

Dynamics of information exchange in endogenous social networks

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We develop a model of information exchange through communication and investigate its implications for information aggregation in large societies. An *underlying state* determines payoffs from different actions. Agents decide which other agents to form a costly *communication link* with, incurring the associated cost. After receiving a *private signal* correlated with the underlying state, the agents exchange information over the induced *communication network* until they take an (irreversible) action. We define *asymptotic learning* as the fraction of agents who take the correct action, converging to 1 as a society grows large. Under truthful communication, we show that asymptotic learning occurs if (and under some additional conditions, also only if) in the induced communication network most agents are a short distance away from “information hubs,” which receive and distribute a large amount of information. Asymptotic learning therefore requires information to be aggregated in the hands of a few agents. We also show that while truthful communication may not always be a best response, it is an equilibrium when the communication network induces asymptotic learning. Moreover, we contrast equilibrium behavior with a socially optimal strategy profile, that is, a profile that maximizes aggregate welfare. We show that when the network induces asymptotic learning, equilibrium behavior leads to maximum aggregate welfare, but this may not be the case when asymptotic learning does not occur. We then provide a systematic investigation of what types of cost structures and associated social cliques (consisting of groups of individuals linked to each other at zero cost, such as friendship networks) ensure the emergence of communication networks that lead to asymptotic learning. Our result shows that societies with

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too many and sufficiently large social cliques do not induce asymptotic learning, because each social clique has sufficient information by itself, making communication with others relatively unattractive. Asymptotic learning results either if social cliques are not too large, in which case communication across cliques is encouraged, or if there exist very large cliques that act as information hubs.

KEYWORDS. Information aggregation, learning, search, social networks.

JEL CLASSIFICATION. C72, D82, D83, D85.

1. INTRODUCTION

Most social decisions, ranging from product and occupational choices to voting and political behavior, rely on the information agents gather through communication with friends, neighbors, and co-workers as well as information obtained from news sources and prominent webpages. A central question in social science concerns the dynamics of communication and information exchange, and whether such dynamics lead to the effective aggregation of dispersed information. Our objective in this paper is to develop a tractable benchmark model to study the dynamics of belief formation and information aggregation through communication and the choices that individuals make concerning whom to communicate with. A framework for the study of these questions requires communication to be strategic, time-consuming, and/or costly, since otherwise all information could be aggregated immediately by simultaneous communication among the agents. Our approach focuses on dynamic and costly communication (and we also allow strategic communication, though this turns out to be less important in the present context).

As a motivating example, consider a group of consumers who are contemplating the purchase of one among a number of competing new products. Each consumer has a prior about the benefits of each available option (for example, through advertising or prior experience with similar products), and in addition can communicate with her friends and neighbors about their views and experiences. Communication is costly both because of the direct costs this may entail (including costs in processing information), and because obtaining information from friends, neighbors, and co-workers involves delays. Once a particular choice has been made, reversing it is costly. Moreover, new information obtained soon after an action is taken (e.g., purchase of a product) is limited, as customers find it hard to precisely identify their valuations. Markets for several products and services naturally fit our framework. Duflo and Saez in a series of papers (Duflo and Saez 2002, 2003) provide evidence that retirement decisions by employees in a university are largely influenced by the information they receive from their social connections. Sorensen (2006) uses data from the University of California to empirically examine the role of social learning in employees' choices of health plans. His analysis reveals a significant social effect, which is present even when the model allows for department-specific employee heterogeneity. In a different context, Nair et al. (2010) and Iyengar et al. (2011) study the role of "opinion leaders" and word-of-mouth communication in the diffusion of new prescription drugs among physicians. They show that physicians' behavior is significantly influenced by prominent colleagues in their peer groups.

Finally, there is strong empirical evidence that individuals are more likely to invest in the stock market if their peers are also investing (Hong et al. 2004), and that word-of-mouth effects play a crucial role in the portfolio choices of mutual fund managers (Hong et al. 2005).¹

Our model provides a stylized but general environment to study this type of problems. An *underlying state* of the world determines the action with the highest payoff, which is assumed to be the same for all agents.² Each agent receives a *private signal* correlated with the underlying state and can communicate with her direct neighbors. We assume that the social network is also endogenous and results from the costly formation of links in the first stage of the game. Thereafter, agents communicate with their neighbors until they irreversibly choose an action. Earlier actions are preferred to later ones because of discounting, and communication is time-consuming because at later stages of the game, the neighbors of an agent will be able to acquire and communicate more information. This setup thus enables us to understand the trade-offs in the new product diffusion example mentioned in the previous paragraph and also to study the endogenous formation of a social network simultaneously with the process of communication over that network.

We characterize the equilibria of this network formation and communication game, and then investigate the structure of these equilibria as the society becomes large (i.e., for a sequence of games). Our main focus is on how well information is aggregated, which we capture with the notion of asymptotic learning. We say that there is *asymptotic learning* if the fraction of agents taking the correct action converges to 1 (in probability) as the society becomes large.

Our analysis proceeds in several stages. First, we take the communication graph as given and assume that agents are nonstrategic in their communication, that is, they disclose truthfully all the information they possess when communicating. Under these assumptions, we provide a condition that is sufficient and (under an additional mild assumption) necessary for asymptotic learning. Intuitively, this condition requires that most agents are a short distance away from *information hubs*, which comprise agents who have a very large (in the limit, infinite) number of connections.³ Two different types of information hubs can be conduits of asymptotic learning in our benchmark model. The first are *information mavens* who receive communication and aggregate information from many other agents. If most agents are close to an information maven, asymptotic learning is guaranteed. The second type of hubs are *social connectors* who communicate to many agents, enabling them to spread their information widely.⁴ Social connectors are only useful for asymptotic learning if they are close to mavens so

¹Another natural application is the adoption of new technologies. Conley and Udry (2010) and Bandiera and Rasul (2006) provide evidence that technology adoption by farmers in Ghana and Mozambique, respectively, is influenced by the information they obtain from their social networks. In this case, individuals are learning about both the opinions and the experiences of others.

²This is not a crucial assumption as long as agents know each others' preferences, since our model does not feature payoff externalities.

³We also derive conditions under which ϵ, δ -asymptotic learning occurs at an equilibrium strategy profile. We say that ϵ, δ -asymptotic learning occurs when at least $1 - \epsilon$ fraction of the population takes an ϵ -optimal action with probability at least $1 - \delta$.

⁴Both of these terms are inspired by Gladwell (2000).

that they can distribute their information. Thus asymptotic learning is also obtained if most agents are close to a social connector, who is in turn a short distance away from a maven. The intuition for why such information hubs and almost all agents being close to information hubs are necessary for asymptotic learning is instructive: were it not so, a large fraction of agents would prefer to act before waiting for sufficient information to arrive. But then a nontrivial fraction of those agents would take the incorrect action and, moreover, they would also disrupt the information flow for the agents to whom they are connected. The advantage of the first part of our analysis is that it enables a relatively simple characterization of equilibria and the derivation of intuitive conditions for asymptotic learning.

Second, we show that even if individuals misreport their information (which they may want to do to delay the action of their neighbors and obtain more information from them in future communication), it is an equilibrium of the strategic communication game to report truthfully whenever truthful communication leads to asymptotic learning. Interestingly, the converse is not necessarily true: strategic communication may lead to asymptotic learning in some special cases in which truthful communication precludes learning. From a welfare perspective, we show a direct connection between asymptotic learning and the maximum aggregate welfare that can be achieved by any strategy profile: when asymptotic learning occurs, all equilibria are (asymptotically) socially efficient, that is, they achieve the maximum welfare. However, when asymptotic learning does not occur, equilibrium behavior can lead to inefficiencies that arise from the fact that agents do not internalize the positive effect of delaying their action and continuing information exchange. Thus our analysis identifies a novel information externality that is a direct product of the agents being embedded in a network: the value of an agent to her peers does not only originate from her initial information, but also from the paths she creates between different parts of the network through her social connections. It is precisely the destruction of these paths when the agent takes an action that may lead to a welfare loss in equilibrium.

Our characterization results on asymptotic learning can be seen both as positive and negative. On the one hand, to the extent that most individuals obtain key information from either individuals or news sources (websites) approximating such hubs, efficient aggregation of information may be possible in some settings. We show in particular that hierarchical graph structures where agents in the higher layers of the hierarchy can communicate information to many agents at lower layers lead to asymptotic learning.⁵ On the other hand, communication structures that do not feature such hubs appear more realistic in most contexts, including communication between friends, neighbors, and co-workers.⁶ Our model thus emphasizes how each agent's incentive to act sooner rather than later makes information aggregation significantly more difficult.

Third, armed with the analysis of information exchange over a given communication network, we turn to the study of the endogenous formation of this network. We

⁵An additional challenge when significant information is concentrated in the hands of a few hubs may arise because of misalignment of interests, which our approach ignores.

⁶In particular, the popular (though not always empirically plausible) random graph models such as preferential attachment and Poisson (Erdős–Rényi) graphs do not lead to asymptotic learning.

assume that the formation of communication links is costly, though there also exist *social cliques*, groups of individuals who are linked to each other at zero cost. These can be thought of as “friendship networks” that are linked for reasons unrelated to information exchange and thus act as conduits of such exchange at low cost. Agents have to pay a cost at the beginning to communicate with (receive information from) those who are not in their social clique. Even though network formation games have several equilibria, the structure of our network formation and information exchange game enables us to obtain relatively sharp results on what types of societies lead to endogenous communication networks that ensure asymptotic learning. In particular, we show that societies with too many (disjoint) and sufficiently large social cliques induce behavior that is inconsistent with asymptotic learning. The reason why relatively large social cliques may discourage efficient aggregation of information is that because they have enough information, communication with others (from other social cliques) becomes unattractive. As a consequence, the society gets segregated into a large number of disjoint social cliques that do not share information. In contrast, asymptotic learning occurs in equilibrium if social cliques are not too large so that it is worthwhile for at least some members of these cliques to communicate with members of other cliques, forming a structure in which information is shared across (almost) all members of the society. Asymptotic learning also occurs when there exist very large social cliques that act as information hubs.

These results also illustrate an interesting feature of the information exchange process: an agent’s willingness to perform costly search (which here corresponds to forming a link with another social clique) is decreasing with the precision of the information that is readily accessible to her. This gives a natural explanation for informational segregation: agents do not internalize the benefits for the group of forming an additional link, leading to a socially inefficient information exchange structure. It further suggests a form of the *informational Braess paradox*,⁷ whereby the introduction of additional information may have adverse effects for the welfare of a society by discouraging the formation of additional links for information sharing (see also [Morris and Shin 2002](#) and [Duffie et al. 2009](#) for a related result). Consider, for example, the website of a film critic that can be viewed as a good but still imprecise information source (similar to a reasonable-sized social clique in our model). Other agents can access the critic’s information and form an opinion about a movie quickly. However, this precludes information sharing among the agents and may lead to a decrease in aggregate welfare.

Our paper is related to several strands of the literature on social and economic networks.⁸ First, it is related to the large and growing literature on *social learning*. Much of this literature focuses on Bayesian models of observational learning, where each individual learns from the actions of others taken in the past. A key impediment to information aggregation in these models is the fact that actions do not reflect all of the information that an individual has and this can induce a pattern reminiscent of a herd, where individuals ignore their own information and copy the behavior of others (see, for

⁷In the original Braess paradox, the addition of a new road may increase the delays faced by all motorists in a Nash equilibrium.

⁸Here we briefly describe the papers that are closest to our work. [Jackson \(2008\)](#) and [Goyal \(2007\)](#) provide excellent surveys of the extensive literature on social and economic networks.

example, Bikhchandani et al. 1992, Banerjee 1992, Moscarini et al. 1998, and Smith and Sørensen 2000, as well as Bala and Goyal 1998, for early contributions, and see Gale and Kariv 2003, Banerjee and Fudenberg 2004, Smith and Sørensen 2010, Acemoglu et al. 2011, and Mueller-Frank 2013 for models of Bayesian learning with richer observational structures). While observational learning is important in many situations, a large part of information exchange in practice is through communication.

Several papers in the literature study communication, though typically they use non-Bayesian or “myopic” rules (for example, Ellison and Fudenberg 1995, DeMarzo et al. 2003, Acemoglu et al. 2010, and Golub and Jackson 2010). A major difficulty faced by these approaches, often precluding Bayesian and dynamic game theoretic analysis of learning in communication networks, is the complexity of updating when individuals share their *ex post* beliefs (because of the difficulty of filtering out common sources of information). We overcome this difficulty by adopting a different approach, whereby individuals can directly communicate their signals and information is “tagged,” that is, signals are communicated along with their sources. This leads to a tractable structure for updating beliefs and enables us to study perfect Bayesian equilibria of a dynamic game of network formation, communication, and decision-making. It also reverses one of the main insights of these papers, also shared by the pioneering social learning work by Bala and Goyal (1998), that the presence of “highly connected” or “influential” agents, or what Bala and Goyal (1998) call a *royal family*, acts as a significant impediment to the efficient aggregation of information. On the contrary, in our model the existence of such highly connected agents (information hubs, mavens, or connectors) is crucial for the efficient aggregation of information. Moreover, the existence of such highly connected agents also reduces incentives for nontruthful communication and is the key input into our result that truthful communication can be an equilibrium. The recent paper by Duffie et al. (2009) is also noteworthy: in their model, agents are randomly matched according to endogenously determined search intensities, and because they focus on an environment with a continuum of agents, communication of beliefs in their setup is equivalent to exchanging signals, and thus enables them to avoid the issues that arise in the previous literature. Their main focus is on characterizing equilibrium search intensities as a function of the information that an agent already has access to. In contrast to our work, there is no explicit network structure. Möbius et al. (2010) empirically compare a non-Baysian model of communication (similar to the one adopted by Golub and Jackson 2010) with a model in which, similar to ours, signals are communicated and agents are Bayesian. Although their study is not entirely conclusive on whether agents behave according to one or the other model, their evidence broadly supports the Bayesian alternative. Finally, Fan et al. (2012) build on our model and investigate other notions of learning.

Our work is also related to the growing literature on *network formation*, since communication takes place over endogenously formed networks.⁹ Bala and Goyal (2000) model strategic network formation as a noncooperative game and study its equilibria under various assumptions on the benefits of forming a link. In particular, they distinguish between *one-way* and *two-way* flow of benefits, depending on whether a link

⁹For a comprehensive survey on the literature in network formation, see Jackson (2005).

benefits only the agent who decides to form it or both participating agents. They identify a number of simple structures that arise in equilibrium: the empty network, the wheel, the star, and the complete network. More recently, [Galeotti et al. \(2006\)](#) and [Galeotti \(2006\)](#) study the role of heterogeneity among agents in the network structures that arise in equilibrium. Closer to our work is [Hojman and Szeidl \(2008\)](#), who study a network formation model where the benefits from connecting to other agents have decreasing returns to scale (which is also the case in our model of information exchange because of endogenous reasons). The main focus of the network formation literature has been on characterizing equilibrium structures and comparing them with patterns observed in real world networks (e.g., small distances between agents, high centrality etc.). In most of the literature, the benefits and costs associated with forming a link are exogenous. A novel aspect of our work is that the benefits of forming links are endogenously determined through the subsequent information exchange. Our focus is also different: although we also obtain characterization results on the shape of the network structures that arise in equilibrium (e.g., ring structures emerge as equilibrium configurations under some conditions as in [Bala and Goyal 2000](#)), our focus is on whether these structures lead to asymptotic learning. Interestingly, while network formation games have a large number of equilibria, the simple structure of our model enables us to derive relatively sharp results about environments in which the equilibrium networks lead to asymptotic learning.

Finally, our paper is related to the literature on *strategic communication*, pioneered by the cheap talk framework of [Crawford and Sobel \(1982\)](#). While cheap talk models have been used to study information aggregation with one receiver and multiple senders (e.g., [Morgan and Stocken 2008](#)) and multiple receivers and a single sender (e.g., [Farrell and Gibbons 1989](#)), most relevant to our paper are two recent papers that consider strategic communication over general networks, [Galeotti et al. \(2011\)](#) and [Hagenbach and Koessler \(2010\)](#). A major difference between these works and ours is that we consider a model where communication is allowed for more than one time period, thus enabling agents to receive information outside their immediate neighborhood (at the cost of a delayed decision), and we also endogenize the network over which communication takes place. Alternatively, our framework assumes that an agent's action does not directly influence others' payoffs, while such payoff interactions are the central focus of [Galeotti et al. \(2011\)](#) and [Hagenbach and Koessler \(2010\)](#); in our model, the incentives for strategic communication arise solely for informational purposes. Our paper is also related to the existing work by [Ambrus et al. \(2013\)](#), where the sender and the receiver communicate strategically through a chain of intermediaries. Their primary focus is information intermediation; thus communication takes place over multiple rounds, but it is restricted to be on a ordered line from the sender to the receiver, where each agent sends information only once.

The rest of the paper is organized as follows. [Section 2](#) develops a general model of information exchange among rational agents, who are embedded in a communication network. Also, it introduces the two main environments we study. [Section 3](#) contains our main results on asymptotic learning given a communication graph. It also includes

a welfare discussion that draws the connection between learning and efficient communication. Finally, it illustrates how our results can be applied to a number of random graph models. [Section 4](#) incorporates endogenous network formation into the information exchange model. Our main result in this section shows the connection between incentives to form communication links and asymptotic learning. [Section 5](#) concludes. All proofs are presented in [Appendix B](#).

2. A MODEL OF INFORMATION EXCHANGE IN SOCIAL NETWORKS

In the first part of this paper, we focus on modeling information exchange among agents over a given communication network. In the second part ([Section 4](#)), we investigate the question of endogenous formation of this network. We start by presenting the information exchange model for a finite set $\mathcal{N}^n = \{1, 2, \dots, n\}$ of agents. We also describe the limit economy as $n \rightarrow \infty$.

2.1 Actions, payoffs, and information

Each agent $i \in \mathcal{N}^n$ chooses an irreversible action $x_i \in \mathbb{R}$. Her payoff depends on her action and an underlying *state of the world* $\theta \in \mathbb{R}$, which is an exogenous random variable. In particular, agent i 's payoff when she takes action x_i and the state of the world is θ is given by $\psi - (x_i - \theta)^2$, where ψ is a constant.

The state of the world θ is unknown and agents observe noisy signals about it. In particular, we assume that θ is drawn from a Normal distribution with known mean μ and precision ρ . Each agent receives a *private signal* $s_i = \theta + z_i$, where the z_i 's are idiosyncratic, independent from one another and θ , and normally distributed with common mean $\bar{\mu}$ (normalized to 0) and precision $\bar{\rho}$ (variance $1/\bar{\rho}$).¹⁰ Finally, we assume that $\psi > \bar{\psi} \geq 1/(\rho + \bar{\rho})$.¹¹

2.2 Communication

Our focus is on information aggregation when agents are embedded in a network that imposes communication constraints. In particular, agent i forms beliefs about the state of the world from her private signal s_i , as well as information she obtains from other agents through a given *communication network* G^n , which, as will be described shortly, represents the set of communication constraints imposed on them. We assume that time $t \in [0, \infty)$ is continuous and there is a common discount rate $r > 0$. Communication times are stochastic. In particular, communication times are exponentially distributed with parameter $\lambda > 0$. Equivalently, agents “wake” up and communicate simultaneously with their neighbors when a Poisson clock with rate λ ticks.¹² Thus the probability that communication occurs in time interval $[t, t + dt)$ is equal to λdt . At a given

¹⁰The assumption that all agents receive signals with equal precision is for simplicity and can be relaxed, as our analysis in [Section 4](#) shows (see, in particular, [footnote 23](#)).

¹¹As shown in [Section 3.1](#), the expected utility of an agent when she takes an action at $t = 0$ based only on her private signal is given by $\psi - 1/(\rho + \bar{\rho})$. Waiting is costly when $\psi > \bar{\psi} = 1/(\rho + \bar{\rho})$ and, in particular, it is costlier the larger the constant ψ is.

¹²We assume that communication between pairs of agents occurs simultaneously as opposed to at independent and identically distributed (i.i.d.) times for each pair for simplicity. When communication occurs

time instant t , agent i decides whether to take action x_i (and receive payoff $\psi - (x_i - \theta)^2$ discounted by e^{-rt}) or “wait” to obtain more information in subsequent communication rounds from her peers. Throughout the rest of the paper, we say that the agent exits at time t if she chooses to take the irreversible action at time t .

