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Communication and Confidence in Financial Networks

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Abstract: We develop an asset pricing model in which agents communicate information in social networks prior to trading. An agent who is more confident in her private information attaches a greater weight on her private signal than on a signal received from communication when transmitting her information. The model generates novel implications: First, proximity between agents in networks affects correlation of asset demands. Second, the impact of agents' private information on asset prices depends on network structures. Third, irrespective of network structures, market liquidity, trading volume, price volatility and informational efficiency of prices are all higher with communication than without. Interestingly, information communication can alternatively explain some intriguing empirical facts which were attributed to overconfidence in the existing studies.

Key words: communication; confidence; overconfidence; circle network; star network

JEL codes: C90, D80, G10

No man is an island, entire of itself; every man is a piece of the continent, a part of the main.

-------- Jone Donne, early seventeenth English poet[1]

Word-of-mouth transmission of ideas appears to be an important contributor to day-to-day or hour-to-hour stock market fluctuation.

-------- Robert Shiller (2000, p. 155)

1. Introduction

Information communication takes various forms in financial networks where traders discuss news, share ideas and learn from each other. The existing literature on asset pricing under asymmetric information mainly focuses on the information aggregation or transmission role played by asset prices and on the resulting trading patterns under different trading schemes or market arrangements (O'Hara, 1995; Foucault, Pagano, & Roell, 2013). The social structures where traders directly interact with one another have been largely unexplored. Heterogeneous traders are assumed to make strategic decisions by monopolistically exploiting their own private information about the fundamental value of assets, and they completely ignore word-of-mouth communication and any other information exchange channels even when they have personal contact with competitors. In a sense, each trader resides alone in a spatially disconnected island.

A growing empirical literature has documented that information communication in financial networks affects individual trading behavior and market trading patterns. The purpose of this paper is to incorporate information

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[1] Quoted from *Meditation XVII* in *Devotions upon Emergent Occasions.*

communication in different financial networks into the strategic rational expectations framework *à la* Kyle (1985) and to study its asset pricing and welfare implications.[2] In particular, we propose a framework in which risk-neutral informed traders (henceforth called *agents*) engage in *direct* and *truthful* communication in an exogenously established social structure, represented by circle or star networks.[3] Simple as they are, circle and star networks have attracted most attentions by network economists. For instance, Bala and Goyal (2000) provide theoretical foundation of endogenous network formation. They show that under certain conditions, agents strategically form either circle or star network to share the informational benefits**.** A small number of papers that consider social communication in financial markets also focus on the circle and star networks (see section 2). The novelty of our modeling of communication is twofold. First, the flow of information transmission prior to trading is *one-way directed* and takes a specific form. In the circle network, each agent receives a signal from her closest left side neighbor, and then transmits a linear combination of her own private signal and this network signal to her closest right side neighbor. In the star network, in addition to her private signal, one agent receives another signal and entertains a central position; she similarly transmits a synthetic signal unilaterally to disjointed peripheral agents. The one-way directed information transmission modeling has the advantages that it facilitates equilibrium analysis. In the simplest way, the circle network represents the situation in which information is transmitted symmetrically while the star network captures the asymmetric information communication. As a starting point, analysis of these basic networks will further shed light on our understanding of more complicated ones. Second, when an agent forms the linear aggregation of private and network signals prior to trading, a measure of an agent's confidence degree of her private signal is integrated. More precisely, when aggregating and transmitting her information, the agent who is more confident in private information attaches a greater weight on the private signal than on the network signal received from communication. This modeling is introduced to capture the findings in cognitive psychology that agent tends to believe her private information is better than average (Odean, 1998).

One strand of empirical studies focuses on agents' portfolio choice influenced by their geographic proximity (e.g., Feng & Seasholes, 2004; Hong, Kubik & Stein, 2005; Ivković & Weisbenner, 2007). This phenomenon is explained either by home bias, local informational advantage, or by word-of-mouth information sharing. Our first result connects agents' proximity in financial networks to the correlation of their asset demands. Communication creates information overlapping among agents. When an agent is closer to her neighbors, the correlation of their demands is higher.

Not surprisingly, the impacts of private signal on equilibrium price are distinct in the circle and star networks. Agents in the circle network influences, through their private signals, the equilibrium price in an identical and symmetric manner. The central agent's private signal in the star network has greater influence on equilibrium price because it is exploited by the peripherals too. Trading behavior in the star network therefore provides a plausible explanation for the often observed large price swing in financial markets without prior significant change in fundamentals.

Despite the dissimilarity of agent's information utilization and social influence on price in different networks, we demonstrate that the market trading patterns are similar irrespective of network structures in that market liquidity, expected trading volume, price volatility and the informational efficiency of price, are all higher with communication than without. Communication generates additional more precise information, and agents thus

[2] We explain in section 3 why we illustrate the idea through this framework.

[3] Information manipulation is extensively studied in the literature, we therefore choose to assume it away and highlight the other aspects of communication. Section 2 reviews some studies that consider direct and truthful information disclosure.

trade more aggressively and on average trading volume increases. Equilibrium price becomes more volatile as each private signal has a greater impact on the price. The more intense competition lessens the adverse selection faced by a competitive market-maker thus the market becomes more liquid. At the same time, since more information is revealed to the market-maker who therefore sets price closer to the asset value, as a result price becomes more informative and efficient. These results accord well with the well-known empirical findings of market trading phenomena such as tremendous trading volume and excessive price volatility. Theoretical work has extensively explored the underlying economic mechanisms. Our information communication explanation is new and complements the existing studies.

When an agent attaches a very high confidence degree on her private signal relative to the signal received from communication, we can argue that she is overconfident in her private signal, in other words, she mistakenly believes that her private signal is more precise than others'. We establish that market liquidity, expected trading volume, price volatility and price efficiency in both networks are strictly decreasing in the confidence degree while agents' expected profits are increasing in it. These comparative statics are directly opposite to the existing overconfidence literature which also aims to explain the high market liquidity, expected trading volume, price volatility and price efficiency and investors' low expected profits (Odean, 1998; Wang, 1998; Gervais & Odean, 2001; among others). Very interestingly, some intriguing empirical facts documented by Barber and Odean (2001, 2002) that men or online traders on average trade more frequently but less profitably than women or phone-based traders, previously attributed to the traders' overconfidence tendency, can be alternatively interpreted by the fact that they are more prone to participate in communication regarding asset information relative to their counterparts. Therefore we provide an alternative explanation and these findings have not been previously reported in the literature.

The paper is organized as follows. Section 2 reviews the existing literature. Section 3 extends Kyle's model, defines equilibrium strategies and introduces the modeling of information communication and confidence degrees. Section 4 and 5 derive asset pricing and welfare implications of information communication in the circle and star networks respectively. Section 6 compares the explanations of information communication and overconfidence regarding market trading patterns and individual welfare. Section 7 presents brief concluding remarks. All analytical proofs are relegated to the Appendix.

2. Literature Review

Trading activity is economic as well as sociological. Shiller (2000) provides a broad and in-depth investigation of world-of-mouth communication among financial markets traders. Nonetheless, only until very recently have economists found actual supporting data. Feng and Seasholes (2004) present that isolated groups of investors in one region of a country engage in positive correlated trading behavior at a weekly frequency. Hong, Kubik, and Stein (2004) find that socially active households are more likely to invest in the stock markets. Hong, Kubik, and Stein (2005) show that, even in the absence of local information advantage, a mutual fund manager is more likely to hold or trade a particular stock in any quarter if other managers from different fund families located in the same city are holding or trading that stock. Ivković and Weisbenner (2007) attribute one-quarter to one-half of the correlation between households' stock purchases and stock purchases made by their neighbors to word-of-mouth communication.

The recent popularity of the Internet chat rooms on financial investment as a medium of financial markets discussion attracts a lot of academic attention. Wysocki (1998) reports that message posting forecast next-day trading volume and next-day abnormal stock returns. The firms with high message postings are characterized by high trading volume. Antweiler and Frank (2004a) find that high message posting on a given day is associated with a small negative return and greater volatility on the next day. Antweiler and Frank (2004b) consider a much larger database and show that stocks that are heavily discussed are particularly heavily traded, unusually volatile, and have surprisingly poor subsequent returns. Our paper contributes to both literatures by formally providing economic mechanism that governs the interaction among information communication, trading behavior and asset pricing.

Disproportionately, only a few authors develop analytical models to study the effects of information communication in financial networks. Ozsoylev (2004) studies the existence and properties of equilibrium price when social interaction is incorporated into Hellwig (1980). Ozsoylev (2005) allows agents to directly and truthfully share information in social network with very general structure. He establishes that proximity between agents in network influence agents' asset demand correlation and that communication in network may account for the observed high volatility ratio of price to fundamentals in financial markets. Colla and Mele (2010) consider information communication in a circle network à la Foster and Viswanathan (1996). Han and Yang (2013) show that in the presence of communication, the properties of market liquidity, expected trading volume, price volatility and price efficiency depend crucially on whether private signals are exogenous available or endogenously acquired. Our model generates a number of novel implications regarding asset pricing and trading behavior, and can be seen as a complement to above analytical work. Moreover, the modeling of confidence is a unique feature in our paper, making it is possible to compare our model with overconfidence literature which also produces similar implications consistent with empirical findings.

One-way directed but strategic information communication in an essential star network à la Kyle (1985) has been studied intensively in the voluntary disclosure literature. Bushman and Indjejikian (1995), and Shin and Singh (1999) show that an insider can benefit from disclosing her information to some extent, which is achieved either by eroding the informational advantages of her competitors through market-maker's adjusted pricing strategy, or by diluting competitors' information and regaining monopoly on her additional private signal. Van Bommel (2003) show that a wealth constrained insider gains by spreading rumor such as buy or sell to an audience of followers when each informed follower continues to pass the rumor to a number of uninformed followers. In our paper information communication is modeled as sociological trait associated with trading behavior rather than strategic and beneficial use of information.

