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Social Networks, Information Acquisition, and Asset Prices

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We analyze a rational expectations equilibrium model to explore the implications of information networks for the financial market. When information is exogenous, social communication improves market efficiency. However, social communication crowds out information production due to traders' incentives to "free ride" on informed friends and on a more informative price system. Overall, social communication hurts market efficiency when information is endogenous. The network effects on the cost of capital, liquidity, trading volume, and welfare are also sensitive to whether information is endogenous. Our analysis highlights the importance of information acquisition in examining the implications of information networks for financial markets.

Key words: social communication; price informativeness; information acquisition; asset prices; liquidity; volume; welfare
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1. Introduction

A central topic in the studies of financial markets is how much information will be acquired about stock fundamentals and how much the stock price will reflect investors' diverse information. Starting with Grossman and Stiglitz (1980), a large and growing literature has used rational expectations equilibrium models to study the incentives to acquire costly information and its implications for financial markets. In this literature, investors' information is transmitted indirectly via the market-clearing price, which aggregates information, because investors rationally interpret this price and incorporate its information content into their trading decisions.

A more recent literature has separately investigated how information propagates across agents in financial markets through more direct channels. These studies identify information transmission via social interaction, "word-of-mouth" communication among friends and neighbors, and shared education networks, etc. They document that information sharing through social networks has important consequences for investment decisions such as stock market participation and portfolio choices, and that social networks play a direct role in facilitating the price-discovery process.[1] Network theories have also been applied to understanding systematic risk, corporate governance, and the distribution of primary issues of securities.[2]

This paper combines the two literatures above. We analyze a rational expectations equilibrium model of a competitive market in which traders can learn about a risky asset's payoff from three sources: the market price, costly information acquisition, and communication with other traders via an exogenous social network. When traders decide whether or not to acquire costly information, they take into consideration the expected learning through social communication. In equilibrium, information acquisition and asset prices are determined simultaneously. Traders' conjectures about how much information is revealed through the price are fulfilled by their own acquisition activities.

[1] See, for example, Shiller and Pound (1989), Kelly and O'Grada (2000), Duflo and Saez (2002, 2003), Hong et al. (2004, 2005), Ivković and Weisbenner (2007), Brown et al. (2008), Cohen et al. (2008, 2010), Shive (2010), and Gray and Kern (2011).

[2] See Allen and Babus (2009) for an excellent survey. Easley and Kleinberg (2010) and Jackson (2008, 2010) provide extensive surveys of social-network applications for economic problems, including collaboration among firms, success in job search, educational attainment, and participation in crime.

We seek to achieve three goals. First, we study information acquisition in a financial market with social networks. Second, we examine how network connectedness affects equilibrium market outcomes such as price informativeness, the cost of capital, liquidity, and trading volume. Third, we investigate the interactions between information acquisition and communication of information via social networks by comparing the implications of network connectedness for market outcomes when information is endogenously acquired at a cost versus when information is exogenously given.

We extend the constant absolute risk aversion (CARA)-normal setup in a large economy (e.g., Hellwig 1980, Verrecchia 1982) with a tractable and realistic social network. Our model admits a unique linear rational expectations equilibrium, which we derive analytically. We use comparative statics analysis to generate new predictions about the impact of social networks on price informativeness and other market outcomes.

We show that how a social network affects market outcomes depend crucially on whether private information is exogenously given or endogenously acquired at a cost. By considering both cases, we isolate the circumstances in which the information acquisition assumption leads to different implications for empirical tests. Our key finding is that network connectedness can have exactly opposite effects on market outcomes such as price informativeness and the cost of capital when the fraction of informed traders is fixed exogenously versus when it is endogenously determined.

When information is exogenous in our model, social communication has two risk-reducing effects on the stock. The first effect is straightforward: information sharing enlarges everyone's information set and thus lowers the variance of a stock's payoff conditional on their information. Second, sharing information via social networks causes more information to be impounded into the market price, thereby improving market efficiency. This improved market efficiency further reduces the risk of the stock for everyone. As a consequence, when information is exogenous, social communication increases the trading aggressiveness, lowers the cost of capital, and increases stock liquidity and trading volume.

When information is endogenous, in addition to the two positive effects above, social communication has a negative effect on information production through two free-riding channels. The first channel is "free riding on friends"—i.e., direct communication with informed friends reduces traders' ex ante incentive to acquire costly information on their own. The second channel is "free riding on prices," which is underscored by the Grossman and Stiglitz (1980) model—i.e., an informative price system causes a disincentive to acquire information.

The equilibrium fraction of informed traders depends on network connectedness and the cost of information acquisition. When the information-acquisition cost is either very small or very large, the equilibrium fraction of informed traders is one or zero, respectively. Otherwise, there exists a unique equilibrium fraction of informed traders between zero and one, and it decreases with network connectedness. Social communication then crowds out information production, and as the network connectedness increases, the incentives to stay uninformed and free ride become stronger. More people choose to rely on information shared via social networks and gleaned from the market price rather than to acquire information on their own. We show that the negative effect of social communication on the ex ante incentive to acquire information is strong enough to more than offset its positive effects in reducing risk. As a result, when information is endogenous, social communication lowers price informativeness, raises the cost of capital, and harms liquidity and volume. These implications are exactly the *opposite* of those when information is exogenously given.

The opposite implications of network connectedness for market outcomes are robust to alternative interpretations of the information network. Throughout most of this paper, we interpret and model social network as communication across connected traders, but we can also model them as semipublic information sources that contain leaked private corporate information that only a subset of traders can access. In yet another modeling approach, individuals meet randomly and exchange information as in "word-of-mouth" models (e.g., Banerjee and Fudenberg 2004, Carlin et al. 2011). As we show, all of our results continue to hold in these alternative setups. Our results are also robust to various assumptions about the information-acquisition technology.

Without the network effects, our model reduces to a standard Grossman and Stiglitz (1980) model with differentially informed traders. The newly introduced network effects are unique in the sense that other parameters that have counterparts in the Grossman–Stiglitz model do not generate opposite implications for price informativeness when information is exogenous versus when it is endogenous. For example, in our model, just as in Grossman and Stiglitz (1980), increasing the private signal precision improves price informativeness regardless of whether information is exogenous or endogenous. The equilibrium fraction of informed traders may either increase or decrease with the precision of the signal: even though the value of becoming informed increases due to the higher quality of information, the value of staying uninformed also increases because the price system becomes more informative. In contrast, other things equal, more social communication in our model unambiguously leads to fewer informed traders due to the two free-riding incentives, which in turn hurts price informativeness. This illustrates that our network effects are distinct from the standard Grossman–Stiglitz model with increased signal precision.

Colla and Mele (2010) and Ozsoylev and Walden (2011) show that social communication improves market efficiency when information is exogenous. We complement these studies by showing that once information becomes endogenous, social communication can affect market outcomes in a way that is opposite to that in the exogenous information case, as social communication adversely affects the overall production of knowledge.[3] In addition, we derive implications of social networks for other market outcomes (such as the cost of capital, market liquidity, and trader welfare) that have not been examined in these studies.[4]

Our paper contributes to the extensive literature on costly information acquisition in financial markets, a literature that is spearheaded by the classic papers by Grossman and Stiglitz (1980) and Verrecchia (1982). The idea of endogenous information acquisition has been applied to understanding a wide range of issues in finance, including portfolio choice (Peress 2004, 2010; Van Nieuwerburgh and Veldkamp 2010), the home bias puzzle (Van Nieuwerburgh and Veldkamp 2009), mutual funds behavior (Garcia and Vanden 2009, Kacperczyk et al. 2011), and large price movements (Barlevy and Veronesi 2000, Dow et al. 2010, Mele and Sangiorgi 2010, Garcia and Strobl 2011). Our study extends this literature by incorporating networks into a model of information production and by generating new predictions linking social communication to market outcomes.