As mentioned above, each agent obtains information from other agents through a communication network represented by a directed graph $G^n = (\mathcal{N}^n, \mathcal{E}^n)$, where $\mathcal{E}^n$ is the set of directed edges with which agents are linked. We say that agent j can *obtain information* from i or that agent i can *send information* to j if there is an edge from i to j in graph G^n , that is, $(i, j) \in \mathcal{E}^n$. Let $I_{i,t}^n$ denote the *information set* of agent i at time t and let $\mathcal{I}_{i,t}^n$ denote the set of all possible information sets. Then, for every pair of agents i, j , such that $(i, j) \in \mathcal{E}^n$, we say that agent j *communicates* with agent i or that agent i sends a *message* to agent j and we define the map

$$\underline{m}_{ij,t}^n : \mathcal{I}_{i,t}^n \rightarrow \mathcal{M}_{ij,t}^n \quad \text{for } (i, j) \in \mathcal{E}^n,$$

where $\mathcal{M}_{ij,t}^n \subseteq \mathbb{R}^n$ denotes the set of messages that agent i can send to agent j at time t . For the remainder of the paper, $\underline{m}_{ij,t}^n$ denotes the map from information sets to messages, whereas $m_{ij,t}^n$ denotes an actual message, i.e., $m_{ij,t}^n \in \mathcal{M}_{ij,t}^n$. Note that without loss of generality the k th component of $m_{ij,t}^n$ represents the information that agent i sends to agent j at time t regarding the signal of agent k .¹³ Moreover, the definition of $m_{ij,t}^n$ captures the fact that communication is directed and is allowed only between agents who are linked in the communication network, i.e., j communicates with i if and only if $(i, j) \in \mathcal{E}^n$. The direction of communication should be clear: when agent j communicates with agent i , then agent i sends a message to agent j that could, in principle, depend on the information set of agent i as well as the identity of agent j .

Importantly, we assume that the cardinality (“dimensionality”) of $\mathcal{M}_{ij,t}^n$ is such that communication can take the form of agent i sharing all her information with agent j . This has two key implications. First, an agent can communicate (indirectly) with a much larger set of agents than just her immediate neighbors, albeit with a time delay. For example, the second time agent j communicates with agent i , then j can send information not just about her direct neighbors, but also their neighbors (since presumably she obtained such information during the first communication step). Second, mechanical duplication of information can be avoided. In particular, the second time agent j communicates with agent i , she can repeat her original signal, but this is not recorded as an additional piece of information by agent j , since given the size of the message space $\mathcal{M}_{ij,t}^n$, each piece of information is tagged. This ensures that there need be no confounding of new information and previously communicated information.

simultaneously, the amount of information (number of private signals) that the agent receives at each communication step is deterministic. If communication did not occur simultaneously (for example, if at each tick of the Poisson clock a single link was activated and communication occurred only on that link), agents would have to form beliefs about the amount of information they are likely to receive when they next exchange information.

¹³As will become evident in subsequent discussion, we assume that communication involves exchange of signals and not posterior beliefs. Moreover, information is tagged, i.e., the receiver of the message understands that its k th component is associated with agent k .

Let T_t denote the set of times that agents communicated with their neighbors before time t . That defines the information set of agent i at time $t > 0$ as

$$I_{i,t}^n = \{s_i, m_{ji,\tau}^n, m_{ik,\tau}^n \text{ for all } \tau \in T_t \text{ and } j, k \text{ such that } (j, i) \in \mathcal{E}^n \text{ and } (i, k) \in \mathcal{E}^n\}$$

and $I_{i,0}^n = \{s_i\}$. In particular, the information set of agent i at time $t > 0$ consists of her private signal and all the messages her neighbors sent to i as well as all the messages agent i sent to her neighbors in previous communication times.¹⁴ Agent i 's action at time t is a mapping from her information set to the set of actions, i.e.,

$$\sigma_{i,t}^n : \mathcal{I}_{i,t}^n \rightarrow \{\text{"wait"}\} \cup \mathbb{R}.$$

The trade-off between taking an irreversible action and waiting should be clear at this point. An agent would wait so as to communicate indirectly with a larger set of agents and choose a better action. Alternatively, the future is discounted, therefore, delaying is costly. In particular, agent i 's value function at time t when her information set is $I_{i,t}^n$ is given by the expression

$$U_{i,t}^n(I_{i,t}^n) = \max_{x_i} \left\{ \max_{x_i} \mathbb{E}[\psi - (x_i - \theta)^2 | I_{i,t}^n], \lim_{dt \rightarrow 0} e^{-r dt} \mathbb{E}(U_{i,t+dt}^n(I_{i,t+dt}^n) | I_{i,t}^n) \right\}.$$

Note that this expression involves a double maximization: first, the agent decides whether to wait or to take an irreversible action, and in the case that she decides to take an action, she chooses the one that maximizes her expected instantaneous payoff. It is worthwhile to highlight at this point that the optimal stopping problem for agent i depends crucially on the actions of the rest of the agents, since the latter affect agent i 's information set. For the rest of the paper, U_i^n denotes the expected value function of agent i at time $t = 0$.

We close the section with a number of definitions. We define a *path* between agents i and j in network G^n as a sequence $i_1, \dots, i_K$ of distinct nodes such that $i_1 = i$, $i_K = j$, and $(i_k, i_{k+1}) \in \mathcal{E}^n$ for $k \in \{1, \dots, K-1\}$. The *length* of the path is defined as $K-1$. Moreover, we define the distance of agent i to agent j as the length of the shortest path from i to j in network G^n if such a path exists, i.e.,

$$\text{dist}^n(i, j) = \min\{\text{length of } \mathcal{P} \mid \mathcal{P} \text{ is a path from } i \text{ to } j \text{ in } G^n\}.$$

If no path exists, we let $\text{dist}^n(i, j) = \infty$. Finally, the k -step *neighborhood* of agent i is defined as

$$B_{i,k}^n = \{j \mid \text{dist}^n(j, i) \leq k\},$$

where $B_{i,0}^n = \{i\}$, i.e., $B_{i,k}^n$ consists of all agents who are at most k *links* away from agent i in graph G^n . Intuitively, if agent i waits for k communication steps and all of the intermediate agents receive and communicate information truthfully, i will have access to all of the signals of the agents in $B_{i,k}^n$.

¹⁴It will become clear why the information set of an agent should include the messages she has sent to her neighbors when we introduce strategic communication, i.e., when we allow agents to misrepresent or not fully disclose their information.

2.3 Equilibria of the information exchange game

We refer to the game defined above as the information exchange game. We next define the equilibria of the information exchange game $\Gamma_{\text{info}}(G^n)$ for a given communication network G^n . We use the standard notation σ_{-i} to denote the strategies of agents other than i and we let $\sigma_{i,-t}$ denote the vector of actions of agent i at all times except t . Also, let $\mathbb{P}_\sigma$ and $\mathbb{E}_\sigma$ denote the conditional probability and the conditional expectation, respectively, when agents behave according to profile σ .

DEFINITION 1. An action strategy profile $\sigma^{n,*}$ is a *pure-strategy perfect Bayesian equilibrium* of the information exchange game $\Gamma_{\text{info}}(G^n)$ if for every $i \in \mathcal{N}^n$ and time t , and given the strategies of other agents $\sigma_{-i}^{n,*}$, agent i 's action $\sigma_{i,t}^{n,*}$ obtains expected payoff equal to the value function of agent i at time t , $U_{i,t}^n(I_{i,t}^n)$. We denote the set of equilibria of this game by $\text{INFO}(G^n)$.

Recall that agent i 's strategy profile depends on other agents' strategies through the evolution of the information set $I_{i,t}^n$. For the remainder, we refer to a pure-strategy perfect Bayesian equilibrium simply as an equilibrium (we do not study mixed strategy equilibria). It is important to note here that although equilibria depend on the discount rate r , we do not explicitly condition on r for convenience.

If agent i decides to exit and take an action at time t , then the optimal action would be

$$x_{i,t}^{n,*} = \arg \max_x \mathbb{E}[\psi - (x - \theta)^2 | I_{i,t}^n] = \mathbb{E}[\theta | I_{i,t}^n].$$

Since actions are irreversible, the agent's decision problem reduces to determining the timing of her action. It is straightforward to see that in equilibrium an agent takes the irreversible action immediately after some communication step concludes. Thus an equilibrium strategy profile σ induces an equilibrium timing profile $\tau^{n,\sigma}$, where $\tau_i^{n,\sigma}$ designates the communication step after which agent i exits by taking an irreversible action. The τ notation is convenient to use for the statement of some of our results below. Finally, similar to the set $B_{i,k}^n$, we define the k -step neighborhood of agent i under equilibrium σ as follows: a path $\mathcal{P}^\sigma$ between agents i and j in G^n under σ is a sequence $i_1, \dots, i_K$ of distinct nodes such that $i_1 = i$, $i_K = j$ ($i_k, i_{k+1} \in \mathcal{E}^n$), and $\tau_{i_k}^{n,\sigma} \geq k - 1$, which ensures that it is possible for the information from agent j to reach i in equilibrium. In other words, the information is received by every agent in the path before she takes an irreversible action. Then, we can define

$$\text{dist}^{n,\sigma}(i, j) = \min\{\text{length of } \mathcal{P}^\sigma \mid \mathcal{P}^\sigma \text{ is a path from } i \text{ to } j \text{ in } G^n \text{ under equilibrium } \sigma\}$$

and

$$B_{i,k}^{n,\sigma} = \{j \mid \text{dist}^{n,\sigma}(j, i) \leq k\}.$$

2.4 Assumptions on the information exchange process

The communication model described in Section 2.2 is fairly general. In particular, the model does not restrict the set of messages that an agent can send. Throughout, we maintain the assumption that the communication network G^n is *common knowledge*. Also, we focus on the following two environments defined by Assumptions 1 and 3, respectively.

ASSUMPTION 1 (Truthful communication). *Communication between agents is truthful, i.e.,*

$$m_{ij,t}^n = \begin{cases} \hat{m}_{ij,t}^n & \text{if } |T_t| \leq \tau_i^{n,\sigma} \\ \hat{m}_{ij,\tau_i^{n,\sigma}}^n & \text{otherwise} \end{cases}$$

and

$$(\hat{m}_{ij,t}^n)_\ell = \begin{cases} s_\ell & \text{if } \text{dist}_{i,\ell}^{n,\sigma} \leq |T_t| \\ \in \mathbb{R} & \text{otherwise.} \end{cases}$$

Intuitively, this assumption compactly imposes three crucial features: (i) Communication takes place by sharing signals, so that when agent j communicates with agent i at time t , then agent i sends to j all the information agent i has obtained thus far.¹⁵ (ii) Agents cannot strategically manipulate the messages they sent, i.e., an agent's private signal is *hard information*. Moreover, they cannot refuse to disclose the information they possess. (iii) When an agent takes an irreversible action, then she no longer obtains new information and, thus, can only communicate the information she has obtained until the time of her decision. The latter feature captures the fact that an agent, who engages in information exchange to make a decision, would have weaker incentives to collect new information after reaching that decision. Nevertheless, she can still communicate the information she had previously obtained to other agents. An interesting consequence of this feature is that it imposes dynamic constraints on communication: agent i can communicate with agent j only if there is a directed path between them in the communication network G^n and the agents in the path do not exit early. Our motivating application—new product diffusion—fits the environment defined by Assumption 1, especially in environments for which it is time-consuming to assess the quality of a new technology even after adopting it.¹⁶

¹⁵Figure 1 illustrates the evolution of the information set of an agent: in the first communication step, agent 2 sends to agent 1 only her own private signal, while in the second communication step, she sends the signal of agent 3.

¹⁶An obvious extension (and a very interesting avenue for future research) would be to incorporate information generation after an irreversible action is taken into the current framework. This feature would capture the fact that in some cases agents may obtain additional information after taking an action, e.g., buying a product or adopting a new technology. For example, an agent may obtain a second private signal of higher precision after taking an action.

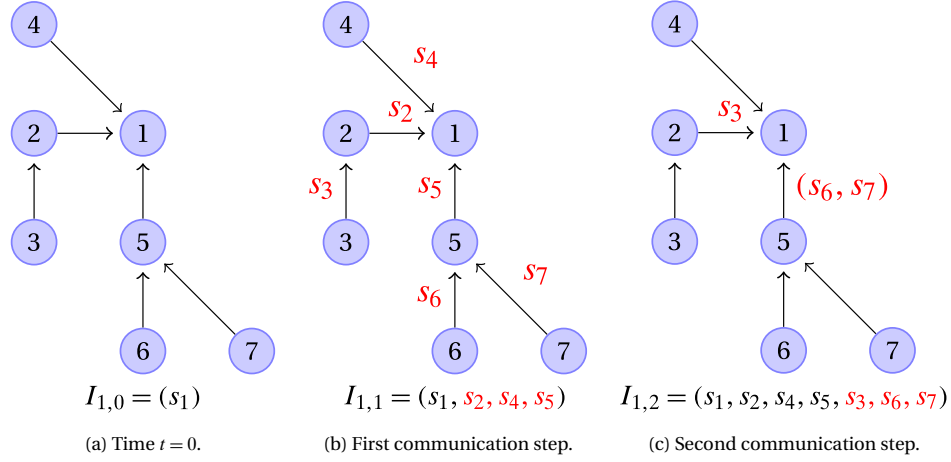


FIGURE 1. The information set of agent 1 under truthful communication.

We call this type of communication *truthful* to stress the fact that the agents cannot strategically manipulate the information they communicate.¹⁷ We discuss the implications of relaxing [Assumption 1](#) by allowing *strategic communication* in [Section 3.4](#).

2.5 Learning in large societies

We are interested in whether equilibrium behavior leads to information aggregation. This is captured by the notion of “asymptotic learning,” which characterizes the behavior of agents over communication networks with growing size.

We consider a sequence of communication networks $\{G^n\}_{n=1}^\infty$, where $G^n = (\mathcal{N}^n, \mathcal{E}^n)$, and refer to this sequence of communication networks as a *society*. A sequence of communication networks induces a sequence of information exchange games, and with a slight abuse of notation we use the term *equilibrium* to denote a sequence of equilibria of the information exchange games. We denote such an equilibrium by $\sigma = \{\sigma^n\}_{n=1}^\infty$, which designates that $\sigma^n \in \text{INFO}(G^n)$ for all n . For any fixed $n \geq 1$ and any equilibrium of the information exchange game $\sigma^n \in \text{INFO}(G^n)$, we introduce the indicator variable

$$M_i^{n,\epsilon} = \begin{cases} 1 & \text{if agent } i \text{ takes an action that is } \epsilon\text{-close to the optimal} \\ 0 & \text{otherwise.} \end{cases}$$

In other words, $M_i^{n,\epsilon} = 1$ (for some ϵ) if and only if agent i chooses irreversible action x_i , such that $|x_i - \theta| \leq \epsilon$.

¹⁷Yet another variant of this assumption would be that agents exit the social network after taking an action and stop communicating entirely. In this case, the results are essentially identical when their action is observed by their neighbors. However, if their action is not observable, then the analysis needs to be modified. In particular, there exist other equilibria where several agents might exit together, expecting others to exit.

The next definition introduces the notion of ϵ, δ -asymptotic learning for a given society.¹⁸

DEFINITION 2. We say that ϵ, δ -asymptotic learning occurs in society $\{G^n\}_{n=1}^\infty$ along equilibrium σ if we have

$$\limsup_{n \rightarrow \infty} \mathbb{P}_\sigma \left(\left[\frac{1}{n} \sum_{i=1}^n (1 - M_i^{n,\epsilon}) \right] > \epsilon \right) < \delta.$$

This definition states that ϵ, δ -asymptotic learning occurs when the probability that at least $(1 - \epsilon)$ fraction of the agents takes an action that is ϵ -close to the optimal action (as the society grows infinitely large) is at least $1 - \delta$.

DEFINITION 3. We say that *perfect asymptotic learning* occurs in society $\{G^n\}_{n=1}^\infty$ along equilibrium σ if we have

$$\lim_{n \rightarrow \infty} \mathbb{P}_\sigma \left(\left[\frac{1}{n} \sum_{i=1}^n (1 - M_i^{n,\epsilon}) \right] > \epsilon \right) = 0$$

for any $\epsilon > 0$. Equivalently, perfect asymptotic learning occurs in society $\{G^n\}_{n=1}^\infty$ along equilibrium σ if ϵ, δ -asymptotic learning occurs in $\{G^n\}_{n=1}^\infty$ along σ for any $\epsilon, \delta > 0$.

Perfect asymptotic learning is naturally a stronger definition (corresponding to ϵ and δ being arbitrarily small in the definition of ϵ, δ -asymptotic learning) and requires all but a negligible fraction of the agents taking the optimal action in the limit as $n \rightarrow \infty$.

3. LEARNING AND EFFICIENT COMMUNICATION

In this section, we present our main results on learning and discuss their implications for the aggregate welfare. Before doing so, we discuss the decision problem of a single agent, which characterizes her optimal stopping time, i.e., the time to take an irreversible action given the strategy profile σ of the rest of the agents. Then we contrast the single agent problem with that of a social planner, whose objective is to maximize expected aggregate welfare. The analysis in the next three subsections assumes that communication is truthful (cf. [Assumption 1](#)).

3.1 Agent i 's problem

The (nondiscounted) expected payoff of agent i taking an action after observing k truthful private signals (including her own) is given by

$$\mathbb{E}[\psi - (\hat{\theta} - \theta)^2 | I_{i,t}^n] = \psi - \text{var}(\hat{\theta} - \theta | I_{i,t}^n) = \psi - \frac{1}{\rho + \bar{\rho}k},$$

¹⁸Note that we could generalize [Definition 2](#) by introducing yet another parameter and study ϵ, δ, ζ -asymptotic learning, in which case we would require that $\lim_{n \rightarrow \infty} \mathbb{P}_\sigma([1/n \sum_{i=1}^n (1 - M_i^{n,\epsilon})] > \zeta) < \delta$.

where recall that ρ and $\bar{\rho}$ are the precisions of the state θ and the idiosyncratic noise, respectively. To obtain the second equality, note that if agent i exits, then the optimal action would be $\hat{\theta} = \mathbb{E}[\theta|I_{i,t}^n]$ and the posterior distribution of θ given the information set $I_{i,t}^n$ has precision equal to $\rho + \bar{\rho}k$.

By the principle of optimality, the value function for agent i at information set $I_{i,t}^n$ and assuming that the rest of the agents behave according to profile σ is given by

$$U_{i,t}^n(I_{i,t}^n) = \max \begin{cases} \psi - \frac{1}{\rho + \bar{\rho}k_{i,t}^{n,\sigma}} \\ \text{(when she takes the optimal irreversible action)} \\ e^{-r dt} \mathbb{E}[\mathbb{E}_\sigma(U_{i,t+dt}^n | I_{i,t+dt}^n) | I_{i,t}^n] \\ \text{(when she decides to wait, i.e., } x = \text{wait)}, \end{cases}$$

where $k_{i,t}^{n,\sigma} = |B_{i,t}^{n,\sigma}|$ denotes the number of distinct private signals agent i has observed up to time t . The first line is equal to the expected payoff for the agent when she chooses the optimal irreversible action under information set $I_{i,t}^n$, i.e., $\mathbb{E}[\theta|I_{i,t}^n]$, and she has observed $k_{i,t}^{n,\sigma}$ private signals, while the second line is equal to the discounted expected continuation payoff. Specifically, if the agent decides to wait' at time t , then she incurs the discounting cost (term $e^{-r dt}$) in exchange for potentially more information, as designated by the information set $I_{i,t+dt}^n$, where $I_{i,t}^n \subseteq I_{i,t+dt}^n$ and $I_{i,t}^n \subset I_{i,t+dt}^n$ if new information is communicated within the time interval $[t, t + dt)$.

The following lemma states that an agent's optimal action takes the form of a threshold rule: there exists a threshold $(k_{i,|T_i|}^{n,\sigma})^*$, such that an agent decides to take an irreversible action at time t as long as she has observed more than $(k_{i,|T_i|}^{n,\sigma})^*$ private signals. Like all other results in this paper, the proof of this lemma is provided in [Appendix B](#).

LEMMA 1. *Suppose that [Assumption 1](#) holds, so that communication is truthful. Then, given communication network G^n and equilibrium $\sigma \in \text{INFO}(G^n)$, there exists a sequence of signal thresholds for each agent i , $\{(k_{i,\tau}^{n,\sigma})^*\}_{\tau=0}^\infty$, that depend on the current communication round, the identity of the agent i , the communication network G^n , and σ such that agent i maximizes her expected utility at information set $I_{i,t}^n$ by taking action $x_{i,t}^n(I_{i,t}^n)$ defined as*

$$x_{i,t}^n(I_{i,t}^n) = \begin{cases} \mathbb{E}[\theta|I_{i,t}^n] & \text{if } k_{i,t}^n \geq (k_{i,|T_i|}^{n,\sigma})^* \\ \text{wait} & \text{otherwise,} \end{cases}$$

where $k_{i,t}^n$ is the number of private signals that agent i has observed up to time t .