The role of interpersonal and interactive communication through social network in decision making has long been recognized in other fields of economic activities. Ellison and Fudenberg (1995) and Bala and Goyal (1998) show that communication in social networks play a major role in technology adoption. DeMarzo, Vayanos and Zwiebel (2003) explore the role of repetitive information communication in social networks to understand behavioral bias in political and marketing issues. Their model can be used to capture local preference for conformity and habit persistence. Jackson (2010) presents an excellent textbook on network economics.

3. The Basic Framework

We model the information communication in the strategic rational expectations model pioneered by Kyle (1985). Introducing information communication into the competitive rational expectation paradigm à la Hellwig

(1980) will not change the main results of this paper since the driving mechanism is still applicable. However, in the latter framework both price and communication convey information across agents which complicates the analysis of conditional expectation formation regarding risky asset value.[4] The advantage of modeling information communication in Kyle (1985) is evident since agents cannot observe price when they submit market order, therefore the communication effect can be demonstrated clearly.

3.1 The Economy

In a security market n risk-neutral privately informed agents and uninformed noise traders submit market orders simultaneously to a risk-neutral competitive market-maker, not knowing the market clearing price when they do so. Trading takes place at time 1 and the single risky asset is liquidated at time 2. The terminal value of the asset $\tilde{v}$ is normally distributed $N = (\bar{v}, \sum)$ (where $\bar{v}$ is assumed, without loss of generality, to be 0. Prior to trading, agent i observes a signal $\tilde{s}_i = \tilde{v} + \tilde{\varepsilon}_i$ where $\tilde{\varepsilon}_i$ is normally and identically distributed N(0, Φ) for $i \in \{1,...,n\} = N$. In the presence of information communication, agent i receives a network signal $\tilde{r}_i$ from another agent, whose exact form depend on network structure and will be made clear in the subsequent sections. Noise traders submit an exogenous random quantity $\tilde{u}$ which is normally distributed N(0, Ω). The random variables $\tilde{v}, \tilde{\varepsilon}_i$ and $\tilde{u}$ are assumed to be mutually independent for all i. The market-maker absorbs the net trade and sets price expecting to earn a zero profit.

Agent i's trading strategy is given by a measurable function X_i: $\mathbb{R}^2 \to \mathbb{R}$, determining her market order as a function of her information set $\tilde{\mathcal{I}}_i = (\tilde{s}_i, \tilde{r}_i)$. For a given strategy, let $\tilde{x}_i = X_i(\tilde{\mathcal{I}}_i)$. A strategy profile $\{X_1, \ldots ,X_n\}$ determines order flow $\tilde{\omega} = \sum_{i=1}^{n} \tilde{x}_i + \tilde{u}$. The market-maker's pricing strategy is given by a measurable function P: $\mathbb{R} \to \mathbb{R}$. Given($X_1, \ldots,X_n, P$), define $\tilde{p} = P(\tilde{\omega})$ and let $\tilde{\pi} = (\tilde{v} - \tilde{p})\tilde{x}_i$ denote the resulting profit for agent i.

Based on her information set, each agent acts strategically by taking into account the fact that her optimal demand, as well as others' order decisions, will influence the asset price and her profit. The market-maker attempts to infer the private information from the order flow and sets price as efficiently as possible to protect himself from adverse selection. These considerations are formally expressed below.

Definition 1 *The Bayesian Nash equilibrium consists of agents' trading strategy profile* $\{X_1, \ldots ,X_n\}$ *and the market-maker's pricing strategy P, such that the following conditions hold:*

(1) Profit maximization: for agenti's any alternative trading strategy $X_i^{'}$,

$$\mathbb{E}\left(\tilde{\pi}_i \mid \tilde{\mathcal{I}}_i\right) \geq \mathbb{E}\left(X_i^{'}(\tilde{\mathcal{I}}_i)\left[\tilde{v} - P\left(\sum_{j\neq i} \tilde{x}_j + X_i^{'}(\tilde{\mathcal{I}}_i) + \tilde{u}\right)\right]\middle| \tilde{\mathcal{I}}_i\right); \tag{1}$$

(2) Market semi-strong efficiency: the pricing strategy P satisfies

$$P\left(\tilde{\omega}\right) = \mathbb{E}\left(\tilde{v}\middle|\tilde{\omega} = \sum_{i=1}^{n} \tilde{x}_i + \tilde{u}\right). \tag{2}$$

We focus on equilibrium with linear strategies and postulate that agent i's trading strategy and the market-maker's pricing strategy are

[4] To distinguish the role played by communication from price, Ozsoylev (2005) has to assume an unrealistically large noise trading variance, so that variations in price mainly reflect variations in noise trading rather than variations in information.

$$X_i\left(\tilde{s}_i,\tilde{r}_i\right) = \alpha_i\tilde{s}_i + \beta_i\tilde{r}_i,\ i \in \mathcal{N},$$
$$P\left(\tilde{\omega}\right) = \lambda\tilde{\omega},$$

respectively. We refer to α_i and β_i as trading intensity parameters associated with private and network signals, and λ as the market liquidity/depth parameter. A low λ means a more liquid (or deeper) market in the sense that the cost of a given trade is low. In the presence of communication, symbol subscripts will be used to indicate network structures.

3.2 Information Communication and Confidence Degree

After observing private signals, agents engage in information communication. Depending on network structures, an agent directly sends and/or receives *truthful* information to/from other agents. The model therefore rules out strategic information transmission and information-based price manipulation.

To fix idea, besides private signal $\tilde{s}_i$, agent *i* receives a network signal, denoted by $\tilde{r}_i$, from information communication in a social network. When a new agent *j* joins the network and connects to agent *i*, the former gets information $\tilde{r}_j$ from the latter as information is assumed to be transmitted in a one-way direction. The content of $\tilde{r}_j$ can take many different forms. For example, agent *i* may choose to send her private signal only, so $\tilde{r}_j = \tilde{s}_i$; or agent *i* may simply pass her network signal, therefore $\tilde{r}_j = \tilde{r}_i$; or agent *i* may disclose all of her information, that is, $\tilde{r}_j = \left\{\tilde{s}_i,\tilde{r}_i\right\}$. The first case is studied by Ozsoylev (2005), Colla and Mele (2010), and Han and Yang (2013), while the last one is considered by Bala and Goyal (2000).[5] Above examples have their own merits, nonetheless other possibilities deserve exploring. In this paper we study a specific form of information communication. Agent *j* is assumed to receive synthetic information from agent *i* that $\tilde{r}_j$ is a linear combination of $\tilde{s}_i$ and $\tilde{r}_i$:

$$\tilde{r}_j = \theta\tilde{s}_i + \left(1-\theta\right)\tilde{r}_i,\ \ i,j \in \mathcal{N}. \tag{5}$$

Where the parameter $\theta \in [0,1]$ is the weight attached to agent *i*'s private signal. When $\theta = 0$ or 1, this communication rule coincides with the first two examples mentioned above. It is also compatible with the full-disclosure example since the weights can be chosen such that $\tilde{r}_j$ becomes the sufficient statistic of $\left\{\tilde{s}_i,\tilde{r}_i\right\}$. A similar information aggregating rule in a repetitive communication model is studied by DeMarzo, Vayanos and Zwiebel (2003). In their model, the weights θ and $1-\theta$ reflect the relative precision of $\tilde{s}_i$ and $\tilde{r}_i$ respectively, that is, the linearly combined information is the sufficient statistic of individual signals regarding asset value; or they embody agent's beliefs about $\tilde{s}_i$ and $\tilde{r}_i$ so that information is not necessarily aggregated efficiently.

In this paper we interpret the weights θ and $1-\theta$ as agent's *confidence* degrees of her private and network signals respectively, and we study the impacts of varyingθ on the resulting individual trading behavior and market trading patterns. For simplicity we assume that all agents select the same θ so it is can be thought of as a measure of public confidence in private signal. Two attractive features of this modeling choice will be evident in the subsequent analysis. First, when agents' confidence degree is very high, its effect on signals' relative precision looks as if agents favorably perceive the precision of private signals compared to that of network signals, i.e.,

[5] In the model of Bala and Goyal (2000), when agent *j* is connected to agent *i* who is linked to agent *k*, then agent *j* will derive benefit from both agents *i* and *k*, even though agent *j* is not connected with agent *k* directly.

agents are *overconfident* in their private signals. Second, the information structures in the circle and star networks, together with the restriction that $\theta \in [0, 1]$, guarantees that network signals are no less precise than agents' private signals, so that agents do not ignore the information content of the network signals.

4. Trading in Circle Network

In this section we study individual trading behavior and market trading patterns in the security market when information communication structure is presented by a circle graph. The environment is identical to what is introduced in section 3 except that *n* informed agents are ordered clockwise, as to say that agent *i* has agent *i*+1 to her left and agent *i*-1 to her right. The graph in Figure 1 is a symbolic representation of a circle network. It implies an abstraction of the reality so communicating agents can be simplified as a set of linked nodes, and arrows indicate the *one-way* directed information transmission.

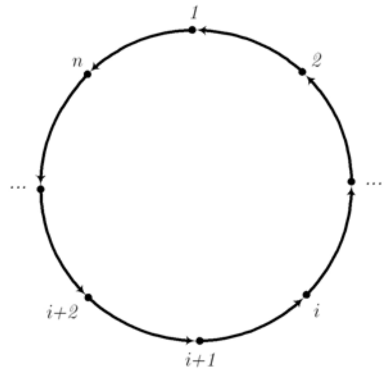

Figure 1 Information Transmission in the Circle Network

Note: The set of linked nodes represents social communication among agents. Arrows indicate the direction of information transmission. For all $i \in \mathcal{N}$, in addition to private signal, agent i receives "synthetic" network signal about the risky asset value from agent *i*+1 (*modn*).

