Kubik and Stein (2005), Ivković and Weisbenner (2007), Brown et al. (2008), Cohen, Frazzini and Malloy (2008), and Shiller (2017), among others.

but is actually a primary driver of behaviors and outcomes.[2]

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 social 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, an 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.

What distinguishes our paper from previous studies on information acquisition is the existence of a network among the traders. Before trading takes place, individuals

[2]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 (2010), and economic networks in the laboratory (Kosfeld (2004), Choi, Kariv and Gallo (2016)).

share 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)).[3] 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.[4]

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.

Despite lowering information disparity among investors, social communication results in more trades and improves market liquidity. With information sharing

[3]In such a society, lying or withholding information is extremely costly. There could be severe psychological costs associated with lying to a trusted friend.

[4]Although our study abstracts away from the issues of imperfect (or noisy) communication of information as well as strategic information revelation, we stress that these are nevertheless important topics to be investigated in future studies.

among investors, a larger fraction of the available information in the market is impounded into asset prices. However, while prices reflect publicly available information, they fail to reflect all privately held information, lending support to the semi-strong form of the efficient market hypothesis (Fama (1970)). In addition, the extent of information aggregation increases with the density of the information network.

Furthermore, we show that 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.

Without any information exchange, traders who acquire information are able to extract information rent from the ones who do not purchase any signal. However, with information leakage to neighbors in the presence of social communication, this rent disappears and gross earnings are indistinguishable between traders acquiring and those not acquiring information. We also find that social communication increases traders' earnings via cost savings from lower information acquisition.

Within the literature on costly information acquisition, studies have shown that the market value of information approaches zero when traders submit sealed bids in an environment with perfect information (Copeland and Friedman (1992), Sunder (1992)). In contrast, in a setting where private information is imperfect, it is valued by the market participants (Ackert, Church and Shehata (1997)). 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. To the best of our knowledge, ours 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.[5]

The remainder of the paper is organized as follows. Section I describes the design and procedures of the experiment, and in section II, we present the data. In section III, we discuss existing theoretical results that relate to our experimental findings and identify the mechanisms likely behind the main results. Section IV concludes.

I. Experimental Design

A. 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 population 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

[5] 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 (Palan (2013) provides a review of such studies). 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), Plott and Sunder (1988)). For a detailed overview of the experimental asset market literature, see Sunder (1995) and Noussair and Tucker (2013). A related line of research has investigated the capacity of prediction markets to aggregate existing knowledge. 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.

sessions lasted approximately two hours and participants earned on average S$24.40 in addition to a show-up fee of S$2.[6]

Upon arrival, subjects were seated at visually isolated computer workstations. Participants were randomly divided into groups of eight.[7] Instructions were read aloud and subjects also received a copy of the instructions.[8] 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.[9] 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 fully revealed to the subjects only at the end of a period.

Traders had the opportunity to exchange several units of a financial 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 open-book continuous double auction trading rules (Smith (1962)) implemented with the z-Tree computer program (Fischbacher (2007)). At the end of

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

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

[8]We provide the instructions in the Internet Appendix.

[9]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, 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.

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 was intended to foster a common belief about the state of nature prior to the private information acquisition decision.

After observing the initial information, traders could acquire up to 5 additional draws at the cost of 3 ECU each.[10] All participants were given sixty seconds to decide on how many additional draws they would like to acquire.[11] 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

[10]Again, each signal was an i.i.d draw from the underlying urn. While our choice of the cost of an additional draw might seem arbitrary, it is not too high and provides reasonable and intuitive observations with respect to the amount of information purchased. Furthermore, it is consistent with previous literature (Page and Siemroth (2017)).

[11]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.

they had. Subjects were told that the information they purchased 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.[12] 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, 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.[13] 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.[14] Throughout the trading stage, pertinent information such as the profile of draws revealed to them, posterior probability of

[12]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.

[13]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 (including transactions by other traders) within the period.

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

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.[15] 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.

B. Treatments

We implemented four treatments and conducted two sessions for each of them. This resulted in six independent groups per treatment as we had three independent eight-person groups in each session. 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

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

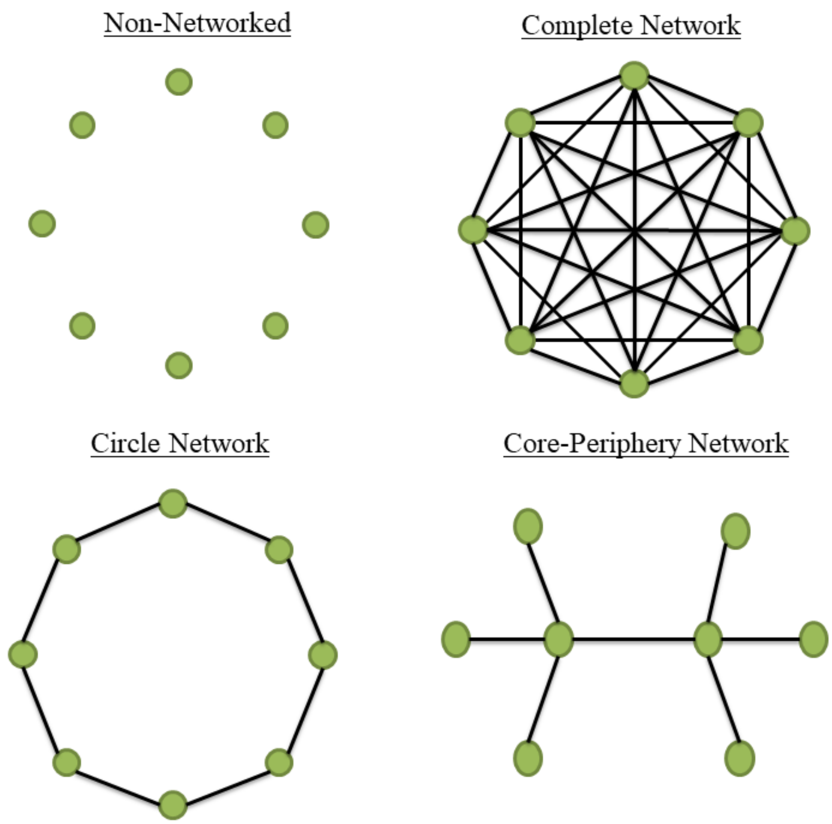

Figure 1. Treatments - information networks among investors. The four treatments differ in the underlying exogenous structure of information network among traders. Each node on the undirected graph represents an investor and a link between two nodes denotes bidirectional exchange of privately acquired signals by them.

as the other core participant. The same participants held the core position each period.[16] 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*.[17] Except the *core-periphery* treatment, participants had equal degree within each of the other

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

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

treatments: the permutation of network positions does not change the total number of connections for each participant. In contrast, the two core subjects had more influential positions than the periphery subjects. Furthermore, the four network structures also differ in density. It is 0 in *non-networked*, 1 in *complete network*, 0.29 in *circle network* and 0.25 in *core-periphery network*.[18]

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 where each trader was connected to every other trader in the market. Consequently, regardless of the amount of information purchased, the available information in the market with complete network was observed publicly by all participants leading to them having 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 fairly similar densities in our setting, one is regular while the other is not.[19] This allows us to explore the impact of regularity of the information exchange network on the incentive to acquire costly information. 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

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

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

information obtained by any player is observed by exactly two others.

II. Results

A. 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 I. 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, implying that subjects in the *complete* and *circle* treatments purchase less number of signals than the other two treatments.

For a detailed investigation of the determinants of information acquisition behavior, we perform an ordered probit regression of the number of information signals acquired by a subject (s_i) using all data and for the *core-periphery* sessions separately. Table II reports the estimated values of the regression coefficients. 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 cut points from the ordered probit regression are not included in Table II for the sake of brevity.