A consequence of [Lemma 1](#) is that an equilibrium strategy profile σ defines both a time at which agent i acts (immediately after communication step $\tau_i^{n,\sigma}$) and the number of signals that agent i has access to when she acts.

3.2 Asymptotic learning

We begin the discussion by introducing the concepts that are instrumental for asymptotic learning: the observation radius and k -radius sets. Recall that an equilibrium of the

information exchange game on communication network G^n , $\sigma^n \in \text{INFO}(G^n)$, induces a timing profile $\tau^{n,\sigma}$, such that agent i takes an irreversible action after $\tau_i^{n,\sigma}$ communication steps. We call $\tau_i^{n,\sigma}$ the *observation radius* of agent i under equilibrium profile σ^n . We also define agent i 's *perfect observation radius*, τ_i^n , as the communication round that agent i would exit, assuming that all other agents never exit. Note that an agent's perfect observation radius is independent of the strategies of other agents and depends only on the network structure. Alternatively, $\tau_i^{n,\sigma}$ is an endogenous object and depends on both the network and the specific equilibrium profile σ . Given the notion of an observation radius, we define k -radius sets (and similarly perfect k -radius sets) as follows.

DEFINITION 4. Let $V_k^{n,\sigma}$ be defined as

$$V_k^{n,\sigma} = \{i \in \mathcal{N} \mid |B_{i,\tau_i^{n,\sigma}}^{n,\sigma}| \leq k\}.$$

We refer to $V_k^{n,\sigma}$ as the k -radius set (along equilibrium σ). Similarly, we refer to

$$V_k^n = \{i \in \mathcal{N} \mid |B_{i,\tau_i^n}^n| \leq k\}$$

as the *perfect k -radius set*.

Intuitively, $V_k^{n,\sigma}$ includes all agents that take an action before they receive signals from more than k other individuals in equilibrium σ . Equivalently, the size of their (indirect) neighborhood by the time they take an irreversible action is no greater than k . From Definition 4, it follows immediately that

$$i \in V_k^{n,\sigma} \Rightarrow i \in V_{k'}^{n,\sigma} \quad \text{for all } k' > k.$$

Proposition 1 below provides conditions for perfect asymptotic learning to occur in any equilibrium profile as a function of only exogenous objects, i.e., the perfect k -radius sets, that depend exclusively on the structure of the communication network (for conditions that guarantee that ϵ , δ -asymptotic learning occurs/does not occur in an equilibrium profile σ , refer to Proposition 8 in Appendix A). Before stating Proposition 1, we define the notion of *leading agents*. Intuitively, a society contains a set of leading agents if there is a negligible fraction of the agents (the leading agents) whose actions affect the equilibrium behavior of a much larger set of agents (the followers). Let $\text{indeg}_i^n = |B_{i,1}^n|$ and $\text{outdeg}_i^n = |\{j \mid i \in B_{j,1}^n\}|$ denote the in-degree and out-degree of agent i in communication network G^n , respectively.

DEFINITION 5. A collection $\{S^n\}_{n=1}^\infty$ of sets of agents is called a set of *leading agents* if the following conditions hold:

- (i) There exists $k > 0$, such that $S^{n_j} \subseteq V_k^{n_j}$ for all $j \in J$, where J is an infinite index set.
- (ii) We have $\lim_{n \rightarrow \infty} (1/n) \cdot |S^n| = 0$, i.e., the collection $\{S^n\}_{n=1}^\infty$ contains a negligible fraction of the agents as the society grows.

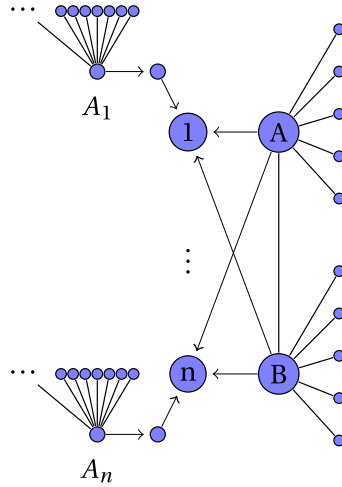


FIGURE 2. Leading agents and asymptotic learning.

- (iii) We have $\lim_{n \rightarrow \infty} (1/n) \cdot |S_{\text{follow}}^n| > \epsilon$ for some $\epsilon > 0$, where S_{follow}^n denotes the set of followers of S^n . In particular,

$$S_{\text{follow}}^n = \{i \mid \text{there exists } j \in S^n \text{ such that } j \in B_{i,1}^n\}.$$

PROPOSITION 1. Suppose that *Assumption 1* holds, so that communication is truthful. Then the following cases occur:

- (i) Perfect asymptotic learning occurs in society $\{G^n\}_{n=1}^\infty$ in any equilibrium σ if

$$\lim_{k \rightarrow \infty} \lim_{n \rightarrow \infty} \frac{1}{n} \cdot |V_k^n| = 0. \quad (1)$$

- (ii) Conversely, if condition (1) does not hold for society $\{G^n\}_{n=1}^\infty$ and the society does not contain a set of leading agents, then perfect asymptotic learning does not occur in any equilibrium σ .

Proposition 1 is not stated as an if and only if result because the fact that condition (1) does not hold in a society does not necessarily preclude perfect asymptotic learning in the presence of leading agents. In particular, depending on their actions, a large set of agents may exit early before obtaining enough information to learn the underlying state or may delay their actions and learn it. **Figure 2** clarifies this point: if the leading agents (agents A and B) delay their irreversible decision for one communication round, then a large fraction of the rest of the agents (agents 1 to n) may take (depending on the discount rate) an irreversible action as soon as they communicate with the leading agents and their neighbors (i.e., after the second communication round concludes), thus, perfect asymptotic learning fails. However, if the leading agents do not “coordinate,” then they exit early and this may lead the rest of the agents to take a delayed (after the third

communication round), but more informed action. Generally, in the presence of leading agents, asymptotic learning may occur in all or some of the induced equilibria, even when condition (1) does not hold.

In the rest of this section, we present two corollaries that help clarify the intuition behind the asymptotic learning result and identify the role of certain types of agents on information spread in a given society. We focus on perfect asymptotic learning, since we can obtain sharper results, though we can state similar corollaries for ϵ , δ -asymptotic learning for any ϵ and δ . All corollaries are again expressed in terms of the network topology. Also, for simplicity, for the rest of this section, we assume that the in-degree and the out-degree of an agent are nondecreasing with n .

In particular, [Corollary 1](#) identifies a group of agents that is crucial for a society to permit asymptotic learning: *information mavens* (a term inspired by [Gladwell 2000](#)), who have high in-degrees (“information hubs”) and can thus act as effective aggregators of information. The importance of information mavens is clearly illustrated by our learning results. Our next definition formalizes this notion.

DEFINITION 6. Agent i is called an *information maven* of society $\{G^n\}_{n=1}^\infty$ if i has an infinite in-degree, i.e., if

$$\lim_{n \rightarrow \infty} \text{indeg}_i^n = \infty.$$

Let $\text{MAVEN}(\{G^n\}_{n=1}^\infty)$ denote the set of mavens of society $\{G^n\}_{n=1}^\infty$.

For any agent j , let $d_j^{\text{MAVEN},n}$ denote the shortest distance defined in communication network G^n between j and a maven $k \in \text{MAVEN}(\{G^n\}_{n=1}^\infty)$. Finally, let W^n denote the set of agents who are at distance at most equal to their perfect observation radius from a maven in communication network G^n , i.e., $W^n = \{j \mid d_j^{\text{MAVEN},n} \leq \tau_j^n\}$.

The following corollary highlights the importance of information mavens for asymptotic learning. Informally, it states that if almost all agents have a short path to a maven, then asymptotic learning occurs.

COROLLARY 1. Suppose that [Assumption 1](#) holds, so that communication is truthful. Then asymptotic learning occurs in society $\{G^n\}_{n=1}^\infty$ if

$$\lim_{n \rightarrow \infty} \frac{1}{n} \cdot |W^n| = 1.$$

According to [Corollary 1](#), asymptotic learning is obtained when almost all agents are at a short distance away from an information maven (less than their observation radius).

As mentioned in the [Introduction](#), a second type of information hub also plays an important role in asymptotic learning. While mavens have high in-degree and are thus able to effectively aggregate dispersed information, they may not be in the right position to distribute this aggregated information. If so, even in a society that has several information mavens, a large fraction of the agents may not benefit from their information. *Social connectors*, on the other hand, are defined as agents who have a high out-degree and, thus, play the role of spreading the information aggregated by the mavens. Before stating the proposition, we define *social connectors*.

DEFINITION 7. Agent i is called a *social connector* of society $\{G^n\}_{n=1}^\infty$ if i has an infinite out-degree, i.e., if

$$\lim_{n \rightarrow \infty} \text{outdeg}_i^n = \infty.$$

The following corollary illustrates the role of social connectors for asymptotic learning.

COROLLARY 2. Suppose that [Assumption 1](#) holds, so that communication is truthful. Consider a society $\{G^n\}_{n=1}^\infty$, such that the set of information mavens does not grow at the same rate as the society itself, i.e.,

$$\lim_{n \rightarrow \infty} \frac{|\text{MAVEN}(\{G^n\}_{n=1}^\infty) \cap \{1, \dots, n\}|}{n} = 0.$$

Moreover, all mavens in the society have bounded out-degree, i.e., there exists $k > 0$ such that

$$\limsup_{n \rightarrow \infty} \text{outdeg}_i^n < k, \quad \text{for all } i \in \text{MAVEN}(\{G^n\}_{n=1}^\infty).$$

Then, for asymptotic learning to occur, the society should contain a social connector within a short distance to a maven, i.e.,

$$d_i^{\text{MAVEN}, n} \leq \tau_i^n, \quad \text{for some social connector } i.$$

Recall that the corollaries were expressed for societies for which both the in-degree and the out-degree of an agent are nondecreasing in the size of the society n . This choice simplified the exposition considerably; if this was not the case, the corollaries would have been expressed in terms of the agents with the largest in-degree and out-degree within the observation radius of an agent for each n .

[Corollary 2](#) thus states that unless the set of mavens grows at the same rate as the society or there are agents who are both mavens and connectors, then information aggregated at the mavens is spread through the out-links of a connector. These two corollaries highlight two ways in which society can achieve perfect asymptotic learning. First, it may contain several information mavens who not only collect and aggregate information, but also distribute it to almost all the agents in the society. Second, it may contain a sufficient number of information mavens who pass their information to social connectors, and almost all the agents in the society are a short distance away from social connectors and thus obtain accurate information from them. This latter pattern is more plausible in practice than one in which the same agents collect and distribute dispersed information. For example, a website or a news source may need to rely on information mavens (journalists, researchers, or analysts) to collect sufficient information and then reach a large number of individuals, and this may permit information to be aggregated efficiently.

The results summarized in [Proposition 1](#), as well as in [Corollaries 1](#) and [2](#), can be seen both as positive and negative, as already noted in the [Introduction](#). On the one

hand, communication structures that do not feature information mavens (or connectors) do not lead to perfect asymptotic learning, and information mavens may be viewed as unrealistic or extreme. On the other hand, as already noted above, much communication in modern societies happens through agents who play the role of mavens and connectors (see again [Gladwell 2000](#)). These are highly connected agents who are able to collect and distribute crucial information. Perhaps more importantly, most individuals obtain some of their information from news sources, media, and websites, which exist partly or primarily for the purpose of acting as information mavens and connectors.¹⁹ In particular, [Reinstein and Snyder \(2005\)](#) exploit the difference in timing between the release of a movie and the posting of a review by two of the most prominent critics, Siskel and Ebert, to argue for the importance of a positive review, especially in movie categories with a lot of uncertainty and little prior information (e.g., narrower release movies). Moreover, they show that a positive review increases the total number of consumers who attend the movie rather than simply shifting consumers to view the movie earlier. Similarly, [Sorensen \(2007\)](#) exploits time lags between the release of a book and its inclusion on the *New York Times* bestsellers list to establish similar results. We view the above evidence as conforming with our findings: in the absence of input from mavens–connectors, information is not aggregated efficiently, since it is their input that induces agents to buy certain products.

The result that asymptotic learning requires the presence of information hubs (information mavens and social connectors) is in contrast to one of the key insights of several non-Bayesian models of learning. Both in [Bala and Goyal \(1998\)](#) and in models based on DeGroot's approach to learning (e.g., [DeMarzo et al. 2003](#) and [Golub and Jackson 2010](#)), the existence of a highly connected individual or group of individuals (a “royal family” in the terminology of [Bala and Goyal 1998](#)) precludes learning because it leads to excessive duplication of information. In our framework, because agents are fully Bayesian and information is tagged, such duplication does not take place and information hubs play a central role in quickly aggregating and disseminating dispersed information. Thus they are conduits rather than barriers to asymptotic learning.

Finally, an important point to highlight is that although our results are shown in a setting where agents may end up passing a number of signals that grows with the size of the society (which might be considered an unappealing feature of the model), our qualitative insights regarding asymptotic learning remain true even if a summary statistic rather than the entire tagged information that an agent has is communicated. In the environment we described, the posterior mean and precision about the state given the messages that an agent has received comprise a sufficient statistic of her information. Thus in this case, the agent can simply exchange this low-dimensional information rather than all the messages she has received. This would be without any loss of generality when the network structure does not contain loops and, therefore, there exists no agent who receives the information of another agent from more than one sources (there is no replication of information). Even when the network contains loops, we show in

¹⁹For example, a news website such as [cnn.com](#) acts as a connector that spreads the information aggregated by the journalists–mavens to interested readers. Similarly, a movie review website, e.g., [imdb.com](#), spreads the aggregate knowledge of movie reviewers to interested movie aficionados.

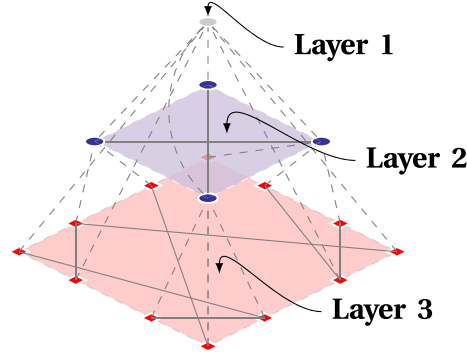


FIGURE 3. Hierarchical society.

Proposition 2 that asymptotic learning obtains when individuals report just their posterior mean under the same conditions as when they report their entire information set.

ASSUMPTION 2 (Low-dimensional communication). *Communication between agents is low dimensional when agents just report their posterior mean about the underlying state θ when communication takes place, i.e., if agent j communicates with agent i at time t , then i sends to j the message*

$$m_{ij,t}^n = \mathbb{E}[\theta | I_{i,t}^n].$$

PROPOSITION 2. *If perfect asymptotic learning occurs in society $\{G^n\}_{n=1}^\infty$ under [Assumption 1](#), then perfect asymptotic learning occurs in society $\{G^n\}_{n=1}^\infty$ under [Assumption 2](#), i.e., when agents just report their posterior mean about the underlying state θ .*

[Proposition 1](#) and [Corollary 1](#) imply that asymptotic learning occurs under [Assumption 1](#) when the underlying network structure features information mavens, i.e., agents with an arbitrarily large in-degree. The intuition behind [Proposition 2](#) above is simply that mavens can still aggregate and distribute a large amount of information, even when they receive low-dimensional communication.

3.3 Asymptotic learning in random graphs

We now illustrate the results outlined in [Section 3.2](#) by applying them to *hierarchical graphs*, a class of random graphs defined below (also see [Figure 3](#)). Note that in the present section, we assume that communication networks are bidirectional or, equivalently, that if agent $i \in B_{j,1}^n$, then $j \in B_{i,1}^n$. Conditional on the realization of the network structure, both the state of the world θ and the private signals are distributed as in the previous sections.

DEFINITION 8 (Hierarchical graphs). A sequence of communication networks $\{G^n\}_{n=1}^\infty$, where $G^n = \{\mathcal{N}^n, \mathcal{E}^n\}$, is called ζ -*hierarchical* (or simply hierarchical) if it was generated by the following process:

- (i) Agents are born and placed into layers. In particular, at each step n , a new agent is born and placed in layer ℓ .
- (ii) Layer index ℓ is initialized to 1 (i.e., the first node belongs to layer 1). A new layer is created (and subsequently the layer index increases by 1) at time period $n \geq 2$ with probability $1/n^{1+\zeta}$, where $\zeta > 0$.
- (iii) Finally, for every n , we have

$$\mathbb{P}((i, j) \in \mathcal{E}^n) = \frac{p}{|\mathcal{N}_\ell^n|},$$

independently for all $i, j \in \mathcal{N}^n$ that belong to the same layer ℓ ,

where $\mathcal{N}_\ell^n$ denotes the set of agents who belong to layer ℓ at step n and p is a scalar, such that $0 < p < 1$. Moreover,

$$\mathbb{P}((i, k) \in \mathcal{E}^n) = \frac{1}{|\mathcal{N}_{<\ell}^n|} \quad \text{and} \quad \mathbb{P}\left(\bigcup_k (i, k) \in \mathcal{E}^n\right) = 1 \quad \text{for all } i \in \mathcal{N}_\ell^n, k \in \mathcal{N}_{<\ell}^n, \ell > 1,$$

where $\mathcal{N}_{<\ell}^n$ denotes the set of agents who belong to a layer with index lower than ℓ at step n .

In words, agents are born sequentially and placed into layers starting from layer 1 (the top layer). As long as the layer index does not increase, a new agent is placed into the same layer as her predecessor. The layer index increases at every step with some probability that decreases with the number of steps (and, thus, ensures that with high probability, layers with high indices contain more agents than layers with low indices). Finally, each agent has an edge with her predecessors in the same layer and with her predecessors in layers with lower indices uniformly at random with some probability. The last property implies that older agents (agents who were born earlier) connect to more agents.

Intuitively, a hierarchical sequence of communication networks resembles a pyramid, where the top contains only a few agents and as we move toward the base, the number of agents grows. The following argument provides an interpretation of the model. Agents on top layers can be thought of as “special” nodes, that the rest of the nodes have a high incentive to connect to. Moreover, agents tend to connect to other agents in the same layer, as they share common features with them (which can be interpreted as a form of *homophily*). As a concrete example, academia can be thought of as such a pyramid, where the top layer includes the few institutions, then the next layer includes academic departments, then research labs, and finally at the lower levels reside the web-pages of professors and students.

PROPOSITION 3. *Suppose that [Assumption 1](#) holds, so that communication is truthful, and consider society $\{G^n\}_{n=1}^\infty$. There exist $\bar{r} > 0$ and a function $\zeta(\eta)$ such that perfect asymptotic learning occurs in society $\{G^n\}_{n=1}^\infty$ with probability at least $1 - \eta$ if the sequence of communication networks $\{G^n\}_{n=1}^\infty$ is $\zeta(\eta)$ -hierarchical and the discount rate is $r < \bar{r}$.*

The probability η that perfect asymptotic learning fails is related here to the stochastic process that generated the graph. We can also show that the popular preferential attachment and Erdős–Renyi graphs do not lead to asymptotic learning (we omit these results to save space). This can be interpreted as implying that asymptotic learning is unlikely in several important networks. Nevertheless, these network structures, though often used in practice, do not provide a good description of the structure of many real life networks. In contrast, our results show that asymptotic learning takes place in hierarchical graphs, where special agents are likely to receive and distribute information to lower layers of the hierarchy. Although this result is useful in pointing out certain structures where information can be aggregated efficiently, our analysis on the whole suggests that the conditions for perfect asymptotic learning are somewhat stringent.

3.4 Strategic communication

Next we explore the implications of relaxing the assumption that agents cannot manipulate the messages they send. In particular, we replace [Assumption 1](#) with the following assumption.

ASSUMPTION 3 (Strategic communication). *Communication between agents is strategic if*

$$m_{ij,t}^n \in \mathbb{R}^n$$

for all agents i, j and time t .

This assumption highlights that strategic communication does not impose any constraints on the messages exchanged (except that they belong to $\mathbb{R}^n$). In particular, $m_{ij,t}^n$ is a decision variable of agent i at time t and it is measurable with respect to the information available to agent i at time t . Allowing strategic communication adds an extra dimension in an agent's strategy, since the agent can choose not to disclose (part) of her information set in the hope that this increases her expected payoff. In contrast with “cheap talk” models, externalities in our framework are purely informational. Thus an agent may have an incentive not to disclose (part of) her information as a means to obtain more information from the information exchange process (by inducing a later exit decision from her neighbors).²⁰

[Figure 4](#) illustrates how incentives for nontruthful communication may arise. Here, agent B may have an incentive not to disclose her information to agent A. In particular, for a set of parameter values, we have that if agent B is truthful to A, then A takes an action after the first communication round. Alternatively, if B does not disclose her information to A, then A waits for an additional time period and B obtains access to the information of agents 9, 10, and 11.

