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Communication networks in markets

Edoardo Gallo

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Abstract

This paper proposes a dynamic model of bargaining to analyze decentralized markets where buyers and sellers obtain information about past deals through their social network. There is a unique equilibrium outcome which depends crucially on the peripheral (least connected) individuals in each group. The main testable predictions are that groups with high density and/or low variability in the number of connections across individuals allow their members to obtain a better deal. These predictions are tested in a lab experiment through 4 treatments that vary the network that groups of 6 subjects are assigned to. The results of the experiment lend support to the theoretical predictions: subjects converge to a high equilibrium demand if they are assigned to a network that is dense and/or has low variability in number of connections across members. An extension explores an alternative set-up in which buyers and sellers belong to the same social network: if the network is regular and the agents are homogeneous then the unique equilibrium division is 50-50.

JEL: C73, C78, C91, C92, D83.

Keywords: network, communication, experiment, noncooperative bargaining, 50-50 division.

*Address: University of Cambridge and Queens' College, Cambridge CB3 9ET, UK. Email: *edo@econ.cam.ac.uk*.
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The peculiar character of the problem of a rational economic order is determined precisely by the fact that the knowledge of the circumstances of which we must make use never exists in concentrated or integrated form, but solely as the dispersed bits of incomplete and frequently contradictory knowledge which all the separate individuals possess. [...] The problem is thus in no way solved if one can show that all of the facts, if they were known to a single mind [...], would uniquely determine its solution; instead we must show how a solution is produced by the interactions of people each of whom possesses only partial knowledge.

F. A. von Hayek, "The use of knowledge in society." AER, XXFXV (4), September 1945.[1]

1 Introduction

Individuals who belong to close-knit groups often enjoy an advantage in market interactions. For instance, Greif [1993] describes how in the 11th century Maghribi merchants joined into tightly integrated communities to facilitate trading across the Mediterranean in an environment characterized by a high degree of uncertainty and incomplete information. Rauch [2001] reviews empirical evidence that the presence of ethnic immigrant communities significantly increases international trade volumes, especially for commodities whose price is variable or uncertain. This paper combines a theoretical model and an experiment to explore one type of advantage that these groups provide, and to relate the internal structure of the group to observed market outcomes.

The core idea is that belonging to a group gives an informational advantage: individuals who are part of a group use their interactions to gather information about past transactions which they employ in future bilateral negotiations. This advantage is relevant in markets that are characterized by incomplete information, uncertainty about the price of the goods, and private bilateral negotiations. In these markets an individual is unable to collect information on the current price of a good due to the unobservability of private transactions, and therefore she turns to other members of her group to gather information about recent transactions before starting a trade.

In the first part of the paper I develop a bargaining model between agents belonging to different groups in which the equilibrium outcome depends on the structure of interactions within each group. The model is an extension of the evolutionary bargaining framework first formulated by Young [1993a]. The bargaining procedure and the behavior of agents is the same as in Young's model: buyers and sellers are randomly matched to play the Nash demand game and buyers (sellers) choose an optimal reply to a sample of previous demands made by sellers (buyers) with probability $1-\epsilon$, and a non-optimal reply, i.e. a "mistake," with probability ϵ.[2]

The novel element introduced here is the modeling of the process by which agents receive information to play the game: information travels through a communication network that connects the agents in each group. Specifically, the amount of information that buyer b receives from another buyer b' is the realization of a Poisson process connecting b to b'. Thus, the total information sample that b receives before the bargaining round consists of all the information coming from the realization of the Poisson processes that connect b to the other buyers she communicates with. A network g^B is an abstract representation of the average communication flows in the group of buyers: the strength of a link $g_{bb'}$ is equal to the rate of the Poisson process connecting b to b'.

[1] Quoted in Young [1998].

[2] The role of buyers and sellers is completely interchangeable: the description of the model will focus on buyers only for expository purposes. Throughout the paper, the buyer is female and the seller is male.

Theorem 1 proves that if the communication networks of buyers and sellers are connected and if they are not complete networks then the process without mistakes always converges to a convention where each buyer always makes the same demand x and each seller always makes the same demand $1 - x$. The proof shows that this condition on the network structure guarantees that the information available to each agent on the history of demands is sufficiently incomplete to avoid the whole process getting stuck in a cycle. Thus, the network structure naturally provides the incompleteness of information which Young [1993b] exogenously imposes to prove that adaptive play converges to a convention for any weakly acyclic game.

Theorem 2 proves that the process with mistakes converges to a unique stable division, which is the asymmetric Nash bargaining solution (ANB) with weights that depend on the network structure. Specifically, the weights are determined by the subset of peripheral agents in each group with the least number of and/or weakest communication links. A consequence of this result is that, given a budget of links to allocate, the optimal internal structure for a group are quasi-regular networks, i.e. networks where all the agents are connected by strong links and have a very similar number of connections.

Corollary 1 derives the main testable predictions of the paper by exploiting the relation between the network structure and the outcome of the bargaining process proven in Theorem 2. It shows that individuals belonging to a group with a high density of connections and/or a low variability of connections across individuals will fare better. The changes in the network structure are modeled in terms of first and second order stochastic dominance shifts in the weighted degree distribution of the network, i.e. variations in the relative frequencies of agents with different number of connections.

As Manski [1993] points out, the causal identification of the role of network structure in empirical data is mired with difficulties, and therefore in the second part of the paper the validity of the model is tested by using a lab experiment. Subjects are told that they are traders in a market and they will be trading with a seller played by a computer. At each trading round there are 17 vouchers at stake: if the sum of the subject and the seller's demands is greater than 17 the subject gets 0 vouchers, otherwise she gets the number of vouchers she demanded. The treatment variable is the assignment of subjects to groups of 6 that differ in the underlying network that allows communication among subjects. Each subject plays 50 rounds of trading in the same position in a network, and the only network information she sees is the (fictitious) initials of the other subjects she is connected to. At the beginning of a trading round a subject receives a sample of information about the demands made by the seller in past transactions with the other subjects she is connected to. This information is randomly sampled by the computer from the history of play and it is the only information a subject has prior to making a demand. At the end of the trading round, the subject receives feedback on whether she has won the vouchers she demanded or not, before the next trading round begins. There are 4 treatments that differ in the communication network of the group subjects are assigned to: a regular network of degree 4 ($R4$), a circle network ($C1$), a star network (ST), and a circle with spokes network ($C2$), which are shown in Figure 1.

Theorem 2 and Corollary 1 allow us to formulate several hypotheses on the differences in outcomes across treatments. Theorem 2 states that ($H1$) subjects in the same group converge to the same demand. Each subject in $R4$ has more connections than any subject in any of the other networks so, by Corollary 1, ($H2$) subjects in $R4$ demand more vouchers after convergence than subjects in any other network. All subjects in $C1$ have the same number of connections, while subjects in $C2$ and ST belong to networks with similar density but higher variability of connections than $C1$, so by Corollary 1 ($H3$) subjects in $C1$ demand more vouchers after convergence than

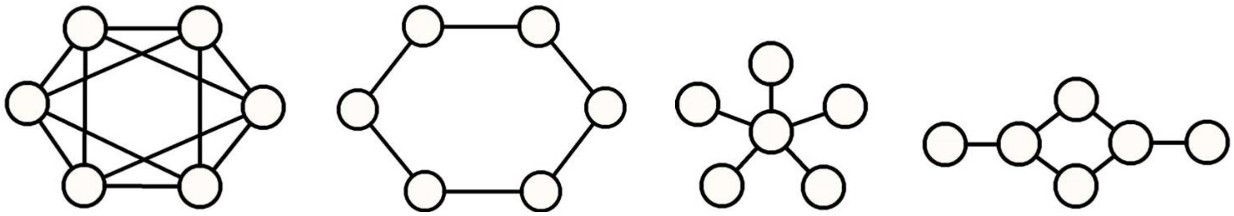

Figure 1: Networks used in the experiment. From left to right: regular network of degree 4 ($R4$), circle network ($C1$), star network (ST), and circle with spokes network ($C2$).

subjects in $C2$ and ST. Theorem 2 implies that ($H4$) subjects in the $C2$ and ST networks demand the same number of vouchers after convergence. The statement of Theorem 2 also implies that after convergence there will be no difference across subjects in the same network. Thus, ($H5$) the subject at the center of the ST network demands the same number of vouchers after convergence as the subjects assigned at the periphery, and ($H6$) in the $C2$ network the subjects demand the same number of vouchers after convergence independently of their position in the network.