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

TABLE I
Period-Average Summary Statistics

This table presents the values of s_i, $\mathbb{1}\{s_i > 0\}$, net profit and number of transactions for each treatment, averaged across all periods of all sessions. The standard deviations are in parentheses. 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 between the values 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.

	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

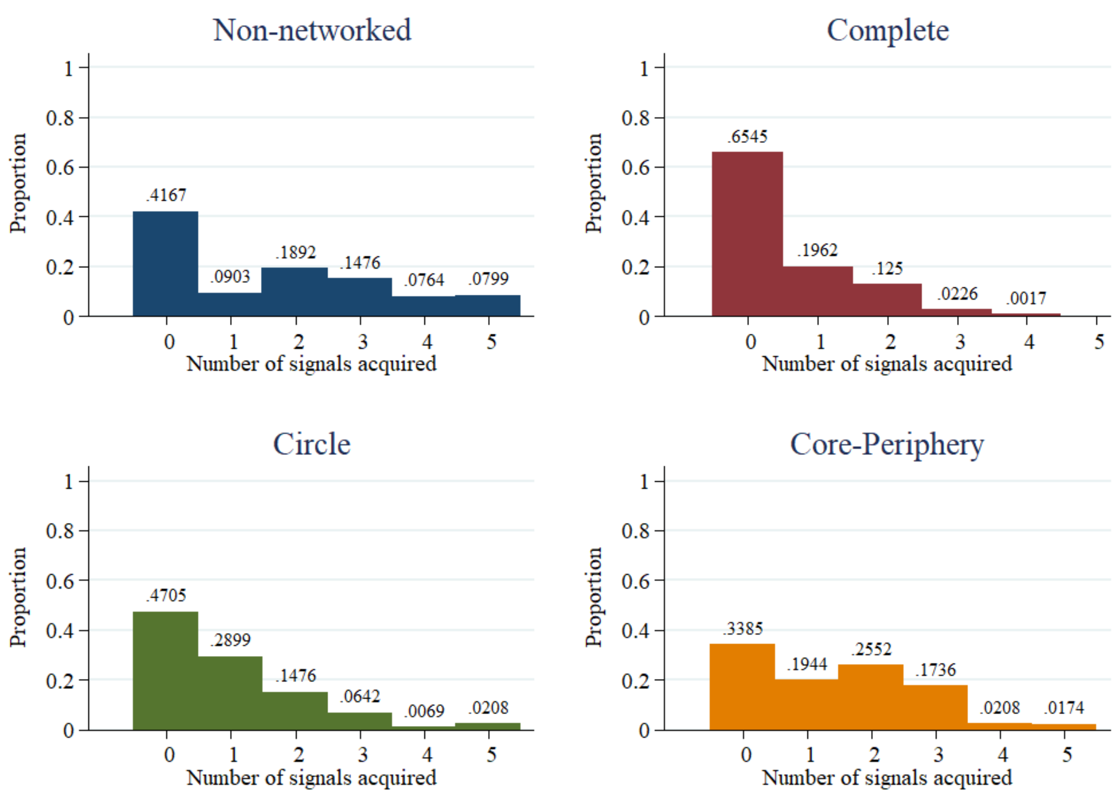

Figure 2. Histogram of information acquisition choices in each treatment. The figure displays the distribution of information acquisition choices with the unit of observation being the number of signals acquired by a subject in a period within a session. Each treatment has 576 observations.

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.[20]

The average marginal effects from the ordered probit regression are separately displayed in Table III. Tables II and III show that there is a significant negative effect of knowledge sharing on information acquisition behavior when the network is regular. Table III suggests that the likelihood of not acquiring information ($s_i = 0$) goes up by 18% in *circle* and 38% in *complete* network, compared to the *non-networked* treatment. All the marginal effects are significant for each possible value of s_i. Compared to the situation without any social communication, participants acquire less information in the regular networks in the anticipation of free riding on the signals acquired by their neighbors. On the other hand, communication via the *core-periphery* information network does not significantly impact the information acquisition behavior in comparison to the "no communication" benchmark.

Table IV displays the results of regression of (a) the number of signals acquired in the market ($S_{mkt.}$) and (b) the number of participants who acquired information in the market ($N_{mkt.}$) on treatment dummies and average values of the demographic variables in the market. The standard errors are clustered at the level of indepen-

[20]These variables are *risk aversion* (measure of how risk averse a subject is; ranges from 1 to 11 corresponding to the respective subject's switching point in the Holt-Laury risk-elicitation procedure, 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).

TABLE II

Ordered Probit Regression of Number of Signals Acquired

This table presents the results of an ordered probit regression of the number of signals acquired (s_i) for all data and within the *core-periphery* treatment. The standard errors (clustered at the level of individual subject) are in parentheses. The baseline is the *non-networked* treatment for all data and *core* for *core-periphery* sub-sample. 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. ** indicates significance at the 5% level while *** indicates significance at the 1% level.

	All data		*Core-periphery*	
Complete	-1.09***	(0.18)		
Circle	-0.50***	(0.18)		
Core	0.04	(0.22)		
Periphery	-0.28	(0.19)	-0.54**	(0.26)
Inconclusive initial draw	0.20***	(0.04)	0.09	(0.15)
Inconclusive initial draw×*Periphery*			0.43**	(0.18)
Risk aversion	-0.06**	(0.03)	0.04	(0.06)
Age	-0.08	(0.05)	-0.06	(0.09)
Male	-0.09	(0.15)	0.03	(0.33)
Economics/Business major	-0.37***	(0.13)	-0.47**	(0.21)
Quantitative skill	-0.03	(0.03)	0.02	(0.07)
Trading experience	-0.34	(0.35)	-0.08	(0.68)
Period	-0.04***	(0.01)	-0.04**	(0.02)
No. of observations	2304		576	
Clusters	192		48	

TABLE III

Average Marginal Effects

This table presents the average marginal effects from the ordered probit regression of s_i for all data and within the *core-periphery* treatment. The standard errors (clustered at the level of individual subject) are in parentheses. The baseline is the *non-networked* treatment for all data and *core* for *core-periphery* sub-sample. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

All data	$s_i = 0$	$s_i = 1$	$s_i = 2$	$s_i = 3$	$s_i = 4$	$s_i = 5$
Complete	0.38***	-0.03***	-0.12***	-0.12***	-0.04***	-0.07***
	(0.06)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
Circle	0.18***	-0.01**	-0.06***	-0.06***	-0.02**	-0.03**
	(0.06)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Core	-0.01	0.00	0.00	0.00	0.00	0.00
	(0.08)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)
Periphery	0.10	-0.01	-0.03	-0.03	-0.01	-0.02
	(0.07)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Core-periphery	$s_i = 0$	$s_i = 1$	$s_i = 2$	$s_i = 3$	$s_i = 4$	$s_i = 5$
Periphery	0.18**	0.02	-0.05*	-0.10**	-0.02*	-0.02
	(0.09)	(0.01)	(0.03)	(0.05)	(0.01)	(0.02)

dent group.[21] Table IV shows that information sharing among investors located on a regular network decreases the aggregate number of signals acquired in the market: by 6.8 draws in *circle* and by 9.9 draws in *complete* network. The number of traders who acquired information drops significantly only for the *complete* network when compared with the baseline of *non-networked* treatment. On the other hand, $S_{mkt.}$ and $N_{mkt.}$ are both similar between the *non-networked* and *core-periphery* sessions. Thus, the temptation to free ride on information signals purchased by neighbors crowds out the production of information in the market, but only when the information network is regular.