Let (σ^n, m^n) denote an action–message strategy profile, where $m^n = \{m_1^n, \dots, m_n^n\}$ and $m_i^n = [m_{ij,\tau}^n]_{\tau=0,1,\dots}$ for j such that $i \in B_{j,1}^n$. Also let $\mathbb{P}_{\sigma^n, m^n}$ refer to the conditional probability when agents behave according to the action–message strategy profile (σ^n, m^n) .

²⁰Recall that when an agent exits, then she does not communicate new information (but she can still communicate the information she obtained up to the time of her exit).

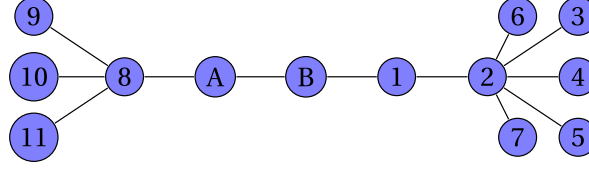


FIGURE 4. Agents may have an incentive to misreport/not disclose their information.

DEFINITION 9. An action–message strategy profile $(\sigma^{n,*}, m^{n,*})$ is a *pure-strategy perfect Bayesian equilibrium* of the information exchange game $\Gamma_{\text{info}}(G^n)$ if for every $i \in \mathcal{N}^n$ and communication round τ , we have

$$\mathbb{E}_{(\sigma^{n,*}, m^{n,*})}(U_{i,\tau}^n | I_{i,\tau}^n) \geq \mathbb{E}_{((\sigma_{i,\tau}^n, \sigma_{i,-\tau}^n, \sigma_{-i}^{n,*}), (m_{i,\tau}^n, m_{i,-\tau}^n, m_{-i}^{n,*}))}(U_{i,\tau}^n | I_{i,\tau}^n)$$

for all $m_{i,\tau}^n$, $m_{i,-\tau}^n$, and $\sigma_{i,\tau}^n$, $\sigma_{i,-\tau}^n$. We denote the set of equilibria of this game by $\text{INFO}(G^n)$.

Similarly, we extend the definitions of asymptotic learning (cf. Definitions 2 and 3). We show that strategic communication does not harm perfect asymptotic learning. The main intuition behind this result is that it is weakly dominant for an agent to report her private signal truthfully to a neighbor with a high in-degree (maven), as long as others are truthful to the maven.

PROPOSITION 4. If perfect asymptotic learning occurs in society $\{G^n\}_{n=1}^\infty$ under truthful communication (cf. Assumption 1), then there exists an equilibrium (σ, m) , such that perfect asymptotic learning occurs in society $\{G^n\}_{n=1}^\infty$ along equilibrium (σ, m) when we allow strategic communication (cf. Assumption 3).

This proposition therefore implies that the focus on truthful reporting was without much loss of generality as far as perfect asymptotic learning is concerned. In any communication network in which there is perfect asymptotic learning, even if agents can strategically manipulate information, there is arbitrarily little benefit in doing so. Thus, the main lessons about asymptotic learning derived above apply regardless of whether communication is strategic.

However, this proposition does not imply that all learning outcomes are identical under truthful and strategic communication. In particular, as illustrated in Figure 5, strategic communication may lead agents to take a better action with higher probability than under truthful communication (cf. Assumption 1). The main reason for this (counterintuitive) fact is that under strategic communication, an agent may delay taking an action compared to the nonstrategic environment. Therefore, the agent obtains more information from the communication network and, consequently, chooses an action, that is closer to optimal. In particular, in the example illustrated in Figure 5, if agents A and B decide not to disclose their information, then agents $1, \dots, n$ may delay their action so as to communicate with the neighbors of $A_1, \dots, A_n$ and thus take an action based on more information.

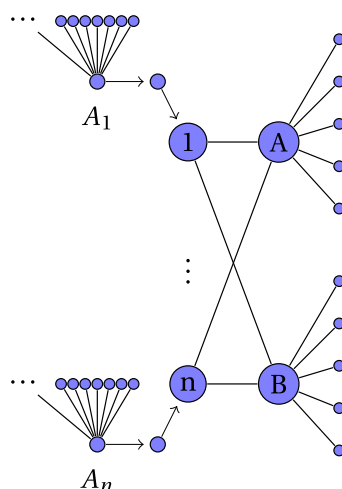


FIGURE 5. Strategic communication may lead to better actions.

Finally, note that relaxing [Assumption 1](#) by imposing no restrictions on the messages that agents exchange would lead to multiple equilibria. In particular, a “babbling” equilibrium always exists: agents send uninformative messages and ignore the messages they receive from their peers. A complete characterization of the equilibria of the information exchange game under strategic communication is beyond the scope of this paper. Our main goal in this section was to show that perfect asymptotic learning is robust (at least in some equilibria) to strategic communication. Moreover, we illustrated that the introduction of strategic communication has nontrivial welfare implications even in the case when externalities among agents are purely informational.

3.5 Welfare

In this subsection, we turn to the question of *efficient* communication and compare equilibrium allocations (communication and action profiles in equilibrium) with those that would be dictated by the welfare-maximizing social planner. We identify conditions under which a social planner can improve over an equilibrium strategy profile. In doing so, we illustrate that communication over social networks might be inefficient because agents do not internalize the positive externality that delaying their action generates for their peers.²¹

A social planner whose objective is to maximize the aggregate expected welfare of the population of n agents would implement the timing profile that is a solution to the

²¹We compare equilibrium outcomes to the best society could do under the constraint that information available to the agents at the beginning of the horizon cannot be redistributed among them before the information exchange process. In other words, our efficiency benchmark is the optimal mapping from information available to each agent to actions that maximize the aggregate utility. [Angeletos and Pavan \(2007\)](#) use a similar benchmark to compare equilibrium use and the social value of information for a class of economies that feature externalities among the agents and heterogeneous information.

optimization problem

$$\max_{\text{sp}^n} \sum_{i=1}^n \mathbb{E}_{\text{sp}^n}[U_i^n],$$

where $\text{sp}^n = (\tau_1^{n,\text{sp}}, \dots, \tau_n^{n,\text{sp}})$ and $\tau_i^{n,\text{sp}}$ implies that agent i stops exchanging information and takes an action after $\tau_i^{n,\text{sp}}$ communication rounds. With some abuse of notation, for the rest of this section, we denote by sp^n the *optimal allocation*, i.e., the solution to the optimization problem defined above.

Similarly with the asymptotic analysis for equilibria, we define a sequence of optimal allocations for societies of growing size, $\text{sp} = \{\text{sp}^n\}_{n=1}^\infty$. We are interested in identifying conditions under which the social planner can/cannot achieve an *asymptotically* better allocation than an equilibrium (sequence of equilibria) σ , i.e., we are looking at the expression

$$\lim_{n \rightarrow \infty} \frac{\sum_{i \in N^n} \mathbb{E}_{\text{sp}^n}[U_i^n] - \sum_{i \in N^n} \mathbb{E}_\sigma[U_i^n]}{n}.$$

The next proposition shows a direct connection between learning and efficient communication.

PROPOSITION 5. *Consider society $\{G^n\}_{n=1}^\infty$. If condition (1) holds, i.e.,*

$$\lim_{k \rightarrow \infty} \lim_{n \rightarrow \infty} \frac{1}{n} |V_k^n| = 0,$$

then

- (i) *perfect asymptotic learning occurs in all equilibria σ*
- (ii) *all equilibria are asymptotically efficient, i.e.,*

$$\lim_{n \rightarrow \infty} \frac{\sum_{i \in N^n} \mathbb{E}_{\text{sp}^n}[U_i^n] - \sum_{i \in N^n} \mathbb{E}_\sigma[U_i^n]}{n} = 0$$

for all equilibria σ .

However, communication is not always efficient. In what follows, we contrast the decision problem of an individual agent i with that of the social planner and show when equilibria can be inefficient. With a slight abuse of notation, $U_i^n(k, \sigma)$ denotes the expected payoff of agent i when agents behave according to profile σ and the agent has observed k signals. Agent i decides to take an irreversible action at time t and not to wait for an additional dt , when other agents behave according to σ , if (see [Appendix B](#))

$$\frac{r + \lambda}{\lambda} \left(\psi - \frac{1}{\rho + \bar{\rho} k_{i,t}^{n,\sigma}} \right) \geq U_i^n(k_{i,t}^{n,\sigma} + |B_{i,|T_t|+1}^{n,\sigma}| - |B_{i,|T_t|}^{n,\sigma}|, \sigma). \quad (2)$$

Similarly, in the corresponding optimal allocation, agent i exits at time t and does not wait if

$$\begin{aligned} & \frac{r + \lambda}{\lambda} \left(\psi - \frac{1}{\rho + \bar{\rho} k_{i,t}^{n,\text{sp}}} \right) \\ & \geq U_i^n(k_{i,t}^{n,\text{sp}} + |B_{i,|T_i|+1}^{n,\text{sp}}| - |B_{i,|T_i|}^{n,\text{sp}}|, \text{sp}) + \sum_{j \neq i} \mathbb{E}_{\text{sp}}[U_j^n | i \text{ waits at } t] - \mathbb{E}_{\text{sp}}[U_j^n | i \text{ exits at } t]. \end{aligned} \quad (3)$$

Comparison of (2) with (3) shows the reason why equilibria may be inefficient in this setting: when determining when to act, agent i does not take into account the positive externality that a later action exerts on others. This externality is expressed by the summation on the right-hand side of (3) (which is always nonnegative).

We next derive sufficient conditions under which a social planner outperforms an equilibrium allocation σ . Consider agents i and j such that $i \in B_{j,1}^n$ and $\tau_j^{n,\sigma} > \tau_i^{n,\sigma} + 1$, which implies that $B_{j,\tau_j}^{n,\sigma} \supset B_{i,\tau_i}^{n,\sigma}$ (i.e., agent j communicates with a superset of the agents that i communicates with before taking an action). Also, let $k_{ij,\tau_i}^{n,\sigma}$ denote the additional agents that j would observe if i delayed her irreversible action by dt . Then the aggregate welfare of the two agents increases if the following condition holds:

$$U_j^n(k_{j,\tau_j}^{n,\sigma} + k_{ij,\tau_i}^{n,\sigma}) + U_i^n(k_{i,\tau_i}^{n,\sigma} + k_{ij,\tau_i}^{n,\sigma}) > U_j^n(k_{j,\tau_j}^{n,\sigma}) + \frac{r + \lambda}{\lambda} U_i^n(k_{i,\tau_i}^{n,\sigma}).$$

Let set $D_{k,\ell}^{n,\sigma}$ denote the set of agents $j \in D_{k,\ell}^{n,\sigma}$ under the following conditions:

- (i) If $k_{j,\tau_j}^{n,\sigma} \leq k$.
- (ii) If there exists an agent $i \in B_{j,1}^{n,\sigma}$ such that $\tau_j^{n,\sigma} > \tau_i^{n,\sigma} + 1$ and if i exits at $\tau_i^{n,\sigma} + 1$, then j gains access to at least ℓ additional signals.

Intuitively, set $D_{k,\ell}^{n,\sigma}$ contains agents who would obtain higher payoff in expectation if one of their neighbors delayed taking her irreversible action. In particular, under equilibrium profile σ , agent $j \in D_{k,\ell}^{n,\sigma}$ takes an action after observing at most k signals. If her neighbor i delayed her action by one communication round, then she would have access to at least $k + \ell$ signals by the time of her action.

The following proposition provides a sufficient condition for an equilibrium to be inefficient. It simply states that if there is a sufficiently large set of agents who would obtain higher expected payoff if one of their neighbors deviates from equilibrium profile σ by delaying her action, then (i) the equilibrium profile σ is inefficient and (ii) asymptotic learning does not occur at σ for an appropriate choice of parameters.

PROPOSITION 6. *Consider society $\{G^n\}_{n=1}^\infty$ and equilibrium $\sigma = \{\sigma^n\}_{n=1}^\infty$. Assume that $\lim_{n \rightarrow \infty} |D_{k,\ell}^{n,\sigma}|/n > \xi > 0$ for k, ℓ that satisfy*

$$\frac{r}{\lambda} \psi + \frac{2}{\rho + \bar{\rho}(k + \ell)} < \left(2 + \frac{r}{\lambda}\right) \frac{1}{\rho + \bar{\rho}k}.$$

Then there exists a $\zeta > 0$, such that

$$\lim_{n \rightarrow \infty} \frac{\sum_{i \in N^n} \mathbb{E}_{\text{sp}^n}[U_i^n] - \sum_{i \in N^n} \mathbb{E}_\sigma[U_i^n]}{n} > \zeta,$$

i.e., equilibrium σ is asymptotically inefficient. Moreover, there exist ϵ, δ such that ϵ, δ -asymptotic learning fails in equilibrium σ .

We close this section with a discussion on the implications of increasing the information that agents have access to at the beginning of the information exchange process. Consider the following setting: agents at time $t = 0$ have access to k public signals in addition to their private signal. This results in the following trade-off: on the one hand, agents are better informed about the underlying state, but then, on the other hand, they have less incentive to delay taking an action, and obtain and share information with others. In particular, one can show that when all agents have access to the same k public signals, then information sharing will be reduced compared to a setting without public signals, in the sense that agents take an irreversible action earlier. Moreover, in some cases, the presence of public signals leads to a strict decrease in the aggregate welfare. Thus more information is not necessarily better for the aggregate welfare of the agents.²² In view of this result, the recent surge of user-generated content in the form of product reviews and recommendations may not be as beneficial as it is sometimes argued, since there is some evidence (although not conclusive) that online recommendation systems tend to steer consumers toward popular choices and reduce product diversity (see Sorensen 2007 and Fleder and Hosanagar 2009).

4. NETWORK FORMATION

We have so far studied information exchange among agents over a given communication network $G^n = (\mathcal{N}^n, \mathcal{E}^n)$. We now analyze how this communication network emerges. We assume that link formation is costly. In particular, *communication costs* are captured by an $n \times n$ nonnegative matrix C^n , where C_{ij}^n denotes the cost that agent i has to incur to form the directed link (j, i) with agent j . As noted previously, a link's direction coincides with the direction of the flow of messages. In particular, agent i incurs a cost to form in-links. We refer to C^n as the *communication cost matrix*. We assume that $C_{ii}^n = 0$ for all $i \in \mathcal{N}^n$. Our goal in this section is to provide conditions under which the network structures that emerge as equilibria of the network formation game defined below guarantee asymptotic learning. Our results indicate that easy access to information may preclude asymptotic learning, as it reduces the incentives for further information sharing. Moreover, asymptotic learning may depend on how well agents coordinate in equilibrium: we show that there may be multiple equilibria that induce sparser/denser network structures and lead to different answers for asymptotic learning.

We define agent i 's *link formation strategy*, g_i^n , as an n -tuple such that $g_i^n \in \{0, 1\}^n$ and $g_{ij}^n = 1$ implies that agent i forms a link with agent j . The cost agent i has to incur if

²²This result is similar in spirit to those in Duffie et al. (2009) and in Morris and Shin (2002), both of which show how greater availability of public information may reduce welfare.

she implements strategy g_i^n is given by

$$\text{Cost}(g_i^n) = \sum_{j \in \mathcal{N}} C_{ij}^n \cdot g_{ij}^n.$$

The link formation strategy profile $g^n = (g_1^n, \dots, g_n^n)$ induces the communication network $G^n = (\mathcal{N}^n, \mathcal{E}^n)$, where $(j, i) \in \mathcal{E}^n$ if and only if $g_{ij}^n = 1$.

We extend our environment to the two-stage *network learning game* $\Gamma(C^n)$, where C^n denotes the communication cost matrix. The two stages of the network learning game can be described as follows:

Stage 1 (Network formation game): Agents choose their link formation strategies simultaneously. The link formation strategy profile g^n induces the communication network $G^n = (\mathcal{N}^n, \mathcal{E}^n)$. We refer to Stage 1 of the network learning game, when the communication cost matrix is C^n , as the *network formation game* and we denote it by $\Gamma_{\text{net}}(C^n)$.

Stage 2 (Information exchange game): Agents communicate over the induced network G^n as studied in previous sections.

We next define the equilibria of the network learning game $\Gamma(C^n)$. Note that we use the standard notation g_{-i} and σ_{-i} to denote the strategies of agents other than i . Also, we let $\sigma_{i,-t}$ denote the vector of actions of agent i at all times except t .

DEFINITION 10. A pair $(g^{n,*}, \sigma^{n,*})$ is a *pure-strategy perfect Bayesian equilibrium* of the network learning game $\Gamma(C^n)$ if the following conditions hold:

- (a) We have $\sigma^{n,*} \in \text{INFO}(G^n)$, where G^n is induced by the link formation strategy $g^{n,*}$.
- (b) For all $i \in \mathcal{N}^n$, $g_i^{n,*}$ maximizes the expected payoff of agent i given the strategies of other agents $g_{-i}^{n,*}$, i.e.,

$$g_i^{n,*} \in \arg \max_{g_i^n \in \{0,1\}^n} \mathbb{E}_\sigma[\chi_i(g_i^n, g_{-i}^{n,*})] \equiv \mathbb{E}_\sigma(U_i^n | I_{i,0}^n) - \text{Cost}(g_i^n)$$

for all $\sigma \in \text{INFO}(\tilde{G}^n)$, where $\tilde{G}^n$ is induced by link formation strategy $(g_i^n, g_{-i}^{n,*})$.

We denote the set of equilibria of this game by $\text{NET}(C^n)$.

Similar to the analysis of the information exchange game, we consider a sequence of communication cost matrices $\{C^n\}_{n=1}^\infty$, where for fixed n ,

$$C^n : \mathcal{N}^n \times \mathcal{N}^n \rightarrow \mathbb{R}^+ \quad \text{and} \quad C_{ij}^n = C_{ij}^{n+1} \quad \text{for all } i, j \in \mathcal{N}^n. \quad (4)$$

For the remainder of the section, we focus on the *social cliques communication cost structure*. The properties of this communication structure are stated in the next assumption.

ASSUMPTION 4. Let $c_{ij}^n \in \{0, c\}$ for all pairs $(i, j) \in \mathcal{N}^n \times \mathcal{N}^n$, where $c < (1/\rho + \bar{\rho})$. Moreover, let $c_{ij} = c_{ji}$ for all $i, j \in \mathcal{N}^n$ (symmetry) and let $c_{ij} + c_{jk} \geq c_{ik}$ for all $i, j, k \in \mathcal{N}^n$ (triangle inequality).

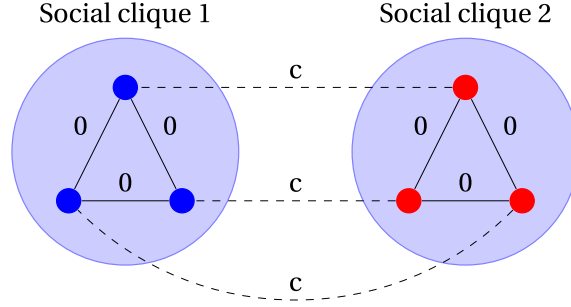


FIGURE 6. Social cliques.

The assumption that $c < 1/(\rho + \bar{\rho})$ rules out the degenerate case where no agent forms a costly link. The symmetry and triangle inequality assumptions are imposed to simplify the definition of a social clique, which is introduced next. Suppose [Assumption 4](#) holds. We define a *social clique* (cf. [Figure 6](#)) $H^n \subset \mathcal{N}^n$ as a set of agents such that

$$i, j \in H^n \quad \text{if and only if} \quad c_{ij} = c_{ji} = 0.$$

Note that this set is well defined since, by the triangle inequality and symmetry assumptions, if an agent i does not belong to social clique H^n , then $c_{ij} = c$ for all $j \in H^n$. Hence, we can uniquely partition the set of nodes $\mathcal{N}^n$ into a set of K^n pairwise disjoint social cliques $\mathcal{H}^n = \{H_1^n, \dots, H_{K^n}^n\}$. We use the notation $\mathcal{H}_k^n$ to denote the set of pairwise disjoint social cliques that have cardinality greater than or equal to k , i.e., $\mathcal{H}_k^n = \{H_i^n, i = 1, \dots, K^n \mid |H_i^n| \geq k\}$. We also use $\text{SC}^n(i)$ to denote the social clique that agent i belongs to. Social cliques represent groups of individuals who are linked to each other at zero cost. These can be thought of as friendship networks, which are linked for reasons unrelated to information exchange and thus can act as conduits of such exchange at low cost. Agents can exchange information without incurring any costs (beyond the delay necessary for obtaining information) within their social cliques. However, if they wish to obtain further information from outside their social cliques, they have to pay a cost at the beginning so as to form a link.²³

We consider a sequence of communication cost matrices $\{C^n\}_{n=1}^\infty$ that satisfy condition (4) and [Assumption 4](#), and we refer to this sequence as a *communication cost structure*. As shown above, the communication cost structure $\{C^n\}_{n=1}^\infty$ uniquely defines sequences, $\{\mathcal{H}^n\}_{n=1}^\infty$ and $\{\mathcal{H}_k^n\}_{n=1}^\infty$ for $k > 0$, which are sets of pairwise disjoint social cliques. Our goal is to identify conditions on the communication cost structure that lead to the emergence of networks that guarantee asymptotic learning. For brevity, we focus entirely on perfect asymptotic learning. Similar results can be obtained for ϵ, δ -asymptotic learning.