The results of the experiment lend support to the theoretical predictions. Despite adopting a demanding definition of convergence, 83% of the markets converge to a stable demand and 77% converge to a stable demand and never move away from it ($H1$). Subjects in $R4$ converge to a significantly higher demand than subjects in $C2$ and ST in all markets, and a significantly higher demand than subjects in $C1$ in the markets that have converged ($H2$). Subjects in $C1$ converge to a significantly higher demand than subjects in ST in all markets, and a significantly higher demand than subjects in $C2$ in the markets that achieved convergence ($H3$). There is no significant difference between the ST and $C2$ treatments ($H4$), and a subject's demand is independent of her position in the network in both the ST ($H5$) and $C2$ ($H6$) treatments.

The final part of the paper analyzes two extensions of the basic model, which fulfill a dual purpose. First, they show the generality of the results in the main set-up by relaxing the assumptions that the groups of buyers and sellers are separate and that only direct communication is possible. Second, they demonstrate that the introduction of the network leads to a rich set of results that would not be possible to obtain in Young [1993a]'s original framework.

The first extension explores how the theoretical predictions change if buyers and sellers belong to the same communication network. The unique stable division is still the ANB solution in Theorem 2. Despite the equilibrium prediction being unchanged, the desirable architectures and the comparative statics lead to very different results, which highlights how the introduction of the network leads to new insights that are not accessible to a model without the network. Specifically, the desirable architectures for the buyers are now core-periphery networks: the buyers form a core network where they are connected by strong links and they have a very similar number of connections, while the sellers are at the periphery where each one of them is connected by one link to a buyer. Moreover, a denser communication network leaves the ANB unchanged, but less variability of connections across individuals narrows down the difference between the shares of the two groups. If the network is a regular network, then the solution is the *50-50* division. This is a novel mechanism for the emergence of the *50-50* division that has not been advanced in previous contributions, including Young [1993a]'s result which is based on the presence of agents that exchange roles and can be both buyers and sellers at different times.

The second extension explores how the theoretical predictions change if we allow for indirect communication, which means that information can travel more than one step in the network and therefore an agent can receive information from friends, friends of friends, and so on up to a distance r. The theoretical results generalize in a natural way. The generalized version of Theorem 1 states that if the communication networks of buyers and sellers are connected and there is at least a pair of agents at a social distance greater than r then the process without mistakes converges to a convention. The generalized version of Theorem 2 proves that the process with mistakes converges to the asymmetric Nash bargaining solution (ANB) with weights that are determined by the subset of agents in each group with the least decay r-centrality, which is a metric that captures the amount of information an agent receives from her social network up to a distance r.

The remaining part of this section surveys the related literature. Section 2 presents the model. Section 3 derives the bargaining solution and analyzes its relation with the network structure. Section 4 presents the design of the experiment and section 5 analyzes the results. Section 6 investigates a different set-up of the model where buyers and sellers belong to the same communication network. Section 7 extends the model to allow for indirect communication. Section 8 concludes. Appendix A contains the proofs omitted in the main text.

1.1 Related literature

In previous contributions there are at least two complementary explanations of why belonging to a group leads to a competitive advantage in a market with incomplete information. The first one was originally advanced by Greif [1993]: an individual trader in a group can rely on the other members of the group to inflict a costly punishment to a cheater by cutting all future trade between any member of the group and the cheater. He illustrates this with a simple model in a repeated game framework, and he draws on historical records to discuss its relevance for trading.

The second explanation is the core idea behind the model presented here: an individual in a group has access to information from other group members, and this leads to a competitive advantage in a market where information is incomplete. Rauch and Casella [2003] proposed a model where information-sharing within ethnic groups influences resource allocation in international trade markets affected by incomplete information. Rauch and Trindade [2002] show that the information-sharing story fits observed international trade flows better than the collective punishment one. One of the key differences between this paper and these previous contributions is that it explicitly models the role of the network structure of interactions within a group.

Methodologically, this paper is based on the evolutionary bargaining framework first formulated by Young [1993a]. The novel element introduced here is the modeling of the process by which agents receive information to play the game: information travels through a communication network that connects the agents in each group. The introduction of the network demands the construction of a different Markov process to describe the evolution of the system, which requires a novel equilibrium analysis. The equilibrium outcome depends on the underlying network and therefore this allows a comparative statics analysis which would not be feasible in the model without the network. Moreover, section 6 analyzes the case when buyers and sellers belong to the same communication network: the equilibrium outcome is unchanged, but the comparative statics predictions are different, and this type of analysis is only feasible in the model with the network.

In the economics of networks literature a number of papers investigate how a network that constrains agents' interactions affects the outcome of a bargaining process. Selected contributions include Calvó-Armengol [2001], Calvó-Armengol [2003], Corominas-Bosch [2004], Polanski [2007] and Manea [2011]. The framework adopted here is conceptually different. In all the references listed above, the network is a constraint on the interactions that agents are allowed to have. On the other hand, in this paper the network is a constraint on the information about past bargains that agents have as they enter a bargaining round. Moreover, the focus of this paper is also different. Previous work in the literature investigates how the position of one agent in a network affects her individual payoffs. Here the aim of the paper is to understand how the overall structural properties of the network determine the payoff that every individual in the whole group receives, independently on their position in the network.

Two strands in the economics of networks literature examine the role of communications networks. The first one investigates the role of communication networks in labour markets, selected contributions include Montgomery [1991], Calvó-Armengol and Jackson [2007], and Galeotti and Merlino [2013]. These papers focus on how the structure of communication networks is a determinant of aggregate labour market dynamics such as unemployment, wages, and inequality. The second is two papers by Hagenbach and Koessler [2010] and Galeotti et al. [2013] who extend the classical cheap talk framework to a network setting. The focus of this paper is on the role of communication networks in determining outcomes in markets with bilateral bargaining, and it is the first paper to investigate the role of communication networks in this domain.

This paper also contributes to a growing area of research at the intersection of the economics of networks and the experimental economics literature. The experimental methodology allows an unambiguous causal identification of the effect of network structure by creating the network structure in the lab and making it the treatment variable. There are still a limited number of papers in this vein of work, possibly due to the large number of subjects required and the fact that some types of relations (e.g. friendship) are difficult to create in the lab. Some examples in the economic literature are Corominas-Bosch and Charness [2007] who test Corominas-Bosch [2004]'s bargaining model, Rosenkranz and Weitzel [2012] who investigate a public good game on a network, Gallo and Yan [2014] who investigate a game of strategic complements on a network, Gërxhani et al. [2013] who study employer information networks, Charness et al. [2014] who investigate network games with incomplete information, and Gale and Kariv [2009] and Choi et al. [2013] who test models of trading. This paper is the first experimental investigation of a theoretical model that relates the structure of a communication network to the realized market outcome. Moreover, it is the first experimental investigation of the role of the network as a constraint on information flows, which seems a natural type of relation to investigate in an experimental setting because it is easily created by designing a communication protocol among the workstations the subjects are assigned to.