Prior to trading, an agent, say *i*+1, obtains information from her closest left side neighbor *i*+2. Agent *i*+1 then determines a linear combination of her private and network signals, then transmits the synthetic information to her closest right side neighbor *i*, and so on. It is assumed that the lack of geographical or socioeconomic proximity prevents agent *i*+2 from directly communicating with agent *i*. We therefore have the expression for the network signal:

$$\tilde{r}_i = \theta \tilde{s}_{i+1} + \left(1-\theta\right)\tilde{r}_{i+1} \pmod{n},\ \ i \in \mathcal{N},\ \ \theta \in (0,1]. \tag{6}$$

The modular arithmetic with modulus *n*, denoted by (mod n) is used if necessary. For example, five agents after $(n\text{-}2)^{th}$ agent is the third agent.

Although the circle network considered is something of a modeling device, it is not too unrealistic. First, Bala and Goyal (2000) show that under certain conditions agents will strategically form a circle network when beneficial information transmission is one-way directed. It is conceivable that, at least in short period, these agents will rely on this established network to exchange information. Second, the modeling captures some important features of communication in financial markets. For example, the successive circulation of investment newsletter and financial press, and the orderly and continuous discussion on Internet stock message boards resemble quite closely the one-way directed communication in the circle network.

Assume away repetitive information transmission, the circle network dictates that

$$\tilde{r}_i = \tilde{r}_{i+n} \pmod{n},\ i \in \mathcal{N}. \tag{7}$$

When $\theta \in [0, 1]$, (6) and (7) together yield

$$\tilde{r}_i = \frac{\theta \sum_{k=0}^{n-1} (1-\theta)^k \tilde{s}_{i+k+1}}{1-(1-\theta)^n} = \tilde{v} + \frac{\theta \sum_{k=0}^{n-1} (1-\theta)^k \tilde{\varepsilon}_{i+k+1}}{1-(1-\theta)^n} \pmod{n},\ i \in \mathcal{N}, \tag{8}$$

thus information received from the closest left side neighbor not only contains her private signal but also aggregates signals of agents linked by the closest left side neighbor, and signals of those who are linked by agents linked by the closet left side neighbor, and so on. It is noteworthy that the weights of $\tilde{s}_{i+k+1}$, the private signals of agent *i*'s left side neighbors, for k = 0, …, n-1, are ranked in a descending order in $\tilde{r}_i$ and the weights sum up to one.

When $\theta = 1$, (8) is replaced with

$$\tilde{r}_i = \tilde{s}_{i+1} \pmod{n},\ i \in \mathcal{N}, \tag{9}$$

so agent *i*'s network signal is just the private signal of her closest left side neighbor.

It is easy to show that the network signal is distributed identically as

$$\tilde{r}_i \sim \mathbf{N}\left(0,\ \Sigma + \frac{\theta}{2-\theta} \frac{1+(1-\theta)^n}{1-(1-\theta)^n} \Phi\right),\ i \in \mathcal{N} \text{ and } \theta \in (0,1]. \tag{10}$$

The equilibrium trading and pricing strategies in the circle network are similarly defined as Definition 1 except that network signal $\tilde{r}_i$ in information set $\tilde{\mathcal{I}}_i$ is given by (8) and (9) when $\theta \in (0,1)$ and $\theta = 1$ respectively. Subscript $\circ$ is used below to indicate the circle network. A unique symmetric linear equilibrium is solved and the results are collected in Theorem 1.

Theorem 1 *In the circle network, there exists a unique symmetric linear equilibrium*

$$X_{\circ i}(\tilde{s}_i, \tilde{r}_i) = \alpha_\circ \tilde{s}_i + \beta_\circ \tilde{r}_i,\ i \in \mathcal{N}, \tag{11}$$

$$P_\circ(\tilde{\omega}) = \lambda_\circ \left(\sum_{i=1}^{n} \tilde{x}_{\circ i} + \tilde{u} \right). \tag{12}$$

Where the trading intensity parameters $\alpha_\circ$ and $\beta_\circ$, and the liquidity parameter $\lambda_\circ$ are given by

$$\alpha_\circ = \frac{\theta}{2-\theta} \beta_\circ$$

$$\beta_\circ = (2-\theta) \sqrt{\frac{\left[1-(1-\theta)^n\right]\Omega}{4n\left[1-(1-\theta)^n\right]\Sigma + 2n\theta[1+(1-\theta)^{n-1}]\Phi}}$$

$$\lambda_\circ = \frac{\Sigma}{\sqrt{\Omega}} \frac{\sqrt{2n\left[1-(1-\theta)^n\right]\left(2\left[1-(1-\theta)^n\right]\Sigma + \theta[1+(1-\theta)^{n-1}]\Phi\right)}}{2(n+1)\left[1-(1-\theta)^n\right]\Sigma + [(3\theta-2)(1-\theta)^{n-1} + 2 + \theta]\Phi}$$

The second order condition $\lambda_\circ > 0$ is satisfied.

The impacts of exogenous parameters (n, Σ, Φ, Ω) on equilibrium properties have been intensively explored in the extensions to Kyle (1985) without information communication. Their roles in the communication economy are similar. For instance, the market liquidity parameter is decreasing in the number of informed agents n because more competition leads to a decrease in the adverse selection faced by the market-maker. In the circle network an increase in n also increases the precision of network signal, which further reinforces the competition between agents, enabling market to be even more liquid. Similarly, the variance of noise trading Ω does not affect price volatility and price efficiency because agents scale up their trading intensities in response to an increase in the amount of noise trading, no matter whether there is information communication or not. Since the confidence degree θ is a new parameter in the model, we only focus on its effects on individual trading behavior and market trading patterns to preserve space in the following equilibrium analysis.

4.1 Demand Correlation and Proximity

The empirical studies by Feng and Seasholes (2004), Hong, Kubik, and Stein (2004, 2005), and Ivković and Weisbenner (2007) suggest that the closer is the geographic proximity between agents, the more correlated is their trading behavior. Other than the possible local information advantage, one way to formalize this observation is to show the relationship between correlation of agents' demands and their proximity is decreasing. Proposition 1 shows that this is indeed the case.

Proposition 1 *In the circle network, when* $n \geq 4$*, we have:*[6]

(1) *The correlation of agent demands is non-increasing in agents' proximity for* $\theta = 1$. *In particular, the correlation of an agent and her closest neighbors' demands is the largest.*

$$corr\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i\pm 1}\right) > corr\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i+\ell}\right) = corr\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i+j}\right) \pmod{n},\ 2 \leq \left|\ell\right| < \left|j\right| \leq n\ /\ 2.$$

(2) *The correlation of agent demands is strictly decreasing in agents' proximity for* $\theta \in (0, 1)$.

$$corr\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i+\ell}\right) > corr\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i+j}\right),\ \pmod{n},\ 1 \leq \left|\ell\right| < \left|j\right| \leq n\ /\ 2.$$

When $\theta = 1$, we have $\alpha_\circ = \beta_\circ$ and for $i \in \mathcal{N}$,

$$corr\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i\pm 1}\right) = \frac{4\Sigma + \Phi}{4\Sigma + 2\Phi} \pmod{n},$$

$$corr\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i+j}\right) = \frac{2\Sigma}{2\Sigma + \Phi},\ 2 \leq \left|j\right| \leq \frac{n}{2},\ \pmod{n}.$$

It's clear that the correlation of an agent and her closest left/right neighbor's demands is the largest as the overlapping of private signals is the greatest. A stronger monotone relationship is established when $\theta \in (0, 1)$. The reason is straightforward: when agent $i + \ell$ is closer to i than $i + j$, her private signal has more influence on i's demand. At the same time, although agent i's private signal has more influence on $i + j$'s demand, the latter's influence is dominated by the former's. As a result, the correlation of demands between agents i and $i + \ell$ is larger than that between agents i and $i + j$.

In our model proximity could be broadly determined by ethnical, cultural and socioeconomic factors, and the same idea is applicable in other financial decisions. For instance, Kelly and Ó Gráda (2000) examine the behavior of Irish depositors in a New York bank during two panics in 1850s. The social network of these recent immigrants, which was largely determined by place of origin in Ireland and neighborhood in New York, turns out to be the prime determinant of behavior. Duflo and Saez (2002) discover that individual's decision to enroll in particular employer-sponsored retirement plans and the choice of the mutual fund vendor are affected by the choices of his

[6] When n = 2 or 3 the proposition is trivial.

co-workers. Cohen, Frazzini, and Malloy (2008, 2010) respectively find that mutual fund managers and sell-side analysts gain a comparative information advantage through their social networks; specifically, through educational ties with senior officers and board members of the firms.

4.2 Market Patterns and Expected Profit

In this subsection, we demonstrate the remarkable effects of communication and confidence degree on market trading patterns and agent's expected profit. Proposition 2 is crucial for its intuitive appealing in understanding the main results.

Proposition 2 *In the circle network, precision of the network signal* $\tilde{r}_i$ *is strictly higher than that of the private signal* $\tilde{s}_i$ *when confidence degree* $\theta \in (0, 1)$, *and it is strictly decreasing in* $\theta \in (0, 1]$ *for each agent* $i \in \mathcal{N}$.

Recall the expression of network signal (8) when $\theta \in (0, 1)$, the i.i.d. nature of noise terms in private signals, after weighted by confidence degree and linearly aggregated together, naturally make the network signal to be more precise than any private signal regarding the asset value. The monotonicity result comes from two facts. First, in an agent's network signal, the θ-dependent weights of signals of her left side neighbors are ranked in a descending order; Second, the θ-dependent weights sum up to one. Therefore when confidence degree increases, these weights vary over a broader range which cause the network signal to be more volatile, or equivalently, less precise.