²³It is straightforward to see that social cliques of different sizes are isomorphic to agents having access to signals of varying precision.

PROPOSITION 7. Suppose that *Assumption 1* holds, so that communication is truthful, and let $\{C^n\}_{n=1}^\infty$ satisfy *Assumption 4*, i.e., $\{C^n\}_{n=1}^\infty$ is a social cliques communication cost structure. Then there exists a constant $\bar{k} = \bar{k}(c)$ such that the following statements hold:

(a) Suppose that

$$\limsup_{n \rightarrow \infty} \frac{|\mathcal{H}_{\bar{k}}^n|}{n} \geq \epsilon \quad \text{for some } \epsilon > 0. \quad (5)$$

Then perfect asymptotic learning does not occur in any network equilibrium (g, σ) .

(b) Suppose that

$$\lim_{n \rightarrow \infty} \frac{|\mathcal{H}_{\bar{k}}^n|}{n} = 0 \quad \text{and} \quad \lim_{n \rightarrow \infty} |H_\ell^n| = \infty \quad \text{for some } \ell. \quad (6)$$

Then perfect asymptotic learning occurs in all network equilibria (g, σ) when the discount rate r satisfies $0 < r < \bar{r}$, where $\bar{r} > 0$ is a constant.

(c) Suppose that there exists $M > 0$ such that

$$\lim_{n \rightarrow \infty} \frac{|\mathcal{H}_{\bar{k}}^n|}{n} = 0 \quad \text{and} \quad \limsup_{n \rightarrow \infty} |H_\ell^n| < M \quad \text{for all } \ell, \quad (7)$$

and let agents be patient, i.e., consider the case when the discount rate $r \rightarrow 0$.²⁴ Then there exists $\bar{c} > 0$ such that we have two cases:

- (i) If $c \leq \bar{c}$, perfect asymptotic learning occurs in all network equilibria (g, σ) .
- (ii) If $c > \bar{c}$, there exists at least one network equilibrium (g, σ) where there is no perfect asymptotic learning and there exists at least one network equilibrium (g, σ) where perfect asymptotic learning occurs.

Even though network formation games have several equilibria, the structure of our network formation and information exchange game enables us to obtain a fairly complete characterization of what types of environments lead to the formation of networks that subsequently induce perfect asymptotic learning. In particular, the first part of *Proposition 7* shows that perfect asymptotic learning cannot occur in any equilibrium if the number of sufficiently large social cliques increases at the same rate as the size of the society. This is intuitive; when this is the case, there are many social cliques of sufficiently large size that none of their members wishes to engage in further costly communication with members of other social cliques. But since several of these do not contain an information hub, social learning is precluded.

In contrast, the second part of the proposition shows that if the number of disjoint and sufficiently large social cliques is limited (grows less rapidly than the size of the society) and some of them are large enough to contain information hubs, then perfect

²⁴Formally, we study the expression $\lim_{n \rightarrow \infty} \lim_{r \rightarrow 0} \mathbb{P}_{(g, \sigma)}([(1/n) \sum_{i=1}^n (1 - M_i^{n, \epsilon})] > \epsilon)$.

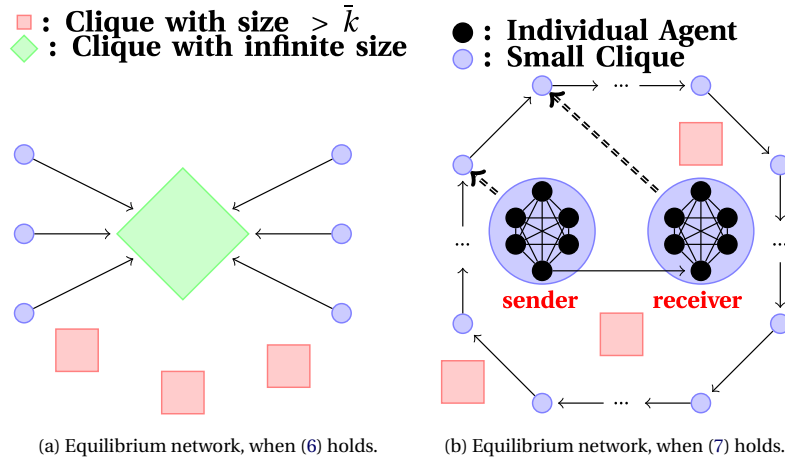


FIGURE 7. Network formation among social cliques.

asymptotic learning takes place in all equilibria²⁵ (provided that the future is not heavily discounted). In this case, as shown by Figure 7(a), sufficiently many social cliques connect to the larger social cliques acting as information hubs, ensuring effective aggregation of information for the great majority of the agents in the society. It is important that the discount factor is not too small; otherwise, smaller cliques do not find it beneficial to form links with larger cliques.

The third part of the proposition outlines a more interesting configuration, potentially leading to perfect asymptotic learning. In this case, many small social cliques form an “informational ring” (Figure 7(b)). Each is small enough that it finds it beneficial to connect to another social clique, provided that this other clique also connects to others and obtains further information. This intuition also clarifies why such information aggregation takes place only in some equilibria. The expectation that others do not form the requisite links leads to a coordination failure. Interestingly, however, if agents are sufficiently patient and the cost of link formation is not too large, the coordination failure equilibrium disappears, because it becomes beneficial for each clique to form links with another one, even if further links are not forthcoming. Finally, the ring structure is a direct consequence of the fact that agents are patient (and has been shown to emerge as an equilibrium configuration in other models of network formation, e.g., Bala and Goyal 2000).

5. CONCLUSION

We have developed a framework for the analysis of information exchange through communication and investigated its implications for information aggregation in large societies. An underlying state determines the payoffs from different actions. Agents decide

²⁵The result no longer holds when we replace Assumption 1 with Assumption 3, as there would then exist additional equilibria (e.g., babbling equilibria) in the information exchange stage, which would lead to different equilibrium network configurations in the first stage.

which agents to form a communication link with, incurring the associated cost. After receiving a private signal correlated with the underlying state, they exchange information over the induced communication network until taking an (irreversible) action.

Our model draws close attention to two main features of social learning: First, the timing of actions is often endogenous and it is determined by the trade-off between the cost of waiting and the benefit of becoming more informed over time about the underlying environment. Second, the communication network typically imposes constraints on the rate at which an agent acquires information and plays an important role in whether agents end up taking “good” actions.

Our focus has been on asymptotic learning, defined as the fraction of agents who take the correct action converging to 1 in probability as a society grows large. We showed that asymptotic learning occurs if and, under some additional mild assumptions, only if the induced communication network includes information hubs and most agents are at a short distance from a hub. Thus asymptotic learning requires information to be aggregated in the hands of a few agents. This kind of aggregation also requires truthful communication, which we show is an equilibrium even when we allow for strategic communication in large societies (partly as a consequence of the fact that there is no conflict among the agents concerning which action is the best). This insight offers a sharp contrast to a result often seen in the social learning literature: in our setting, the existence of highly connected agents is a necessary condition for learning, not an impediment to it. In particular, in several myopic models of learning, widely observed individuals obstruct learning, since their private information is overrepresented in the communication process. In our approach, agents are fully Bayesian and information is tagged and, thus, such duplication of information is avoided. To the contrary, hubs facilitate efficient information aggregation and are prerequisites for asymptotic learning.

Our welfare analysis identifies a novel information externality that arises in communication over networks. Individuals serve two roles: they are both sources of information, but they enable the transmission of information between different parts of the network through their social connections as well. This leads to an interesting insight on the dynamics of information exchange over networks: more precise signals (or larger social cliques) reduce the incentives for communication and may lead to a decrease in aggregate welfare. Interestingly, this information externality can explain in a fully Bayesian model the empirical observation that agents’ actions are often grouped according to their social network position (for a myopic learning model that delivers the same prediction, see [DeMarzo et al. 2003](#)).

We also provide a systematic investigation of what types of cost structures and associated social cliques that consist of groups of individuals linked to each other at zero cost (such as friendship networks) ensure the emergence of communication networks that lead to asymptotic learning. Our main result on network formation shows that societies with too many (disjoint) and sufficiently large social cliques do not form communication networks that lead to asymptotic learning, because each social clique would have sufficient information to make communication with others not sufficiently attractive. Asymptotic learning results if social cliques are not too large so as to encourage communication across cliques.

Beyond the specific results presented in this paper, we believe that the modeling framework developed here opens the way for a more general analysis of the impact of the structure of social networks on social learning. An interesting avenue for future research would be to investigate how our results would change in the presence of ex ante or ex post heterogeneity of preferences. Another notable direction is to consider an environment where agents exchange information over multiple issues (and end up taking multiple actions), i.e., communication is over a multidimensional state of the world ($x, \theta \in \mathbb{R}^k$). Then we conjecture that a one-dimensional quantity that captures the agent's position in the network would be sufficient to predict her actions along all dimensions.²⁶

APPENDIX A: ϵ, δ -ASYMPTOTIC LEARNING

In [Appendix A](#), we present a generalization of [Proposition 1](#). In particular, we provide conditions that guarantee that ϵ, δ -asymptotic learning occurs/does not occur in a society under equilibrium profile σ . Recall that $\text{erf}(x) = (2/\sqrt{\pi}) \int_0^x e^{-t^2} dt$ denotes the *error function* of the normal distribution. The proof of the proposition can be found in [Appendix B](#).

PROPOSITION 8. *Suppose that [Assumption 1](#) holds, so that communication is truthful. Then,*

- (a) *ϵ, δ -asymptotic learning does not occur in society $\{G^n\}_{n=1}^\infty$ under equilibrium profile σ if there exists $k, \eta > 0$ such that*

$$\liminf_{n \rightarrow \infty} \frac{1}{n} \cdot |V_k^{n, \sigma}| \geq \eta > \epsilon \quad \text{and} \quad \text{erf}\left(\epsilon \sqrt{\frac{\rho + k\bar{\rho}}{2}}\right) < (1 - \delta)(1 - \epsilon/\eta). \quad (8)$$

- (b) *ϵ, δ -asymptotic learning occurs in society $\{G^n\}_{n=1}^\infty$ under equilibrium profile σ if there exists $k, \zeta > 0$ such that*

$$\limsup_{n \rightarrow \infty} \frac{1}{n} \cdot |V_k^{n, \sigma}| \leq \zeta < \epsilon \quad \text{and} \quad \text{erf}\left(\epsilon \sqrt{\frac{\rho + \bar{\rho}k}{2}}\right) > 1 - \frac{\delta(\epsilon - \zeta)}{1 - \zeta}. \quad (9)$$

This proposition provides conditions such that ϵ, δ -asymptotic learning takes place (or does not take place). Intuitively, asymptotic learning is precluded if there exists a significant fraction of the society that takes an action before seeing a large set of signals, since in this case there is a large enough probability that these agents will take an action far away from the optimal one. The proposition quantifies the relationship between the fraction of agents taking actions before seeing a large set of signals and the quantities

²⁶A similar result, i.e., that agents' beliefs over multiple issues can be characterized by a unidimensional measure, was established in [DeMarzo et al. \(2003\)](#). There, the result was an outcome of the overrepresentation of the prior information of "central" agents. In our model, this is no longer possible as information is tagged and agents are Bayesian. However, agents choose the timing of their actions and we expect that their network distance to information hubs will be sufficient to predict their actions over multiple issues.

ϵ and δ . Because agents are estimating a normal random variable from noisy observations (where the noise is also normally distributed), their probability of error is captured by the error function $\text{erf}(x)$, which is naturally decreasing in the number of observations. In particular, the probability that an agent with k signals takes an action at least ϵ away from the optimal action is equal to $\text{erfc}(\epsilon\sqrt{(\rho + \bar{\rho}k)/2})$, and this enables us to characterize the fraction of agents that will take an action at least ϵ away from the optimal one in terms of the set $V_k^{n,\sigma}$ as well as ϵ and δ . We thus obtain sufficient conditions for both ϵ, δ -learning to take place and for it to be incomplete. Finally, recall that equilibria and subsequently k -radius sets depend on the discount rate (thus, different discount rates result in different answers for ϵ, δ -learning). In this context, [Proposition 8](#) implies that if ϵ, δ -learning occurs in a society under an equilibrium profile when the discount rate is r , then there exists an equilibrium profile for which ϵ, δ -learning occurs in that society for all $r' < r$, i.e., when agents are more patient.

APPENDIX B: PROOFS

Proofs for Section 3

PROOF OF LEMMA 1. Recall that, by the principle of optimality, agent i 's optimal continuation payoff at information set $I_{i,t}^n$, when the rest of the agents behave according to strategy profile σ , is given by

$$U_{i,t}^n = \max \begin{cases} \psi - \frac{1}{\rho + \bar{\rho}k_{i,t}^n} \\ \text{(when she takes the optimal irreversible action)} \\ e^{-rdt} \mathbb{E}[\mathbb{E}_\sigma(U_{i,t+dt}^n | I_{i,t+dt}^n) | I_{i,t}^n] \\ \text{(when she decides to wait, i.e., } x = \text{wait),} \end{cases}$$

where $k_{i,t}^n$ denotes the number of distinct private signals agent i has observed up to time t . The first line is equal to the expected payoff for the agent when she chooses the optimal irreversible action under information set $I_{i,t}^n$, i.e., $\mathbb{E}[\theta | I_{i,t}^n]$, and she has observed $k_{i,t}^n$ private signals, while the second line is equal to the discounted expected continuation payoff.

For the latter, note first that since the discount rate r is greater than zero, agent i will exit after a finite number of communication rounds. Thus the following set represents the number of signals agent i observes if she decides to wait for 1, 2, ... communication rounds:

$$\{k_{i,t}^n + |B_{i,|T_t|+1}^{n,\sigma}| - |B_{i,|T_t|}^{n,\sigma}|, k_{i,t}^n + |B_{i,|T_t|+2}^{n,\sigma}| - |B_{i,|T_t|}^{n,\sigma}|, \dots\}.$$

Note that given the other agents' strategy profiles, the quantities $|B_{i,|T_t|+s}^{n,\sigma}|$ are deterministic for every s . This is a consequence of the normality assumption on the private signals. In particular, when signals are normal, agents exit after they observe a given number of signals and this number does not depend on the actual realization of the signals (as opposed to if the signals were binary, for example). Moreover, since communication follows a Poisson process with rate λ , we obtain that the expected delay t_s before an additional s communication rounds are completed satisfies $\mathbb{E}(e^{-rt_s}) = (\lambda/(\lambda + r))^s$. Therefore, if agent i decides to wait for s additional communication rounds and to take an

action after the additional s th communication round is completed, her expected utility is given by

$$\left(\frac{\lambda}{\lambda+r}\right)^s \left(\psi - \frac{1}{\rho + \bar{\rho}(k_{i,t}^n + |B_{i,|T_t|+s}^{n,\sigma}| - |B_{i,|T_t|}^{n,\sigma}|)}\right).$$

Note that since we assume that signals are identically distributed and independent, the value function can simply be expressed as a function of the number of distinct signals in $I_{i,t}^n$, $k_{i,t}^n$ and profile σ . The agent chooses to take an irreversible action and not to wait if

$$\begin{aligned} \psi - \frac{1}{\rho + \bar{\rho}k_{i,t}^n} &\geq e^{-r dt} \mathbb{E}[\mathbb{E}_\sigma(U_{i,t+dt}^n | I_{i,t+dt}^n) | I_{i,t}^n] \\ &\geq \max_s \left(\frac{\lambda}{\lambda+r}\right)^s \left(\psi - \frac{1}{\rho + \bar{\rho}(k_{i,t}^n + |B_{i,|T_t|+s}^{n,\sigma}| - |B_{i,|T_t|}^{n,\sigma}|)}\right). \end{aligned} \quad (10)$$

Note that the right-hand side of (10) is upper bounded by $\lambda(\lambda+r)\psi$ (since $s \geq 1$), whereas the left-hand side is increasing in the number of private signals $k_{i,t}^n$ and in the limit is equal to ψ . This establishes the lemma. $\square$

The next lemma will be used in the rest of the Appendix. It shows that the probability of choosing an action that is more than ϵ away from the optimal for agent $i \in V_k^{n,\sigma}$, i.e., $\mathbb{P}_\sigma(M_i^{n,\epsilon} = 0)$, is uniformly bounded away from 0.

LEMMA 2. *Let $k > 0$ be a constant, such that the k -radius set $V_k^{n,\sigma}$ is nonempty. Then*

$$\mathbb{P}(M_i^{n,\epsilon} = 0) \geq \text{erfc}\left(\epsilon \sqrt{\frac{\rho + \bar{\rho}k}{2}}\right) \quad \text{for all } i \in V_{k,\sigma}^n,$$

where $\text{erfc}(x) = 1 - \text{erf}(x) = 1 - (2/\sqrt{\pi}) \int_0^x e^{-t^2} dt$ is the complementary error function. Moreover, if $i \notin V_k^{n,\sigma}$, then

$$\mathbb{P}(M_i^{n,\epsilon} = 0) < \text{erfc}\left(\epsilon \sqrt{\frac{\rho + \bar{\rho}k}{2}}\right).$$

PROOF. Note that because of our normality assumption, after observing ℓ private signals, the posterior distribution of θ is normal with precision $\rho + \bar{\rho}\ell$. Then the probability that $M_i^{n,\epsilon} = 0$ is simply equal to the probability that the error does not belong to the interval $[-\epsilon, \epsilon]$, i.e.,

$$\mathbb{P}(M_i^{n,\epsilon} = 0) = \text{erfc}\left(\epsilon \sqrt{\frac{\rho + \bar{\rho}\ell}{2}}\right).$$

The lemma follows since agent $i \in V_k^{n,\sigma}$ and thus she takes an irreversible action after observing at most k private signals. Similarly, we obtain the expression for an agent $i \notin V_k^{n,\sigma}$. $\square$

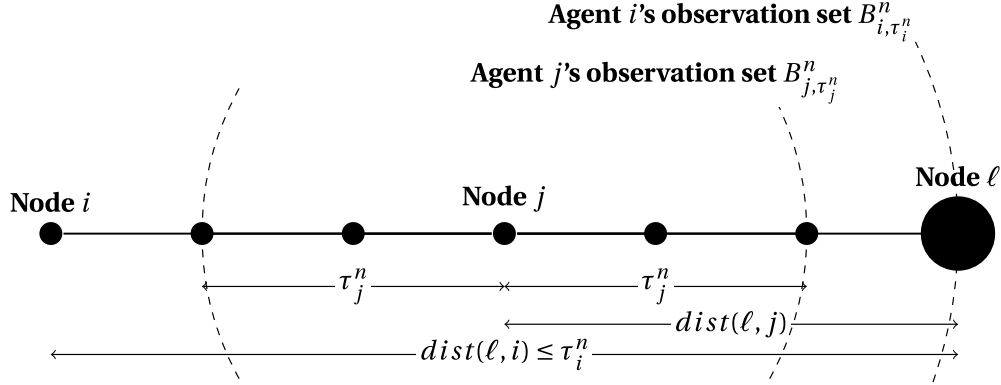


FIGURE 8. Proof of Proposition 9.

Let $j_i^n = \arg \max_{k \in B_{i, \tau_i^n}^n} \text{indeg}_k^n$ and define set X as

$$X = \left\{ i \in \mathcal{N} \mid \lim_{n \rightarrow \infty} \text{indeg}_{j_i^n}^n = \infty \right\}.$$

In other words, consider the agent with the maximum in-degree in i 's neighborhood. Then i belongs to set X if the maximum in-degree grows to infinity as the society grows larger. Note that the superscript n at the definition of j implies that the agent with the maximum in-degree depends on the size of the society and might be different for different n 's.