The model is applicable to markets where there is incomplete information about the price of a homogeneous commodity: there are no posted prices and the agents communicate with each other to learn about the current price. Similarly to classical bargaining models, each transaction is a private, bilateral negotiation between two agents and the outcome in equilibrium will depend on the risk profile of the agents in each group. However, the agents are boundedly rational: they base their bid on information on past transactions they have collected from other agents in their group, and they are unaware of the game they are playing or of the utility profile of their opponent. There are many markets that share these characteristics in contexts such as developing countries[3], illegal trade, and the wholesale business. For instance, many wholesale fish markets are characterized by

[3] In many markets in developing countries prices tend to fluctuate due to exogenous factors affecting the supply chain. Moreover, the lack of strong institutions is an obstacle to the adoption of publicly displayed prices allowing the proliferation of decentralized bilateral transactions. See, e.g, Aker [2008] for evidence from grain markets in Niger.

private, bilateral transactions and prices fluctuate due to exogenous factors such as wind and wave height that affect the volume of the daily catch of fish.[4] Gallo [2009] analyzes a dataset of prices in the Fulton wholesale fish market collected by Graddy [1995], and finds evidence that the observed pricing pattern is consistent with the predictions of the model presented in this paper.

In summary, the main contribution of this paper is twofold. First, the theoretical part constructs a model to investigate the role of a group's communication structure in markets where there is incomplete information. This provides a theoretical underpinning to previous empirical studies that emphasized the informational role of social structure in determining market outcomes. Second, the experimental part is the first investigation of the role played by communications networks in determining market outcomes in an experimental setting. It provides an empirical validation of the causal relation of the structure of a group's communication network on the equilibrium market outcome.

2 The Model

This section presents the main elements of the model: the network concepts used, the adaptive play bargaining process, and the Markov process which describes the evolution of the system.

Networks. A *weighted, undirected network* g is represented by a symmetric matrix $[g_{ij}]^{n\times n}$, where $g_{ij} \in \mathbb{R}_+$. The entry g_{ij} indicates the *strength* of the *communication link* between i and j. If $g_{ij} > 0$ then agents i and j are connected and they communicate directly with each other. If $g_{ij} = 0$ then i and j are not connected in the communication network. Throughout this paper let $g_{ii} \equiv \overline{g}$, i.e. an agent is connected with herself and the strength of this self-connection is the same for all agents.

The *neighborhood* of i in g is $L_i(g) = \{j \in N | g_{ij} > 0\}$.[5] $d_i(g) \equiv |L_i(g)|$ denotes the size of i's neighborhood, or the *degree* of i, in g. $z_i(g) \equiv \sum_{j\in L_i(g)} g_{ij}$ is the *weighted degree* of i in g. Let $Z(g) = \max_{i\in N} z_i(g)$ be the maximum weighted degree of any agent in the network g. A *complete network* is a network that belongs to the class of networks $g^C = \{g|g_{ij} > 0, \forall i, j \in N\}$ where every pair of agents is connected. A *regular network* $g_{d,a}$ of degree d and link strength a is a network that belongs to the class of networks $\overline{g}_{d,a} = \{g|g_{ij} = \{0, a\}; d_i(g) \equiv d;\ \forall i, j \in N; a \in \mathbb{R}_+\}$. A *regular weighted network* g_k of weighted degree k is a network that belongs to the class of networks $\overline{g}_k = \{g|z_i(g) = k;\ \forall i \in N;\ k \in \mathbb{R}_+\}$.

Adaptive play bargaining process. Consider two finite, non-empty and disjoint groups of individuals $B = \{1, ..., n_B\}$ and $S = \{1, ..., n_S\}$: the buyers and sellers. In each period t one buyer and one seller drawn at random meet to divide a pie of size normalized to one. They play the Nash demand game: b demands a fraction x_t and s demands a fraction y_t, if $x_t + y_t \leq 1$ then b and s get their demands, otherwise they get nothing. Assume that the set of possible divisions is discrete and finite, and let δ be the smallest possible division. The sequence $h = \{(x_1, y_1), ..., (x_t, y_t)\}$ is the complete *global history* up to and including period t. Each agent remembers the last m rounds of the bargaining game that she has played, where m stands for the memory of the agent and $m > \max\{Z(g^B), Z(g^S)\}$.

Agents receive information to play the game as follows. Suppose agent $b \in B$ is picked to play the game at $t + 1$: in the $\Delta t = 1$ time period she receives information from some of the other

[4]Kirman [2001] provides a detailed description of wholesale fish markets.

[5]Note that this definition is slightly different than the standard one adopted in the literature because it allows for i's neighborhood to include i as well. This is because in our framework agent i's own degree g_{ii} is allowed to be positive. This difference affects the ensuing definitions as well.

buyers in B about past bargaining rounds. Information arrival is modeled as a Poisson process. Specifically, in the $\Delta t = 1$ time interval, the probability $P(s_{bj}(\Delta t = 1) = k)$ that b receives a sample $s_{bj}(\Delta t = 1)$ of k past bargains from agent j is equal to:

$$P(s_{bj}(\Delta t = 1) = k) = \frac{e^{-g_{bj}} g_{bj}^k}{k!}$$

where g_{bj} is the rate of arrival of information to b from j. By standard properties of Poisson processes, the expected amount of information b receives from j before each bargaining round is $E[P(s_{bj})] = g_{bj}$. Thus, we have that $\sum_{j \in L_b(g)} E[P(s_{bj})] = E[P(s_b)] = \sum_{j \in L_b(g)} g_{bj} = z_b(g)$, and therefore before each bargaining round the expected size of the sample of past demands is $\lceil z_b(g) \rceil$, where $\lceil . \rceil$ is the ceiling function to round it up to the nearest integer. Clearly, at each point in time the realization of the Poisson process that determines how much information b receives from j may be higher or lower than g_{bj}, but over a long period of time the average amount of information per time period that b receives from j will be equal to g_{bj}. Thus, the network g captures the average information flows between each pair of agents in the group over a long period of time.[6]

The variability of an agents' information sample over time poses significant challenges to an analytical investigation of the model. In order to overcome this, throughout the paper I impose the *mean-field assumption* that the *total* amount of information an agent b receives is the same across bargaining rounds. More formally, assume that the size of the information sample of the buyer b is constant and equal to the amount of information b receives in expectation given the Poisson processes involving b, i.e. $s_b(t) \equiv \lceil \sum_{j \in B} g_{bj} \rceil = \lceil z_b(g) \rceil$. Note that this assumption still allows for the realization of each individual Poisson process to vary, and it fixes only the sum of the realizations of all the Poisson processes. Thus, in some bargaining rounds agent b may receive most of the information from her neighbor b', while in other rounds b' may not provide any information. However, the total size of the information sample b receives before playing each bargaining round is always the same.

Agents are boundedly rational as they are not aware of the game they are embedded in and they base their decision exclusively on the information they receive. Specifically, agents do not have prior knowledge or beliefs about the utility function of the other side, and they do not know the distribution of utility functions in the general population. Agent b chooses an optimal reply to the cumulative probability distribution $G(y)$ of the demands y_j made by sellers in the sample that she receives, where $G(y) = \frac{h}{s_b(t)}$ if and only if there are exactly h demands y_l in the sample $s_b(t)$ such that $y_l \leq y$.