We are interested in the implications of information communication and confidence degree on market patterns such as market liquidity, expected trading volume, price volatility and price efficiency. The market liquidity is captured by λ. Total trading volume $\tilde{V}$ aggregates trades that are crossed between traders, informed or uninformed, and net demand presented to the market-maker, thus it is defined by

$$\tilde{V} = \frac{1}{2}\left(\sum_{i=1}^{n}\left|\tilde{x}_i\right| + \left|\tilde{u}\right| + \left|\tilde{\omega}\right|\right) \tag{16}$$

Where the coefficient 1/2 corrects the double counting when summing trades over all traders. Price volatility is the variance of equilibrium price $\tilde{p}$. Price efficiency, or informational efficiency (informativeness) of price is either measured by the posterior precision of $\tilde{v}$ or the residual variance of $\tilde{v}$, conditional on equilibrium price $\tilde{p}$ (or order flow $\tilde{\omega}$). They are informationally equivalent so we adopt the first. Additionally, we also study the impact of communication and confidence degree on an agent's unconditional expected profit.

Proposition 3 *When* $n > 1$, *market liquidity, expected trading volume, price volatility and price efficiency in the circle network are strictly higher with communication than without. Moreover, when* $n > 2$, *they are strictly decreasing in confidence degree* $\theta \in (0, 1]$ *in the presence of communication.*

The intuition for the first part is as follows. Agents trade more aggressively simply because they can exploit more available information which is also more precise regarding asset value. Information communication causes prices to be more sensitive to changes in agents' private signals and less sensitive to changes in noise traders' demand. The market-maker realizes that agents trade more intensely and accordingly moves price less in response to changes in order flow than he would if agents abstain from communication. In other words, he flattens the supply curve, therefore increasing market liquidity. Because communicating agents trades more in response to private signals, their expected trading increases relative to that of noise traders. Consequently the signal-to-noise ratio in total order flow increases and the market-maker is able to make better inference about agents' signals. The price he sets then varies more in response to changes in private signals which increases the price volatility. From a different perspective, although the market-maker has flattened the supply curve, thus dampening volatility for any given level of expected order flow, the increased order flow generated by communicating agents more than offsets this dampening, and results in increased volatility. At the same time, the better inference enables the market-maker to form a more accurate posterior expectation of asset value and to set price that is, on average, closer to asset value. The informativeness or efficiency of prices is thus improved.

This analysis reveals that communicating agents trade more aggressively relative to isolated agents, whatever the confidence degree of the former, is the key to understand the comparative statics of market trading patterns. The monotonicity result of the second part comes from the mechanism given in Proposition 2. A higher confidence degree of communicating agents leads to relatively less accurate network signals, which impair agents' assessment of asset value. As a consequence they trade cautiously, thereby market liquidity, price volatility and price efficiency become smaller. The monotonicity result does not hold when $n = 2$, since when information is transmitted between two agents, each agent can infer other's private signal directly. Consequently, θplays no role in affecting agent's trading behavior and market patterns.

The tremendous trading volume in financial markets is a challenge to the no-trade theorem developed by Milgrom and Stoky (1982) in that differences in information alone cannot explain the observed levels of trading volume. Several motives have been extensively explored in the literature. The competitive and strategic noisy rational expectations models, pioneered by Grossman and Stiglitz (1980) and Kyle (1985) respectively, demonstrate that private information and noise (liquidity) trading are the major motive for trade. Although noise trading is not necessarily irrational, ascribing the enormous trading volume to noise trading is unappealing theoretically and empirically. Our model suggests that once information communication is considered, the burden for the required level of noise trading can be lessened. More recently, heterogeneous prior beliefs has been proposed as another significant motive for trade. The high levels of trading volume in Harris and Raviv (1993) and Kandel and Pearson (1995) arise from differences of opinion about an asset value, while in Odean (1998) and Wang (1998) they are attributed to agents' overconfidence in private signal's precision. Our information communication explanation can accommodate these motives, thus help us to better understand the trading phenomena. The recent burgeoning of stock message boards also provides supportive evidence reviewed earlier. Our model's predications are consistent with these findings.

Communication is a sociological need for human being. In many cooperative contexts communication brings welfare improvement. Nonetheless, do agents gain from information communication when they are strategically competing against one another? The answer is not crystal clear. Communication is beneficial as well as costly. Agents are able to better assess the asset's risk due to more precise network signals, but they lose monopoly on private signals simultaneously. Proposition 4 reveals that the latter outweighs the former in the circle network.

Proposition 4 *When $n > 1$, an agent's unconditional expected profit in the circle network is lower with communication than without. Moreover, when $n > 2$, it is strictly increasing in confidence degree* $\theta \in (0, 1]$.

A key element underlying this welfare impairment result is that agents are risk neutral. To such agents the advance in risk assessment is not very attractive. Additional more accurate information generated from communication, accompanied by less monopoly on private signals, leads to more intense competition among agents which helps the market-maker to better infer the asset value, thus equilibrium price is on average set closer to the asset value. Consequently, each agent suffers from the communication. This intuition is echoed by the second part of this proposition. Agents are relatively better off even though higher confidence degree of private signal makes the network signal to be less precise.

This result raises the concern that information communication in financial markets is undesirable and the circle network cannot be established in the very beginning. Such pessimistic conclusion is nonetheless too hasty. As pointed out by Hong, Kubik and Stein (2004), agents get pleasure from conversation about financial markets with friends who are also fellow participants. Moreover, if agents are risk averse, the benefit of communication may exceed its cost. On the one hand, the advantage of more precise network signal, favored by risk-averse agents, may dominate the monopoly loss in private signals. On the other hand, risk-averse agents generally trade cautiously so market-maker gains less informational advantage, resulting in a wider profit margin. This effect is strengthened when the number of agents is small, or equivalently, the competition is less intense. Indeed, Eren and Ozsoylev (2006) use numerical solution to formalize these observations in a two risk-averse agents Kyle model. We choose to study the risk-neutral case because of its analytical clarity.

5. Trading in Star Network

We next consider a new financial network in which information communication structure is represented by a star graph. The information structure is similar to what is introduced in section 3, except that one agent, conveniently labeled as agent 1, receives additional information and is surrounded by other $n-1$ disconnected agents who do not participate in information communication. To fix notations, agent1 has a private signal $\tilde{s}_1$ and receives signal $\tilde{r}_1 = \tilde{v} + \tilde{\varepsilon}_0$. For simplicity we assume that $\tilde{\varepsilon}_0 \sim N(0,\Phi)$ and $\tilde{\varepsilon}_0, \tilde{\varepsilon}_1, \tilde{\varepsilon}_i$ for $i \in N \setminus \{1\}$ are identically and independently distributed. Moreover, $\tilde{v}, \tilde{\varepsilon}_0$ and $\tilde{u}$ are mutually independent.

The central agent 1 truthfully transmits a linear combination of $\tilde{s}_1$ and $\tilde{r}_1$ to all other peripheral agents prior to trading in a similar manner specified before:

$$\tilde{r}_i = \theta \tilde{s}_1 + (1-\theta)\tilde{r}_1, \quad i \in \mathcal{N} \setminus \{1\}, \theta \in [0,1]. \tag{17}$$

The weight θ reflects the central's confidence degree of her private signal and is assumed to be known to the peripherals. Clearly θ = 1/2 causes $\tilde{r}_i$ to be the sufficient statistic of $\tilde{s}_1$ and $\tilde{r}_1$, but the central agent may choose θ > 1/2 because of a personal attachment of her private signal. Figure 2 depicts the flow of information transmission in the star network.

This modeling device captures in a stylized way a number of real-life situations. First, the central agent may choose to share information simply because of legal requirements. For instance, the SEC requires public traded company to fully disclose corporate events information that will affect stock's subsequent performance. Still, in practice company has discretion to display distinct information with different emphases. Second, financial analysts or some information gurus who are willing to communicate their information from multiple sources have a large audience not only in traditional financial press and media but also in virtual worlds such as Internet stock message boards.

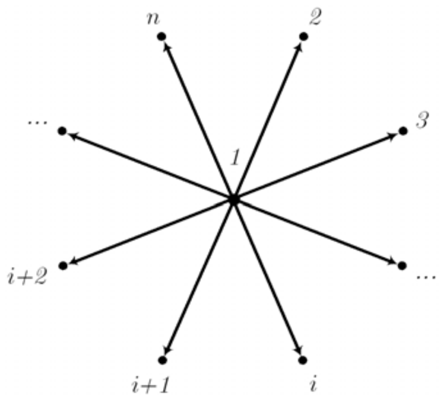

Figure 2 Information Transmission in the Star Network

Note: The set of linked nodes represents social communication among agents. Arrows indicate the direction of information transmission. For all $i \in \mathcal{N} \setminus \{1\}$, in addition to private signal $\tilde{s}_i$, peripheral agent *i* receives "synthetic" signal $\tilde{r}_i$ about the risky asset' value from central agent 1.