PROPOSITION 9. Suppose that Assumption 1 holds, so that communication is truthful. Then perfect asymptotic learning occurs in society $\{G^n\}_{n=1}^\infty$ in any equilibrium σ if

$$\lim_{n \rightarrow \infty} \frac{1}{n} |X| = 1.$$

PROOF. Consider equilibrium profile σ and society $\{G^n\}_{n=1}^\infty$ such that

$$\lim_{n \rightarrow \infty} \frac{1}{n} |X| = 1.$$

Let $j_i^{n, \sigma} = \arg \max_{k \in B_{i, \tau_i^n}^{n, \sigma}} \text{indeg}_k^n$ and define set Z^σ as the set of agents

$$Z^\sigma = \left\{ i \in \mathcal{N} \mid \lim_{n \rightarrow \infty} \text{indeg}_{j_i^{n, \sigma}}^n = \infty \right\}.$$

Next, we show that $X = Z^\sigma$.

Consider $i \in X$ and let $\mathcal{P}^n = \{\ell, i_1, \dots, i_K, i\}$ denote the shortest path in communication network G^n between i and agent $\ell = j_i^n$, i.e., ℓ is such that $\ell = \arg \max_{k \in B_{i, \tau_i^n}^n}$. Let N_0 be such that $\max_{z \in B_{i, \tau_i^n}^n} \text{indeg}_z^n > k$ for all $n > N_0$, where k is sufficiently large. Then we show that (refer to Figure 8) for $n > N_0$,

$$\ell \in B_{s, \tau_s^n}^n \quad \text{for all } s \in \mathcal{P}^n. \quad (11)$$

Assume for the sake of contradiction that condition (11) does not hold. Then let

$$j = \arg \min_{j'} \{\text{dist}^n(\ell, j') \mid j' \in \mathcal{P}^n \text{ and } \text{dist}^n(\ell, j') > \tau_{j'}^n\},$$

where we recall that τ_i^n denotes the perfect observation radius of agent i . For agents i, j we have $\tau_i^n > \tau_j^n$ and $\text{dist}(j, i) + \tau_j^n < \text{dist}(\ell, i) \leq \tau_i^n$, since otherwise $\ell \in B_{j, \tau_j^n}^n$. This implies that $B_{j, \tau_j^n}^n \subset B_{i, \tau_i^n}^n$. Furthermore,

$$\psi - \frac{1}{\rho + \bar{\rho}|B_{j, \tau_j^n}^n|} > \left(\frac{\lambda}{\lambda + r} \right)^{\text{dist}(\ell, j) - \tau_j^n} \left(\psi - \frac{1}{\rho + \bar{\rho}k} \right).$$

In particular, the left-hand side is equal to the expected payoff of agent j if she takes an irreversible action at time τ_j^n after receiving $|B_{j, \tau_j^n}^n|$ observations, whereas the right-hand side is a lower bound on the expected payoff if agent j delays taking an action until after she communicates with agent ℓ . The inequality follows from the definition of the observation radius for agent j . Alternatively, since for agent i , $\ell \in B_{i, \tau_i^n}^n$, we have

$$\psi - \frac{1}{\rho + \bar{\rho}(|B_{j, \tau_j^n}^n|)} < \left(\frac{\lambda}{\lambda + r} \right)^{\text{dist}(\ell, i) - \text{dist}(j, i) - \tau_j^n} \left(\psi - \frac{1}{\rho + \bar{\rho}(k + k')} \right) \quad \text{for some } k' > 0.$$

For k large enough, we conclude that $\text{dist}(\ell, j) > \text{dist}(\ell, i) - \text{dist}(j, i)$, which is a contradiction. This implies that (11) holds.

To complete the proof, we need to show that if $s \in \mathcal{P}^n$, where $\mathcal{P}^n$ is the shortest path defined above, i.e., the shortest path from agent $i \in X$ to the agent with the largest in-degree in her neighborhood $B_{i, \tau_i^n}^n$ (call the latter ℓ), then $\ell \in B_{s, \tau_s^n}^{n, \sigma}$ for every equilibrium σ . We will show the claim by induction on the distance from agent ℓ . Obviously, the claim is true for length equal to zero. Suppose that the claim is true for distance at most t . Then we will show that the claim is true for distance $t + 1$. Let w denote the agent $w \in \mathcal{P}^n$ and $\text{dist}(w, \ell) = t + 1$. Then, from above, $\ell \in B_{w, \tau_w^n}^n$. Moreover, from the induction hypothesis, for an agent i in the shortest path from w to ℓ , we have that $\ell \in B_{i, \tau_i^n}^{n, \sigma}$, which implies that $\text{dist}^{n, \sigma}(w, \ell) = \text{dist}^n(w, \ell)$. Thus for k sufficiently large (i.e., for $n > N_0$), $\ell \in B_{w, \tau_w^n}^{n, \sigma}$, i.e., agent w will not exit before communicating with ℓ . If this was not the case, then we would have that $\ell \notin B_{w, \tau_w^n}^n$, i.e., $w \notin \mathcal{P}^n$. Note that the crucial point in this part of the proof was that all agents in the path from w to ℓ do not exit before communicating with ℓ along equilibrium strategy profile σ .

Finally, by the hypothesis of the proposition, i.e., $\lim_{n \rightarrow \infty} (1/n)|X| = 1$, we conclude that $\lim_{n \rightarrow \infty} (1/n)|Z^\sigma| = 1$ for any equilibrium σ . The latter implies that

$$\lim_{k \rightarrow \infty} \lim_{n \rightarrow \infty} \frac{1}{n} |V_k^{n, \sigma}| = 0,$$

thus asymptotic learning occurs along equilibrium σ from [Proposition 8](#). $\square$

PROOF OF PROPOSITION 1. The first part of Proposition 1 follows directly from Proposition 9, since

$$\lim_{k \rightarrow \infty} \lim_{n \rightarrow \infty} \frac{1}{n} |V_k^n| = 0 \quad \Rightarrow \quad \lim_{n \rightarrow \infty} \frac{1}{n} |X| = 1,$$

and the fact that agents exit after a finite number of communication rounds (since the discount rate r is greater than zero).

To conclude the proof, we need to show that if asymptotic learning occurs along some equilibrium σ when condition (1) does not hold, then the society contains a set of leading agents. In particular, consider a society $\{G^n\}_{n=1}^\infty$ in which condition (1) does not hold and equilibrium $\sigma = \{\sigma^n\}_{n=1}^\infty$ along which asymptotic learning occurs in the society. This implies that there should exist a subset $\{R^{n,\sigma}\}_{n=1}^\infty$ of agents and an $\epsilon > 0$ such that $\lim_{n \rightarrow \infty} (1/n) |R^{n,\sigma}| > \epsilon$, and there is an infinite index set J for which

$$i \in R^{n_j,\sigma} \quad \text{and} \quad \tau_i^{n_j} < \tau_i^{n_j,\sigma} \quad \text{for } j \in J \quad (12)$$

and

$$|B_{i,\tau_i}^{n_j}| < |B_{i,\tau_i}^{n_j,\sigma}|. \quad (13)$$

From equations (12) and (13), we obtain that there exists a collection of agents $\{S^n\}_{n=1}^\infty$ such that the following statements hold:

- (i) We have $R^{n,\sigma} \subseteq S^n_{\text{follow}}$. If this were not true, then agents in $R^{n,\sigma}$ would not obtain any information from the network along σ and, thus, would not learn.
- (ii) There exists a $k > 0$ such that $S^n \subseteq V_k^n$.
- (iii) We have $\lim_{n \rightarrow \infty} (1/n) |S^n| = 0$, since otherwise asymptotic learning would not occur under equilibrium σ .

Note that $\{S^n\}_{n=1}^\infty$ is a set of leading agents (cf. Definition 5) and Proposition 1(ii) follows. $\square$

PROOF OF PROPOSITION 2. Consider $\epsilon, \delta > 0$ and recall from Corollary 1 that asymptotic learning occurs when almost all agents are at a short distance away from an information maven. Let i be a maven and let $\bar{n}$ be such that $\text{indeg}_i^n > k$ for $n > \bar{n}$, where k is such that $\text{erfc}(\epsilon\sqrt{(\rho + \bar{\rho}k)/2}) < \delta$. Then Lemma 2 implies that

$$\mathbb{P}(|\mathbb{E}[\theta | I_{i,t_1}^n] - \theta| > \epsilon) < \delta \quad \text{for all } n > \bar{n} \quad (14)$$

holds for maven i , where t_1 is the first time when communication takes place. Note that (14) holds even under the assumption of low-dimensional communication (cf. Assumption 2), since an agent can infer the private signals of her direct neighbors from the messages she receives in the first communication round (if agent j sends a message to agent i at time $t = t_1$, then $m_{ji,t_1}^n = \mathbb{E}[\theta | s_j] = s_j$).²⁷

²⁷ Agent j 's information set before communication first takes place contains only her private signal.

Furthermore, consider any agent j who is directly connected to maven i , i.e., $i \in B_{j,1}^n$. Then, after the second communication round, the information monotonicity

$$\mathbb{P}(|\mathbb{E}[\theta|I_{j,t_2}^n] - \theta| > \epsilon) \leq \mathbb{P}(|\mathbb{E}[\theta|I_{i,t_1}^n] - \theta| > \epsilon), \quad (15)$$

holds for agent j 's information set, where t_2 denotes the second time when communication takes place. This relies on the simple observation that one strategy available to the agents that communicate directly with a maven is to imitate the action taken by the maven. Similarly, the observation can be generalized for the direct neighbors of j (who communicate indirectly with the maven in two communication rounds) and for the neighbors of the neighbors of j and so on. The claim follows by combining (15) with the arguments in the proof of [Proposition 1](#). $\square$

PROOF OF PROPOSITION 3. Consider the following two events A and B .

Event A: Layer 1 (the top layer) has more than k agents, where $k > 0$ is a scalar.

Event B: The total number of layers is more than k .

From the definition of a hierarchical sequence of communication networks, we have

$$\mathbb{P}(A) = \prod_{i=2}^k \left(1 - \frac{1}{i^{1+\zeta}}\right) < \exp\left(-\sum_{i=2}^k \frac{1}{i^{1+\zeta}}\right). \quad (16)$$

Also,

$$\mathbb{P}(B) \leq \frac{\mathbb{E}(\mathcal{L})}{k} = \frac{1}{k} \sum_{i=2}^{\infty} \frac{1}{i^{1+\zeta}}, \quad (17)$$

from Markov's inequality, where $\mathcal{L}$ is a random variable that denotes the number of layers in the hierarchical society. Let $\zeta(\eta)$ be small enough and let k (and consequently n) be large enough such that $\sum_{i=2}^k 1/(i^{1+\zeta}) > \log(4/\eta)$ and $\sum_{i=2}^{\infty} 1/(i^{1+\zeta}) < k \cdot \eta/4$. For those values of ζ and k , we obtain $\mathbb{P}(A) < \eta/4$ and $\mathbb{P}(B) < \eta/4$. Next, consider the event $C = A^c \cap B^c$, which from (16) and (17) has probability $\mathbb{P}(C) > 1 - \eta/2$ for the values of ζ and k chosen above. Moreover, we consider the following event.

Event D: The agents on the top layer are information mavens, i.e., $\lim_{n \rightarrow \infty} |B_{i,1}^n| = \infty$ for all $i \in \mathcal{N}_1^n$. We claim that event D occurs with high probability if C occurs, i.e., $\mathbb{P}(D|C) > 1 - \eta/2$, which implies

$$\mathbb{P}(C \cap D) = \mathbb{P}(D|C)\mathbb{P}(C) > (1 - \eta/2)^2 > 1 - \eta.$$

In particular, note that conditional on event C occurring, the total number of layers and the total number of agents in the top layer is at most k . From the definition of a hierarchical society, agents in layers with index $\ell > 1$ have an edge to a uniform agent who belongs to a layer with lower index, with probability 1. Therefore, if we denote the degree of an agent in a top layer by $\mathcal{D}_1^n$, we have

$$\mathcal{D}_1^n = \sum_{i=1}^{\mathcal{T}_2^n} \mathcal{I}_{i,1}^{\text{level } 2} + \dots + \sum_{i=1}^{\mathcal{T}_{\mathcal{L}}^n} \mathcal{I}_{i,1}^{\text{level } \mathcal{L}}, \quad (18)$$

where $\mathcal{T}_i^n$ denotes the random number of agents in layer i and $\mathcal{I}_{i,1}^{\text{level } j}$ is an indicator variable that takes value 1 if there is an edge from agent i to agent 1 (here level j denotes that i belongs to level j). Again from the definition, we have $\mathbb{P}(\mathcal{I}_{i,1}^{\text{level } j} = 1) = 1 / \sum_{\ell=1}^{j-1} \mathcal{T}_\ell^n$, where the sum in the denominator is simply the total number of agents who lie in layers with lower index, and, finally, $\mathcal{T}_1^n + \dots + \mathcal{T}_\ell^n = n$. We can obtain a lower bound on the expected degree of an agent in the top layer conditional on event C by viewing (18) as the optimization problem

$$\begin{aligned} \min & \frac{x_2}{x_1} + \dots + \frac{x_k}{x_1 + \dots + x_{k-1}} \\ \text{s.t.} & \sum_{j=1}^k x_j = n \\ & 0 \leq x_1 \leq k \\ & 0 \leq x_2, \dots, x_{k-1}, \end{aligned}$$

since the number of layers is bounded by k , as we condition on C . By solving the problem, we obtain that the objective function is lower bounded by $\phi(n)$, where $\phi(n) = O(n^{1/k})$ for every n . Then

$$\begin{aligned} \mathbb{E}[\mathcal{D}_1^n | C] &= \sum_{\ell=2}^k \sum_{\substack{k_1 \leq k, \dots, k_\ell \\ k_1 + \dots + k_\ell = n}} \mathbb{P}(\mathcal{L} = \ell, \mathcal{T}_1^n = k_1, \dots, \mathcal{T}_\ell^n = k_\ell | C) \\ &\quad \cdot \mathbb{E}[\mathcal{D}_1^n | C, \mathcal{L} = \ell, \mathcal{T}_1^n = k_1, \dots, \mathcal{T}_\ell^n = k_\ell] \quad (19) \\ &\geq \sum_{\ell=2}^k \sum_{\substack{k_1 \leq k, \dots, k_\ell \\ k_1 + \dots + k_\ell = n}} \mathbb{P}(\mathcal{L} = \ell, \mathcal{T}_1^n = k_1, \dots, \mathcal{T}_\ell^n = k_\ell | C) \cdot \phi(n) = \phi(n), \end{aligned}$$

where (19) follows since $\mathbb{E}[\mathcal{D}_1^n | C, \mathcal{L} = \ell, \mathcal{T}_1^n = k_1, \dots, \mathcal{T}_\ell^n = k_\ell] \geq \phi(n)$ for all values of ℓ ($2 \leq \ell \leq k$) and $k_1, \dots, k_\ell$ ($k_1 \leq k, k_1 + \dots + k_\ell = n$) from the optimal solution of the optimization problem. The same lower bound applies for all agents in the top layer. Similarly, we have for the variance of the degree of an agent in the top layer (we use $\ell, k_1, \dots, k_\ell$ as a shorthand for $\mathcal{L} = \ell, \mathcal{T}_1^n = k_1, \dots, \mathcal{T}_\ell^n = k_\ell$)

$$\begin{aligned} \text{var}[\mathcal{D}_1^n | C] &= \sum_{\ell=2}^k \sum_{\substack{k_1 \leq k, \dots, k_\ell \\ k_1 + \dots + k_\ell = n}} \mathbb{P}(\ell, k_1, \dots, k_\ell | C) \cdot \text{var}[\mathcal{D}_1^n | C, \ell, k_1, \dots, k_\ell] \\ &= \sum_{\ell=2}^k \sum_{\substack{k_1 \leq k, \dots, k_\ell \\ k_1 + \dots + k_\ell = n}} \mathbb{P}(\ell, k_1, \dots, k_\ell | C) \cdot (k_2 \text{var}(\mathcal{I}_{i,1}^{\text{level } 2}) + \dots + k_\ell \text{var}(\mathcal{I}_{i,1}^{\text{level } \ell})) \quad (20) \end{aligned}$$

$$\begin{aligned}
&\leq \sum_{\ell=1}^k \sum_{\substack{k_1 \leq k, \dots, k_\ell \\ k_1 + \dots + k_\ell = n}} \mathbb{P}(\ell, k_1, \dots, k_\ell | C) \cdot (k_2 \mathbb{E}(I_{i,1}^{\text{level } 2}) + \dots + k_\ell \mathbb{E}(I_{i,1}^{\text{level } \ell})) \\
&= \mathbb{E}[\mathcal{D}_1^n | C],
\end{aligned} \tag{21}$$

where (20) follows by noting that conditional on event C and the number of layers and the agents in each layer being fixed, the indicator variables (defined above) are independent and (21) follows since the variance of an indicator variable is smaller than its expectation. We conclude that the variance of the degree is smaller than the expected value, and from Chebyshev's inequality, we conclude that

$$\mathbb{P}(D) \geq \mathbb{P}\left(\bigcap_{i \in \mathcal{N}_1^n} \frac{\mathcal{D}_i^n}{\phi(n)} > \zeta\right) > 1 - \eta/2,$$

where $\zeta > 0$, i.e., with high probability, all agents in the top layer are information mavens (recall that $\lim_{n \rightarrow \infty} \phi(n) = \infty$).

We have shown that when event $C \cap D$ occurs, there is a path of length at most k (the total number of layers) from each agent to an agent at the top layer, i.e., an information maven, with high probability. Therefore, if the discount rate r is smaller than some bound ($r < \bar{r}$), then perfect asymptotic learning occurs by [Corollary 1](#). Finally, we complete the proof by noting that $\mathbb{P}(C \cap D) > (1 - \eta/2)^2 > 1 - \eta$. $\square$

PROOF OF PROPOSITION 4. [Proposition 4](#) is a direct consequence of the next lemma, which intuitively states that there is no incentive to lie to an agent who has a large number of neighbors, assuming that everybody else is truthful. For the remainder of the proof, we restrict attention to strategies for all agents except the deviating party, where the recipient of a message considers its content to be truthful, unless she spots an inconsistency with other messages she has received in previous time periods, in which case she ignores the later message. If an inconsistency is spotted between messages received in the same time period, the recipient ignores all those messages.

LEMMA 3 (Truthful communication to a high degree agent). *There exists a scalar $k > 0$, such that truth-telling to agent i , with $\text{indeg}_i^n \geq k$, in the first time period is an equilibrium of $\text{INFO}(G^n)$. Formally,*

$$(\sigma^{n, \text{truth}}, m^{n, \text{truth}}) \in \text{INFO}(G^n),$$

where $m_{ji,0}^{n, \text{truth}} = s_j$ for $j \in B_{i,1}^n$.

PROOF. The proof is based on the following argument. Suppose that all agents in $B_{i,1}^n$ except j report their signals truthfully to i . Moreover, let $|B_{i,1}^n| \geq k$, where k is a large constant (see below). Then it is a weakly dominant strategy for j to report her signal truthfully to i , since j 's message is not *pivotal* for agent i , i.e., i will take an irreversible action after the first communication step, no matter what j reports. In particular, let $\bar{k}$

be such that $\psi - 1/(\rho + (\bar{k} - 1)\bar{\rho}) > \lambda/(\lambda + r)\psi$ (such a $\bar{k}$ exists when $r > 0$). The left-hand side of the expression is the expected payoff of agent i in an equilibrium profile, where she receives $k - 1$ truthful messages in the first communication step (measured at the time that the first communication step occurs). The right-hand side is an upper bound on the expected continuation payoff. Note that if $|B_{i,1}^n| \geq k \geq \bar{k}$ and all but j report their signal truthfully, then i will exit after the first communication step (no matter what j reports). Moreover, agent j will exit in the second communication round after receiving the information from agent i . Therefore, it is weakly dominant for agent j to report truthfully to agent i in the first communication round. $\square$

Corollary 1 implies that asymptotic learning occurs thanks to high degree agents—mavens. In particular, for asymptotic learning to occur in a society along equilibrium σ when communication is truthful, it has to be that all but a negligible fraction of the agents acquire information from mavens. Given this fact and **Lemma 3**, we obtain that there exists an equilibrium (σ, m) where asymptotic learning occurs, even when we allow for strategic communication (an agent can simply act on the information propagated by the mavens and ignore all other information).