Agent b has a concave and strictly increasing von Neumann-Morgenstern utility function $u(x)$. Assume that $u(x)$ is defined for all $x \in [0, 1]$ and that it is normalized so that $u(0) = 0$. Buyer b's expected payoff from demanding x is then equal to $Eu(x) \equiv u(x)G(1 - x)$. Thus, b chooses x_{t+1} so as to maximize $Eu(x)$, and if there are several values of x to choose from then each one of them is chosen with positive probability.

The set-up for seller s is analogous, and the utility function of the sellers will be denoted by $v(y)$.

Markov process. Let $\mathbf{S}$ be the state space, whose elements are sets of vectors $\mathbf{s} = \{\mathbf{v}_1, ..., \mathbf{v}_n\}$, where $\mathbf{v}_i$ stands for agent i's memory, which is a vector of size m, and $n \equiv n_B + n_S$. If $i \in B$ then $\mathbf{v}_i = \{y^i_{k-m+1}, ..., y^i_k\}$, i.e. the entries of $\mathbf{v}_i$ are the m last demands made by sellers in bargaining

[6] Note also that there is no need to assume that the Poisson process is truncated given that the memory m can be arbitrarily large.

rounds involving i. Similarly, if $i \in S$ then $\mathbf{v}_i = \{x^i_{k-m+1}, ..., x^i_k\}$. Let $q_b(x \mid \mathbf{s})$ be agent b's best-reply distribution, i.e. $q_b(x \mid \mathbf{s}) > 0$ if and only if demanding x is b's best-reply to a sample received when the system is in state $\mathbf{s}$. Analogously, $q_s(y \mid \mathbf{s})$ is seller s's best-reply distribution.

Assume that the process starts at an arbitrary time $t_0 > n \cdot m$, and denote the initial state by $\mathbf{s}^0$. At each $t > t^0$, one pair of agents $(b, s) \in B \times S$ is drawn at random with probability $\pi(b, s)$, where $\pi(b, s) > 0$, $\forall(b, s) \in B \times S$. At time t, consider a state $\mathbf{s} = \{\mathbf{v}_b, \mathbf{v}_s, \mathbf{v}_{-b}, \mathbf{v}_{-s}\}$, where $\mathbf{v}_b = \{y^b_{k-m+1}, ..., y^b_k\}$, $\mathbf{v}_s = \{x^s_{k-m+1}, ..., x^s_k\}$, and $\{\mathbf{v}_{-b}, \mathbf{v}_{-s}\}$ denote the vectors that stand for the memories of all other agents $k \neq b, s$. Define $\mathbf{s}'$ to be a successor of $\mathbf{s}$ if it has the form $\mathbf{s}' = \{\mathbf{v}'_b, \mathbf{v}'_s, \mathbf{v}_{-b}, \mathbf{v}_{-s}\}$, where $\mathbf{v}'_b = \{y^b_{k-m+2}, ..., y^b_{k+1}\}$ and $\mathbf{v}'_s = \{x^s_{k-m+2}, ..., x^s_{k+1}\}$. The transition probability $P_{\mathbf{ss}'}$ of moving from state $\mathbf{s}$ to state $\mathbf{s}'$ is then equal to:

$$P_{\mathbf{ss}'} = \sum_{b \in B} \sum_{s \in S} \pi(b, s) q_b(x_{t+1} \mid \mathbf{s}) q_s(y_{t+1} \mid \mathbf{s}) \tag{1}$$

Mistakes. In the process described so far agents always give a best reply to the sample they happen to pick. In reality, people make mistakes for a variety of reasons: human beings are poor at computing probabilities and they might miscalculate the expected utility from an offer, they are prone to get distracted, they experiment, or sometimes they are outright irrational. The following is a more formal definition of a mistake.

Definition 1. Let $\mathbf{s} = \{\mathbf{v}_b, \mathbf{v}_s, \mathbf{v}_{-b}, \mathbf{v}_{-s}\}$ and let $\mathbf{s}' = \{\mathbf{v}'_b, \mathbf{v}'_s, \mathbf{v}_{-b}, \mathbf{v}_{-s}\}$ be a successor of $\mathbf{s}$, where $\mathbf{v}_b = \{y^b_{k-m+1}, ..., y^b_k\}$, $\mathbf{v}_s = \{x^s_{k-m+1}, ..., x^s_k\}$, $\mathbf{v}'_b = \{y^b_{k-m+2}, ..., y^b_{k+1}\}$ and $\mathbf{v}'_s = \{x^s_{k-m+2}, ..., x^s_{k+1}\}$. The demand x^s_{k+1} is a mistake by b if it is not a best response to any sample b could have received given that the system is in state $\mathbf{s}$. A mistake y^s_{k+1} by s is defined similarly.

Another concept that will be useful in the analysis of the perturbed process is the *resistance* in moving from one state $\mathbf{s}$ to another state $\mathbf{s}'$.

Definition 2. Let $\mathbf{s}$ and $\mathbf{s}'$ be two states of the system. The *resistance* $r(\mathbf{s}, \mathbf{s}')$ is the least number of mistakes required for the system to go from state $\mathbf{s}$ to $\mathbf{s}'$.

Note that if $\mathbf{s}'$ is a successor of $\mathbf{s}$ then $r(\mathbf{s}, \mathbf{s}') \in \{0, 1, 2\}$ given that the maximum number of mistakes in any one-time transition is two, i.e. both the buyer and seller involved in that bargaining round make a mistake.

Now let ϵ be the absolute probability that agents in the model make mistakes. Denote by $w_b(x \mid \mathbf{s})$ the buyer's conditional probability of choosing x given that the current state is $\mathbf{s}$ and that she is not giving a best-response offer to the sample picked, and define $w_s(y \mid \mathbf{s})$ analogously. Assume $\epsilon > 0$ and that $w_b(x \mid \mathbf{s})$, $w_s(y \mid \mathbf{s})$ have full support.

This process also yields a stationary Markov chain on $\mathbf{S}$ that can be described by the probability of moving from a state $\mathbf{s}$ to a successor state $\mathbf{s}'$, similarly to equation (1) above. Assume that the process starts at an arbitrary time $t_0 > n \cdot m$, and denote the initial state by $\mathbf{s}^0$. At each $t > t^0$ one pair of agents $(b, s) \in B \times S$ is drawn at random with probability $\pi(b, s)$, where $\pi(b, s) > 0$, $\forall(b, s) \in B \times S$. Let $\mathbf{s}$ be the state at time t, and let $\mathbf{s}'$ be a successor of $\mathbf{s}$, where $\mathbf{s}$ and $\mathbf{s}'$ are defined above. The transition probability $P^\epsilon_{\mathbf{ss}'}$ of moving from state $\mathbf{s}$ to state $\mathbf{s}'$ is then equal to:

$$\begin{aligned} P^\epsilon_{\mathbf{ss}'} = \sum_{b \in B} \sum_{s \in S} \pi(b, s) [(1-\epsilon)^2 q_b(x_{t+1} \mid \mathbf{s}) q_s(y_{t+1} \mid \mathbf{s}) + \epsilon^2 w_b(x_{t+1} \mid \mathbf{s}) w_s(y_{t+1} \mid \mathbf{s})] + \\ + \epsilon(1-\epsilon) w_b(x_{t+1} \mid \mathbf{s}) q_s(y_{t+1} \mid \mathbf{s}) + \epsilon(1-\epsilon) w_s(x_{t+1} \mid \mathbf{s}) q_b(y_{t+1} \mid \mathbf{s}) \end{aligned} \tag{2}$$

The limit of the perturbed process is clearly the unperturbed one: $\lim_{\epsilon \to 0} P^\epsilon_{\mathbf{ss}'} = P_{\mathbf{ss}'}$.