Our paper is broadly related to two additional literatures. The first is recent studies on information percolation (e.g., Duffie and Manso 2007, Duffie et al. 2009, Andrei 2011, Carlin and Manso 2011, Hong et al. 2011). This literature focuses on the dynamic process of information propagation and the evolution of agents' beliefs over time. We instead emphasize the impact of an information network on the ex ante incentive to acquire information, and we study how this information-acquisition effect in turn influences the relationship between market outcomes and network connectedness after information has propagated through the network. The second is the information-sale literature (e.g., Admati and Pfleiderer 1986, 1988; Fishman and Hagerty 1995; Garcia and Vanden 2009; Garcia and Sangiorgi 2011). This literature studies the optimal information-selling strategy by exploring how various information-selling mechanisms affect the profit of the information provider. In contrast, we abstract from the information-pricing side and study the consequences of information sharing for market outcomes.

The remainder of this paper is organized as follows. Section 2 introduces the model. Section 3 solves the financial market equilibrium, taking as given a fixed fraction of informed traders, and §4 solves the information market equilibrium, in which the fraction of informed traders is endogenously determined, along with the financial market equilibrium. In both of these sections, we focus on how market outcomes such as price informativeness, the cost of capital, liquidity, and trading volume vary with the extent of social communication. Section 5 explores the robustness of our results to some generalizations and alternative model setups, and §6 concludes. Detailed proofs are presented in a separate online appendix (available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1787041).

2. The Model

We study an economy similar to that studied by Hellwig (1980), but we extend the analysis to allow for information production and network communication. There is one period, and there are two tradable assets in the economy: a risk-free asset, which has a constant value of 1, and a risky asset, a stock, which has an initial price of $\tilde{p}$ per share and an uncertain future value, to be realized at the end of the period, denoted by $\tilde{v}$. We assume that $\tilde{v} \sim N(\bar{v}, 1/\rho_v)$, with $\bar{v} > 0$ and $\rho_v > 0$.

The economy is populated by two types of traders: rational traders and noise traders. Rational traders have CARA utility with a risk-aversion coefficient $\gamma > 0$. At the beginning of the period, before they decide on their demand for the risky asset, these traders can choose whether or not to spend a cost $c > 0$ to acquire diverse private signals regarding the stock payoff. We call these rational traders who acquire private signals *informed*; the traders who do not acquire signals are called *uninformed*. Let μ be the fraction of informed traders in the population. Noise traders provide liquidity in the sense that they supply

[3] Our paper is similar in spirit to that of Carlin et al. (2011), who argued that libertarian paternalism reduces information-acquisition incentives.

[4] Colla and Mele (2010) examined the asset pricing implications of a specific network structure—i.e., the cyclical network—and they focused on trade correlations among investors. Ozsoylev and Walden (2011) studied general forms of network structures and identified the conditions under which linear rational expectations equilibria exist.

$\tilde{x}$ units of stock per capita to the market. We assume that $\tilde{x} \sim N(\bar{x}, 1/\rho_x)$, with $\bar{x} > 0$ and $\rho_x > 0$.

What distinguishes our model from previous studies on information acquisition is the existence of a network among the traders. Prior to trading, traders communicate their acquired information to those connected with them in the network. The network is assumed to be exogenous, because social networks are often formed ex ante, and their formation is frequently independent of the information to be transferred (e.g., Cohen et al. 2008). We can interpret networks as friendships, club memberships, and social media. More broadly, being connected through the network can also be viewed as using common information sources, such as newsletters or information leakages.

We adopt the island-connection network in the social-network literature (e.g., Jackson 2008).[5] There are G groups (islands) in the economy, each of which has N traders, where both G and N are positive integers. Informed traders are evenly distributed among groups, so that each group has μN informed traders. Within any group, all traders are fully connected in the sense that they share signals with each other, but there are no connections across groups. We refer to traders in the same group as "friends."

Parameter N is equivalent to Ozsoylev and Walden's (2011) concept of "network connectedness." Formally, in the paper by Ozsoylev and Walden (2011), two traders are defined as being linked if they share their private signals, and traders' connectedness is the number of their links. In our model, all traders share their private signals (if they have one) with all other $N-1$ traders within the same network, and thus, according to Ozsoylev and Walden's (2011) definition, N captures each trader's connectedness.

Turning to the information structure, each informed trader receives a noisy signal about the stock payoff $\tilde{v}$. Specifically, an informed trader i in a group g (after paying the cost c) observes a signal of the following form:

$$\tilde{s}_{i,g} = \tilde{v} + \tilde{\varepsilon}_{i,g}, \quad \text{with } \tilde{\varepsilon}_{i,g} \sim N(0, 1/\rho_\varepsilon) \text{ and } \rho_\varepsilon > 0. \quad (1)$$

We assume that other members of the same group receive a noisy version $\tilde{y}_{i,g}$ of this signal through social communication with trader i:

$$\tilde{y}_{i,g} = \tilde{s}_{i,g} + \tilde{\eta}_{i,g}, \quad \text{with } \tilde{\eta}_{i,g} \sim N(0, 1/\rho_\eta) \text{ and } \rho_\eta > 0. \quad (2)$$

We assume that $(\tilde{v}, \{\tilde{\varepsilon}_{i,g}, \tilde{\eta}_{i,g}\}_{i,g}, \tilde{x})$ are mutually independent. Conditional on $\tilde{v}$, the precision of signal $\tilde{y}_{i,g}$ obtained from network information sharing is

$$\rho_y \equiv (\rho_\varepsilon^{-1} + \rho_\eta^{-1})^{-1} \in (0, \rho_\varepsilon), \quad (3)$$

which is lower than the precision of the private signal ρ_ε. This loss in signal precision captures communication barriers as well as the incentives of traders to partly withhold their information when they communicate with others. As $\rho_\eta \to 0$, traders cannot share private information with friends, and social networks do not play a role in determining market outcomes, which reduces our model to a standard setup as studied by Verrecchia (1982).

We summarize the timeline of our model as follows. At the beginning of the period, rational traders choose whether to spend a cost c to acquire private signals. Groups are then formed, and informed rational traders are evenly assigned to groups. Informed traders receive their own signals and communicate with their friends. The financial market opens and trading occurs among rational traders and noise traders. At the end of the period, stock payoffs are received, and all rational traders consume.

We follow closely the large economy analysis in Hellwig (1980) and Ozsoylev and Walden (2011). Specifically, there are G groups, each with N traders in each. The total number of traders is then GN. A fraction μ of all traders in each group is informed. To solve the market equilibrium in a given large economy, we let the number G of groups tend to infinity while holding the size N of each group constant. We also fix the per-capita supply of risky assets so that the aggregate risk-bearing capacity in the economy does not change as the number of traders grows larger. One benefit of studying a large economy is that it facilitates an analytic solution for the rational expectations equilibrium. Furthermore, in a large competitive market, traders are "negligibly small" and act as price takers, and therefore their behavior of truthfully communicating information with friends is incentive compatible.

The equilibrium concept that we use is the rational expectations equilibrium, as in Grossman and Stiglitz (1980). In the financial market, traders maximize their expected utility conditioning on the information they have acquired (if any), the information received from friends, and the market-clearing stock price. In the information market, traders decide whether to pay the cost to become informed to maximize their indirect utility from trading.

3. Financial Market Equilibrium for a Given Fraction of Informed Traders

In this section, we solve for the financial market equilibrium, taking the fraction μ of informed traders as given. Then we analyze how network connectedness affects market outcomes such as price informativeness and the cost of capital. We need to solve a fixed-point problem for the rational expectations equilibrium.

[5] In §§5.3 and 5.4, we consider two alternative models of networks and show that our results are robust.

On the one hand, individuals can infer some useful information from the stock prices they observe, and thus their equilibrium demand will depend on the distribution of equilibrium prices. On the other hand, because prices must equate supply and demand in the market, the distribution of equilibrium prices also depends on the demand of individuals.