PROOF OF PROPOSITION 5. The first part follows directly from **Proposition 1**(i). The second part is derived using similar arguments as those in the proof of **Proposition 9**. In particular, for all but a negligible fraction of the agents and k, n large enough it holds that $X_k^n = Z_k^{n,\sigma}$ for all σ . Moreover, for $i \in X_k^n \cap Z_k^{n,\sigma}$, $\tau_i^n = \tau_i^{n,\sigma}$. This implies that all equilibria are asymptotically efficient, since the expected payoff an agent achieves in the “no exit” benchmark, i.e., in the idealized setting that the agent exits optimally when she assumes that no other agent exits, is an upper bound on the payoff that the agent can achieve under any strategy profile (and, in particular, under the socially optimal allocation). $\square$

PROOF OF PROPOSITION 6. The claim follows by noting that the social planner could choose the following strategy profile: for each $j \in D_{k,\ell}^{n,\sigma}$, delay i ’s irreversible action by at least one communication step, where i is an agent such that if i delays, then j gains access to at least ℓ additional signals. Moreover, it is straightforward to see that there exist ϵ, δ for which ϵ, δ -learning fails. $\square$

Proofs for Section 4

PROOF OF PROPOSITION 7. First we make an observation that is used frequently in the subsequent analysis. Consider an agent i such that $H_{SC(i)}^n \in \mathcal{H}_{\bar{k}}^n$, where $\bar{k}$ is an integer appropriately chosen (see below), i.e., the size of the social clique of agent i is greater than or equal to $\bar{k}$, $|H_{SC(i)}^n| \geq \bar{k}$. Suppose agent i does not form a link with cost c with any agents outside her social clique. If she makes a decision at time $t = 0$ based on her signal only, her expected payoff is $\psi - 1/(\rho + \bar{\rho})$. If she waits for one period, she has access to the signals of all the agents in her social clique (i.e., she has access to at

least $\bar{k}$ signals), implying that her expected payoff would be bounded from below by $\lambda/(r + \lambda)(\psi - 1/(\rho + \bar{\rho})\bar{k})$. Hence, her expected payoff $\mathbb{E}[\psi_i(g^n)]$ satisfies

$$\mathbb{E}[\psi_i(g^n)] \geq \max \left\{ \psi - \frac{1}{\rho + \bar{\rho}}, \frac{\lambda}{r + \lambda} \left(\psi - \frac{1}{\rho + \bar{\rho}\bar{k}} \right) \right\}$$

for any link formation strategy g^n and along any $\sigma \in \text{INFO}(G^n)$ (where G^n is the communication network induced by g^n). Suppose now that agent i forms a link with cost c with an agent outside her social clique. Then her expected payoff is bounded from above by

$$\mathbb{E}[\psi_i(g^n)] < \max \left\{ \psi - \frac{1}{\rho + \bar{\rho}}, \frac{\lambda}{r + \lambda} \left(\psi - \frac{1}{\rho + \bar{\rho}\bar{k}} \right), \left(\frac{\lambda}{\lambda + r} \right)^2 \psi - c \right\},$$

where the third term in the maximum is an upper bound on the payoff she could get by having access to the signals of all agents she is connected to in two time steps (i.e., signals of the agents in her social clique and in the social clique that she is connected to). Combining the preceding two relations, we see that an agent i with $H_{\text{SC}(i)}^n \in \mathcal{H}_k^n$ will *not* form any costly links in any network equilibrium, i.e.,

$$g_{ij}^n = 1 \quad \text{if and only if} \quad \text{SC}(j) = \text{SC}(i) \quad \text{for all } i \text{ such that } |H_{\text{SC}(i)}^n| \geq \bar{k}, \quad (22)$$

where $\bar{k}$ is the smallest constant such that

$$\frac{\lambda}{r + \lambda} \left(\psi - \frac{1}{\rho + \bar{\rho}\bar{k}} \right) \geq \left(\frac{\lambda}{\lambda + r} \right)^2 \psi - c.$$

(a) Condition (5) implies that for all sufficiently large n , we have

$$|\mathcal{H}_{\bar{k}}^n| \geq \xi n, \quad (23)$$

where $\xi > 0$ is a constant. For any ϵ with $0 < \epsilon < \xi$, we have

$$\begin{aligned} \mathbb{P} \left(\sum_{i=1}^n \frac{1 - M_i^{n,\epsilon}}{n} > \epsilon \right) &= \mathbb{P} \left(\left[\sum_{i: |H_{\text{SC}(i)}^n| < \bar{k}} \frac{1 - M_i^{n,\epsilon}}{n} + \sum_{i: |H_{\text{SC}(i)}^n| \geq \bar{k}} \frac{1 - M_i^{n,\epsilon}}{n} \right] > \epsilon \right) \\ &\geq \mathbb{P} \left(\sum_{i: |H_{\text{SC}(i)}^n| \geq \bar{k}} \frac{1 - M_i^{n,\epsilon}}{n} > \epsilon \right). \end{aligned}$$

The right-hand side of the preceding inequality can be rewritten as

$$\begin{aligned} \mathbb{P} \left(\sum_{i: |H_{\text{SC}(i)}^n| \geq \bar{k}} \frac{1 - M_i^{n,\epsilon}}{n} > \epsilon \right) &= 1 - \mathbb{P} \left(\sum_{i: |H_{\text{SC}(i)}^n| \geq \bar{k}} \frac{1 - M_i^{n,\epsilon}}{n} \leq \epsilon \right) \\ &= 1 - \mathbb{P} \left(\sum_{i: |H_{\text{SC}(i)}^n| \geq \bar{k}} \frac{M_i^{n,\epsilon}}{n} \geq w - \epsilon \right), \end{aligned}$$

where $w = \sum_{i \mid |H_{SC(i)}^n| \geq \bar{k}} 1/n$. By (23), it follows that for n sufficiently large, we have $w \geq \xi$. Using Markov's inequality, the preceding relation implies

$$\mathbb{P}\left(\sum_{i \mid |H_{SC(i)}^n| \geq \bar{k}} \frac{1 - M_i^{n,\epsilon}}{n} > \epsilon\right) \geq 1 - \frac{\sum_{i \mid |H_{SC(i)}^n| \geq \bar{k}} \mathbb{E}[M_i^{n,\epsilon}]}{n} \cdot \frac{1}{w - \epsilon}. \quad (24)$$

By Lemma 2 and observation (22), for an agent i with $|H_{SC(i)}^n| \geq \bar{k}$, it holds that

$$\mathbb{P}(M_i^{n,\epsilon} = 0) \geq \text{erfc}\left(\epsilon \sqrt{\frac{\rho + |H_{SC(i)}^n| \bar{\rho}}{2}}\right),$$

and, therefore,

$$\mathbb{E}[M_i^{n,\epsilon}] \leq 1 - \text{erfc}\left(\epsilon \sqrt{\frac{\rho + |H_{SC(i)}^n| \bar{\rho}}{2}}\right).$$

Now assuming that social cliques are ordered by size (H_1^n is the biggest), we can rewrite (24) as

$$\begin{aligned} \mathbb{P}\left(\sum_{i \mid |H_{SC(i)}^n| \geq \bar{k}} \frac{1 - M_i^{n,\epsilon}}{n} > \epsilon\right) &\geq 1 - \frac{\sum_{j=1}^{|H_k^n|} |H_j^n| (1 - \text{erfc}(\epsilon \sqrt{(\rho + |H_j^n| \bar{\rho})/2}))}{(w - \epsilon) \cdot n} \\ &\geq 1 - \frac{w \cdot (1 - \zeta)}{w - \epsilon} \geq 1 - \frac{\xi \cdot (1 - \zeta)}{\xi - \epsilon} > \delta. \end{aligned}$$

Here, the second inequality is obtained since the largest value for the sum is achieved when all summands are equal and $\zeta = \text{erfc}(\epsilon \sqrt{\rho + \bar{k} \bar{\rho}/2})$. The third inequality holds using the relation $w \geq \xi$ and choosing appropriate values for ϵ, δ .

This establishes that for all sufficiently large n , we have

$$\mathbb{P}\left(\sum_{i=1}^n \frac{1 - M_i^{n,\epsilon}}{n} > \epsilon\right) > \delta > 0,$$

which implies

$$\limsup_{n \rightarrow \infty} \mathbb{P}\left(\sum_{i=1}^n \frac{1 - M_i^{n,\epsilon}}{n} > \epsilon\right) > \delta$$

and shows that perfect asymptotic learning does not occur in any network equilibrium.

(b) We show that if the communication cost structure satisfies condition (6), then asymptotic learning occurs in all network equilibria $(g, \sigma) = (\{g^n, \sigma^n\})_{n=1}^\infty$. For an illustration of the resulting communication networks when condition (7) holds, refer to Figure 7(a). Let $B_i^n(G^n)$ be the *neighborhood* of agent i in communication network G^n (induced by the link formation strategy g^n),

$$B_i^n(G^n) = \{j \mid \text{there exists a path } \mathcal{P} \text{ in } G^n \text{ from } j \text{ to } i\},$$

i.e., $B_i^n(G^n)$ is the set of agents in G^n whose information agent i can acquire over a sufficiently large (but finite) period of time.

We first show that for any agent i such that $\limsup_{n \rightarrow \infty} |H_{SC(i)}^n| < \bar{k}$, her neighborhood in any network equilibrium satisfies $\lim_{n \rightarrow \infty} |B_i^n| = \infty$. We use the notion of an isolated social clique to show this. For a given n , we say that a social clique H_ℓ^n is *isolated* (at a network equilibrium (g, σ)) if no agent in H_ℓ^n forms a costly link with an agent outside H_ℓ^n in (g, σ) . Equivalently, a social clique H_ℓ^n is not isolated if there exists at least one agent $j \in H_\ell^n$, such that j incurs cost c and forms a link with an agent outside H_ℓ^n .

We show that for an agent i with $\limsup_{n \rightarrow \infty} |H_{SC(i)}^n| < \bar{k}$, the social clique $H_{SC(i)}^n$ is not isolated in any network equilibrium for all sufficiently large n . Using condition (6), we can assume without loss of generality that social cliques are ordered by size from largest to smallest and that $\lim_{n \rightarrow \infty} |H_1^n| = \infty$. Suppose that $H_{SC(i)}^n$ is isolated in a network equilibrium (g, σ) . Then the expected payoff of agent i is upper bounded (similarly to above)

$$\mathbb{E}[\psi_i(g^n)] \leq \max \left\{ \psi - \frac{1}{\rho + \bar{\rho}}, \frac{\lambda}{r + \lambda} \left(\psi - \frac{1}{\rho + \bar{\rho}(\bar{k} - 1)} \right) \right\}.$$

Using the definition of $\bar{k}$, it follows that for some $\epsilon > 0$,

$$\mathbb{E}[\psi_i(g^n)] \leq \max \left\{ \psi - \frac{1}{\rho + \bar{\rho}}, \left(\frac{\lambda}{r + \lambda} \right)^2 \psi - c - \epsilon \right\}. \quad (25)$$

Suppose next that agent i forms a link with an agent $j \in H_1^n$. Her expected payoff $\mathbb{E}[\chi_i(g^n)]$ satisfies

$$\mathbb{E}[\chi_i(g^n)] \geq \left(\frac{\lambda}{r + \lambda} \right)^2 \cdot \left(\psi - \frac{1}{\rho + \bar{\rho}|H_1^n|} \right) - c,$$

since in two time steps, she has access to the signals of all agents in the social clique H_1^n . Since $\lim_{n \rightarrow \infty} |H_1^n| = \infty$, there exists some N_1 such that

$$\mathbb{E}[\chi_i(g^n)] > \left(\frac{\lambda}{\lambda + r} \right)^2 \psi - c - \epsilon \quad \text{for all } n > N_1.$$

Comparing this relation with (25), we conclude that under the assumption that $r < \bar{r}$ (for appropriate $\bar{r}$), the social clique $H_{SC(i)}^n$ is not isolated in any network equilibrium for all $n > N_1$.

Next, we show that $\lim_{n \rightarrow \infty} |B_i^n| = \infty$ in any network equilibrium. To arrive at a contradiction, assume that $\limsup_{n \rightarrow \infty} |B_i^n| < \infty$ in some network equilibrium. This implies that $\limsup_{n \rightarrow \infty} |B_i^n| < |H_1^n|$ for all $n > N_2 > N_1$. Consider some $n > N_2$. Since $H_{SC(i)}^n$ is not isolated, there exists some $j \in H_{SC(i)}^n$ such that j forms a link with an agent h outside $H_{SC(i)}^n$. Since $\limsup_{n \rightarrow \infty} |B_i^n| < |H_1^n|$, agent j can improve her payoff by changing her strategy to $g_{jh}^n = 0$ and $g_{jh'}^n = 1$ for $h' \in H_1^n$, i.e., j is better off deleting her existing costly link and forming one with an agent in social clique H_1^n . Hence, for any network equilibrium, we have

$$\lim_{n \rightarrow \infty} |B_i^n| = \infty \quad \text{for all } i \text{ with } \limsup_{n \rightarrow \infty} |H_{SC(i)}^n| < \bar{k}. \quad (26)$$

We next consider the probability that a nonnegligible fraction (ϵ -fraction) of agents take an action that is at least ϵ away from optimal with probability at least δ along a network equilibrium (g, σ) . For any n , we have, from Markov's inequality,

$$\mathbb{P}\left(\sum_{i=1}^n \frac{1 - M_i^{n,\epsilon}}{n} > \epsilon\right) \leq \frac{1}{\epsilon} \cdot \sum_{i=1}^n \frac{\mathbb{E}[1 - M_i^{n,\epsilon}]}{n}. \quad (27)$$

We next provide upper bounds on the individual terms in the sum on the right-hand side. We have

$$\mathbb{E}[1 - M_i^{n,\epsilon}] \leq \operatorname{erfc}\left(\epsilon \sqrt{\frac{\rho + \bar{\rho}|B_i^n|}{2}}\right). \quad (28)$$

Consider an agent i with $\limsup_{n \rightarrow \infty} |H_{\text{SC}(i)}^n| < \bar{k}$ (i.e., $|H_{\text{SC}(i)}^n| < \bar{k}$ for all n large). By (26), we have $\lim_{n \rightarrow \infty} |B_i^n| = \infty$. Together with (28), this implies that for some $\zeta > 0$, there exists some N such that for all $n > N$, we have

$$\mathbb{E}[1 - M_i^{n,\epsilon}] < \frac{\epsilon\zeta}{2} \quad \text{for all } i \text{ with } \limsup_{n \rightarrow \infty} |H_{\text{SC}(i)}^n| < \bar{k}. \quad (29)$$

Consider next an agent i with $\limsup_{n \rightarrow \infty} |H_{\text{SC}(i)}^n| \geq \bar{k}$ and, for simplicity, let us assume that the limit exists, i.e., $\lim_{n \rightarrow \infty} |H_{\text{SC}(i)}^n| \geq \bar{k}$.²⁸

This implies that $|H_{\text{SC}(i)}^n| \geq \bar{k}$ for all large n and, therefore,

$$\sum_{i | \limsup_{n \rightarrow \infty} |H_{\text{SC}(i)}^n| \geq \bar{k}} \frac{\mathbb{E}[1 - M_i^{n,\epsilon}]}{n} \leq \sum_{j=1}^{|\mathcal{H}_k^n|} \frac{|H_j^n|}{n} \cdot \operatorname{erfc}\left(\epsilon \sqrt{\frac{\rho + \bar{\rho}|H_j^n|}{2}}\right) \leq \frac{|\mathcal{H}_k^n|}{n} \cdot \bar{k},$$

where the first inequality follows from (28). Using condition (6), i.e., $\lim_{n \rightarrow \infty} |\mathcal{H}_k^n|/n = 0$, this relation implies that there exists some $\tilde{N}$ such that for all $n > \tilde{N}$, we have

$$\sum_{i | \limsup_{n \rightarrow \infty} |H_{\text{SC}(i)}^n| \geq \bar{k}} \frac{\mathbb{E}[1 - M_i^{n,\epsilon}]}{n} < \frac{\epsilon\zeta}{2}. \quad (30)$$

Combining (29) and (30) with (27), we obtain for all $n > \max\{N, \tilde{N}\}$,

$$\mathbb{P}\left(\sum_{i=1}^n \frac{1 - M_i^{n,\epsilon}}{n} > \epsilon\right) < \zeta,$$

where $\zeta > 0$ is an arbitrary scalar. This implies that

$$\lim_{n \rightarrow \infty} \mathbb{P}\left(\sum_{i=1}^n \frac{1 - M_i^{n,\epsilon}}{n} > \epsilon\right) = 0$$

²⁸The case when the limit does not exist can be proven by focusing on different subsequences. In particular, along any subsequence $\mathcal{N}_i$ such that $\lim_{n \rightarrow \infty, n \in \mathcal{N}_i} |H_{\text{SC}(i)}^n| \geq \bar{k}$, the same argument holds. Along any subsequence $\mathcal{N}_i$ with $\lim_{n \rightarrow \infty, n \in \mathcal{N}_i} |H_{\text{SC}(i)}^n| < \bar{k}$, we can use an argument similar to the previous case to show that $\lim_{n \rightarrow \infty, n \in \mathcal{N}_i} |B_i^n| = \infty$ and, therefore, $\mathbb{E}[1 - M_i^{n,\epsilon}] < \epsilon\zeta/2$ for n large and $n \in \mathcal{N}_i$.

for all ϵ , showing that perfect asymptotic learning occurs along every network equilibrium.

(c) The proof proceeds in two parts. First, we show that if condition (7) is satisfied, learning occurs in at least one network equilibrium (g, σ) . In particular, we explicitly profile a strategy profile (g, σ) such that when condition (7) is satisfied, (g, σ) is a network equilibrium along which learning occurs. Then we show that there exists a $\bar{c} > 0$, such that if $c < \bar{c}$, then learning occurs in all network equilibria. We complete the proof by showing that if $c > \bar{c}$, then there exist network equilibria in which asymptotic learning fails, even when condition (7) holds. We consider the case when agents are patient, i.e., the discount rate $r \rightarrow 0$. We consider $\bar{k}$, such that $c > 1/(\rho + \bar{\rho}\bar{k})$ and $c < 1/(\rho + \bar{\rho}(\bar{k} - 1)) - \epsilon'$ for some $\epsilon' > 0$ (such a $\bar{k}$ exists). Finally, we assume that $c < 1/(\rho + \bar{\rho})$, since otherwise no agent would have an incentive to form a costly link.

Part 1: We assume, without loss of generality, that social cliques are ordered by size (H_1^n is the smallest). Let $\mathcal{H}_{<\bar{k}}^n$ denote the set of social cliques of size less than $\bar{k}$, i.e., $\mathcal{H}_{<\bar{k}}^n = \{H_i^n, i = 1, \dots, K^n \mid |H_i^n| < \bar{k}\}$. Finally, let $\text{rec}(j)$ and $\text{send}(j)$ denote two special nodes for social clique H_j^n , the *receiver* and the *sender* (they might be the same node). We claim that (g^n, σ^n) described below and depicted in Figure 7(b) is an equilibrium of the network learning game $\Gamma(C^n)$ for n large enough and r sufficiently close to zero,

$$g_{ij}^n = \begin{cases} 1 & \text{if } \text{SC}(i) = \text{SC}(j), \text{ i.e., } i, j \text{ belong to the same social clique} \\ 1 & \text{if } i = \text{rec}(\ell - 1) \text{ and } j = \text{send}(\ell) \text{ for } 1 < \ell \leq |\mathcal{H}_{<\bar{k}}^n| \\ 1 & \text{if } i = \text{rec}(|\mathcal{H}_{<\bar{k}}^n|) \text{ and } j = \text{send}(1) \\ 0 & \text{otherwise,} \end{cases}$$

and $\sigma^n \in \text{INFO}(G^n)$, where G^n is the communication network induced by g^n . In this communication network, social cliques with size less than $\bar{k}$ are organized in a directed *ring*, and all agents i , such that $|H_{\text{SC}(i)}^n| < \bar{k}$, have the same neighborhood, i.e., $B_i^n = B^n$ for all such agents. Note that in this network equilibrium, only the receivers of each social clique form costly links (it is exactly those links that facilitate the exchange of information among different cliques).

Next, we show that the strategy profile (g^n, σ^n) described above is indeed an equilibrium of the network learning game $\Gamma(C^n)$. We restrict attention to large enough n 's.

In particular, let N be such that $\sum_{i=1}^{|\mathcal{H}_{<\bar{k}}^N|} |H_i^N| > \bar{k}$ and consider any $n > N$ (such N exists from condition (7)). Moreover, we assume that the discount rate is sufficiently close to zero. We consider the following two cases.