3 Equilibrium analysis

This section presents the results of the equilibrium analysis. Section 3.1 shows that the process without mistakes converges to a convention as long as the network is not complete. Section 3.2 derives the stochastically stable division and analyzes its relation with the network structure. Section 3.3 characterizes the desirable communication network structure for the members of a group and discusses the relevance of this result to a long-standing debate in the sociology literature.

3.1 Convergence

First, consider the unperturbed process P. The first step in the analysis is to define an appropriate concept of stability for this system, and to show that in the long-term the process will reach it. Intuitively, the system will be in a stable state if after a certain time t any buyer will always make the same demand x because the sellers have always demanded $1-x$, and vice versa for the sellers. The following definition states this more formally.

Definition 3. A state $\mathbf{s}$ is a convention if any $\mathbf{v}_i \in \mathbf{s}$ with $i \in B$ is such that $\mathbf{v}_i = (1-x, ..., 1-x)$, and any $\mathbf{v}_j \in \mathbf{s}$ with $j \in S$ is such that $\mathbf{v}_j = (x, ..., x)$, where $0 < x < 1$. Hereafter, denote this convention by $\mathbf{x}$.

It is straightforward to see that the convention $\mathbf{x}$ is an absorbing state of P. If a buyer receives a sample in which all sellers' demands are equal to $1-x$ then she will demand x. Similarly, if a seller receives a sample in which all buyers' demands are equal to x then he will demand $1-x$. Clearly, this will go on forever so $\mathbf{x}$ is an absorbing state of P.

Lemma 1. *Every convention $\boldsymbol{x}$ is an absorbing state of the Markov process P in (1).*

The following theorem shows that if information about the history of play is sufficiently incomplete then the process P converges to a convention. The incompleteness of information is delivered by the network structure: if the network is not complete then some agents do not receive information on past demands in rounds played by individuals that do not belong to their neighborhoods.

Theorem 1. *Assume both g^B and g^S are connected and they are not complete networks. The bargaining process converges almost surely to a convention.*

The example networks in Figure 2 help understanding the intuition behind the proof. The goal is to show that from any initial state $\mathbf{s}$ there is a positive probability p independent of t of reaching a convention within a finite number of steps. The assumption that g^B is not a complete network implies that there are at least two agents b' and b'' such that $g_{b'b''} = 0$. Moreover, given that g^B is connected, there are at least two agents like b' and b'' such that the intersection of their neighborhoods includes at least one agent b. The same applies to the sellers' network, where agents s and s'' are the equivalent of agents b' and b'' respectively.

Now, consider the following path which happens with positive probability from any state $\mathbf{s}$ at time t. First, b and s are picked to play the game for m periods, they draw samples σ and σ' respectively, they demand best-replies x and y respectively, and therefore we have a run $\xi = \{(x, y), ..., (x, y)\}$ such that $\mathbf{v}_b = (y, ..., y)$ and $\mathbf{v}_s = (x, ..., x)$. Second, b' and s' are picked to play the game for m periods, they draw samples from $\mathbf{v}_b$ and $\mathbf{v}_s$ each time, they demand best-replies $1-y$ and $1-x$ respectively, and therefore we have a run $\xi' = \{(1-y, 1-x), ..., (1-y, 1-x)\}$ such

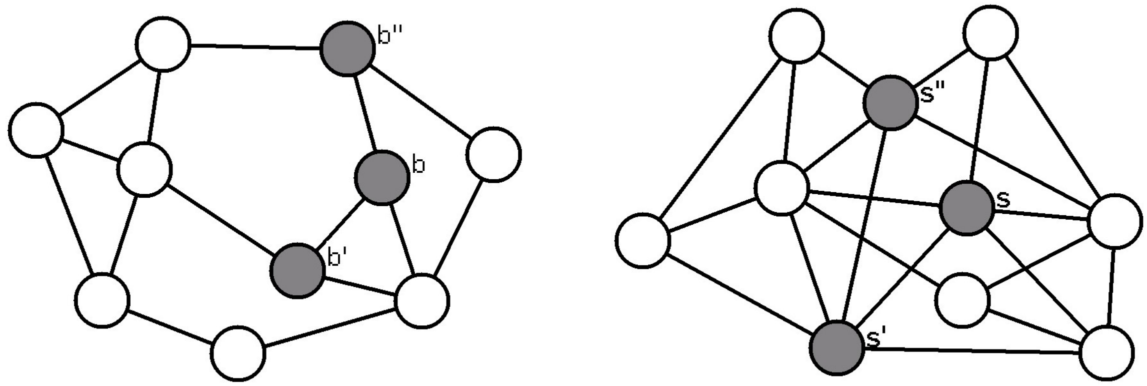

Figure 2: Example networks of buyers (left) and sellers (right). Gray-colored nodes are mentioned in the text to give intuition about the proof.

that $\mathbf{v}_{b'} = (1-x, ..., 1-x)$ and $\mathbf{v}_{s'} = (1-y, ..., 1-y)$. Third, b'' and s'' are picked to play the game for m periods, they draw samples from $\mathbf{v}_b$ and $\mathbf{v}_{s'}$ each time, they demand best-replies $1-y$ and y respectively, and therefore we have a run $\xi'' = \{(1-y, y), ..., (1-y, y)\}$ such that $\mathbf{v}_{b''} = (y, ..., y)$ and $\mathbf{v}_{s''} = (1-y, ..., 1-y)$. Hereafter it is clear that there is a positive probability of reaching a convention $\mathbf{x} = (1-y, y)$.

Theorem 1 in Young [1993b] proves adaptive play converges almost surely to a convention in any weakly acyclic game with n agents as long as information is sufficiently incomplete. In Young [1993b]'s the incompleteness of the information is given by bounds on the size of the sample the agents can draw to base their play on. Here the incompleteness of information is given by the network structure: if the network is not complete there will be agents who cannot sample some past rounds because they were played by agents in their group with whom they do not communicate.[7]

Section 7 extends the model to a setting where indirect communication is allowed so that agents receive information from friends of their friends up to a social distance r. The statement of the theorem extends naturally to this setting: if there are at least two agents at a distance higher than r then there is convergence to a convention. The rationale is the same: there is incompleteness of information because at least two agents are not able to sample the whole history of past demands. Clearly, Theorem 1 above is the special case for $r = 1$.

3.2 Network structure and the market outcome

Theorem 1 proves that the system converges to a stable division, but any division is a potential solution so it is silent on how the stable outcome depends on the structure of the groups and the preferences of the agents. In order to make progress in this direction, one needs to consider the perturbed process P^ϵ. Given that the distributions w_b and w_s have full support, P^ϵ is irreducible. Thus, P^ϵ has a unique stationary distribution. Moreover, P^ϵ is strongly ergodic, i.e. $\forall \mathbf{s} \in S$, μ^ϵ_s is with probability one the relative frequency with which state $\mathbf{s}$ will be observed in the first t periods as $t \to \infty$. A well-known stability concept for this kind of perturbed process is a *stochastically stable convention* by Foster and Young [1990].

[7]It is straightforward to extend this argument and therefore the result of Theorem 2 to a set-up where agents are heterogeneous in their risk-aversion.

Definition 4. A convention $\mathbf{s}$ is stochastically stable if $\lim_{\epsilon \to 0} \mu^{\epsilon}_{\mathbf{s}} > 0$. A convention $\mathbf{s}$ is strongly stable if $\lim_{\epsilon \to 0} \mu^{\epsilon}_{\mathbf{s}} = 1$.