In equilibrium, the price $\tilde{p}$ aggregates information possessed by rational traders. In large economies, there are infinitely many informed traders, and the noise in traders' signals washes out in the aggregate. Thus, $\tilde{p}$ is a function of the stock payoff $\tilde{v}$. In addition, the price is also affected by noise trading $\tilde{x}$, and as a result $\tilde{p}$ also depends on $\tilde{x}$. In a linear rational expectations equilibrium, traders conjecture the following price function:

$$\tilde{p} = \alpha_0 + \alpha_v \tilde{v} - \alpha_x \tilde{x}. \tag{4}$$

In this price function, α_x measures the effect of noise trading on prices—more liquid markets have a smaller α_x—so we measure stock liquidity by $1/\alpha_x$.

The information contained in the price is equivalent to the signal $\tilde{\theta}$:

$$\tilde{\theta} \equiv \frac{\tilde{p} - \alpha_0 + \alpha_x \bar{x}}{\alpha_v} = \tilde{v} - \frac{\alpha_x}{\alpha_v}(\tilde{x} - \bar{x}), \tag{5}$$

which is normally distributed, with mean $\tilde{v}$ and precision ρ_θ given by

$$\rho_\theta \equiv (\alpha_v/\alpha_x)^2 \rho_x. \tag{6}$$

The endogenous parameter ρ_θ and the ratio of α_v/α_x reflect the *informativeness* of $\tilde{p}$ about the stock payoff $\tilde{v}$. Both are also measures of *market efficiency*. To see this, note that the literature (e.g., Peress 2010, Ozsoylev and Walden 2011) measures market efficiency by the precision of stock payoff conditional on its price—i.e., by $1/\mathrm{Var}(\tilde{v} \mid \tilde{p})$. By Equations (5) and (6), applying Bayes' rule delivers $1/\mathrm{Var}(\tilde{v} \mid \tilde{p}) = \rho_v + \rho_\theta$. Because ρ_v and ρ_x are fixed, we can measure market efficiency by ρ_θ, or equivalently by α_v/α_x. We use the terms "price informativeness" and "market efficiency" interchangeably.

The CARA-normal setup implies that the demand function of trader i in group g is

$$d_i(\tilde{p}; \mathcal{F}_{i,g}) = \frac{E(\tilde{v} \mid \mathcal{F}_{i,g}) - \tilde{p}}{\gamma \,\mathrm{Var}(\tilde{v} \mid \mathcal{F}_{i,g})}; \tag{7}$$

$\mathcal{F}_{i,g}$ is trader i's information set, including price $\tilde{p}$. Specifically, the information set for the uninformed trader in group g is $\mathcal{F}_g^{UN} = \{\tilde{p}; \tilde{y}_{1,g}, \ldots, \tilde{y}_{\mu N, g}\}$, and that for an informed trader i in group g is $\mathcal{F}_{i,g}^{IN} = \mathcal{F}_g^{UN} \cup \{\tilde{s}_i\}$. Applying Bayes' rule to compute the conditional moments and plugging them into Equation (7), we can write the demand function in an explicit form:

$$\begin{aligned} d_i(\tilde{p}; \mathcal{F}_{i,g}) &= \frac{1}{\gamma}\left[\rho_v \bar{v} + \rho_\theta \tilde{\theta} + \rho_y \sum_{j=1}^{\mu N} \tilde{y}_{j,g} + 1_{\{i=IN\}}(\rho_\varepsilon \tilde{s}_i - \rho_y \tilde{y}_{i,g})\right] \\ &\quad - \frac{1}{\gamma}[\rho_v + \rho_\theta + \mu N \rho_y + 1_{\{i=IN\}}(\rho_\varepsilon - \rho_y)]\tilde{p}, \end{aligned} \tag{8}$$

where $1_{\{i=IN\}}$ is equal to 1 if trader i is informed and equal to 0 otherwise.

At the equilibrium price $\tilde{p}$, per-capita demand equals per-capita supply:

$$\lim_{G\to\infty} \frac{1}{G} \sum_{g=1}^{G} \left[\frac{1}{N} \sum_{i=1}^{N} d_i(\tilde{p}; \mathcal{F}_{i,g})\right] = \tilde{x}. \tag{9}$$

We follow Schneider (2009) and incorporate the large economy feature (i.e., "$G \to \infty$") into the definition of the market-clearing condition in Equation (9). The fixed-point problem for the rational expectations equilibrium is reduced to finding α_0, α_v, and α_x in the equilibrium price function (4) that satisfy the market-clearing condition (9). The result is summarized in the following proposition.

Proposition 1. *There exists a unique linear rational expectations equilibrium in the financial market, with price function*

$$\tilde{p} = \alpha_0 + \alpha_v \tilde{v} - \alpha_x \tilde{x},$$

where

$$\alpha_0 = \frac{\rho_v \bar{v} + (\alpha_v/\alpha_x)\rho_x \bar{x}}{\rho_v + \rho_\theta + \mu\rho_\varepsilon + \mu(N-1)\rho_y},$$

$$\alpha_v = \frac{\rho_\theta + \mu\rho_\varepsilon + \mu(N-1)\rho_y}{\rho_v + \rho_\theta + \mu\rho_\varepsilon + \mu(N-1)\rho_y},$$

$$\alpha_x = \frac{(\alpha_v/\alpha_x)\rho_x + \gamma}{\rho_v + \rho_\theta + \mu\rho_\varepsilon + \mu(N-1)\rho_y},$$

where

$$\frac{\alpha_v}{\alpha_x} = \frac{\mu\rho_\varepsilon + \mu(N-1)\rho_y}{\gamma} \quad \textit{and}$$

$$\rho_\theta = \frac{\mu^2[\rho_\varepsilon + (N-1)\rho_y]^2 \rho_x}{\gamma^2}.$$

Next, we use Proposition 1 to examine the implications of social communication for a variety of market outcomes by conducting comparative statics analysis with respect to the network-connectedness parameter N.

Market Efficiency. Proposition 1 shows that market efficiency ρ_θ is positively related to the following expression:

$$\mu\rho_\varepsilon + \mu(N-1)\rho_y = \underbrace{\mu N}_{\text{\# of signals}} \times \underbrace{\left(\frac{1}{N}\rho_\varepsilon + \frac{N-1}{N}\rho_y\right)}_{\text{average precision of each signal}}. \tag{10}$$

The term μN represents the number of informed traders (and hence signals) in one group. The term $((1/N)\rho_\varepsilon + ((N-1)/N)\rho_y)$ is the average precision of each signal across N traders in a group—one trader observes the signal perfectly, and the remaining traders observe a noisy version of it. Their joint effects determine how much information is incorporated into prices. Because $\partial[\mu\rho_\varepsilon + \mu(N-1)\rho_y]/\partial N = \mu\rho_y > 0$ for a fixed $\mu > 0$, increasing the network connectedness N has a positive effect on market efficiency ρ_θ in a setting with exogenous information. This result is consistent with Malinova and Smith (2006), Colla and Mele (2010), and Ozsoylev and Walden (2011), and its intuition is straightforward: sharing information among more friends causes more information to be impounded into the price, thereby improving market information efficiency.

Cost of Capital. Following Easley and O'Hara (2004), we define the cost of capital as the expected return from holding the risky stock $E(\tilde{v} - \tilde{p})$. By Proposition 1, we have

$$E(\tilde{v} - \tilde{p}) = \frac{\gamma\bar{x}}{\rho_v + \rho_\theta + \mu\rho_\varepsilon + \mu(N-1)\rho_y}. \tag{11}$$

The denominator in the above equation is the average conditional precision of stock payoff $\tilde{v}$ across all traders: ρ_v is the prior precision, ρ_θ is the precision gleaned from prices, $\mu\rho_\varepsilon$ is the precision from the signals directly observed by informed traders, and $\mu(N-1)\rho_y$ is the precision from communicating with informed friends. Thus, $1/(\rho_v + \rho_\theta + \mu\rho_\varepsilon + \mu(N-1)\rho_y)$ measures the average risk regarding the stock payoff and determines the cost of capital.