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, the regressions show that various demographic variables affect the propensity to gather costly signals. Table II shows that, on an average, participants who are more risk averse acquire less information. A major in economics or business studies has a negative effect on the incentive to purchase additional information.

Focusing only on the *core-periphery* sessions, Tables II and III 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 earlier observation that the incentive to acquire information declines with the number of neighbors. So, the *core-periphery* network setting fails to align with our main result on the free-riding incentive that we obtain in the other two network structures. Furthermore, we find that a trader located at the core position is more

[21] Given that there are three independent groups per session and two sessions per treatment, we have a total of 24 clusters, with each treatment having six independent clusters.

TABLE IV

OLS Regression of Number of Signals Acquired and Number of Subjects Acquiring Signals

This table presents the results of an OLS regression analysis, with the dependent variable being the number of signals acquired in the market ($S_{mkt.}$) in (1) and the number of participants who acquired information in the market ($N_{mkt.}$) in (2). The baseline is the *non-networked* treatment. The standard errors (clustered at the level of independent group) are in parentheses. 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*, ratio of traders being male, ratio of subjects with an Economics or Business major, average quantitative skill of the traders and average trading experience in the market. ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1) $S_{mkt.}$		(2) $N_{mkt.}$	
Complete	-9.92***	(2.06)	-2.42***	(0.47)
Circle	-6.84***	(2.21)	-0.11	(0.47)
Core-periphery	-2.67	(1.80)	0.28	(0.36)
Inconclusive initial draw	1.53***	(0.46)	0.59***	(0.19)
Average risk aversion	-1.33	(1.23)	-0.75**	(0.31)
Average age	-0.78	(1.78)	0.05	(0.36)
Male ratio	3.51	(5.19)	-0.13	(1.39)
Economics/Business ratio	-2.85	(3.91)	-2.54**	(0.93)
Average quantitative skill	0.91	(1.06)	-0.09	(0.31)
Average trading experience	-13.63	(11.33)	-3.07	(2.28)
Period	-0.29***	(0.07)	-0.13***	(0.03)
Constant	33.99	(41.80)	11.31	(8.30)
No. of observations	288		288	
No. of clusters	24		24	
R^2	0.57		0.53	

likely (equally likely) to acquire information than the periphery when the initial information is conclusive (inconclusive).[22] 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.

Result 1: *Information exchange among neighbors over a regular network gives rise to incentive to free ride on others' acquired costly signals and results in lower overall amount of information in the market.*

Given that signals acquired by an individual are also shown to her neighbors in the presence of social communication, information is like a local public good in our setting. The free-riding effect is reminiscent of the same effect found in the context of experiments on the provision of public goods (Andreoni (1988), Ledyard (1995), Chaudhuri (2011)). Experiments have shown that subjects consistently attain outcomes that are closer to the free riding levels than the Pareto efficient levels (Andreoni (1988)), and that the phenomenon of free riding can exacerbate if the group size is large (Isaac, Walker and Thomas (1984), Isaac and Walker (1988)).

Although counter-intuitive, we provide evidence that participants at the core invest more in information gathering activity than the ones at periphery, even without any immediate benefits. This can be related to the observation from other studies where information is typically acquired and shared in networks with a core-periphery structure, with a small core of agents gathering information for distribution to a larger group (Weimann (1994), Bala and Goyal (2000), Galeotti and Goyal (2010)).[23] 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

[22] When the initial information is inconclusive, we cannot reject the null hypothesis that the sum of coefficients of the variables *Periphery* and "Inconclusive initial draw × *Periphery*" is 0.

[23] For example, a small number of individuals is responsible for the vast majority of articles on Wikipedia (Voss (2005), Ortega, Gonzalez-Barahona and Robles (2008)). Similarly, on open source software (OSS) projects, there are usually a few developers that contribute most of the code while others contribute too little (von Krogh and von Hippel (2006)).

than the ones at periphery.

B. Trading Volume and Liquidity

How does social communication affect market trading volume and liquidity?

Table I 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.[24] The results are displayed in Table V. Information sharing has a positive effect on market trading activity. At the same time, larger information acquisition in the market is associated with larger trading volume.

Table V also shows the OLS regression results of liquidity measures. The following two measures of market liquidity are used: (a) the market spread each period, defined as the average of the bid-ask spread evaluated at each transaction in a period[25], and (b) the market depth, defined as the average of the ask depth times ask price and bid depth times bid price.[26] While the spread between the bid and ask prices is a natural measure of liquidity (Amihud and Mendelson (1986)), market

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

[25]In the calculation of the bid-ask spread, in the event that a bid is accepted to form a contract but no ask is entered, following Campbell et al. (1991) we define the "standing offer" as 9.99, the maximum possible price that the system will accept; if there is an offer price being accepted, but no bid, we define the "standing bid" as 0.01, the minimum possible price that is accepted by the system. This definition requires only the weak assumption that any seller would be willing to sell at 9.99 and any buyer would be willing to buy for 0.01. An alternative is to exclude the observations when there is either no bid or no ask at the time of contract; our results remain the same if we use this alternative method.

[26]We use the \$*Depth* as defined in Chordia, Roll and Subrahmanyam (2001). The bid (ask) depth at a given price is the cumulative volume of current buy (sell) orders on the book at that price or higher (lower).

depth is another widely used measure (Chordia, Roll and Subrahmanyam (2001)). The higher transaction volume with information sharing is also accompanied by narrower bid-ask spread and greater depth. This points towards higher liquidity with information exchange among investors.

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

Even after controlling for the aggregate number of signals in the market, the nature of information as captured by the *Bayesian posterior*, and the demographic variables of the participants, the market volume increases with social communication. This suggests that trading is not primarily motivated by information disparity. If it were, we would have observed far less trading activity in our treatments with information exchange than the *non-networked* sessions.

The above observation is not entirely unexpected for the following two reasons. First, receiving information from several sources increases the confidence of a trader in the cumulative information held by her. This results in a higher participation in the asset market. Second, and more importantly, there is 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 deeply rooted in the financial economics literature. In a related but different context, Glosten and Milgrom (1985) identify a similar problem faced by a specialist

TABLE V

OLS Regression of Market Trade Volume, Bid-Ask Spread, and Depth

This table presents the results of OLS regression analysis of market trade volume and liquidity measures. The dependent variable is the market trade volume in a period in (1), the average of the bid-ask spread evaluated at each transaction in a period in (2), and the market depth in a period in (3). Market depth is defined as the average of the ask depth times ask price and bid depth times bid price in a period. The baseline is the *non-networked* treatment. The standard errors (clustered at the level of independent group) are in parentheses. $S_{mkt.}$ is the number of signals acquired in the market. Bayesian posterior is defined as the posterior probability of urn A given all draws in the market. All the regressions include demographic variables as additional regressors. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1) Trade Volume	(2) Bid-Ask Spread	(3) Depth
$S_{mkt.}$	0.30***	-0.01	0.49***
	(0.10)	(0.02)	(0.14)
Complete	2.83*	-0.97***	7.31***
	(1.42)	(0.30)	(1.80)
Circle	2.04	-0.63*	0.81
	(2.17)	(0.36)	(2.56)
Core-periphery	2.42*	-1.00***	2.97**
	(1.19)	(0.35)	(1.38)
Bayesian posterior	-3.75***	0.18	13.43***
	(1.03)	(0.18)	(2.01)
Period	0.07	-0.03	0.18
	(0.09)	(0.02)	(0.11)
Constant	43.96***	1.02	-16.22**
	(15.11)	(1.62)	(6.98)
No. of observations	288	286	288
No. of clusters	24	24	24
R^2	0.41	0.19	0.43

while trading with a customer with superior information.