Intuitively, in the long-run stochastically stable conventions will be observed much more frequently than unstable conventions when the probability ϵ of mistakes is small. A strongly stable convention will be observed almost all the time. In order to compute the stochastically stable convention, one can construct a weighted, directed network $[r_{\mathbf{s}^i\mathbf{s}^j}]^{k\times k}$, where the nodes are the states $\mathbf{s} \in \mathbf{S}$, the links are the resistances $r_{\mathbf{s}^i\mathbf{s}^j}$ connecting $\mathbf{s}^i$ to $\mathbf{s}^j$, and k is the total number of states in $\mathbf{S}$. Define an ***x**-tree* $t_{\mathbf{x}} \in T_{\mathbf{x}}$ to be a collection of links in $[r_{\mathbf{s}^i\mathbf{s}^j}]^{k\times k}$ such that, from every node $\mathbf{x}' \neq \mathbf{x}$, there is a unique directed path to $\mathbf{x}$ and there are no cycles. The stochastic potential $\gamma(\mathbf{x})$ of a convention $\mathbf{x}$ is the least resistance among all $t_{\mathbf{x}} \in T_{\mathbf{x}}$. Let μ^0 be a stationary distribution of the unperturbed process P, so $\lim_{\epsilon \to 0} \mu^{\epsilon}_{\mathbf{s}} = \mu^0$. Theorem 4 in Young [1993b] proves that $\mu^0 > 0$, i.e. $\mathbf{s}$ is stochastically stable, if and only if $\mathbf{s} = \mathbf{x}$ is a convention and $\gamma(\mathbf{x})$ has minimum stochastic potential among all conventions.

The methodology outlined above can be applied to find the division which the process will converge to. Define $B_{min} = \{j \in B \mid \lceil z_j(g^B)\rceil \leq \lceil z_b(g^B)\rceil, \forall b \in B\}$ to be the subset of buyers with the least weighted degree. Let $z^{min}_b(g^B) = \lceil z_j(g^B)\rceil$ for $j \in B_{min}$. Equivalent definitions apply to the sellers. The first step is to compute the minimum resistance to moving from the convention $\mathbf{x}$ to the basin of a different convention $\mathbf{x}'$. This is done in the following lemma.

Lemma 2. *The minimum resistance to moving from **x** to a state in some other basin is $\lceil R(x)\rceil$, where:*

$$R(x) = \min\left\{ z^{min}_b(g)\left(1 - \frac{u(x-\delta)}{u(x)}\right), z^{min}_s(g)\frac{v(1-x)}{v(1-\delta)}, z^{min}_s(g)\left(1 - \frac{v(1-x-\delta)}{v(1-x)}\right)\right\} \quad (3)$$

The intuition is as follows. Some agents have to make mistakes in order for the system to move from one convention to a state in the basin of another convention. The agents who will switch with the least number of mistakes in their sample are the ones who receive the smallest samples. This explains the factors $z^{min}_b(g)$ and $z^{min}_s(g)$ in equation (3). Now, consider the case when some sellers make a mistake. The smallest mistake they can make is to demand a quantity δ more than the conventional demand $1 - x$. If they do this, buyers will attempt to resist up to the point when the utility from getting the conventional amount x some of the time, i.e. when sellers do not make a mistake, is equal to the utility from getting the lower amount $x - \delta$ all the time. This gives the first term in equation (3). The third term is the equivalent of the first one, but this time the buyers make a mistake and demand δ more than the conventional amount x.

Another possibility is that some buyers make a mistake, but this time they demand less than the conventional amount x. The "worst" mistake, from the buyers' point of view, would be to demand the minimum amount δ. If they do this, sellers will only switch at the point when the utility from getting the higher amount $1 - \delta$ some of the time, i.e. when buyers make a mistake, is higher than the utility from getting the conventional amount x all the time. This gives the second term in equation (3). There should also be a fourth term, i.e. the equivalent of the second one with the roles of buyers and sellers reversed, but it is not included in equation (3) because it is never strictly smaller than the last term.

The expression for $R(x)$ in (3) is the minimum of three monotone functions: the first two are strictly decreasing in x, while the last one is strictly increasing in x. Thus, $R(x)$ is first strictly increasing and then strictly decreasing as x increases, so it achieves its maximum at a unique value

x^*.[8] Using this fact, the following theorem shows that there is a unique stable division, which is the asymmetric Nash bargaining solution with weights that depend on the agents in each group with the least weighted degrees.

Theorem 2. *There exists a unique stable division* $(x^*, 1-x^*)$*. It is the one that maximizes the following product:*

$$u^{z_b^{min}}(x)v^{z_s^{min}}(1-x) \tag{4}$$

In other words, it is the asymmetric Nash bargaining solution with weights $z_b^{min}(g^B)$ *and* $z_s^{min}(g^S)$*.*

If the precision δ is sufficiently small then over time the two groups will settle on a conventional division, which is the asymmetric Nash bargaining solution. This solution crucially depends on the communication networks that buyers and sellers use to learn about past bargaining rounds to determine what to demand once they are picked to play. More precisely, ceteris paribus (i.e. agents' risk-aversion in the two groups is the same), the division depends on the agents in the group with the least number and/or weakest communication links.[9] The intuition is that these agents will be the least informed when it comes to play the game, and therefore they will be the most susceptible to respond to mistakes from the other side. Over time, this susceptibility weakens the bargaining position of the whole group. Obviously, as in standard bargaining models, the solution also depends on the utilities of the agents. Ceteris paribus (i.e. the least connected agents in each group have the same weighted degree), a group with less risk-averse agents will have a stronger bargaining position because these agents are more likely to take chances, and therefore they are more demanding.

The proof of the theorem follows from two lemmas from Young [1993a]. The first lemma shows that a division $(x, 1-x)$ is generically stable if and only if x maximizes the function $R(x)$ in equation (3). The second lemma shows that the maxima of $R(x)$ converge to the asymmetric Nash bargaining solution which maximizes the product in (4). This solution is clearly analogous to the one in Theorem 3 in Young [1993a]. The key difference is that the solution in Theorem 2 above depends explicitly on the internal communication structure of the groups of buyers and sellers. This allows the derivation of the comparative statics results in Corollary 1, which relate changes in network structure to variations in the equilibrium division in an intuitive way. Moreover, section 7 extends the model to a setting where indirect communication is allowed and reveals a richer dependence of the equilibrium division on the network structure. Specifically, in the extended model the statement of Theorem 2 is unchanged except for the weights that are now determined by the agents with the smallest *decay r-centrality*, a metric that captures the number and/or strength of connections in their extended neighborhood up to a distance r.

A standard and intuitive tool to analyze the effects of changes in the network structure is to look at first order stochastic dominance ($FOSD$) and second order stochastic dominance ($SOSD$) shifts in the degree distribution. The *weighted degree distribution* of a network is a description of the relative frequencies of agents that have different degrees. Let $p(z)$ denote the weighted degree distributions of network g, i.e. the fraction of nodes that have weighted degree z in network g, and let $\mu[p(z)]$ denote the mean of the distribution. The following are more formal definitions of these notions.

[8] Technically, $R(x)$ can achieve its maximum at one value x^* or at two values x^* and $x^* + \delta$. As $\delta \to 0$ these two values clearly converge to a unique maximum x^*.

[9] It is straightforward to extend the result of Theorem 2 to a set-up where agents are heterogeneous in their risk-aversion, see Young [1993a].

Definition 5. A distribution p' first order stochastic dominates (FOSD) another distribution p if $\rho'(x) \leq \rho(x)$ for any $x \in [0, Z]$, where $\rho(x) = \sum_{z=0}^{x} p(z)$ is the cumulative distribution of $p(z)$. The FOSD shift is variance-preserving if $Var[p(z)] = Var[p'(z)]$.