For a given $\mu > 0$, $\partial(\rho_v + \rho_\theta + \mu\rho_\varepsilon + \mu(N-1)\rho_y)/\partial N = \partial\rho_\theta/\partial N + \mu\rho_y > 0$. Thus, increasing N, the network connectedness, reduces the cost of capital. This result is driven by two reinforcing effects of an increase in the network connectedness. The direct effect occurs because more information sharing via social connections makes everyone better informed and less uncertain about the stock payoff. This increases the aggregate demand for the stock, and in turn the equilibrium price. This effect is captured by the term $\mu(N-1)\rho_y$ in the denominator of Equation (11). The indirect effect occurs through the revelation of information by the stock price: holding fixed the fraction of informed traders, μ, social communication causes the equilibrium price to reveal more information to all traders, which makes the stock less risky and further reduces the cost of capital. This second effect is captured by the term ρ_θ in the denominator of Equation (11). These two effects combine to make social communication reduce the cost of capital in an economy with exogenous information.

Liquidity. The stock liquidity can be measured by $1/\alpha_x$. By Equation (4), a change of noise trading by one unit moves the price by α_x. A market is liquid (deep) when α_x is low—i.e., when a noise trading shock is absorbed without moving the price much. Traders provide liquidity to the market by submitting demand schedules and stand willing to trade conditionally on the market price. Liquidity is equal to the average responsiveness of rational traders to the market price (Vives 2008).

To understand what drives liquidity, we use Proposition 1 to decompose the rational traders' demand functions in Equation (8) into two components:

$$\begin{aligned} d_i(\tilde{p}; \mathcal{F}_{i,g}) &= \underbrace{\textstyle\sum_{j=1}^{\mu N} \gamma^{-1}\rho_y(\tilde{y}_{j,g} - \tilde{p}) + 1_{\{i=IN\}}[\gamma^{-1}\rho_\varepsilon(\tilde{s}_i - \tilde{p}) - \gamma^{-1}\rho_y(\tilde{y}_{i,g} - \tilde{p})]}_{\text{speculation on private signals}} \\ &\quad + \underbrace{\frac{\rho_v}{(\alpha_v/\alpha_x)\rho_x + \gamma}(\bar{v} - \tilde{p})}_{\text{market-making (adv. sel.)}} + \frac{(\alpha_v/\alpha_x)\rho_x}{(\alpha_v/\alpha_x)\rho_x + \gamma}\bar{x}. \end{aligned} \tag{12}$$

This decomposition follows Vives (2008). It highlights two reasons for rational trading in our model. First, traders speculate on their private signals, buying or selling depending on whether the price is lower or higher than the signals. Second, they buy or sell when the price is below or above the prior expectation $\bar{v}$ of the stock's payoff. We label this demand component "market-making" following Vives (2008).[6]

In their market-making activities, traders face an adverse selection problem because they cannot disentangle information-driven trades from noise-driven trades. When there is more prior uncertainty (ρ_v is low) and more informed trading (α_v/α_x is high), the adverse selection becomes more severe, and traders protect themselves by reducing the trading intensity ($\rho_v/((\alpha_v/\alpha_x)\rho_x + \gamma)$ is low).

By Equation (12), the price responsiveness of the market-making component of a trader's demand is $AdvSel \equiv \rho_v/((\alpha_v/\alpha_x)\rho_x + \gamma)$, regardless of whether the trader is informed or uninformed. The price

[6] Specifically, Vives (2008, p. 118) interpreted this market-making component as a Walrasion investor trading the stock to exploit the difference between the ex ante estimate of the asset payoff and its price—"traders sell (buy) when the price is above (below) the prior expectation of the asset value, i.e., they lean against the wind. This is the typical behavior of market makers."

responsiveness of the speculation component for an informed trader is $Spec_I \equiv \gamma^{-1}(\mu N - 1)\rho_y + \gamma^{-1}\rho_\varepsilon$, whereas for an uninformed trader it is $Spec_U \equiv \gamma^{-1}\mu N\rho_y$. The average price responsiveness of the speculation component is $\mu Spec_I + (1-\mu)Spec_U = \alpha_v/\alpha_x$, which follows from the definitions of $Spec_I$ and $Spec_U$ and Proposition 1. Therefore, liquidity can be decomposed into two components, as follows:

$$\frac{1}{\alpha_x} = \underbrace{(\mu Spec_I + (1-\mu)Spec_U)}_{\text{speculation}} + \underbrace{AdvSel}_{\text{adv. sel.}} = \frac{\alpha_v}{\alpha_x} + \frac{\rho_v}{(\alpha_v/\alpha_x)\rho_x + \gamma}. \tag{13}$$

Equation (13) shows that price informativeness α_v/α_x affects liquidity $1/\alpha_x$ through two competing channels. First, a high α_v/α_x means that the price responsiveness of the speculation component of rational traders' demand is large on average, which tends to improve liquidity. Second, a high α_v/α_x also means that the proportion of information-driven trade is high, which worsens the adverse selection problem and reduces market liquidity. The relative force of these two competing channels determines whether the effect of price informativeness on liquidity is positive or negative. Direct computation shows that $\partial(1/\alpha_x)/\partial(\alpha_v/\alpha_x) > 0$ if and only if

$$\frac{\alpha_v}{\alpha_x} > \sqrt{\frac{\rho_v}{\rho_x}} - \frac{\gamma}{\rho_x}; \tag{14}$$

that is, price informativeness improves liquidity if and only if the market is sufficiently informationally efficient.

Given the result that social communication increases price informativeness α_v/α_x in economies with exogenous information (i.e., $\partial(\alpha_v/\alpha_x)/\partial N > 0$ for a fixed $\mu > 0$), we know that increasing network connectedness N will improve liquidity $1/\alpha_x$ if and only if the market is sufficiently informationally efficient; that is, $\partial(1/\alpha_x)/\partial N = (\partial(1/\alpha_x)/\partial(\alpha_v/\alpha_x))(\mu\rho_y/\gamma) > 0$ if and only if $\alpha_v/\alpha_x = (\mu[\rho_\varepsilon + (N-1)\rho_y])/\gamma > \sqrt{\rho_v/\rho_x} - \gamma/\rho_x$.

The effects of social communication on market efficiency, the cost of capital, and liquidity are summarized in the following proposition.

Proposition 2. *When the information is exogenous, increasing network connectedness improves market efficiency and lowers the cost of capital; that is, for a fixed $\mu > 0$, $\partial\rho_\theta/\partial N > 0$, and $\partial E(\tilde{v} - \tilde{p})/\partial N < 0$. Increasing network connectedness improves liquidity if and only if the market is sufficiently informationally efficient; that is, for a fixed $\mu > 0$, $\partial(1/\alpha_x)/\partial N > 0$ if and only if $(\mu[\rho_\varepsilon + (N-1)\rho_y])/\gamma > \sqrt{\rho_v/\rho_x} - \gamma/\rho_x$.*

Volume and Welfare. The per-capita trading volume is defined as follows:

$$\tilde{q} \equiv q(\tilde{v}, \tilde{x}) = \frac{1}{2}\left(\lim_{G\to\infty} \frac{1}{G}\sum_{g=1}^{G}\left[\frac{1}{N}\sum_{i=1}^{N}|d_i(\tilde{p}; \mathcal{F}_{i,g})|\right] + |\tilde{x}|\right), \tag{15}$$

which is a function of the underlying random variables $(\tilde{v}, \tilde{x})$.

The welfare of rational traders is the expected value of the equilibrium indirect utility. Direct computation shows that the welfare (certainty equivalent) of an uninformed trader and that of an informed trader, respectively, are

$$CE_U = \frac{1}{2\gamma}\log\left[\frac{\mathrm{Var}(\tilde{v}-\tilde{p})}{\mathrm{Var}(\tilde{v}-\tilde{p}\,|\,\mathcal{F}_g^{UN})}\right] + \frac{[E(\tilde{v}-\tilde{p})]^2}{2\gamma\mathrm{Var}(\tilde{v}-\tilde{p})}, \tag{16}$$

$$CE_I = \frac{1}{2\gamma}\log\left[\frac{\mathrm{Var}(\tilde{v}-\tilde{p})}{\mathrm{Var}(\tilde{v}-\tilde{p}\,|\,\mathcal{F}_{i,g}^{IN})}\right] + \frac{[E(\tilde{v}-\tilde{p})]^2}{2\gamma\mathrm{Var}(\tilde{v}-\tilde{p})}. \tag{17}$$

Equations (16) and (17) show that the welfare of rational traders increases with the expected stock return (cost of capital) and decreases with the variance of stock return.