C. Information Aggregation

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 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 (see the long-dashed curve plotted in Figure 3). The risk-neutral fundamental value of the asset is depicted by the straight short-dashed line starting from the origin. 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, that is, $LAD =$ |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-networked* sessions, we perform a regression with the LAD as the dependent variable and the treatment dummies as the regressors. Table VI 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

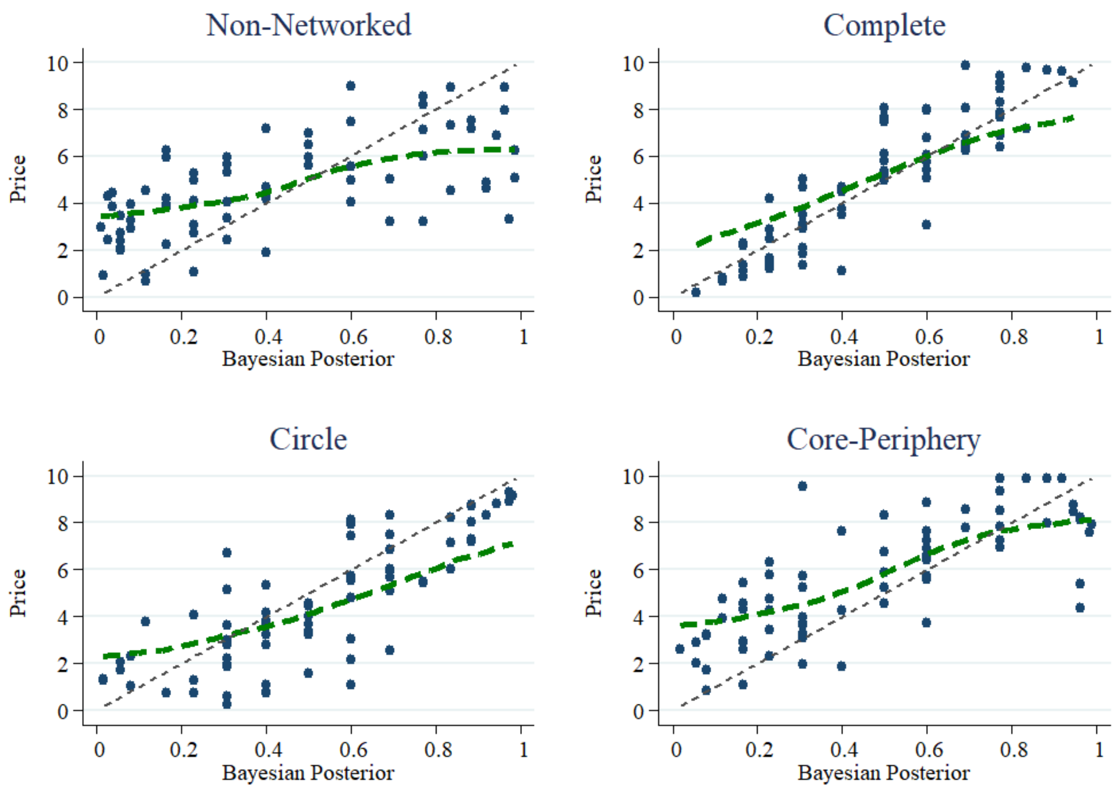

Figure 3. Precision of market prices in each treatment. The long-dashed curve displays the average price conditional on the Bayesian posterior in a market ($\mathbb{E}$(Price|Bayesian posterior)). The estimation is computed by local linear regression, using Epanechnikov kernel bandwidth of 0.2. The risk-neutral fundamental value of the asset is depicted by the straight short-dashed line starting from the origin.

TABLE VI

OLS Regression of Linear Absolute Deviation

This table presents the results of OLS regression analysis of 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 and the independent variables are the treatment dummies and *period*. The standard errors (clustered at the level of independent group) are in parentheses. ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Coefficient
Complete	-1.19*** (0.22)
Circle	-0.68*** (0.24)
Core-periphery	-0.42** (0.19)
Period	-0.02 (0.03)
Constant	2.19*** (0.25)
No. of observations	286
No. of clusters	24
R^2	0.12

denser the network, the lower is the LAD.

Figure 3 indicates 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 VII 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 VII

TABLE VII

Average Under-reaction across Treatments

This table presents the average value of *under-reaction* for each treatment. 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. The 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.

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

displays the p-values from Wilcoxon signed-rank test of the null hypothesis that *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.

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.*

The result presented above highlights the positive role of social communication for market efficiency in the context of aggregation of diverse information held by traders. A trader's private information is expected to be 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 this assists the asset price in better reflecting the information present in the market.

Figure 4 further shows the individual transaction *LAD* with the transaction number on the x-axis.[27] The *LAD* is declining with additional trades with information exchange, especially for *complete* and *circle* treatments. The opposite is true for the *non-networked* sessions with the prices moving away from the fundamental value with subsequent trades. Statistically, Kendall's Tau from a Mann-Kendall test for monotonic trend 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. Convergence to the fundamental value is observed only in the *complete* network where each trader holds the same posterior. Thus, public information is eventually reflected in the asset prices, with the higher volume and improved liquidity facilitating the convergence process. On the other hand, in the presence of information disparity, as in the treatments other than the *complete* network, prices fail to reflect all information available in the market.

Result 4: *Prices are able to reflect public information when social communication takes place over a complete network but fail to aggregate all private information available in the market when information exchange occurs through an incomplete network.*

Wolfers and Zitzewitz (2004) discuss that people tend to overvalue small probabilities and undervalue near certainties in prediction markets.[28] In order to check whether we observe this in our experiments as well, we calculate the average price initiated by an individual submitting a limit order in each treatment. The mean

[27]The figures are similar if we separately plot the LAD of transactions initiated by traders who acquire information and those initiated by the ones who do not purchase any signal.

[28]This is similar to the "favorite-long shot bias" in horse races, in which bettors tend to overvalue extreme long shots (Thaler and Ziemba (1988)) and the "volatility smile" in options, which involves overpricing of strongly out-of-the-money options and underpricing of strongly in-the-money options (Bates (1991), Rubinstein (1994)).