Using subscript $\star$ to denote the star network, the equilibrium is similarly defined as Definition 1 except that $\tilde{\mathcal{I}}_1 = \left(\tilde{s}_1, \tilde{r}_1\right)$ and $\tilde{\mathcal{I}}_i = \left(\tilde{s}_i, \tilde{r}_i\right)$ for $i \in \mathcal{N} \setminus \left\{1\right\}$ where $\tilde{r}_i$ is defined in (17). Assuming symmetric linear trading strategies among peripheral agents, we have:

Theorem *In the star network, there exists a unique linear equilibrium*

$$
\begin{aligned}
X_{\star 1}\left(\tilde{s}_1, \tilde{r}_1\right) &= \alpha_\star \tilde{s}_1 + \beta_\star \tilde{r}_1, \\
X_{\star i}\left(\tilde{s}_i, \tilde{r}_i\right) &= \gamma_\star \tilde{s}_i + \delta_\star \tilde{r}_i,\ i \in \mathcal{N} \setminus \left\{1\right\}, \\
P_\star\left(\tilde{\omega}\right) &= \lambda_\star \left(\tilde{x}_{\star 1} + \sum_{i=2}^{n} \tilde{x}_{\star i} + \tilde{u}\right).
\end{aligned}
$$

Where the trading intensity parameters $a_\star, \beta_\star, \gamma_\star$ and $\delta_\star$, and the liquidity parameter $\lambda_\star$ are given by

$$
\begin{aligned}
\alpha_\star &= \frac{\sqrt{\Omega}([2n\left(1-\theta\right)^2 + 2\theta + 1]\Sigma + 2\left[n\left(1-\theta\right)\left(1-2\theta\right) + \theta\right]\Phi)}{\sqrt{2\left(a\Sigma^3 + b\Sigma^2\Phi + c\Sigma\Phi^2 + d\Phi^3\right)}}, \\
\beta_\star &= \frac{\sqrt{\Omega}\left([2n\theta^2 - 2\theta + 3]\Sigma + 2\left[n\theta\left(2\theta - 1\right) - \theta + 1\right]\Phi\right)}{\sqrt{2\left(a\Sigma^3 + b\Sigma^2\Phi + c\Sigma\Phi^2 + d\Phi^3\right)}}, \\
\gamma_\star &= \frac{\sqrt{2\Omega} n\left(1 - 2\Theta\right)\left(\Sigma + \Phi\right)}{\sqrt{a\Sigma^3 + b\Sigma^2\Phi + c\Sigma\Phi^2 + d\Phi^3}}, \\
\delta_\star &= \frac{2\gamma_\star}{n\left(1 - 2\Theta\right)}, \\
\lambda_\star &= \frac{\Sigma}{\sqrt{2\Omega}} \frac{\sqrt{a\Sigma^3 + b\Sigma^2\Phi + c\Sigma\Phi^2 + d\Phi^3}}{e\Sigma^2 + f\Sigma\Phi + g\Phi^2},
\end{aligned}
$$

Where $\Theta = \theta\left(1 - \theta\right)$, and the full expression for *a, b, c, d, e, f* and *g* are given explicitly in the Appendix. The second order condition $\lambda_\star > 0$ is satisfied.

A prominent feature of the central agent's equilibrium trading strategy stands out. After transmitting a positive and linear combination of her private and received signals, she may optimally select a trading strategy in which one trading intensity coefficient is possibly negative. For instance, fix variance parameters, when the central agent integrates a high confidence degree of her private signal in information transmission, the peripherals can better assess and exploit the central's private signal. At the same time if the number of the peripherals is large so that competition is very intense, the central may gain by choosing a negative trading intensity on her private signal.

We can address the relation between agents' proximity and correlation of their demands again if information communication structure can be broadly represented by multiple identical but disjoint star networks. It is easily shown that the correlation of demands of agents in the same star is larger than the correlation of demands of agents located across different stars. In other words, the correlation of agent demands is decreasing in their proximity.

5.1 Private Signal's Social Influence

We are concerned about the influence of one agent's private signal on other agents' trading behavior and equilibrium asset price. Apparently, in the circle network each agent's signal's influence is symmetric and identical. When information is asymmetrically transmitted in the star network, this property is altered significantly. For example, Ozsoylev (2004) shows that, when a star network is introduced into Hellwig (1980), the influence of a central agent's signal on equilibrium price is infinitely large when the number of peripheral agents approaches infinity. However, this is not the case in our model.

Proposition 5 *In the star network, the central agent's private signal has a greater influence on equilibrium price than any other peripheral agent's signal. However, the influence ratio is finite for all* $n > 1$. *That is, for all realized private signals and equilibrium price, we have*

$$1 < \frac{\partial p_\star \,/\, \partial s_1}{\partial p_\star \,/\, \partial s_i} < 3,\ i \in \mathcal{N} \setminus \{1\}.$$

Intuitively, each peripheral agent in our model, who cannot observe the equilibrium price, takes into account the fact that the central agent's synthetic information is also utilized by others, she thereby optimally underreacts to this received signal, especially when the number of the peripherals is large. The influence of the central's private and received signals is controlled deliberately by the peripherals' trading intensities choice. While all the peripherals in Ozsoylev (2004) trade competitively without the same strategic consideration so that each exploits the received signal up to her risk aversion and signal precision. As the number of the peripherals goes to infinity, the central's private signal is absorbed into the equilibrium price without bound.[7]

Ozsoylev (2004) nicely remarks that competitive trading in the star network provides a possible explanation for the large price swing, like bubble or crash, in financial markets without prior significant change in fundamentals. However, our finite influence ratio result seems to be more plausible, as any single agent's influence on financial markets is reasonably limited.

5.2 Market Patterns and Expected Profit

The intuitive Proposition 2 in section 4.2 helps us to understand individual trading behavior and market trading patterns in the circle network. Analogously, in the star network we have a similar result.

Proposition 6 *In the star network, precision of the network signal* $\tilde{r}_i$ *is strictly higher than that of* $\tilde{s}_i$

[7] Ozsoylev (2004) also assumes that the variance of liquidity trading goes to infinity in order to separate the role of social interaction from the role played by price. In our model the level of noise trading does not matter for this result.

when confidence degree $\theta \in (0, 1)$ *for each agent* $i \in N\backslash\{1\}$*, and it is strictly decreasing (increasing) in* $\theta \in [1/2, 1]$$(\theta \in [0, 1/2])$.

For our purpose we will focus on the case $\theta \in [1/2, 1]$ in the following analysis.

We have seen that a private signal's influence on price changes drastically when communication takes place in different networks. Is this the same case for market trading patterns as summarized by market liquidity, trading volume, price volatility and price efficiency? The answer is no.

Proposition 7 *When n > 1, market liquidity, expected trading volume, price volatility and price efficiency in the star network are higher with communication than without. Moreover, they are strictly decreasing in confidence degree* $\theta \in [1/2, 1]$.

When a peripheral receives a more accurate network signal from the central, on average agents as a whole trade more intensely. The market-maker infers information and sets price in similar way as described in section 4.2. We conclude that regardless of network structures, information communication generates market trading patterns more similar to what are observed in practice than implied by no communication economy. The monotonicity result is a direct consequence of Proposition 6.

As above, we turn to examine agents' unconditional expected profits.

Proposition 8 *Unconditional expected profit of the central agent in the star network is lower with communication than without, and it is strictly increasing in confidence degree* $\theta \in [1/2, 1]$. *The opposite is true for that of peripheral agents. The total expected profits are lower relative to those in the no communication economy.*

Intuitively, by spreading the synthetic information, the central agent loses monopoly on her private information. If she chooses not to do so, her expected profit is apparently higher than that of a single peripheral agent since she has an additional and exclusive information. The peripherals compete against one another and against the central agent not only on the common received signal but also on their own monopolistic private signals. Roughly, the received signal helps them earn higher expected profit than what is delivered in the no communication economy, and their exclusive private signals ensure them to gain more relative to the central agent. Unfortunately, the peripheral's total gain is dominated by the central's loss, and it is not possible to construct a compensation scheme between the central and the peripheral agents to have everyone better off. However, as we argued above, when agents are risk aversion of when they have other considerations, the information communication can make everyone happier. Interestingly, Ozsoylev, Walden, Yavuz, and Bildik (2014) find empirical evidence that central investors earn higher returns and trade earlier than peripheral investors with respect to information events, which can be rationalized by a two-period trading model.

6. Communication and Overconfidence

In the circle network, Proposition 2 demonstrates that when an agent is more confident in private signal prior to trading, the resulting more volatile network signal makes private signal, whose variance is actually unchanged, to be relatively more precise. The same is true in the star network when the central agent's confidence degree is in the range [1/2, 1]. These properties make our modeling of confidence to be comparable with that of overconfidence because the latter is usually captured by an agent's tendency to overestimate the precision of private signal and underestimate that of others or public information. In other words, when an agent exhibits high confidence degree or when she displays overconfidence in private signal, the effects on signals' relative precision are alike. Odean (1998), Wang (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Gervais and Odean

(2001) show that, in different extensions of Kyle (1985) without communication, market liquidity, expected trading volume, price volatility and price efficiency are all higher while an insider's expected profit is lower when she is overconfident in her private signal. More significantly, in their models these market patterns are strictly increasing in the insider's overconfidence degree, and the reverse is true for the expected profit. The intuition is straightforward, when an insider is more overconfident in private signal, she trade more intensely. The reasons of higher market liquidity, price volatility and price efficiency are similar as outlined in section 4.2. The insider's expected profit decreases simply because her demand is suboptimal.[8] These comparative statics are directly opposite to Propositions 3 and 4 in the circle network when $\theta \in (0, 1]$, and are again distinct from Propositions 6 and 7 in the star network when $\theta \in [1/2, 1]$.

The impacts of overconfidence on investors' trading behavior and welfare have been examined extensively. By studying position statement and trading activity for a large sample of households, Barber and Odean (2000) discover that those that trade most earn the lowest annual return. After considering other possible motivations for trading such as liquidity, risk-based rebalancing, and taxes, they attribute high trading levels and the resulting poor performance to individual investors' overconfidence. In subsequent studies, Barber and Odean (2001) document that men trade more than women but trading reduces men's net annual returns by more percentage points as opposed to that for women. Barber and Odean (2002) report that when investors switch from phone-based to online trading, they trade more actively and less profitably than before. These patterns are consistent with the findings by Antweiler and Frank (2004a, 2004b). For the former, they cite psychological research that men are more overconfident than women in areas such as finance. For the latter, they explain that online investors perform well prior to switch, therefore are more overconfident in their abilities in the new trading platform. As online investors have access to vast quantities of investment date, their illusions of knowledge and control further foster their overconfidence.