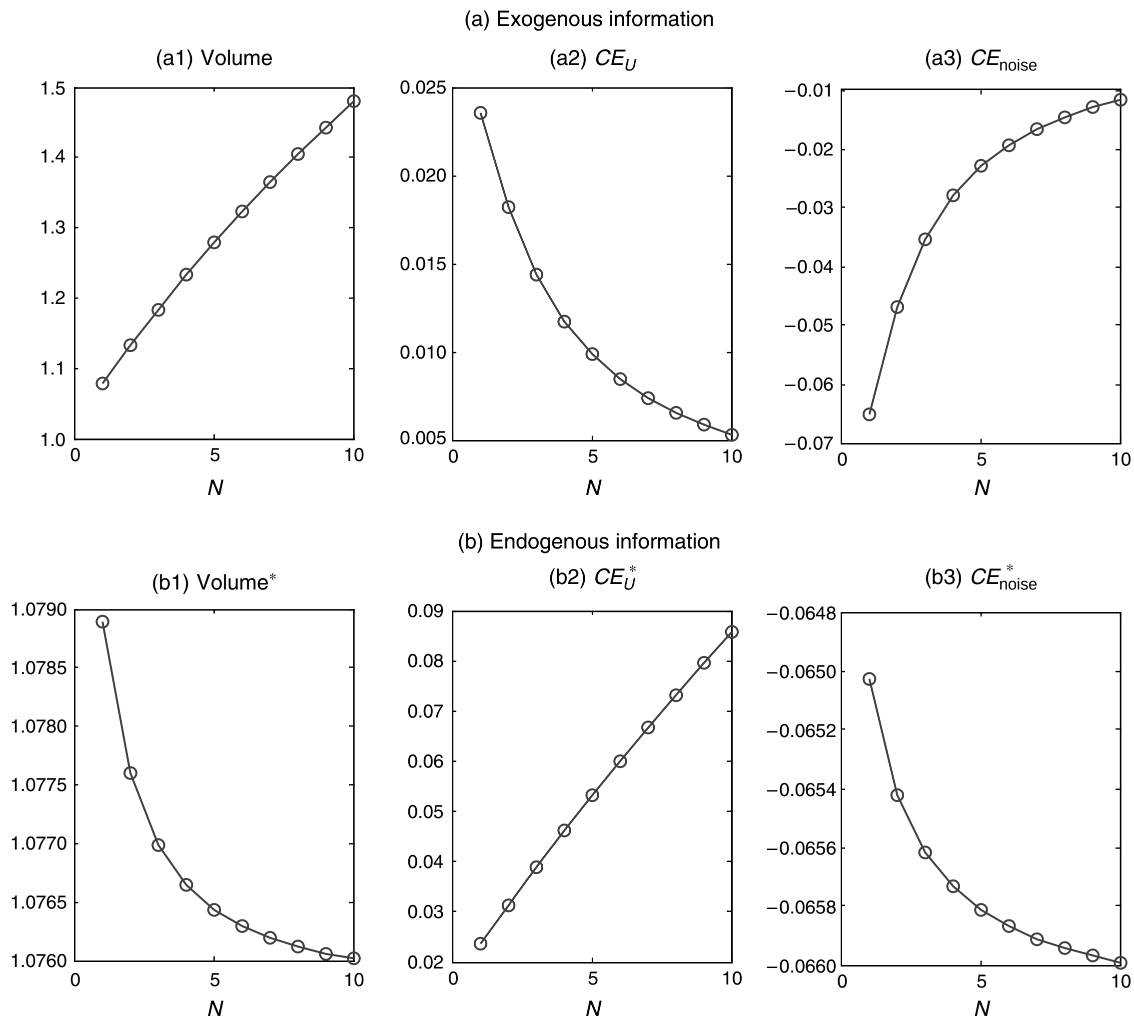
Following the literature (e.g., Chowdhry and Nanda 1991, Leland 1992, Easley et al. 2011), we use the expected revenue to proxy for the welfare of noise traders to capture the idea that they prefer to realize their liquidity needs at the smallest possible expected opportunity cost, as follows:

$$CE_{\text{noise}} \equiv E[(\tilde{p} - \tilde{v})\tilde{x}] = -E(\tilde{v} - \tilde{p})\bar{x} - \alpha_x \mathrm{Var}(\tilde{x}). \tag{18}$$

Equation (18) shows that the welfare of noise traders is negatively affected by the cost of capital and positively affected by liquidity.

The complexity of the expression for volume and welfare precludes analytical analysis. Instead, we illustrate the volume and welfare implications of social communication with numerical examples in Figure 1. We take one period to be one year and choose reasonable values for model parameters. The expected payoff of the risky asset $\bar{v}$ is normalized to be 1, and the ex ante payoff precision ρ_v is 25, which gives an annual volatility of approximately 20%. The risk aversion parameter γ is 2. We normalize the per-capita supply of the risky asset to 1 (i.e., $\bar{x} = 1$) and set $\rho_x = 10$, which corresponds to an annual volatility of liquidity supply equal to about 30% of total supply. We follow Gennotte and Leland (1990) in setting the rational trader's signal-to-noise ratio as 0.2—i.e., $(\rho_\varepsilon/\rho_v) = 0.2$, which gives $\rho_\varepsilon = 5$. We assume the precision of a private signal is reduced by one half when it is communicated via a social network (i.e., $\rho_y/\rho_\varepsilon = 1/2$), which gives $\rho_\eta = 5$. The fraction of

Figure 1 **Volume and Welfare Effects of Network Connectedness**



Notes. This figure plots how network connectedness N affects volume, the welfare of uninformed rational traders, and the welfare of noise trader. The upper panels are economies with exogenous information, where the fraction of informed traders is fixed at $\mu = 0.73$. The lower panels are economies with endogenous information, where the cost of aquiring private information is set at $c = 0.02$. The other parameter values are $\rho_v = 25$, $\rho_\varepsilon = \rho_\eta = 5$, $\rho_x = 10$, $\gamma = 2$, and $\bar{v} = \bar{x} = 1$.

informed traders μ is set at 0.73 in the upper panels of Figure 1.[7]

Panel (a1) of Figure 1 suggests that social communication increases trading volume when information is exogenous. This is because increasing social communication lowers the risk faced by rational traders, so that they will trade stocks more aggressively, thus driving up the average trading volume. Panels (a2) and (a3) suggest that social communication may harm rational traders and benefit noise traders. This occurs through the cost-of-capital effect of social communication: more social communication lowers the cost of capital when information is exogenous; the welfare of rational traders increases with the cost of capital (see Equation (16)), whereas the welfare of noise traders is negatively affected by the cost of capital (see Equation (18)).

4. Information Market Equilibrium: Endogenous Information Acquisition

We now analyze the decision made by rational traders on whether to pay the cost c and acquire a private signal of precision ρ_ε. We will show that once information is endogenous, the implications

[7] The results in Figure 1 are generally robust for a wide range of values for the model parameters. This robustness holds true for both economies with exogenous information and those with endogenous information. Specifically, we fix $\bar{v} = \bar{x} = 1$, $\rho_v = 25$, and $\gamma = 2$, vary four parameters $\{\mu, \rho_x, \rho_\varepsilon, \rho_y\}$ for economies with exogenous information, and vary $\{c, \rho_x, \rho_\varepsilon, \rho_y\}$ for those with endogenous information. We find that the volume and welfare results illustrated by Figure 1 hold for the vast majority of economies.

of social communication for market outcomes can be opposite to those in economies with exogenous information.