Case 1: Agent i is not a receiver. Then $g_{ij}^n = 1$ if and only if $\text{SC}(j) = \text{SC}(i)$. Agent i 's neighborhood as noted above is set B^n , which is such that $\psi - 1/(\rho + \bar{\rho}|B^n|) > \psi - c$ from the assumption on n , i.e., $n > N$, where N is such that $\sum_{i=1}^{|\mathcal{H}_{<\bar{k}}^N|} |H_i^N| > \bar{k}$. Agent i can communicate with all agents in B^n in at most $|\mathcal{H}_{<\bar{k}}^n|$ communication steps. Therefore, her expected payoff is lower bounded by

$$\mathbb{E}[\chi_i(g^n)] \geq \left(\frac{\lambda}{\lambda + r} \right)^{|\mathcal{H}_{<\bar{k}}^n|} \cdot \left(\psi - \frac{1}{\rho + \bar{\rho}\bar{k}} \right) > \psi - c$$

under any equilibrium σ^n for r sufficiently close to zero. Agent i can deviate by forming a costly link with agent m , such that $SC(m) \neq SC(i)$. However, this is not profitable since from above, her expected payoff under (g^n, σ^n) is at least $\psi - c$ (which is the maximum possible payoff if an agent chooses to form a costly link).

Case 2: Agent i is a receiver, i.e., there exists exactly one j , such that $SC(j) \neq SC(i)$ and $g_{ij}^n = 1$. Using a similar argument as above, we can show that it is not profitable for agent i to form an additional costly link with an agent m , such that $SC(m) \neq SC(i)$. Alternatively, agent i could deviate by setting $g_{ij}^n = 0$. However, then her expected payoff would be

$$\begin{aligned} \mathbb{E}[\chi_i(g^n)] &= \max \left\{ \psi - \frac{1}{\rho + \bar{\rho}}, \frac{\lambda}{r + \lambda} \left(\psi - \frac{1}{\rho + \bar{\rho}|H_i^n|} \right) \right\} \\ &\leq \max \left\{ \psi - \frac{1}{\rho + \bar{\rho}}, \frac{\lambda}{r + \lambda} \left(\psi - \frac{1}{\rho + \bar{\rho}(\bar{k} - 1)} \right) \right\} < \psi - c - \epsilon' \\ &< \left(\frac{\lambda}{r + \lambda} \right)^{|\mathcal{H}_{<\bar{k}}^n|} \left(\psi - \frac{1}{\rho + \bar{\rho}|B^n|} \right) - c - \epsilon \end{aligned}$$

for discount rate sufficiently close to zero. Therefore, deleting the costly link is not a profitable deviation. Similarly, we can show that it is a (weakly) dominant strategy for the receiver not to replace her costly link with another costly link.

We showed that (g^n, σ^n) is an equilibrium of the network learning game. Note that we described a link formation strategy in which social cliques connect to each other in a specific order (in increasing size). There is nothing special about this ordering and any permutation of the first $|\mathcal{H}_{<\bar{k}}^n|$ cliques is an equilibrium as long as they form a directed ring. Finally, any node in a social clique can be a receiver or a sender.

Next, we argue that asymptotic learning occurs in network equilibria $(g, \sigma) = \{(g^n, \sigma^n)\}_{n=1}^\infty$, where for all $n > N$, N is a large constant, and g^n has the form described above. As shown above, all agents i for which $H_{SC(i)}^n < \bar{k}$ have the same neighborhood, which we denoted by B^n . Moreover, $\lim_{n \rightarrow \infty} |B^n| = \infty$, since social cliques with size less than $\bar{k}$ are connected to the ring and, by condition (7), $\lim_{n \rightarrow \infty} \sum_{i: |H_i^n| < \bar{k}} |H_i^n| = \infty$. For discount rate r sufficiently close to zero and from arguments similar to those in the proof of part (b), we conclude that asymptotic learning occurs in network equilibria (g, σ) .

Part 2: We have shown a particular form of network equilibria in which asymptotic learning occurs. The following proposition states that for a discount rate sufficiently close to zero, network equilibria fall in one of two forms.

PROPOSITION 10. *Suppose Assumptions 1 and 4 and condition (7) hold. Then an equilibrium (g^n, σ^n) of the network learning game $\Gamma(C^n)$ can be in one of the following two forms.*

- (i) (Incomplete) ring equilibrium: Social cliques with indices $\{1, \dots, j\}$, where $j \leq |\mathcal{H}_{<\bar{k}}^n|$, form a directed ring as described in Part 1 and the rest of the social cliques

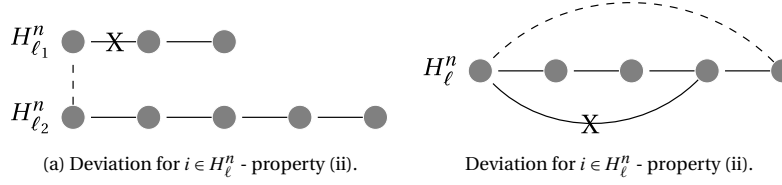


FIGURE 9. Communication networks under condition (7).

are isolated. We call those equilibria ring equilibria and, in particular, a ring equilibrium is called complete if $j = |\mathcal{H}_{<\bar{k}}^n|$, i.e., if all social cliques with size less than $\bar{k}$ are not isolated.

- (ii) Directed line equilibrium: Social cliques with indices $\{1, \dots, j\}$, where $j \leq |\mathcal{H}_{<\bar{k}}^n|$, and a clique with index $|\mathcal{H}_{\bar{k}}^n|$ (the largest clique) form a directed line with the latter being the endpoint. The rest of the social cliques are isolated.

PROOF. Let (g^n, σ^n) be an equilibrium of the network learning game $\Gamma(C^n)$. Monotonicity of the expected payoff as a function of the number of signals observed implies that if clique H_{ℓ}^n is not isolated, then no clique with index less than ℓ is isolated in the communication network induced by g^n . In particular, let $\text{rec}(\ell)$ be the receiver of social clique H_{ℓ}^n and let $\mathbb{E}[\psi_{\text{rec}(\ell)}(g^n)]$ be her expected payoff. Consider an agent i such that $\text{SC}(i) = \ell' < \ell$ and, for the sake of contradiction, $H_{\ell'}^n$ is isolated in the communication network induced by g^n . Social cliques are ordered by size; therefore, $|H_{\ell'}^n| \leq |H_{\ell}^n|$. Now, we use the monotonicity mentioned above. Consider the expected payoff of i ,

$$\begin{aligned} \mathbb{E}[\psi_i(g^n)] &= \max \left\{ \psi - \frac{1}{\rho + \bar{\rho}}, \frac{\lambda}{\lambda + r} \left(\psi - \frac{1}{\rho + \bar{\rho}|H_{\ell'}^n|} \right) \right\} \\ &\leq \max \left\{ \psi - \frac{1}{\rho + \bar{\rho}}, \frac{\lambda}{\lambda + r} \left(\psi - \frac{1}{\rho + \bar{\rho}|H_{\ell}^n|} \right) \right\} < \mathbb{E}[\psi_{\text{rec}(\ell)}(g^n)], \end{aligned} \quad (31)$$

where the last inequality follows from the fact that agent $\text{rec}(\ell)$ formed a costly link. Consider a deviation $g_i^{n, \text{deviation}}$ for agent i , in which $g_{i, \text{rec}(\ell)}^{n, \text{deviation}} = 1$ and $g_{ij}^{n, \text{deviation}} = g_{ij}^n$, i.e., agent i forms a costly link with agent $\text{rec}(\ell)$. Then

$$\mathbb{E}[\psi_i(g^{n, \text{deviation}})] \geq \frac{\lambda}{\lambda + r} \mathbb{E}[\psi_{\text{rec}(\ell)}(g^n)] > \mathbb{E}[\psi_i(g^n)]$$

from (31) and for a discount rate sufficiently close to zero. Therefore, social clique $H_{\ell'}^n$ will not be isolated in any network equilibrium (g^n, σ^n) .

Next, we show two structural properties that all network equilibria (g^n, σ^n) should satisfy, when the discount rate r is sufficiently close to zero. We say that there exists a path $\mathcal{P}$ between social cliques $H_{\ell_1}^n$ and $H_{\ell_2}^n$ if there exists a path between some $i \in H_{\ell_1}^n$ and $j \in H_{\ell_2}^n$. Also, we say that the in-degree (out-degree) of social clique $H_{\ell_1}^n$ is k , if the sum of in-links (out-links) of the nodes in $H_{\ell_1}^n$ is k , i.e., $H_{\ell_1}^n$ has in-degree k if $\sum_{i \in H_{\ell_1}^n} \sum_{j \notin H_{\ell_1}^n} g_{ij}^n = k$.

- (i) Let $H_{\ell_1}^n, H_{\ell_2}^n$ be two social cliques that are not isolated. Then there should exist a directed path $\mathcal{P}$ in G^n induced by g^n between the two social cliques.
- (ii) The in-degree and out-degree of each social clique is at most 1.

Figure 9 provides an illustration of why the properties hold for patient agents. In particular, for property (i), let $i = \text{rec}(H_{\ell_1}^n)$ and $j = \text{rec}(H_{\ell_2}^n)$, and assume, without loss of generality, that $|B_i^n| \leq |B_j^n|$. Then, for discount rate sufficiently close to zero and from monotonicity of the expected payoff, we conclude that i has an incentive to deviate, delete her costly link, and form a costly link with agent j . Property (ii) follows due to similar arguments. From the above, we conclude that the only two potential equilibrium topologies are the (incomplete) ring and the directed line with the largest clique being the endpoint under the assumptions of the proposition. $\triangleleft$

So far we have shown a particular form of network equilibria that arise under condition (7), in which asymptotic learning occurs. We also argued that under condition (7), only (incomplete) ring or directed line equilibria can arise for network learning game $\Gamma(C^n)$. In the remainder, we show that there exists a bound $\bar{c} > 0$ on the common cost c for forming a link between two social cliques, such that if $c < \bar{c}$, all network equilibria (g, σ) that arise satisfy that g^n is a complete ring equilibrium for all $n > N$, where N is a constant. In those network equilibria, asymptotic learning occurs as argued in Part 1. Alternatively, if $c > \bar{c}$, coordination among the social cliques may fail and additional equilibria arise in which asymptotic learning does not occur. Let

$$\bar{c}^n = \min_{k \geq k_1} \left\{ -\frac{1}{\rho + \bar{\rho}(\sum_{j=1}^k |H_j^n| + |H_{k+1}^n|)} + \frac{1}{\rho + \bar{\rho}|H_{k+1}^n|} \right\},$$

where k_1 is such that $\sum_{j=1}^{k_1} |H_j^n| \geq |H_{K^n}^n|$ (size of the largest clique). Moreover, let $\bar{c} = \liminf_{n \rightarrow \infty} \bar{c}^n$. The following proposition concludes the proof.

PROPOSITION 11. *Suppose Assumptions 1 and 4 and condition (7) hold. If $c < \bar{c}$, asymptotic learning occurs in all network equilibria (g, σ) . Otherwise, there exist equilibria in which asymptotic learning does not occur.*

PROOF. Let the common cost c be such that $c < \bar{c}$, where $\bar{c}$ is defined as above, and consider a network equilibrium (g, σ) . Let N be a large enough constant and consider the corresponding g^n for $n > N$. We claim that g^n is a complete ring equilibrium for all such n . Assume for the sake of contradiction that the claim is not true. Then, from Proposition 10, g^n is either an incomplete ring equilibrium or a directed line equilibrium. We consider the former case (the latter case can be shown with similar arguments). There exists an isolated social clique H_ℓ^n , such that $|H_\ell^n| < \bar{k}$ and all cliques with index less than ℓ are not isolated and belong to the incomplete ring. However, from the definition of $\bar{c}$, we obtain that an agent $i \in H_\ell^n$ would have an incentive to connect

to the incomplete ring; thus we reach a contradiction. In particular, consider the link formation strategy for agent i :

$$g_{im}^{n,\text{deviation}} = 1 \quad \text{for agent } m \in H_{\ell-1}^n \quad \text{and} \quad g_{ij}^{n,\text{deviation}} = g_{ij}^n \quad \text{for } j \neq m.$$

Then

$$\begin{aligned} \mathbb{E}[\chi_i^n(g^{n,\text{deviation}})] &\geq \left(\frac{\lambda}{\lambda+r}\right)^{|H_{<\bar{k}}^n|} \left(\psi - \frac{1}{\rho + \bar{\rho}(\sum_{j=1}^{\ell-1} |H_j^n| + |H_\ell^n|)}\right) - c \\ &> \max\left\{\psi - \frac{1}{\rho + \bar{\rho}}, \frac{\lambda}{\lambda+r} \left(\psi - \frac{1}{\rho + \bar{\rho}|H_\ell^n|}\right)\right\} = \mathbb{E}[\chi_i^n(g^n)], \end{aligned}$$

where the strict inequality follows from the definition of $\bar{c}$ for r sufficiently close to zero. Thus we conclude that if $c < \bar{c}$, then g^n is a complete ring for all $n > N$, where N is a large constant, and we conclude from Part 1 that asymptotic learning occurs in all network equilibria (g, σ) . On the contrary, if $c > \bar{c}$, then there exists an infinite index set W , such that for all n in the (infinite) subsequence, $\{n_w\}_{w \in W}$, there exists a k , such that

$$\frac{1}{\rho + \bar{\rho}(\sum_{j=1}^k |H_j^n| + |H_{k+1}^n|)} - c < \frac{1}{\rho + \bar{\rho}|H_{k+1}^n|}. \quad (32)$$

Moreover, $|H_{k+1}^n| < \bar{k}$ and $\sum_{j=1}^k |H_j^n| \geq |H_{k+1}^n|$. We conclude that for (32) to hold, it has to be that $\sum_{j=1}^k |H_j^n| < R$, where R is a uniform constant for all n in the subsequence. Consider $(g, \sigma)_{n=1}^\infty$, such that for every n in the subsequence, g^n is such that social cliques with index greater than k (as described above) are isolated and the rest form an incomplete ring or a directed line and $\sigma^n = \text{INFO}(G^n)$, where G^n is the communication network induced by g^n . From above, we obtain that for $c > \bar{c}$, (g^n, σ^n) is an equilibrium of the network learning game $\Gamma(C^n)$. Perfect asymptotic learning, however, fails in such an equilibrium, since for every $i \in N^n$, $|B_i^n| \leq R$, where B_i^n denotes the neighborhood of agent i . $\square$

Proofs for Appendix A

PROOF OF PROPOSITION 8. First, we show that learning fails if condition (8) holds, i.e., there exists a $k > 0$, such that

$$\eta = \liminf_{n \rightarrow \infty} \frac{1}{n} \cdot |V_k^{n,\sigma}| > \epsilon \quad \text{and} \quad \text{erf}\left(\epsilon \sqrt{\frac{\rho + \bar{\rho}k}{2}}\right) < (1 - \delta)(1 - \epsilon/\eta). \quad (33)$$

From condition (33), we obtain that there exists an infinite index set J such that for the sequence of communication networks restricted to index set J , i.e., $\{G^{n_j}\}_{j=1}^\infty$, it holds that

$$|V_k^{n_j}| \geq \eta \cdot n_j \quad \text{for } j \in J.$$

Now restrict attention to index set J , i.e., consider $n = n_j$ for some $j \in J$. Then

$$\begin{aligned} \mathbb{P}_\sigma \left(\frac{1}{n} \sum_{i=1}^n M_i^{n,\epsilon} > 1 - \epsilon \right) &= \mathbb{P}_\sigma \left(\frac{1}{n} \left[\sum_{i \in V_k^{n,\sigma}} M_i^{n,\epsilon} + \sum_{i \notin V_k^{n,\sigma}} M_i^{n,\epsilon} \right] > 1 - \epsilon \right) \\ &\leq \mathbb{P}_\sigma \left(\frac{1}{n} \left[\sum_{i \in V_k^{n,\sigma}} M_i^{n,\epsilon} + n - |V_k^{n,\sigma}| \right] > 1 - \epsilon \right) \\ &= \mathbb{P}_\sigma \left(\frac{1}{n} \sum_{i \in V_k^{n,\sigma}} M_i^{n,\epsilon} > \frac{|V_k^{n,\sigma}|}{n} - \epsilon \right), \end{aligned}$$

where the inequality follows since we let $M_i^{n,\epsilon} = 1$ for all $i \notin V_k^{n,\sigma}$. Next we use Markov's inequality

$$\mathbb{P}_\sigma \left(\frac{1}{n} \sum_{i \in V_k^{n,\sigma}} M_i^{n,\epsilon} > \frac{|V_k^{n,\sigma}|}{n} - \epsilon \right) \leq \frac{\mathbb{E}_\sigma [\sum_{i \in V_k^{n,\sigma}} M_i^{n,\epsilon}]}{n \cdot (|V_k^{n,\sigma}|/n - \epsilon)}.$$

We can view each summand above as an independent Bernoulli variable with success probability bounded above by $\text{erfc}(\epsilon\sqrt{(\rho + \bar{\rho}k)/2})$ from Lemma 2. Thus

$$\begin{aligned} \frac{\mathbb{E}_\sigma [\sum_{i \in V_k^{n,\sigma}} M_i^{n,\epsilon}]}{n \cdot (|V_k^{n,\sigma}|/n - \epsilon)} &\leq \frac{|V_k^{n,\sigma}| \text{erf}(\epsilon\sqrt{(\rho + \bar{\rho}k)/2})}{n \cdot (|V_k^{n,\sigma}|/n - \epsilon)} \\ &\leq \frac{\eta}{\eta - \epsilon} \text{erf}\left(\epsilon\sqrt{\frac{\rho + \bar{\rho}k}{2}}\right) < 1 - \delta, \end{aligned}$$

where the second inequality follows from the fact that n was chosen such that $|V_k^{n,\sigma}| \geq \eta \cdot n$. Finally, the last expression follows from the choice of k (cf. condition (8)). We obtain that for all $j \in J$, it holds that

$$\mathbb{P}_\sigma \left(\left[\frac{1}{n_j} \sum_{i=1}^{n_j} (1 - M_i^{n_j,\epsilon}) \right] > \epsilon \right) \geq \delta.$$

Since J is an infinite index set, we conclude that

$$\limsup_{n \rightarrow \infty} \mathbb{P}_\sigma \left(\left[\frac{1}{n} \sum_{i=1}^n (1 - M_i^{n,\epsilon}) \right] > \epsilon \right) \geq \delta;$$

thus ϵ, δ -asymptotic learning is incomplete when (8) holds.

Next, we prove that condition (9) is sufficient for ϵ, δ -asymptotic learning. As mentioned above, if agent i takes an irreversible action after observing ℓ signals, then the probability that $M_i^{n,\epsilon} = 1$ is equal to

$$\mathbb{P}_\sigma(M_i^{n,\epsilon} = 1) = \text{erf}\left(\epsilon\sqrt{\frac{\rho + \bar{\rho}\ell}{2}}\right). \quad (34)$$

Similar to above, we have

$$\begin{aligned} \mathbb{P}_\sigma \left(\left[\frac{1}{n} \sum_{i=1}^n (1 - M_i^{n,\epsilon}) \right] > \epsilon \right) &\leq \mathbb{P}_\sigma \left(\left[\frac{1}{n} \sum_{i \notin V} (1 - M_i^{n,\epsilon}) \right] > \epsilon - \frac{|V|}{n} \right) \\ &\leq \frac{\mathbb{E}_\sigma [\sum_{i \notin V} (1 - M_i^{n,\epsilon})]}{n(\epsilon - |V|/n)}, \end{aligned} \quad (35)$$

where $V = \{i \mid |B_{i,\tau_i}^{n,\sigma}| \leq k\}$ and the second inequality follows from Markov's inequality. By combining (34) and (35), and letting $k_i^{n,\sigma}$ denote the number of private signals that agent i observed before taking an action,

$$\frac{\mathbb{E}_\sigma [\sum_{i \notin V} (1 - M_i^{n,\epsilon})]}{n(\epsilon - |V|/n)} \leq \frac{\sum_{i \notin V} 1 - \text{erf}(\epsilon \sqrt{\rho + \bar{\rho} k_i^{n,\sigma}/2})}{n(\epsilon - |V|/n)}. \quad (36)$$

We have

$$\text{erf}\left(\epsilon \sqrt{\frac{\rho + \bar{\rho} k_i^{n,\sigma}}{2}}\right) > 1 - \frac{\delta(\epsilon - \zeta)}{1 - \zeta} \quad (37)$$

for all $i \notin V$ from the definition of k (cf. condition (9)). Thus combining (35), (36), and (37), we obtain

$$\mathbb{P}_\sigma \left(\left[\frac{1}{n} \sum_{i=1}^n (1 - M_i^{n,\epsilon}) \right] > \epsilon \right) < \delta \text{ for all } n > N,$$

where N is a sufficiently large constant, which implies that condition (9) is sufficient for asymptotic learning. $\square$

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