Interestingly, these empirical findings can be alternatively account for by the implications of information communication. Casual observation and anecdotal evidence suggest that relative to women, men are more prone to exchange news regarding asset performance and wealth accumulation. Similarly, it is routine for online traders to participate in information sharing and discussion on Internet stock message boards. Our model predicts that information sharing leads to excessive trading and return performance impairment.

Apparently, information communication and overconfidence explanations are largely complementary in explaining market trading patterns and individual profits. But in some aspects they are also competing against each other. In particular, earlier psychological experiments, requiring participants to respond to questions in isolated environment, seldom consider the communication and peer effects in affecting their confidence degrees, while recent redesigned experiments have documented that the agent's underconfidence is also prevalent in decision making (Klayman, Soll, González, & Barlas, 1999). Prompted by these findings, Xia (2014) provides reasonable conditions that excessive price volatility, high trading volume and price informativeness can be associated with underconfidence in a competitive economy à la Hellwig (1985). García, Sangiorgi and Urošević (2007) show that, when overconfident and rational agents coexist and information is endogenously acquired, agent's overconfidence is irrelevant to price volatility under certain conditions. Glaser and Weber (2007) also question the connection between overconfidence and trading volume by examining experimental data and field data together. In light of these, future research can be directed to test the validity and robustness of information communication and overconfidence theories. Interestingly, Xia (2012) shows that, when facing trade disclosure

[8] Their conclusions can be extended to the case in which the single overconfident insider is replaced by multiple ones.

requirements, overconfident insiders trade less than underconfident ones in order to prevent information from revealing to market-makers. This result again questions the conventional wisdom that overconfident insiders always trade more aggressively.

7. Concluding Remarks

Recently a remarkable amount of empirical research has concentrated on testing the implications of information communication in financial markets, surprising though this body of work has elicited little in terms of theoretical work. We extend Kyle (1985) by introducing one-way direct and truthful information transmission in the circle and star networks. Despite the restrictive modeling choice, this endeavor is encouraging as the model generates implications that are consistent with empirical findings from individual trading behavior to market trading patterns. In our paper, the comparative statics of investors' confidence degree on market trading patterns and individual welfare are contrary to those of overconfidence literature, therefore further scrutiny of communication and overconfidence explanations using empirical data is needed to enhance our understanding.

Several directions of further research await exploring. On the empirical side, it is interesting to examine the time series and cross sectional implications of information communication in asset prices. For instance, a rise in volatility among publicly traded companies has been documented. Is this an outcome that during last few decades the attention of news media and financial press were more in favor of publicly traded companies?

On the theoretical side, some key questions are in order. First and foremost, as pointed out earlier, incorporating information communication into Kyle (1985) has the advantage that the effect of communication on trading can be distinguished from the information aggregation role played by equilibrium price. A limitation of the analysis is that agents' non-strategic information communication prior to trading appears to be at odds with their strategic use of information afterwards. The analysis would be more illuminating if the incentive compatibility of information communication can be characterized in the strategic rational expectation framework. The aforementioned voluntary disclosure literature may help fill the gap and we plan to delve into it in the next project.[9] Second, the synergy of network economics and finance is a new and promising area. Information communication, or other sociological traits of trading behavior in social network, may raise a lot of unexplored questions. For instance, what are the asset pricing implications if investors are more inclined to share good news and withhold bad news, or vice versa? The investigation shall shed light on our understanding of other puzzling phenomena in economics and finance.

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[9] One conjecture is that traders are willing to communicate information truthfully before strategic trading when there are multiple assets and information acquisition is costly. It could be beneficial for each agent to obtain information of individual asset and share the information.

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Appendix Proofs of Main Results

Proof of Theorem 1 When proving the theorem we do not have to treat cases θ∈(0, 1) and θ = 1 separately. Only the distribution of $\tilde{r}_i$ is relevant in maximization and the distribution of $\tilde{r}_i$ when θ = 1 is the limit of that when θ∈ (0, 1). The proof has three steps.

Step one: Agent *i*, taking (thm1a) with subscript $j \neq i$, and (thm1b) as given, chooses $x_{\circ i}$ to solve:

$$\max_{x_{\circ i}} \mathbb{E}\left(x_{\circ i}\left[\tilde{v}-\lambda_{\circ}\left(\sum_{j\neq i}\left(\alpha_{\circ}\tilde{s}_j+\beta_{\circ}\tilde{r}_j\right)+x_{\circ i}+\tilde{u}\right)\right]\middle|\tilde{s}_i=s_i,\tilde{r}_i=r_i\right),$$

which is equivalent to (def1a) with $\mathcal{I}_i=\left(s_i,r_i\right)$ and can be rewritten as

$$\max_{x_{\circ i}} x_{\circ i}\left(\left[1-\lambda_{\circ}\alpha_{\circ}\left(n-1\right)\right]\mathbb{E}\left(\tilde{v}\mid s_i,r_i\right)-\lambda_{\circ}x_{\circ i}-\lambda_{\circ}\alpha_{\circ}\sum_{j\neq i}\mathbb{E}\left(\tilde{\varepsilon}_j\mid s_i,r_i\right)-\lambda_{\circ}\beta_{\circ}\sum_{j\neq i}\mathbb{E}\left(\tilde{r}_j\mid s_i,r_i\right)\right).$$

The solution is given by

$$x^*_{\circ i}=\frac{1}{2\lambda_{\circ}}\left[1-\lambda_{\circ}\alpha_{\circ}\left(n-1\right)\right]\mathbb{E}\left(\tilde{v}\mid s_i,r_i\right)-\frac{1}{2}[\alpha_{\circ}\sum_{j\neq i}\mathbb{E}\left(\tilde{\varepsilon}_j\mid s_i,r_i\right)+\beta_{\circ}\sum_{j\neq i}\mathbb{E}\left(\tilde{r}_j\mid s_i,r_i\right)].$$

The second order condition is $\lambda_{\circ}>0$.

Because all random variables are normally distributed with zero means, by the Projection Theorem, there exist constants a_1, a_2,

b_1, b_2, c_1 and c_2 such that:

$$\mathbb{E}\left(\tilde{v} \mid s_i, r_i\right) = a_1 s_i + a_2 r_i, \tag{A1a}$$

$$\sum_{j\neq i} \mathbb{E}\left(\tilde{\varepsilon}_j \mid s_i, r_i\right) = b_1 s_i + b_2 r_i, \tag{A1b}$$

$$\sum_{j\neq i} \mathbb{E}\left(\tilde{r}_j \mid s_i, r_i\right) = c_1 s_i + c_2 r_i. \tag{A1c}$$

The equilibrium dictates

$$\alpha_\circ = \frac{\left[1-\lambda_\circ\alpha_\circ\left(n-1\right)\right]a_1}{2\lambda_\circ} - \frac{\left(\alpha_\circ b_1 + \beta_\circ c_1\right)}{2} \text{ and } \beta_\circ = \frac{\left[1-\lambda_\circ\alpha_\circ\left(n-1\right)\right]a_2}{2\lambda_\circ} - \frac{\left(\alpha_\circ b_2 + \beta_\circ c_2\right)}{2},$$

therefore we have

$$\alpha_\circ = \frac{A}{\lambda_\circ} \text{ and } \beta_\circ = \frac{B}{\lambda_\circ}, \tag{A2}$$

Where

$$A = \frac{a_1\left(2+c_2\right) - a_2 c_1}{\left[2+b_1+a_1\left(n-1\right)\right]\left(2+c_2\right) - \left[b_2+a_2\left(n-1\right)\right]c_1}, \tag{A3a}$$

$$B = \frac{a_2\left(2+b_1\right) - a_1 b_2}{\left[2+b_1+a_1\left(n-1\right)\right]\left(2+c_2\right) - \left[b_2+a_2\left(n-1\right)\right]c_1}. \tag{A3b}$$

Note that A and B are independent of $\lambda_\circ$.

The pricing rule set by the market-maker must satisfy (2). Taking (11) as given, (12) satisfies (2) if

$$\lambda_\circ = \frac{cov\left(\tilde{v}, \tilde{\omega}_\circ\right)}{var\left(\tilde{\omega}_\circ\right)} = \frac{n\left(\alpha_\circ+\beta_\circ\right)\Sigma}{n^2\left(\alpha_\circ+\beta_\circ\right)^2\Sigma + n\left(\alpha_\circ+\beta_\circ\right)^2\Phi + \Omega}.$$

Substituting in for $\alpha_\circ$ and $\beta_\circ$ given by (A2) yields

$$\lambda_\circ = \sqrt{\frac{\left[n\left(A+B\right) - n^2\left(A+B\right)^2\right]\Sigma - n\left(A+B\right)^2\Phi}{\Omega}}. \tag{A4}$$

Step two: The expression of network signal is

$$\tilde{r}_i = \tilde{v} + \frac{\theta\sum_{k=0}^{n-1}\left(1-\theta\right)^k\tilde{\varepsilon}_{i+k+1}}{1-\left(1-\theta\right)^n}, \quad \text{when } \theta \in \left(0,1\right),$$
$$\tilde{r}_i = \tilde{s}_{i+1}, \text{ when } \theta = 1.$$

Define V to be the variance-covariance matrix of vector $\begin{bmatrix}\tilde{s}_i & \tilde{r}_i\end{bmatrix}^{\mathrm{T}}$, for $\theta \in (0,1]$,

$$V = \begin{bmatrix} \Sigma+\Phi & \Sigma + \frac{\theta\left(1-\theta\right)^{n-1}}{1-\left(1-\theta\right)^n}\Phi \\ \Sigma + \frac{\theta\left(1-\theta\right)^{n-1}}{1-\left(1-\theta\right)^n}\Phi & \Sigma + \frac{\theta}{2-\theta}\frac{1+\left(1-\theta\right)^n}{1-\left(1-\theta\right)^n}\Phi \end{bmatrix}.$$

For ease of notation, define

$$C = \frac{1-(1-\theta)^{n-1}}{1-(1-\theta)^{n}}\Phi \text{ and } D = |V|, \tag{A5a}$$

i.e., D is the determinant of V.