To determine the equilibrium fraction of informed traders, we compare the expected indirect utility of an uninformed trader with that of an informed trader in a group with μN informed friends. An argument similar to that of Grossman and Stiglitz (1980) shows that the expected net benefit of the private signal to a potential purchaser is

$$B(\mu; N) = \sqrt{1 + \frac{\rho_\varepsilon}{\rho_v + \rho_\theta + \mu N \rho_y}} - e^{\gamma c}. \tag{19}$$

Here, we explicitly express B as a function of N to emphasize the dependence of learning benefit on network connectedness.

The learning-benefit function B determines the equilibrium fraction μ^* of informed traders. It decreases with μ: the more informed investors there are, the more informative the price system is, and hence the lower the benefit of acquiring the private signal. If $B(0; N) \leq 0$, then no one wants to be informed. If $B(1; N) \geq 0$, then a potential buyer is strictly better off by being informed, regardless of how many informed traders there are in the market. Therefore, all traders become informed. These extreme cases are less interesting. For the rest of this paper, we make the standing assumption that $B(1; N) < 0 < B(0; N)$, or equivalently,

$$\sqrt{1 + \frac{\rho_\varepsilon}{\rho_v + \rho_x(\rho_\varepsilon/\gamma)^2 + \rho_y}} < e^{\gamma c} < \sqrt{1 + \frac{\rho_\varepsilon}{\rho_v}}.$$

Intuitively, the first inequality implies that it is never an equilibrium for everyone to be informed, whereas the second inequality implies that it is always optimal for at least one trader to acquire information. Together, this last assumption and the monotonic relationship between the learning-benefit function B and μ imply the existence of a unique $\mu^* \in (0, 1)$ satisfying $B(\mu^*; N) = 0$. The information market reaches an equilibrium at such a μ^* because traders are indifferent to becoming informed versus uninformed.

Equation (19) shows that social communication decreases the learning benefit through two free-riding channels. First, the direct communication with friends will reduce the ex ante incentive to acquire information. This "free riding on friends" manifests itself through the term $\mu N \rho_y$ in Equation (19), which is the anticipated total precision of signals obtained from friends—μN is the number of informed friends in a group, and ρ_y is the precision of the signal passed on from an informed friend. Second, because traders also learn from market price, social communication further reduces the incentive to acquire private signals because of its positive effect on price informativeness. This "free riding on price" is reflected by the term ρ_θ in Equation (19). As a result, increasing network connectedness N shifts the function $B(\cdot; N)$ downward, leading to a smaller equilibrium fraction μ^* of informed traders.

The following proposition characterizes the information market equilibrium and summarizes the effect of social communication on the equilibrium fraction of informed traders.

Proposition 3. *For any network connectedness N, there is a unique equilibrium fraction of informed traders $\mu^* \in (0, 1)$ that is given by*

$$\mu^* = \frac{(2/N\rho_y)(\rho_\varepsilon/(e^{2\gamma c}-1) - \rho_v)}{1 + \sqrt{1 + 4(\rho_x/\gamma^2)(\rho_\varepsilon/(e^{2\gamma c}-1) - \rho_v)((\rho_\varepsilon/N\rho_y) + (N-1)/N)^2}}.$$

Increasing network connectedness N reduces the endogenous fraction of informed traders.

We next demonstrate that, with endogenous information acquisition, increasing network connectedness N can—through decreasing the equilibrium fraction μ^* of informed traders—reverse the implications for market outcomes under exogenous information.

Market Efficiency. The information market equilibrium is determined by setting $B(\mu^*; N) = 0$, which implies that

$$\rho_v + \rho_\theta^* + \mu^* N \rho_y = \frac{\rho_\varepsilon}{e^{2\gamma c} - 1}, \tag{20}$$

where $\rho_\theta^* = (\mu^{*2}[\rho_\varepsilon + (N-1)\rho_y]^2 \rho_x)/\gamma^2$ is the market efficiency measure evaluated at the equilibrium fraction μ^* of informed traders. The expression of μ^* in Proposition 3 implies that increasing N will increase $\mu^* N \rho_y$, which is the expected precision of signals obtained from friends. Then, to maintain Equation (20), market efficiency ρ_θ^* has to decrease with N. Thus, increasing N will reduce market efficiency when information is endogenous. This result highlights the importance of endogenizing information when exploring the implications of social communication: although social communication improves market efficiency under exogenous information, it deters the production of information and harms market efficiency under endogenous information.

The Cost of Capital. When information is endogenous, the average risk faced by traders increases with network connectedness, and therefore social communication increases the cost of capital, which is also the opposite of the result under exogenous information. To see this, by Equation (20) we can show that the average conditional precision of stock payoff $\tilde{v}$ across all traders (which is the denominator in the expression of the cost of capital in Equation (11)) is determined by the equilibrium fraction μ^* of informed traders:

$$\rho_v + \rho_\theta^* + \mu^* \rho_\varepsilon + \mu^*(N-1)\rho_y = \mu^*(\rho_\varepsilon - \rho_y) + \frac{\rho_\varepsilon}{e^{2\gamma c} - 1}.$$

According to Proposition 3, increasing N decreases μ^*, which leads to a higher average risk faced by rational traders, and thus a higher cost of capital.

Liquidity. The reduced market efficiency ρ_θ^* also has a negative impact on liquidity. Recall that the effects of N on liquidity $1/\alpha_x$ work through price informativeness α_v/α_x, or equivalently, ρ_θ^* (see Equation (13)), and that $\partial(1/\alpha_x)/\partial(\alpha_v/\alpha_x) > 0$ if and only if $\alpha_v/\alpha_x > \sqrt{\rho_v/\rho_x} - \gamma/\rho_x$. Because, in the economy with endogenous information, increasing N will decrease α_v/α_x (i.e., social communication hurts market efficiency), social communication improves liquidity if and only if $(\mu^*[\rho_\varepsilon + (N-1)\rho_y])/\gamma < \sqrt{\rho_v/\rho_x} - \gamma/\rho_x$, or, more intuitively, if and only if the market is sufficiently informationally inefficient. Note that this condition is exactly the opposite of the condition under which social communication improves liquidity under exogenous information.

We summarize the above results in Proposition 4 below. We use the total differentiation operator d/dN to emphasize the fact that the endogenous fraction of informed μ^* depends on N rather than being fixed exogenously as in Proposition 2.

Proposition 4. *When the information structure is endogenous, increasing network connectedness N harms market efficiency ρ_θ^* and raises the cost of capital; that is, $d\rho_\theta^*/dN < 0$ and $dE(\tilde{v} - \tilde{p})/dN > 0$. Increasing network connectedness improves liquidity if and only if the market is sufficiently informationally inefficient; that is, $d(1/\alpha_x^*)/dN > 0$ if and only if $(\mu^*[\rho_\varepsilon + (N-1)\rho_y])/\gamma < \sqrt{\rho_v/\rho_x} - \gamma/\rho_x$.*

Volume and Welfare. Under endogenous information, social communication can affect trading volume and welfare differently from the exogenous information case. We use the same numerical example in Figure 1 to examine how the average trading volume $E(\tilde{q})$, the welfare of uninformed traders CE_U^*, and the welfare of noise traders CE_{noise}^* vary with N, the amount of social communication, when the information market is allowed to optimally adjust to N. In this case, we expect volume to be decreasing in N because, once the fraction of informed traders is endogenous, increasing N will reduce the total amount of information in the market and increase the total risk faced by rational traders, thereby causing them to trade less aggressively. Indeed, panel (b1) of Figure 1 verifies this intuition. Given that the cost of capital increases with N when information is endogenous, the welfare of uninformed traders increases with N and that of noise traders decreases with N, as confirmed by panels (b2) and (b3). In summary, by comparing panels (a1)–(a3) and panels (b1)–(b3) we find that social communication can have exactly the opposite implications for market outcomes when information is endogenous versus when information is exogenous.

5. Discussion

This section first discusses the unique role of network effects in generating opposing implications for price informativeness when information is exogenous versus when it is endogenous. Then we show the robustness of our findings in the baseline model to some variations in model assumptions and alternative ways of modeling network communication.