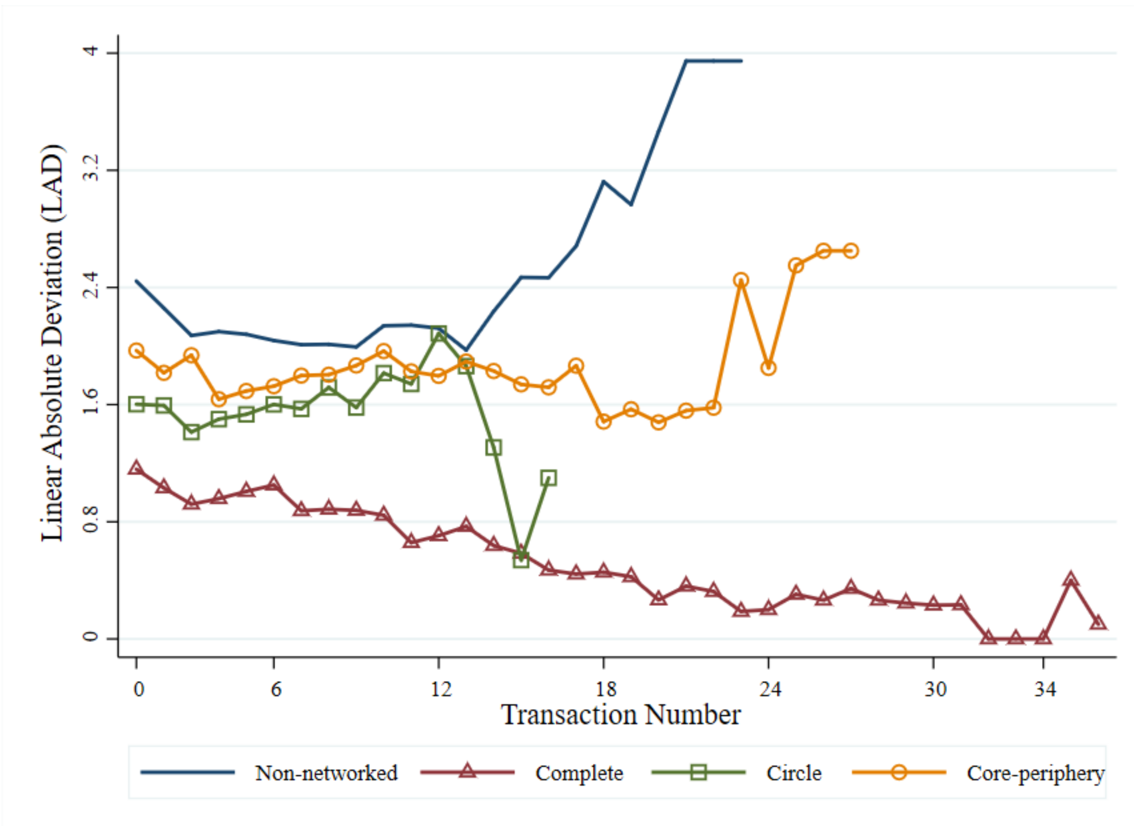

Figure 4. Linear absolute deviation as a function of transaction number in a period. The figure displays, for each treatment, the linear absolute deviation (LAD) for each individual transaction as a function of the order of transaction. The values of LAD are averaged across periods and sessions.

prices for various values of the posterior observed by the individual (calculated using the signals observed by the individual) are shown in Table VIII.[29] The average price initiated by an individual having extremely low posterior probability of state A occurring (that is, for $(0, 0.1]$ and $(0.1, 0.2]$) is much higher in *non-networked* sessions than in any of the two regular network sessions. Similarly, for the high probability event (a posterior of $(0.8, 1]$), prices are undervalued in *non-networked* treatment relative to those in the *complete* or *circle* treatments. This suggests that the instances of "overvaluing small probabilities and undervaluing near certainties" is lowered with social communication over a regular network.[30]

D. Price Informativeness

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 ability, 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. Specifically, we plot the number of times urn A is realized in the experiment conditional on the observed mean price ($\mathbb{E}(\text{Outcome}|\text{Price})$) in each treatment (see the long-dashed curve) and the expected number of times urn A should be realized conditional on the observed mean price (the short-dashed straight line). 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

[29]We group the posterior observed by an individual into 9 bins with a bin size of 10% except for the last bin.

[30]With no information exchange, the traders not acquiring any information observes an individual posterior of either 0.31 or 0.5 or 0.69. On the other hand, with social communication, several other values for the individual posterior are obtained for the traders not acquiring any information as a result of observing their neighbors' signals.

TABLE VIII

Average Price initiated by Limit Order Submitter

This table presents the average (mean) price initiated by the limit order submitter as a function of the individual posterior of the submitter. *Individual posterior* is calculated using the signals observed by the individual subject. The standard deviations are in parentheses.

Individual posterior	*Non-networked*	*Complete*	*Circle*	*Core-periphery*
$(0, 0.1]$	3.26 (0.96)	0.53 (0.55)	1.62 (0.85)	3.22 (1.53)
$(0.1, 0.2]$	3.30 (1.38)	2.03 (1.11)	2.17 (1.33)	3.26 (1.45)
$(0.2, 0.3]$	3.20 (1.75)	3.04 (1.17)	2.43 (1.99)	4.00 (2.02)
$(0.3, 0.4]$	5.00 (1.41)	3.73 (1.34)	2.78 (1.70)	4.79 (2.25)
$(0.4, 0.5]$	5.12 (1.82)	5.64 (1.02)	4.04 (2.69)	5.44 (2.57)
$(0.5, 0.6]$	5.64 (2.54)	5.75 (1.34)	4.80 (2.51)	6.87 (2.39)
$(0.6, 0.7]$	6.50 (1.72)	6.86 (1.02)	7.09 (2.45)	7.53 (2.09)
$(0.7, 0.8]$	6.60 (1.91)	8.13 (1.22)	7.52 (1.58)	7.89 (2.02)
$(0.8, 1]$	8.13 (0.75)	9.42 (0.51)	9.01 (0.53)	7.73 (1.63)

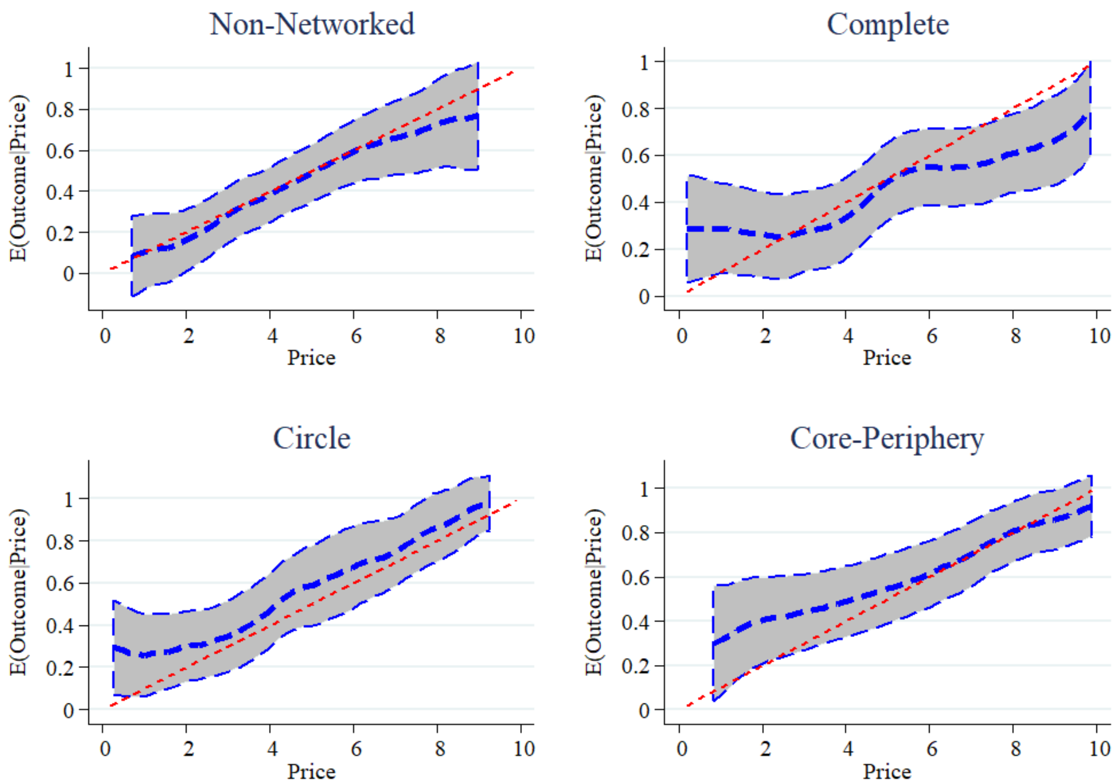

Figure 5. Calibration of market prices in each treatment. The long-dashed curve displays the frequency of outcome being urn A conditional on the observed mean transaction prices ($\mathbb{E}$(Outcome|Price)). The 95% confidence intervals are displayed as well. The short-dashed straight line shows the expected number of times urn A should be realized conditional on the observed mean price in the market.