Definition 6. A distribution p'' strictly second order stochastic dominates (SOSD) another distribution p if $\sum_{z=0}^{x} \rho''(z) \leq \sum_{z=0}^{x} \rho(z)$ for any $x \in [0, Z]$. The SOSD shift is mean-preserving if $\mu[p(z)] = \mu[p''(z)]$.

If $p'(z)$ FOSD $p(z)$ then a network g' is *denser* than a network g. Note that in the context of weighted networks denser means that agents in g' have on average a higher number and/or stronger links than agents in g. If $p''(z)$ SOSD $p(z)$ then a network g'' is *more homogeneous* than a network g. Similarly, more homogeneous means that there is less variability across agents in g'' in terms of the number and/or strength of their connections than across agents in g. We can use this tool to gain further intuition of how the result of Theorem 2 relates the structure of the network to the equilibrium division. The following corollary to Theorem 2 shows how the asymmetric Nash bargaining solution (ANB) varies with changes in the degree distributions of the buyers and sellers' networks.

Corollary 1. *Let $(x^*, 1 - x^*)$ be the ANB for sets of agents B and S that communicate through networks g^B and g^S with weighted degree distributions $p_b(z)$ and $p_s(z)$. Consider the weighted degree distributions $p'_b(z)$ and $p''_b(z)$ of networks g'^B and g''^B respectively, and let $p'_b(z)$ FOSD $p_b(z)$ and $p''_b(z)$ SOSD $p_b(z)$.*

(i) Let $(x^{'*}, 1 - x^{'*})$ be the ANB for sets of agents B and S with degree distributions $p'_b(z)$ and $p_s(z)$. Then $x^{'*} \geq x^*$.

(ii) Let $(x^{''*}, 1 - x^{''*})$ be the ANB for sets of agents B and S with degree distributions $p''_b(z)$ and $p_s(z)$. Then $x^{''*} \geq x^*$.

The same statement holds reversing the roles of buyers and sellers.

The corollary states that individuals who belong to a *denser* social group, i.e. with more numerous and/or stronger connections, will fare better. Similarly, individuals who belong to a *more homogeneous* social group, i.e. with more equally distributed connections in terms of the number and/or strength of links, will also be better off. The intuition is that agents in these groups will have access to more information about past deals experienced by other members in their group. Thanks to this informational advantage, they are less likely to respond to mistakes by the other side, and they are therefore able to maintain an advantageous bargaining position.

Finally, only mild assumptions are required to extend the model to a context with several groups of buyers. Assume that there is one group of sellers and that there are k separate groups of buyers such that buyers communicate within their group but not across groups.[10] The main assumption that is required is that each seller knows which group a buyer belongs to and he only receives information from other sellers on previous transactions with buyers from that group. Moreover, when a seller determines which offer to make to a buyer from a certain group, he does not use information from transactions with buyers in other groups. Mathematically, the whole system can be represented by k different processes that run "in parallel," and the dynamics/outcomes of one process are completely independent from the ones of the other processes. Clearly, the results in this paper apply to each one of these processes. The following corollary presents this set-up more formally and it states its implications.

[10] An equivalent set-up is to assume that there is one group of buyers B connected by a network g^B which is composed of k *components*.

Corollary 2. *Consider one group of sellers S who communicate through g^S, and k groups of buyers $B_1, ..., B_k$ who communicate through separate networks $g^1, \ldots, g^k$ with weighted degree distributions $p_1(z), \ldots, p_k(z)$ respectively. Assume $B_i \cap B_j = \emptyset$ and sellers know which group a buyer b belongs to. Then sellers will reach different conventions with different groups of buyers on the share x_i^* that buyers in B_i get. Moreover:*

(i) If $p_1(z)$ FOSD $p_2(z)$ FOSD $\ldots$ FOSD $p_k(z)$, then $x_1^* \geq x_2^* \geq \ldots \geq x_k^*$

(ii) If $p_1(z)$ SOSD $p_2(z)$ SOSD $\ldots$ SOSD $p_k(z)$, then $x_1^* \geq x_2^* \geq \ldots \geq x_k^*$

This corollary states a clear and testable prediction of the model: in a market with different groups of buyers where communication only occurs within groups, buyers that belong to denser and/or more homogeneous groups will fare better. Sections 4 and 5 investigate the validity of these predictions in an experimental setting.

3.3 The weakness of weak ties

What is the desirable communication structure for the members of a group of individuals that engage in this bargaining process with another group? In order to answer this question, it is useful to define a class of *quasi-regular networks*, which are generated by a given regular network.

Definition 7. Consider the set G of undirected networks with n nodes and at most L links. Let $g_{d,a}$ be a regular network with degree $d = \lfloor \frac{2L}{n} \rfloor$ and link strength a, i.e. it belongs to $\overline{g}_{d,a}$ which is the class of largest regular networks in G. The network $g \in G$ is a quasi-regular network generated by $g_{d,a}$ if it can be obtained by randomly adding k links of any strength to $g_{d,a}$, where $k \in [0, L - \frac{n}{2})$.

A quasi-regular network is a network that is similar to a regular network in the sense that the links are distributed evenly among the nodes and there is minimal degree variation. Note that if $L/n \in \mathbb{N}$, i.e. the links can be exactly divided among the nodes, then the set of quasi-regular network coincides with the class of regular networks $\overline{g}_{d,a}$. If $L/n \notin \mathbb{N}$ then each node has at least as many links as in the generating regular network, and the remaining links are randomly assigned. The following corollary shows that the desirable communication structure for a group is a quasi-regular network.

Corollary 3. *Fix a communication network g^S for the sellers. Consider the set G of all possible communication structures g^B among the n_B buyers such that the total number of links is $L < \frac{n_B}{2}(n_B - 1)$ and the strength of each link is in the $[\underline{s}, \overline{s}]$ range, where $\underline{s}, \overline{s} \in \mathbb{R}_+$. The subset of networks $G_B \subset G$ that gives the highest share to buyers are the quasi-regular networks generated by regular networks in $\overline{g}_{d,\overline{s}}$, where $d = \left\lfloor \frac{2L}{n_B} \right\rfloor$. The same statement holds reversing the roles of buyers and sellers.*

For illustrative purposes it is easier to give the intuition for the case where $L/n_B \in \mathbb{N}$. First, the desirable network must have communication links of maximum strength because they carry more information about past rounds, decreasing in this way buyers' susceptibility to sellers' mistakes. Second, a regular network is desirable because it is the network where the buyers with the lowest degree have the highest possible degree given the constraint L. Informally, (quasi-)regular networks are very steady: they have no weak points that could be more susceptible to sellers' mistakes.

There is a long-standing debate in the sociological literature on what constitutes a desirable network for a group of individuals. A seminal paper by Granovetter [1973] introduced the idea that weak ties play an important role in networks because they connect individuals with few characteristics in common and that have non-overlapping neighborhoods, allowing them to access non-redundant information. For instance, Granovetter [1995] shows that individuals with many weak ties are better at finding employment through their social networks. A rough summary of this view is that networks with a significant fraction of *weak ties* and *high degree variability* are desirable because they facilitate the flow of information.

On the other hand, Coleman [1988] argues that close-knit, homogeneous networks formed by strong bonds are desirable. The rationale is that these strong connections and their even distribution across all group members make it easier to establish an informal, decentralized monitoring of the flow of information. Moreover, there are no peripheral individuals who could be potential defectors. He gives the example of the network of wholesale diamond traders in New York: strong family, religious and community ties ensure that information about any cheating will be quickly available to all the members leading to the exclusion of the cheater from the community. A rough summary of this view is that networks composed exclusively by *strong ties* and *minimal degree variability without peripheral individuals* are desirable because they facilitate monitoring of what is going on in the network.