Next we show that the unknowns in (A3a) and (A3b) are as follows.

$$a_1 = \frac{C}{D}\frac{\theta}{2-\theta}\Sigma, \quad a_2 = \frac{C}{D}\Sigma, \tag{A6a}$$

$$b_1 = -\frac{C}{D}\left[\Sigma + \frac{\theta(1-\theta)^{n-1}}{1-(1-\theta)^{n}}\Phi\right], \quad b_2 = \frac{C}{D}(\Sigma+\Phi), \tag{A6b}$$

$$c_1 = \frac{C}{D}\frac{\theta}{2-\theta}(n\Sigma+\Phi), \quad c_2 = \frac{C}{D}\left[\left(n-\frac{2}{2-\theta}\right)\Sigma + \left(\frac{2(1-\theta)}{2-\theta} - \frac{\theta(1-\theta)^{n-1}}{1-(1-\theta)^{n}}\right)\Phi\right]. \tag{A6c}$$

Note that the unknowns in (A3a) and (A3b) are coefficients in (A1a)-(A1c). Applying the Projection Theorem to (A1a), we have

$$\mathbb{E}(\tilde{v} \mid s_i, r_i) = \frac{C}{D}\left(\frac{\theta}{2-\theta}s_i + r_i\right)\Sigma,$$

therefore we obtain (A6a).

Second, we can show that

$$cov(\tilde{\varepsilon}_j, \tilde{s}_i) = \begin{cases} 0 & \text{if } j \neq i \\ \Phi & \text{if } j = i \end{cases} \text{ and } cov(\tilde{\varepsilon}_j, \tilde{r}_i) = \begin{cases} \frac{\theta(1-\theta)^{n+j-i-1}}{1-(1-\theta)^{n}}\Phi & \text{if } 1 \le j \le i \\ \frac{\theta(1-\theta)^{j-i-1}}{1-(1-\theta)^{n}}\Phi & \text{if } i < j \le n \end{cases}. \tag{A7}$$

Applying the Projection Theorem to (A1b),

$$\sum_{j\neq i}\mathbb{E}(\tilde{\varepsilon}_j \mid s_i, r_i) = \frac{C}{D}\left[-\left(\Sigma + \frac{\theta(1-\theta)^{n-1}}{1-(1-\theta)^{n}}\Phi\right)s_i + (\Sigma+\Phi)r_i\right],$$

we thus obtain (A6b).

Finally, we can show that

$$cov(\tilde{r}_j, \tilde{s}_i) = \begin{cases} \Sigma + \frac{\theta(1-\theta)^{i-j-1}}{1-(1-\theta)^{n}}\Phi & \text{if } 1 \le j < i \\ \Sigma + \frac{\theta(1-\theta)^{n+i-j-1}}{1-(1-\theta)^{n}}\Phi & \text{if } i \le j \le n \end{cases}, \tag{A8}$$

$$cov(\tilde{r}_j, \tilde{r}_i) = \begin{cases} \Sigma + \frac{\theta}{2-\theta}\frac{(1-\theta)^{i-j}+(1-\theta)^{n+j-i}}{1-(1-\theta)^{n}}\Phi & \text{if } 1 \le j \le i \\ \Sigma + \frac{\theta}{2-\theta}\frac{(1-\theta)^{j-i}+(1-\theta)^{n+i-j}}{1-(1-\theta)^{n}}\Phi & \text{if } i \le j \le n \end{cases}. \tag{A9}$$

Applying the Projection Theorem to (A1c),

$$\sum_{j\neq i}\mathbb{E}(\tilde{r}_j \mid s_i, r_i) = \frac{C}{D}\frac{\theta}{2-\theta}(n\Sigma+\Phi)s_i + \frac{C}{D}\left[\left(n-\frac{2}{2-\theta}\right)\Sigma + \left(\frac{2(1-\theta)}{2-\theta} - \frac{\theta(1-\theta)^{n-1}}{1-(1-\theta)^{n}}\right)\Phi\right]r_i,$$

we thus obtain (A6c).

Step three: Now it is ready to capture the algorithm for calculating trading intensity parameters $\alpha_\circ, \beta_\circ$ and liquidity parameter $\lambda_\circ$. We first calculate A and B, defined in (A3a) and (A3b), by substituting (A5a)-(A6c), then $\lambda_\circ$ follows from (A4). Second we get $\alpha_\circ$ and $\beta_\circ$ from (A2). Very lengthy algebra yields the final results given by (13)-(15) in the main text. Next we examine the second order condition. Observe that

$$\lambda_\circ = \frac{\Sigma}{\sqrt{\Omega}} \frac{\sqrt{2n\left[1-\left(1-\theta\right)^n\right]\left(2\left[1-\left(1-\theta\right)^n\right]\Sigma + \theta[1+\left(1-\theta\right)^{n-1}]\Phi\right)}}{2\left(n+1\right)\left[1-\left(1-\theta\right)^n\right]\Sigma + [\left(3\theta-2\right)\left(1-\theta\right)^{n-1} + 2 + \theta]\Phi},$$

because n > 1, θ∈(0, 1] and $\left(3\theta-2\right)\left(1-\theta\right)^n + 2 + \theta = 2\left[1-\left(1-\theta\right)^n\right] + \theta[1+\left(1-\theta\right)^{n-1}]$, thus $\lambda_\circ > 0$ is satisfied.

Proof for Proposition 1. The proof for the first part is provided in the main text. For the second part, since $var\left(\tilde{x}_{\circ i+\ell}\right) = var\left(\tilde{x}_{\circ i+j}\right)$ for any ℓ and *j*, by definition of $corr\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i+\ell}\right)$ we only need to examine the covariance term, that is,

$$cov\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i+\ell}\right) = \alpha_\circ^2 cov\left(\tilde{s}_i, \tilde{s}_{i+\ell}\right) + \alpha_\circ \beta_\circ \left[cov\left(\tilde{s}_i, \tilde{r}_{i+\ell}\right) + cov\left(\tilde{s}_{i+\ell}, \tilde{r}_i\right)\right] + \beta_\circ^2 cov\left(\tilde{r}_i, \tilde{r}_{i+\ell}\right) \quad \text{(A10)}$$

Note the results (A7)-(A9) in the proof of Theorem 1. We have

$$cov\left(\tilde{s}_i, \tilde{r}_{i+\ell}\right) = \Sigma + \frac{\theta\left(1-\theta\right)^{n-\ell-1}}{1-\left(1-\theta\right)^n}\Phi,$$

$$cov\left(\tilde{s}_{i+\ell}, \tilde{r}_i\right) = \Sigma + \frac{\theta\left(1-\theta\right)^{\ell-1}}{1-\left(1-\theta\right)^n}\Phi,$$

$$cov\left(\tilde{r}_i, \tilde{r}_{i+\ell}\right) = \Sigma + \frac{\theta}{2-\theta}\frac{\left(1-\theta\right)^\ell + \left(1-\theta\right)^{n-\ell}}{1-\left(1-\theta\right)^n}\Phi.$$

Substituting these covariance terms and $\alpha_\circ = \left(\theta\beta_\circ\right) / \left(2-\theta\right)$ into (proximity) and examining the terms involving ℓ, we only need to show

$$\left(1-\theta\right)^\ell + \left(1-\theta\right)^{n-\ell}$$

is strictly decreasing in integer $\ell \in (0, n/2]$. Apparently, this is the case. For $i \in \mathcal{N}$, $n \geq 4$ and $1 \leq \ell < j \leq n/2$, we have $corr\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i+\ell}\right) > corr\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i+j}\right)$. The symmetry leads to $corr\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i-\ell}\right) = corr\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i+\ell}\right)$, hence for $1 \leq \left|\ell\right| < \left|j\right| \leq n/2$, we have

$$corr\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i+\ell}\right) > corr\left(\tilde{x}_{\circ i}, \tilde{x}_{\circ i+j}\right).$$

This completes the proof.

Proof for Proposition 2. To see that the precision of $\tilde{r}_i$ is strictly higher than that of $\tilde{s}_i$ for $i \in \mathcal{N}$, it suffices to show

$$\begin{aligned} & var\left(\tilde{r}_i\right) < var\left(\tilde{s}_i\right) \\ \Leftrightarrow\ & \Sigma + \frac{\theta}{2-\theta}\frac{1+\left(1-\theta\right)^n}{1-\left(1-\theta\right)^n}\Phi < \Sigma + \Phi \\ \Leftrightarrow\ & \frac{1-\left(1-\theta\right)}{1-\left(1-\theta\right)^n}\frac{1+\left(1-\theta\right)^n}{1+\left(1-\theta\right)} < 1. \end{aligned} \tag{A11}$$

(All) holds naturally since given θ∈(0, 1) and n > 1, we have $\left(1-\theta\right)^n < 1-\theta$.

To prove the precision of $\tilde{r}_i$ is strictly decreasing in θ∈(0, 1], notice that we have shown that the precision of $\tilde{r}_i$ when θ∈(0, 1) is higher than that when θ = 1. We only need to show $\frac{\theta}{2-\theta}\frac{1+\left(1-\theta\right)^n}{1-\left(1-\theta\right)^n}$ is strictly increasing in θ∈(0, 1). Equivalently, we can verify $\log\left[\frac{\theta}{2-\theta}\frac{1+\left(1-\theta\right)^n}{1-\left(1-\theta\right)^n}\right]$ is strictly increasing in θ∈(0, 1). This requires

$$\frac{1}{\theta} + \frac{1}{2-\theta} - \frac{n\left(1-\theta\right)^{n-1}}{1+\left(1-\theta\right)^n} - \frac{n\left(1-\theta\right)^{n-1}}{1-\left(1-\theta\right)^n} > 0.$$

Simplifying it leads to

$$\left(1-\theta\right)^{2n} + n\theta\left(2-\theta\right)\left(1-\theta\right)^{n-1} < 1.$$

Let $\eta = 1-\theta$, manipulation yields

$$\frac{\eta^{-n}-\eta^n}{n} > \eta^{-1}-\eta. \tag{A12}$$

Given $\eta \in \left(0,1\right)$, it is ready to see that the left hand side of (A12) as a function of *n* is strictly increasing in $n > 0$, so the last inequality holds when $n > 1$.