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.

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 IX 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 in increasing the informativeness of the transaction prices in the market.

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 improves the ability of market to aggregate available information (result 3), it fails to provide enough cumulative information in the market due to the free riding incentive in the information acquisition activity (result 1). This would create a greater bias in the ability of price to predict the underlying urn. 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 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),

TABLE IX

OLS Regression of Forecast Error

This table presents the results of OLS regression analysis of forecast error which is defined as the absolute difference between the mean transaction price and the true value of the asset in a period. The baseline is the *non-networked* treatment and 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). The standard errors (clustered at the level of independent group) are in parentheses. ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1) Forecast error	(2) Forecast error
Complete	-0.02	-0.48
	(0.37)	(0.37)
Circle	-0.24	-0.41
	(0.31)	(0.27)
Core-periphery	-0.32	-0.52
	(0.51)	(0.48)
Accurate information		-2.49***
		(0.34)
Misleading information		0.98**
		(0.37)
Period	-0.07	-0.03
	(0.05)	(0.03)
Constant	4.46***	5.88***
	(0.40)	(0.39)
No. of observations	286	286
No. of clusters	24	24
R^2	0.02	0.43

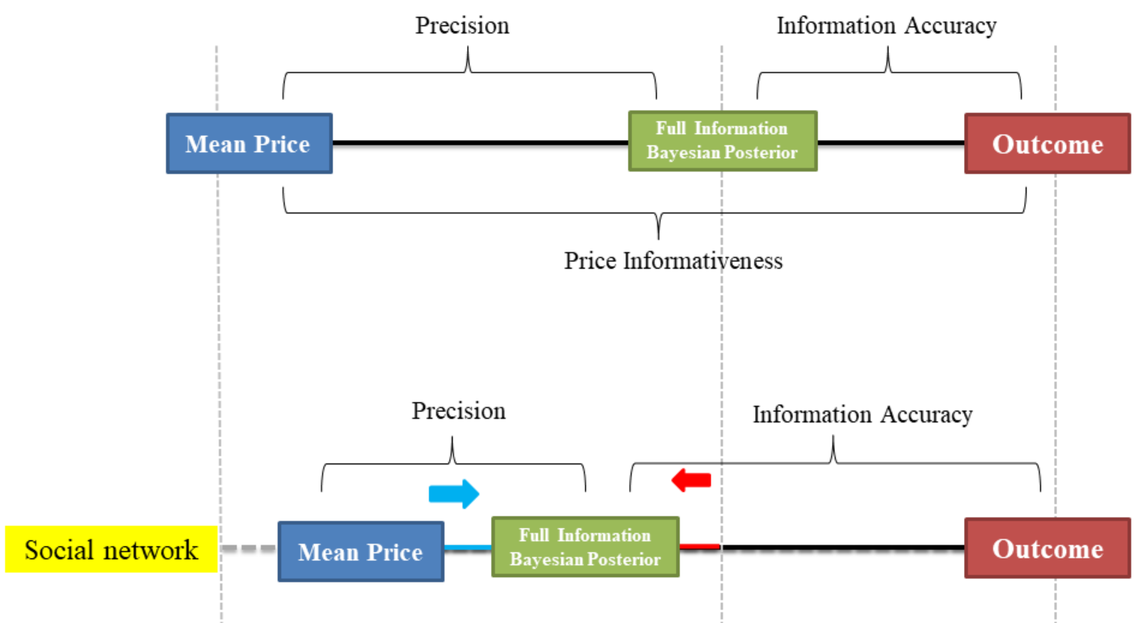

Figure 6. The effect of social communication on the precision and informativeness of asset prices. With social communication, while prices are more precise, the full information Bayesian posterior itself is farther away from the actual outcome due to lower aggregate number of signals in the market.

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 IX 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.

E. Trader Profits and Welfare

Are traders better off with information exchange than without? Does social communication reduce the variation in earnings?

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 between the values of a trader's portfolio at the end and at the start of each period.

With net profits as the dependent variable, we perform an 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 X. Column (1) results show positive and significant effect of the *complete* and *circle* dummies. This suggests that social communication on a regular network tends to increase traders' net profits. However, 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 reflected in the specifications (2) and (3), as well as in (5) where we also include the interaction terms between the number of signals and the treatment dummies. This is consistent with our finding in section II.A. Controlling for the number of signals acquired by a trader and signals acquired by neighbors, 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 ECU. Specification (5) further shows 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*, 2.7 for the subjects at the *core* location and 3.5 for the ones located at the *periphery*.

The fourth and sixth columns of Table X display 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 1.8 points) while misleading information decreases net profits significantly (by 3 points). This indicates 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.

Result 6: *Social communication over a regular network increases traders' earnings via cost savings from lower information acquisition.*

With no exogenously imposed gains from exchange in our environment, trading is a zero-sum game between the traders in the absence of liquidity need and risk aversion. The cost of acquiring information leads to a negative-sum game among all traders. The more information individuals acquire, the lower is the average (net) earnings. With no social benefit of the acquired information (as in our setting), trading along with information acquisition is belief-neutral inefficient compared to the situation of trading with no information acquisition. This is true regardless of

TABLE X

OLS Regression of Net Profits

This table presents the results of OLS regression analysis of net profits. The baseline is the *non-networked* treatment. Column (1) shows regression on *urn* (which 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. Last two columns also include the interaction variables. The standard errors (clustered at the level of individual subject) are in parentheses. ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
Urn	-0.11	0.00	-0.02	0.13	-0.00	0.12
	(0.89)	(0.89)	(0.89)	(0.89)	(0.89)	(0.89)
Complete	3.29***	-0.60	-0.51	-0.41	0.19	0.43
	(1.07)	(0.98)	(1.04)	(1.03)	(1.18)	(1.23)
Circle	2.13**	-0.27	-0.27	-0.20	-0.04	0.18
	(1.05)	(0.92)	(0.97)	(0.94)	(1.03)	(1.07)
Core	0.67	-0.42	-0.29	-0.51	-0.05	1.03
	(1.90)	(1.86)	(1.87)	(1.85)	(2.83)	(2.69)
Periphery	0.69	-0.58	-0.58	-0.41	0.87	0.81
	(1.13)	(0.93)	(0.92)	(0.91)	(1.09)	(1.16)
s_i		-2.82***	-2.90***	-2.89***	-2.53***	-2.58***
		(0.25)	(0.27)	(0.26)	(0.44)	(0.46)
$s_i^{neighbors}$		0.22	0.19	0.22	0.20	0.20
		(0.16)	(0.16)	(0.17)	(0.17)	(0.18)
$s_i \times$ *Complete*					-0.76	-0.76
					(0.84)	(0.82)
$s_i \times$ *Circle*					0.01	-0.11
					(0.59)	(0.59)
$s_i \times$ *Core*					-0.16	-0.84
					(1.07)	(0.94)
$s_i \times$ *Periphery*					-1.01	-0.82
					(0.63)	(0.67)
Accurate information				1.87***		1.80***
				(0.65)		(0.66)
Misleading information				-2.94**		-3.00**
				(1.28)		(1.29)
Constant	-4.80***	-0.28	5.43	4.40	-0.75	4.10
	(1.06)	(0.88)	(4.63)	(4.52)	(0.92)	(4.58)
Demographic variables included	No	No	Yes	Yes	No	Yes
No. of observations	2304	2304	2304	2304	2304	2304
No. of clusters	192	192	192	192	192	192
R^2	0.01	0.08	0.08	0.10	0.08	0.10

the choice of the social welfare function (Brunnermeier, Simsek and Xiong (2014)).[31] Social communication over regular networks lowers information acquisition and increases social welfare.