5.1. The Unique Role of Network Effects

We have shown that the equilibrium fraction of informed traders decreases with network connectedness due to two free-riding incentives: one is to free ride on more informative prices, and the other is to free ride on informed friends via social communication. The first is the Grossman and Stiglitz (1980) effect, in which market prices partially reveal informed agents' signals, causing a disincentive to acquire information. Therefore, our network effects work through the standard Grossman–Stiglitz effect and strengthen it. Ultimately, as we show, the strength of these network effects is such that the disincentive effects of network on information acquisition dominate the positive risk-reducing effect, leading to a negative relationship between price informativeness and network connectedness when information is endogenous, which is the opposite of the case when information is exogenous. Free riding on the information communicated via social networks, which is absent in the standard Grossman–Stiglitz model, is the key factor leading to these opposite implications of network connectedness.

By Proposition 1 and the definition of ρ_y in Equation (3), the equilibrium price informativeness is a function of the endogenous fraction μ^* of informed traders and five exogenous parameters (ρ_ε, ρ_x, γ, N, and ρ_η) as follows:

$$\begin{aligned}\rho_\theta^* &\equiv \rho_\theta(\mu^*; \rho_\varepsilon, \rho_x, \gamma, N, \rho_\eta) \\ &= \mu^{*2}\rho_x\gamma^{-2}[\rho_\varepsilon + (N-1)(\rho_\varepsilon^{-1} + \rho_\eta^{-1})^{-1}]^2. \qquad (21)\end{aligned}$$

The two parameters N and ρ_η are related to networks: $N-1$ is the number of connections that each trader has, and ρ_η is the easiness of communication among friends. For a given parameter $\kappa \in \{\rho_\varepsilon, \rho_x, \gamma, N, \rho_\eta\}$, its *overall* effect on price informativeness is

$$\frac{d\rho_\theta^*}{d\kappa} = \frac{\partial \rho_\theta}{\partial \kappa} + \frac{\partial \rho_\theta}{\partial \mu}\frac{\partial \mu^*}{\partial \kappa}. \qquad (22)$$

The first term $\partial\rho_\theta/\partial\kappa$ captures the *direct* effect of κ on ρ_θ—i.e., the impact when information is exogenous. The second term is the indirect effect: a change in κ will affect the endogenous μ^*, which in turn affects the price informativeness ρ_θ^*. These two terms may have opposite signs, causing the two effects to be countervailing.

We can show that only for the network-related parameters N and ρ_η is the sign of $d\rho_\theta^*/d\kappa$ different from that of $\partial\rho_\theta/\partial\kappa$; that is, the indirect effect is of different sign and larger in magnitude compared to the direct effect. In other words, in our economy, only factors related to network communication can generate a disincentive effect strong enough to reverse the predictions regarding price informativeness when information acquisition is taken into account. In particular, in our model, just as in the Grossman–Stiglitz model, increasing the private signal precision leads to more informative prices, regardless of whether information is exogenous or endogenous. This is in sharp contrast to the opposite implications of network connectedness for price informativeness when information is exogenous versus when it is endogenous. Thus, the network effects in our model are new and not subsumed by any parameters (such as the precision of the private signal) in the Grossman and Stilgitz (1980) model.

5.2. A More General Information-Acquisition Technology

Thus far, we have adopted a simple information-acquisition technology: a trader pays a constant cost in exchange for a signal of a fixed precision. In this subsection, we show that our results remain the same in an extension where signals of various precisions can be acquired at differential costs. Specifically, to acquire a signal with precision ρ_ε, a trader needs to pay a fixed cost $c_F > 0$ and a further variable cost $c_V(\rho_\varepsilon) \geq 0$, where $c_V(\cdot)$ is an increasing and convex function, satisfying $c_V(0) = 0$.

The financial market equilibrium for a given fraction of informed traders is still characterized by Proposition 1. Because traders are ex ante identical, we look for a symmetric equilibrium in the information market in which all informed investors choose the same precision. We consider the interior equilibrium $\mu^* \in (0,1)$. When a fraction μ of the traders are informed and acquire signals with precision ρ_ε, the expected net benefit of a private signal with precision $\rho_{\varepsilon i}$ to a potential purchaser i is

$$B(\rho_{\varepsilon i}; \mu, \rho_\varepsilon; N) = \sqrt{1 + \frac{\rho_{\varepsilon i}}{\rho_v + \rho_\theta + \mu N \rho_y}} - e^{\gamma[c_F + c_V(\rho_{\varepsilon i})]}. \tag{23}$$

This benefit function takes μ, ρ_ε, and N as given for an individual trader i.

The information market equilibrium is determined by two conditions (for two unknowns μ^* and ρ_ε^*). First, the informed and uninformed traders have the same expected utility, as follows:

$$B(\rho_\varepsilon^*; \mu^*, \rho_\varepsilon^*; N) = 0 \Rightarrow \sqrt{1 + \frac{\rho_\varepsilon^*}{\rho_v + \rho_\theta + \mu^* N \rho_y}} - e^{\gamma[c_F + c_V(\rho_\varepsilon^*)]} = 0. \tag{24}$$

Second, given other traders' decisions, each informed trader optimally chooses his signal precision at ρ_ε^* as follows:

$$\left.\frac{\partial B(\rho_{\varepsilon i}; \mu^*, \rho_\varepsilon^*; N)}{\partial \rho_{\varepsilon i}}\right|_{\rho_{\varepsilon i} = \rho_\varepsilon^*} = 0 \Rightarrow \frac{1/(\rho_v + \rho_\theta + \mu^* N \rho_y)}{2\sqrt{1 + (\rho_\varepsilon^*/(\rho_v + \rho_\theta + \mu^* N \rho_y))}} = e^{\gamma[c_F + c_V(\rho_\varepsilon^*)]} \gamma c_V'(\rho_\varepsilon^*). \tag{25}$$

Combining Equations (24) and (25), we have

$$\frac{1}{e^{2\gamma[c_F + c_V(\rho_\varepsilon^*)]}} \frac{e^{2\gamma[c_F + c_V(\rho_\varepsilon^*)]} - 1}{\rho_\varepsilon^*} = 2\gamma c_V'(\rho_\varepsilon^*). \tag{26}$$

Equation (26) implies that ρ_ε^* is independent of network connectedness N; that is, for any N, the value of ρ_ε^* is a constant determined by c_F, $c_V'(\cdot)$, and γ according to Equation (26). All of the results in our baseline model remain valid (just replace ρ_ε and c with ρ_ε^* and $c_F + c_V(\rho_\varepsilon^*)$).

5.3. "Semipublic" Group Signals: An Information-Leakage Model

So far, we have modeled networks as information sharing across traders within a group. To demonstrate the robustness of our results, we consider two alternative model setups in the following two subsections. In this subsection, we interpret the information networks as semipublic information sources or, more specifically, as sources of information that are available only to a subset of traders. For example, this could represent newsletters or information leakages that only a group of traders get to use.[8] Interpreting information leakage as networks serves to broaden the empirical relevance of our study.

We maintain the assumptions from the baseline model about traders, stock payoff, private signals, and information-acquisition technology. We only change the characterization and interpretation of networks; that is, instead of modelling social networks as traders freely sharing information with their friends, we now

[8] Information leakage has been extensively studied in the finance literature (e.g., Van Bommel 2003, Brunnermeier 2005, Irvine et al. 2007, Christophe et al. 2010).

assume that traders have some probability of getting a semipublic signal leaked from a source such as an advisory firm or a corporate insider who owns private information about the stock payoff.

Specifically, we assume a continuum $[0, 1]$ of rational traders and a mass λ of semipublic information sources. The information source $l \in [0, \lambda]$ consists of a signal as follows:

$$\tilde{z}_l = \tilde{v} + \tilde{\delta}_l, \quad \text{where } \tilde{\delta}_l \sim N(0, 1/\rho_\delta),\ \rho_\delta > 0, \tag{27}$$

and $\tilde{\delta}_l$ is independent of $\tilde{\delta}_{l'}$ (for $l' \neq l$) and of all other random variables, $(\tilde{v}, \tilde{x}, \{\tilde{\varepsilon}_i\}_i)$. These signals are semipublic in the sense that each information source l can only be accessed by M traders who are allowed to freely observe the signal $\tilde{z}_l$. We assume that the per-capita supply of potential sources of information leakages λ is very small, so that $\lambda M < 1$. Traders are randomly drawn to access one of the semipublic information sources, and each trader therefore has a probability of $\varphi = \lambda M$ of observing a leaked signal. The parameter φ captures the strength of information leakages, which is the counterpart of network connectedness in our baseline model.