Proof of Theorem 2. The proof consists of two steps.

Step one: Central agent 1, taking (19) for $i \neq 1$, and (20) as given, chooses $x_{\star 1}$ to maximize

$$\mathbb{E}\left(x_{\star 1}\left[\tilde{v}-\lambda_\star\left(x_{\star 1}+\sum_{i=2}^{n}\left(\gamma_\star\tilde{s}_i+\delta_\star\tilde{r}_i\right)+\tilde{u}\right)\right]\middle| s_1,r_1\right) = \frac{\Sigma\left(s_1+r_1\right)}{2\Sigma+\Phi}\left(\left[1-\lambda_\star\gamma_\star\left(n-1\right)\right]x_{\star 1}-\lambda_\star\delta_\star\left(n-1\right)\right)\left[\theta s_1+\left(1-\theta\right)r_1\right]x_{\star 1}-\lambda x_{\star 1}^2 \tag{A13}$$

because

$$\mathbb{E}\left(\tilde{v}\mid s_1,r_1\right) = \mathbb{E}\left(\tilde{s}_i\mid s_1,r_1\right) = \frac{\Sigma\left(s_1+r_1\right)}{2\Sigma+\Phi}. \tag{A14}$$

The second order condition is $\lambda_\star > 0$.

Peripheral agent $i \neq 1$, taking (18), (19) with subscript $j > 1$ and $j \neq i$, and (20) as given, chooses x_i to maximize

$$\begin{aligned}
&\mathbb{E}\left(x_{\star i}\left[\tilde{v}-\lambda_\star\left(\alpha_\star\tilde{s}_1+\beta_\star\tilde{r}_1+x_{\star i}+\sum_{j>1,j\neq i}\left(\gamma_\star\tilde{s}_j+\delta_\star\tilde{r}_j\right)+\tilde{u}\right)\right]\middle| s_i,r_i=r_j\right)\\
=\;& x_{\star i}\mathbb{E}\left(\tilde{v}\mid s_i,s_1\right)-\lambda_\star x_i^2-\lambda_\star x_{\star i}\left[\alpha_\star\mathbb{E}\left(\tilde{s}_1\mid s_i,r_i\right)+\beta_\star\mathbb{E}\left(\tilde{r}_1\mid s_i,r_i\right)\right]\\
&-\lambda_\star x_{\star i}\left[\gamma_\star\sum_{j>1,j\neq i}\mathbb{E}\left(\tilde{s}_j\mid s_i,r_i\right)+\delta_\star\sum_{j>1,j\neq i}\mathbb{E}\left(\tilde{r}_j\mid s_i,r_i\right)\right]
\end{aligned} \tag{A15}$$

The second order condition is $\lambda_\star > 0$.

Define

$$\Theta=\theta\left(1-\theta\right),$$

because of (17),

$$\tilde{r}_i=\theta\tilde{s}_1+\left(1-\theta\right)\tilde{r}_1,$$

applying the Projection Theorem, we have

$$\begin{aligned}
&\mathbb{E}\left(\tilde{v}\mid s_i,r_i\right)=\mathbb{E}\left(\tilde{r}_1\mid s_i,r_i\right)=\mathbb{E}\left(\tilde{s}_j\mid s_i,r_i\right)=\frac{\Sigma\left[\left(1-2\Theta\right)s_i+r_i\right]}{2\left(1-\Theta\right)\Sigma+\left(1-2\Theta\right)\Phi},\\
&\mathbb{E}\left(\tilde{r}_j\mid s_i,r_i\right)=r_i.
\end{aligned}$$

Solving (A13) and (A15) and imposing equilibrium requirement yields

$$\begin{aligned}
\alpha_\star&=\frac{1}{2\lambda_\star}\frac{\Sigma\left[1-\lambda_\star\gamma_\star\left(n-1\right)\right]}{2\Sigma+\Phi}-\frac{\delta_\star\left(n-1\right)\theta}{2},\\
\beta_\star&=\frac{1}{2\lambda_\star}\frac{\Sigma\left[1-\lambda_\star\gamma_\star\left(n-1\right)\right]}{2\Sigma+\Phi}-\frac{\delta_\star\left(n-1\right)\left(1-\theta\right)}{2},\\
\gamma_\star&=\frac{1}{2\lambda_\star}\frac{\left(1-2\Theta\right)\Sigma\left[1-\lambda_\star\left(\alpha_\star+\beta_\star+\left(n-2\right)\gamma_\star\right)\right]}{2\left(1-\Theta\right)\Sigma+\left(1-2\Theta\right)\Phi},\\
\delta_\star&=\frac{1}{2\lambda_\star}\frac{\Sigma\left[1-\lambda_\star\left(\alpha_\star+\beta_\star+\left(n-2\right)\gamma_\star\right)\right]}{2\left(1-\Theta\right)\Sigma+\left(1-2\Theta\right)\Phi}-\frac{\left(n-2\right)\delta_\star}{2}.
\end{aligned}$$

Manipulation leads to (24), i.e., $\delta_\star=\frac{2\gamma_\star}{n\left(1-2\Theta\right)}$ and

$$\begin{aligned}
\alpha_\star&=\frac{1}{\lambda_\star}\frac{\left[2n\left(\theta-1\right)^2+2\theta+1\right]\Sigma+2\left[n\left(1-\theta\right)\left(1-2\theta\right)+\theta\right]\Phi}{2\left(e\Sigma^2+f\Sigma\Phi+g\Phi^2\right)},\\
\beta_\star&=\frac{1}{\lambda_\star}\frac{\left(2n\theta^2-2\theta+3\right)\Sigma+2\left[n\theta\left(2\theta-1\right)-\theta+1\right]\Phi}{2\left(e\Sigma^2+f\Sigma\Phi+g\Phi^2\right)},\\
\gamma_\star&=\frac{1}{\lambda_\star}\frac{n\left(1-2\Theta\right)\Sigma\left(\Sigma+\Phi\right)}{\left(e\Sigma^2+f\Sigma\Phi+g\Phi^2\right)},
\end{aligned} \tag{A17}$$

where

$$e=\left(n+1\right)\left[n\left(1-2\Theta\right)+2\right],\ f=n\left(n+4\right)\left(1-2\Theta\right)+n+1,\text{ and } g=2n\left(1-2\Theta\right).$$

Taking (18) and (19) as given, the market-maker knows that $\tilde{\omega}_\star=\alpha_\star\tilde{s}_1+\beta_\star\tilde{r}_1+\sum_{i=2}^{n}\left(\gamma_\star\tilde{s}_i+\delta_\star\tilde{r}\right)+\tilde{u}$ and sets $\lambda_\star$ in the familiar manner. Substituting in for $\alpha_\star,\beta_\star,\gamma_\star$ and $\delta_\star$ as given in (A17) and (24) yields (25) in the main text:

$$\lambda_{\star} = \frac{cov\left(\tilde{v}, \tilde{\omega}_{\star}\right)}{var\left(\tilde{\omega}_{\star}\right)} = \frac{\Sigma\sqrt{a\Sigma^3 + b\Sigma^2\Phi + c\Sigma\Phi^2 + d\Phi^3}}{\sqrt{2\Omega}\left(e\Sigma^2 + f\Sigma\Phi + g\Phi^2\right)},$$

where

$$\begin{aligned}
a &= 2n\left[n\left(1-2\Theta\right)+2\right]^2, \\
b &= 6n^3\left(1-2\Theta\right)^2 + 4n^2\left(3\Theta^2 - 11\Theta + 4\right) + 4n\left(4-3\Theta\right) + 4\Theta - 5, \\
c &= 6n^3\left(1-2\Theta\right)^2 + 8n^2\left(3\Theta^2 - 4\Theta + 1\right) + \left(4n-2\right)\left(3-4\Theta\right), \\
d &= 2\left(1-2\Theta\right)\left(n^2\left[n-2\left(n+1\right)\Theta\right] + 2n - 1\right).
\end{aligned}$$

Step two: We obtain (21)-(23) in the main text from (A17) and (25). Finally we show that $\lambda_{\star} > 0$ is satisfied. First note that $n > 1$ and $0 \leq \Theta = \theta\left(1-\theta\right) \leq 1/4$, so $1 - 2\Theta \geq 1/2$ and the constants *e*, *f*, and *g* are strictly positive. Secondly, it is easy to show the constants *a*, *b*, *c* and *d* given in are strictly positive. In particular, $b > 0$ follows from $3\Theta^2 - 11\Theta + 4 \geq 23/16$, $4 - 3\Theta \geq 13/4$ and $4n\left(4-3\Theta\right)+4\Theta-5 > 4\left(4-3\Theta\right)+4\Theta-5 = 11-8\Theta \geq 9$. $c > 0$ follows from $3\Theta^2 - 4\Theta + 1 \geq 3/16$, and $3 - 4\Theta \geq 2$, and $d > 0$ follows from $n - 2\left(n+1\right)\Theta \geq n - \left(n+1\right)/2 = \left(n-1\right)/2 > 0$.

Proof of Propositions 3-8. We need to first compute market liquidity, expected trading volume, price volatility, price efficiency and an agent's unconditional expected profit with and without communication, then we make a direct comparison. The details can be found from the author's personal website.