Next, in order to understand whether social communication has any impact on the disparity in traders' earnings, we conduct an OLS regression with the following three measures of inequality in earnings among traders in a period as the dependent variable: absolute difference in the maximum and minimum value of net profit, standard deviation of the net profit, and the Gini coefficient of the value of trader's portfolio at the end of a period defined as $\frac{\sum_{i=1}^{8}\sum_{j=1}^{8}|x_{i,t}-x_{j,t}|}{2\times 8\times \sum_{i=1}^{8} x_{i,t}}$ where $x_{i,t}(x_{j,t})$ denotes the value of portfolio of trader i (fellow traders j) at the end of period t. The independent variables include the treatment dummies, trading period and the demographic variables. The results of the regression are displayed in Table XI. Clearly, when information is exchanged over a regular network, the disparity in traders' performance is lower. This observation is consistent across all three measures of inequality. However, compared to the *non-networked* sessions, there is no significant difference in inequality in the *core-periphery* treatment.[32]

Result 7: *Social communication over a regular network reduces disparity in traders' earnings.*

F. Information Acquirers and Free-Riders: Within Treatment Analysis

Do investors acquiring information trade more than their connected neighbors who free ride on the information? Do traders who acquire information make money

[31] The belief-neutral welfare criterion proposed in Brunnermeier, Simsek and Xiong (2014) requires the planner to be sure of the presence of belief distortions by some agents but without having to precisely identify the objective belief. An allocation is belief-neutral inefficient if it is inefficient under any convex combination of the agents' beliefs.

[32] Similar conclusion is obtained if we use the absolute difference in the maximum and minimum gross profits or the standard deviation of traders' gross profits or the Gini coefficient with traders' (gross) wealth without deducting the cost of information acquisition.

TABLE XI

OLS Regression of Market Inequality Measures

This table presents the results of OLS regression analysis of market inequality measures. The dependent variable is the absolute difference between the maximum and minimum net profit in a period in (1), standard deviation of net profit in a period in (2), and the Gini coefficient of the value of trader portfolio at the end of a period in (3). The baseline is the *non-networked* treatment. The standard errors (clustered at the level of independent group) are in parentheses. All the regressions include demographic variables as additional regressors. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1) $\|max - min\|$ net profit	(2) std. dev. of net profit	(3) Gini coefficient
Complete	-16.55**	-5.20**	-0.05***
	(6.20)	(1.99)	(0.02)
Circle	-15.17***	-5.13***	-0.05***
	(3.96)	(1.30)	(0.01)
Core-periphery	-3.64	-1.09	-0.02
	(4.51)	(1.48)	(0.01)
Period	-0.11	-0.07	-0.00
	(0.58)	(0.19)	(0.00)
Constant	165.00*	64.34**	0.71***
	(94.41)	(28.72)	(0.20)
No. of observations	288	288	288
No. of clusters	24	24	24
R^2	0.08	0.09	0.10

TABLE XII

Average Per-capita Limit and Market Orders

This table presents the average per-capita limit orders and market orders submitted in a period by traders who acquire information and those who don't. In the second and fifth columns, for the *non-networked* treatment, we use the orders submitted by traders who do not acquire information while for the *networked* treatments, we use the orders submitted by free-riders. The standard deviations are in parentheses. The p-values from a t-test of differences in the values for acquirers versus non-acquirers/free-riders are shown as well.

	Limit order			Market order		
	Acquirers	Non-acquirers or free-riders	p-value	Acquirers	Non-acquirers or free-riders	p-value
Non-networked	1.34	1.13	0.23	1.50	0.98	0.02
	(0.84)	(1.04)		(0.83)	(1.54)	
Complete	1.64	1.45	0.34	1.93	1.59	0.09
	(1.44)	(0.91)		(1.08)	(1.37)	
Circle	1.21	0.95	0.05	1.17	0.83	< 0.01
	(0.78)	(0.79)		(0.63)	(0.69)	
Core-periphery	1.63	1.21	0.01	1.61	1.18	0.01
	(0.77)	(1.24)		(0.87)	(1.04)	

on their trading?

For the *non-networked* treatment, in each period, we classify traders into two types: information acquirers (those who acquire at least one signal) and non-acquirers (those who do not purchase any signal at all). In the *networked* treatments, we classify traders into information acquirers and free riders. We define free riders as the ones who themselves do not acquire any information but have at least one neighbor acquiring information. Table XII shows the average per-capita limit and market orders submitted in a period by the two types of traders in each treatment.

We find that there is a positive relationship between information acquisition and trading activity. While the values are always higher for those acquiring information

TABLE XIII

Average Per-capita Gross and Net Profits

This table presents the average per-capita gross profit and net profit in a period for traders who acquire information and those who don't. In the second and fifth columns, for the *non-networked* treatment, we use the profit for traders who do not acquire information while for the *networked* treatments, we use the profit for free-riders. Note that the gross and net profits are the same for non-acquirers/free-riders. The standard deviations are in parentheses. The p-values from a t-test of differences in the values for acquirers versus non-acquirers/free-riders are shown as well.

	Gross profit			Net profit		
	Acquirers	Non-acquirers or free-riders	p-value	Acquirers	Non-acquirers or free-riders	p-value
Non-networked	1.02 (3.73)	-1.53 (8.25)	0.06	-7.10 (3.98)	-1.53 (8.25)	< 0.01
Complete	-0.40 (5.87)	0.18 (4.41)	0.63	-5.14 (6.05)	0.18 (4.41)	< 0.01
Circle	-0.07 (6.85)	0.45 (4.36)	0.64	-5.09 (6.73)	0.45 (4.36)	< 0.01
Core-periphery	-0.29 (4.42)	-0.31 (8.84)	0.99	-6.54 (4.50)	-0.31 (8.84)	< 0.01

than the ones not acquiring or free-riding, the differences are significant in two out of four treatments for limit orders and in all treatments for market orders. It is likely that acquiring information makes individuals overconfident and then these overconfident investors trade more frequently than others ((Odean (1999), Barber and Odean (2001), Scheinkman and Xiong (2003)). Also, those who do not acquire information trade more when the information exchange takes place over a *complete* network: both the per-capita limit order as well as market order are higher in *complete* than in any of the other treatments.

Result 8: *Traders who acquire information generally trade more than their connected neighbors who free ride on the information.*

The average per-capita gross and net profit in a period obtained by the two types of traders in each treatment are shown in Table XIII. Gathering information in the *non-networked* treatment gives the investors an *information edge* over the ones not acquiring any signal: the gross profits of acquirers are significantly higher than the non-acquirers. Table XIII also shows that the net profit of non-acquirers is significantly higher than the corresponding value for acquirers. Thus, although information helps the acquirers in their trading, it is not sufficient to cover the information cost when no information exchange takes place among the investors. Both the gross and net profits are significantly lower for acquirers than their connected neighbors who free ride on the information in all three treatments with social communication. It is likely that the acquirers under-estimate the information leakage to their neighbors and lose the *information edge* with social communication.

Result 9: *In the absence of information exchange, traders who acquire information have an "information edge" over the ones who do not purchase any signal. The "information edge" disappears with social communication.*

III. Discussion

One of the most influential concepts in financial economics is the efficient market hypothesis (Fama (1970)). Our results on information aggregation indicate that prices are far from being strong-form informationally efficient. Our finding for the *complete* market provides evidence supporting semi-strong efficiency. This observation is reinforced by a recent study by Page and Siemroth (2018) which directly estimates the informational content of prices and reports that public information is almost completely reflected in prices, but little private information (less than 50%) is incorporated in prices.[33] It is also important to note that even when prices re-

[33] Page and Siemroth (2018) uses data from multiple double auction experiments in the literature,

flect available public information, it does not do so immediately: convergence to the fundamental value takes time.