In this setup, we can solve the rational expectations equilibrium with a linear price function of the same form as in Equation (4). The endogenous parameters α_v/α_x and ρ_θ that measure the price informativeness are now given by

$$\frac{\alpha_v}{\alpha_x} = \frac{\mu\rho_\varepsilon + \varphi\rho_\delta}{\gamma} \quad \text{and} \quad \rho_\theta = \left(\frac{\mu\rho_\varepsilon + \varphi\rho_\delta}{\gamma}\right)^2 \rho_x. \tag{28}$$

Therefore, when the fraction μ of informed traders is fixed exogenously, increasing the strength φ of information leakage increases market efficiency ρ_θ. We also show that increasing φ reduces the cost of capital $E(\tilde{v} - \tilde{p})$. In addition, increasing φ improves liquidity $1/\alpha_x$ if and only if the market is sufficiently informationally efficient—i.e., if and only if $(\mu\rho_\varepsilon + \varphi\rho_\delta)/\gamma > \sqrt{\rho_v/\rho_x} - \gamma/\rho_x$.

In the information market, the expected net-benefit function of acquiring information is

$$B(\mu; \varphi) = \left(\varphi\sqrt{1 + \frac{\rho_\varepsilon}{\rho_v + \rho_\theta + \rho_\delta}} + (1-\varphi)\sqrt{1 + \frac{\rho_\delta + \rho_\varepsilon}{\rho_v + \rho_\theta}}\right) \cdot \left(\varphi + (1-\varphi)\sqrt{1 + \frac{\rho_\delta}{\rho_v + \rho_\theta + \rho_\varepsilon}}\right)^{-1}, \tag{29}$$

which is obtained by comparing the ex ante expected utility of becoming informed with that of staying uninformed, taking into account the possibilities of receiving a semipublic signal due to information leakage. Increasing φ disincentivizes ex ante information production, causing the equilibrium fraction μ^* of informed traders to decrease. As a result, under endogenous information, market efficiency is reduced, and the cost of capital increases when there is more information leakage; that is, $d\rho_\theta^*/d\varphi < 0$ and $(dE(\tilde{v} - \tilde{p}))/d\varphi > 0$. Furthermore, increasing φ improves liquidity if and only if the market is sufficiently informationally inefficient—i.e., if and only if $(\mu^*\rho_\varepsilon + \varphi\rho_\delta)/\gamma < \sqrt{\rho_v/\rho_x} - \gamma/\rho_x$. These comparative statics results are again exactly the opposite of those under the exogenous information case.

5.4. Random Meeting: A "Word-of-Mouth" Effect Model

This subsection considers an alternative setup that models network communication using the random-meeting approach, which has been used to capture "word-of-mouth" effects (e.g., Banerjee and Fudenberg 2004, Carlin et al. 2011).

Specifically, we extend the standard Grossman and Stiglitz (1980) model by allowing information sharing via random meetings. There is a continuum of rational traders who can acquire a common signal $\tilde{F}$ at a cost c about the stock payoff $\tilde{v}$. Assume that $\tilde{F} \sim N(0, \sigma_F^2)$ and that

$$\tilde{v} = \tilde{F} + \tilde{e}, \tag{30}$$

where $\tilde{e} \sim N(0, \sigma_e^2)$, and $\tilde{e}$ is independent of $\tilde{F}$. The per-capita noise supply of the stock is $\tilde{x} \sim N(\bar{x}, \sigma_x^2)$ (with $\bar{x} > 0$ and $\sigma_x > 0$).

Prior to forming his demand for the stock, each trader has a probability ϕ of meeting with another trader randomly drawn from the population. The meeting of two traders allows them to freely and perfectly share information. The parameter ϕ, which measures the intensity of word-of-mouth communication, is the counterpart of network connectedness in our baseline model. Information sharing via the random meeting effectively increases the fraction of informed traders. Let μ denote the fraction of traders who acquire private signals on their own, and thus a $(1-\mu)$ fraction of traders are initially uninformed. But with probability $\phi\mu$, an uninformed trader would later meet with an informed trader and thus also become informed. As a result, in the trading stage the *effective* mass of informed traders is $\bar{\mu} = \mu + (1-\mu)\phi\mu$.

The rational expectation equilibrium stock price is a function of information $\tilde{F}$ and noise trading $\tilde{x}$ as follows:

$$\tilde{p} = \alpha_0 + \alpha_F\tilde{F} - \alpha_x\tilde{x}, \tag{31}$$

where α_0, α_F, and α_x are endogenous coefficients. As in our baseline model, we define market efficiency as

$$\rho_\theta \equiv \frac{1}{\mathrm{Var}(\tilde{F} \mid \tilde{p})} = \sigma_F^{-2} + (\alpha_F/\alpha_x)^2\sigma_x^{-2}. \tag{32}$$

In equilibrium, the ratio (α_F/α_x) is determined by the effective mass of informed traders as follows:

$$\frac{\alpha_F}{\alpha_x} = \frac{\bar{\mu}}{\gamma\sigma_e^2} = \frac{\mu + (1-\mu)\phi\mu}{\gamma\sigma_e^2}. \tag{33}$$

Combining Equations (32) and (33) delivers $\rho_\theta = \sigma_F^{-2} + ((\mu + (1-\mu)\phi\mu)/(\gamma\sigma_e^2))^2\sigma_x^{-2}$.

For a fixed μ, we have $\partial\rho_\theta/\partial\phi > 0$; that is, word-of-mouth communication improves market efficiency when information is exogenous. We can also show that increasing ϕ lowers the cost of capital; that is, $\partial E(\tilde{v} - \tilde{p})/\partial\phi < 0$. Word-of-mouth communication improves liquidity when information is exogenous if and only if the market is sufficiently informationally efficient. In other words,

$$\frac{\partial(1/\alpha_x)}{\partial\phi} < 0 \text{ iff}$$

$$\frac{\alpha_F}{\alpha_x} > \gamma\sigma_x^2\left[\sqrt{\frac{1}{\gamma^2\sigma_x^2\sigma_F^2} + \frac{\sigma_e^2}{\sigma_F^2}\left(\frac{\sigma_e^2}{\sigma_F^2}+1\right)} - \left(\frac{\sigma_e^2}{\sigma_F^2}+1\right)\right].$$

In the information market, the expected benefit of information to a potential purchaser is

$$B(\mu;\phi) = \phi\mu + (1-\phi\mu)\sqrt{\rho_\theta^{-1}\sigma_e^{-2}+1} - e^{\gamma c}. \tag{34}$$

We can show that increasing ϕ decreases the equilibrium fraction μ^* of informed traders. As a result, when information is endogenous, increasing ϕ harms market efficiency ρ_θ^* and raises the cost of capital. Furthermore, increasing ϕ improves liquidity if and only if the market is sufficiently informationally inefficient. All of these relationships are still the exact opposite of those under exogenous information.

6. Conclusion

Investing in speculative assets is a social activity (Shiller 1989). Recent studies document evidence that social communication plays an important role in financial markets. In this paper, we analyze a rational expectations equilibrium model to study the implications of social communication for market outcomes. Our analysis shows that how networks affect equilibrium outcomes depends crucially on whether information production is taken into account. When the fraction of informed investors is fixed exogenously, social communication improves market efficiency and reduces the cost of capital, improves liquidity for markets with a high level of informational efficiency, and tends to increase trading volume, lower the welfare of rational traders, and improve the welfare of noise traders. Once information is endogenous, the implications of social communication can get reversed because social communication crowds out information production. Our analysis thus highlights the importance of endogenous information acquisition in examining the implications of social networks for financial markets.

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