With no information exchange among investors, if information is costly to obtain, the conventional wisdom is that market prices cannot be fully efficient, since fully revealing prices remove any incentive to acquire information (Grossman (1976)). While the fully revealing rational expectations equilibrium predicts no information acquisition, several 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)). 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. There is no exogenously implemented noise in our framework and thus, the theoretical literature suggests that there should be no information acquisition. However, in our data, we see significant investment in private information gathering activity. We discuss below three main reasons for the apparent over-investment.

First, investors in our experiment purchase more signals as they cannot extract enough information from the price. An important implication of our experiments for future theoretical models is that typically strong assumptions on price efficiency result in unrealistically informative markets and lead to the prediction of extremely low level of information acquisition. Even with no exogenous noise in the system, prices in financial markets need not be fully revealing. More realistic assumptions about the ability of asset prices in aggregating private information are needed to generate more credible results on the incentive to acquire information.

Second, overconfidence can lead to over-investment in private information. Ko

including observations from our *non-networked* and *complete* treatments.

and Huang (2007) study the information acquisition of overconfident instead of rational investors. These overconfident investors acquire costly information even in the absence of noise because they overestimate the value of their private information relative to the aggregated information in prices. They invest these resources in spite of it being unclear that they can even achieve returns that recoup these costs.

Third, the existing theoretical literature provides several reasons that can generate strategic complementarity in information acquisition activity. For example, García and Strobl (2011) show that if an investor's marginal utility of consumption increases in the average consumption of the other investors such that agents are sensitive to the wealth of others, the marginal value of information can increase in the number of agents who acquire it. This cannot be entirely ruled out, at least for some traders, in our setting. Other mechanisms that make information a complementary good, like short-term trades in a model of sequential trade (Chamley (2007)), correlation of noise in supply and fundamentals (Barlevy and Veronesi (2007)) presence of an additional dimension of supply information (Ganguli and Yang (2009)), and investors being ex-ante uninformed about the expected value of the asset fundamentals, and displaying ambiguity aversion (Mele and Sangiorgi (2015)), do not apply in our framework.

Using a Grossman-Stiglitz economy with general preferences instead of the usual constant absolute risk aversion, Peress (2004) shows that the demand for information increases with wealth. All traders in our market start with the same initial endowment of cash and assets, and hence, the wealth effect is absent in our setting. That agents with larger endowments acquire more information has been shown experimentally elsewhere (Page and Siemroth (2017)).

All the above mentioned studies on information acquisition are applicable for our *non-networked* treatment only as they assume no information linkages between investors. There are few theoretical studies on the effect of social communication on market outcomes. Using the specific cyclical network structure, Colla and Mele (2010) find that, compared to a market without network connections, a market with information linkages is characterized by higher volume, efficiency, and in general, higher liquidity. Ozsoylev and Walden (2011) introduce a rational expectations equilibrium model with large information networks and find that the aggregate trading volume is increasing in network connectedness in markets with low variance of network connectedness. Our experimental setup is closer to a model like Colla and Mele (2010) instead of the large information networks analyzed in Ozsoylev and Walden (2011). The results of these two papers, however, do not directly apply to our setting because both these studies assume that information is exogenously given unlike our experiments where information is costly and endogenously acquired.

Han and Yang (2013) is the only theoretical paper to study the effect of social communication on financial market outcomes when information has to be acquired endogenously at a cost. Using a rational expectations equilibrium model, it shows that if the cost of acquiring information is high, fewer people choose to acquire information when they are connected to more friends, which lowers investors' trading aggressiveness, raises cost of capital, and harms liquidity and volume. Moreover, price informativeness is lower with social communication.

Although our observation on the incentive to free ride on others' acquired information with more neighbors is consistent with the central finding of Han and Yang (2013), all the results of that paper are not generalizable to our setting. This is because their results rely on the islands-connections model used in the social network literature. There are a total mass of $\frac{1}{N}$ groups (islands) in the economy, each of which has $N \geq 1$ agents. Within any group every trader is connected to all other traders in the group, but there are no links across groups. This network structure is fundamentally different from the ones we use in our experiments.

Our main result on information acquisition only holds when social communication takes place over a regular network. Current theoretical studies on endogenous information acquisition do not allow us to explain this counter-intuitive finding. Future studies could focus specifically on information networks that are not regular and argue why central agents do not necessarily invest less in information gathering activities than the agents located at the periphery.

The free riding incentive might not be as strong if there are direct gains from exchange. For example, if the dividend from holding a unit of asset differs across individuals, revealing acquired information to neighbors might not be viewed as negative by a trader since this information sharing may open up mutually beneficial trading opportunities.[34] This is in contrast to our environment as there does not exist any exogenously imposed gains from exchange and trading is zero-sum among traders in the absence of risk aversion.

Given the substantial amount of trading volume we observe in our experimental sessions, it is imperative that we discuss the reasons for trading in our setting. Gains from trade could emanate from liquidity needs, such as consumption smoothing incentive in the presence of idiosyncratic income shocks (Asparouhova et al. (2016)) or through the implementation of a penalty in the event of failing to achieve an assigned trading target (Bloomfield, O'Hara and Saar (2009)). To the extent that there is no rational liquidity need present in our setting, we believe that trading takes place for the following two main reasons.

First, heterogeneous beliefs among investors make them trade with each other. If agents end up with different posterior beliefs about the fundamental variable, they

[34]As an illustration, consider the setting where there are two types of investors, type I and type II. Type I investors obtain 10 for every unit of the asset held if the underlying urn is A and 0 per unit if the underlying urn is B. On the other hand, type II investors get 0 (10) per unit of the asset held if the underlying urn is A (B). Sharing information might be beneficial in such a setting.

may have started with different prior beliefs, may have observed different signals, or may have used different updating rules (Xiong (2013)). In the absence of ex ante gains from trade, asymmetric information cannot generate trade among rational agents with a common prior (no-trade theorem of Milgrom and Stokey (1982)). However, it is possible that even rational agents may have heterogeneous prior beliefs (Morris (1995)). Another source of heterogeneous beliefs is overconfidence (Odean (1999), Scheinkman and Xiong (2003)) which causes agents to exaggerate the precision of noisy signals and thus over-react to the signals. When agents over-react to different signals, they may end up with substantially different beliefs.

Second, as argued in Blume, Coury and Easley (2006), if markets are state-contingent incomplete (as in our case), then there will be trade even if information is public and all traders agree on it's meaning. This is because of the presence of risk sharing opportunities among risk averse traders. Thus, observing frequent trades need not imply that investors interpret information differently or that some investors are irrational.

IV. 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 exchanged over a regular network, the probability of acquiring information and amount of signals purchased decreases with the number of neighbors of an investor.[35] Due to cost savings from lower information acquisition, communication via a regular network increases traders' earnings and social welfare.

In general, social communication results in larger trade volume and higher market liquidity. We also 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. 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.

To prevent the environment from becoming too complex, as a starting point of studying the impact of information exchange on incentive to acquire costly information, we implemented the automatic transmission of acquired information. It would be interesting to study the case where information is shared with imperfection. The free-riding effect might not be as strong under noisy information exchange.

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.[36]

[35]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.

[36]In our experiments, the network structure is exogenous and remains static throughout. An

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.[37]

immediate extension of our experiments would be to allow for the co-evolution of the information network.

[37]More generally, the issue of voluntary disclosure of information could be studied in our framework as well.

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