In the context described by this model, Corollary 3 shows that Coleman-type, quasi-regular networks exclusively formed by strong ties are desirable because they allow the effective sharing of information about past demands. However, it is important to understand that this is not an absolute statement about the two views, which are, in fact, complementary. There are two key aspects of this model which determine the desirability of a Coleman-type network in this context. First, the new information that circulates in the network is negative: mistakes made by the other side that individuals in the group should not respond to. Second, the final outcome is the establishment of a norm for the whole group, so the important factor is how structural properties of the group as a whole, not the structural position of single agents, influence the outcome. A regular network with strong ties ensures that each agent has a lot of information about the state of the system so that new negative information has a very low probability of affecting the group. Moreover, the regularity of the networks ensures that there are no weak points where negative information has a higher probability of "entering" the group. On the other hand, in a model where new information is positive and valuable (e.g. innovation, job opportunities) then the desirable network would probably be closer to the Granovetter's type because it would facilitate the effective circulation of positive information.

4 Experiment: Design

The experiment was run at the Center for Experimental Social Sciences (CESS) at Nuffield College (University of Oxford). It consisted of 16 experimental sessions and each session lasted about 40 minutes. In total, 312 subjects participated in the experiment. There were 5 sessions with 24 subjects, 10 sessions with 18 subjects, and 1 session with 12 subjects.[11] The subjects were mainly undergraduate (48.7%) and graduate (36.3%) students at the University of Oxford, and the average age was 23.2 years old. Payoffs were calculated in vouchers and each voucher was worth

[11] The number of participants per session had to be a multiple of 6 because subjects are randomly assigned to groups of 6 (see below for details). If a number of subjects different from $\{12, 18, 24\}$ showed up then the subjects who arrived last received a show-up fee and did not participate in the experiment. Subjects were alerted about this possibility in the invitation email to sign up for the experiment.

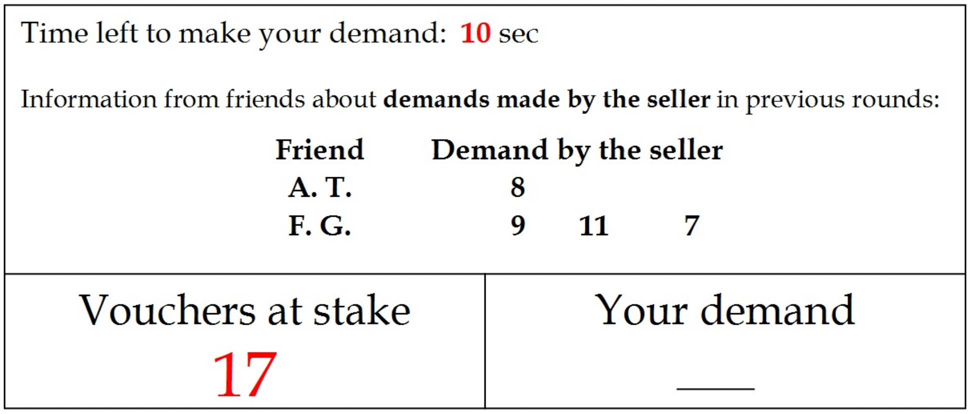

Figure 3: An illustration of what the subjects see on their screen during a trading round.

11p. The average earning for a subject was approximately £7 and each subject was paid in private by a research assistant at the end of each session. The experimental instructions are available in Appendix C.

At the beginning of each session subjects were randomly assigned to workstations which were partitioned to ensure anonymity and the effective isolation of subjects. There was a copy of the experimental instructions at each workstation and the experimenter started reading them after all subjects were seated. The first part of the instructions describes the Nash demand game. Subjects were told that they will be traders in a market and that they will be trading with a seller played by a computer. At each trading round there are 17 vouchers at stake: if the sum of the subject and the seller's demands is greater than 17 the subject gets 0 vouchers, otherwise she gets the number of vouchers she demanded.

After the explanation of the Nash demand game, the subjects are told that they are divided into groups and the experimenter explains the trading procedure. They are shown the representation in Figure 3 of what they will see on their computer screen. Subjects have 15 seconds in each trading round and the first line at the top of their screen is a time counter that tells them how long they have left. At the center of the screen they have information about the demands made by the seller in past transactions with the other buyers that they are connected to. The other buyers are denoted by fictitious initials to preserve anonymity. In the example in Figure 3, the seller has demanded $9, 11, 17$ vouchers in previous transactions with buyer $F.G.$ and 8 vouchers in one previous transaction with seller $A.T.$ The bottom left panel reminds subjects that there are 17 vouchers at stake, which does not change throughout the experiment. In the bottom right panel subjects can input their demand for this trading round. Note that they are only able to input the demand after the time counter has reached 10 seconds left.

After a subject has entered her demand x and all other subjects in her group have entered their demand, a new screen appears that tells the subject one of these 3 outcomes: she has won x vouchers, she has won 0 vouchers because the sum of her demand and the seller's demand was more than 17, or she has won 0 vouchers because she did not input a demand.[12] Subjects are told that there will be 50 trading rounds, and that at the end of the experiment 6 trading rounds will be selected at random for payment: the vouchers earned in those trading rounds are converted into

[12]Subjects failed to input a demand only in 0.001% (30 out of 15,630) of the trading rounds.

pounds using an exchange rate of 1 voucher = $11p$.

Subjects are also told that the computer, which is the seller, will try to earn as many vouchers as possible in the trading and that it will determine its demand based on the previous history of trading with members of the subject's group.[13] The computer seller follows the following algorithm to determine the demand it makes to a subject i: it samples 8 past demands made by members of i's group among all the demands they made in the last 6 rounds, and it makes a demand which is a best response to this sample with 95% probability and it demands an amount at random with 5% probability.

At the end of the instructions the experimenter asks whether there are any questions. After all questions have been answered, the experimenter announces that trading starts and that after 3 trading rounds it will be stopped to allow subjects to clarify any remaining doubts. After all questions have been answered trading resumes and continues without interruptions until the 50th round. At the end of the trading subjects had to fill in a questionnaire and took a modified version of the incentivized test in Holt and Laury [2002] to generate their risk preferences.

There are 4 treatments in the experiment and the only difference across treatments is the network that allowed communication among subjects. Figure 4 illustrates the 4 networks used in the experiment: a regular network of degree 4 ($R4$), a circle network ($C1$), a star network (ST) and a circle with spokes network ($C2$). As it is clear from Figure 3, subjects did not know the network that they were assigned to and they could only see the people that they were connected to (with fictitious names to ensure anonymity). In all the networks the links are unweighted.

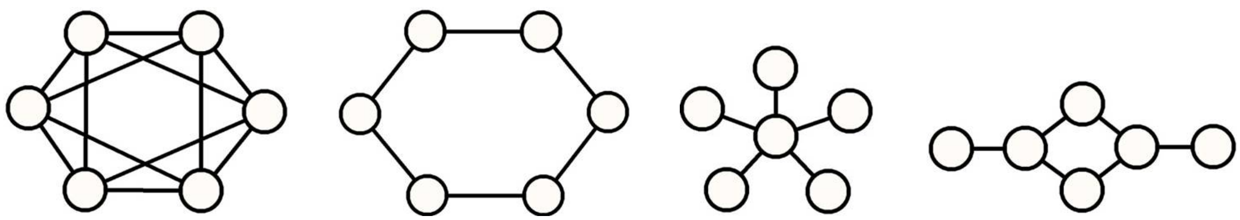

Figure 4: Networks used in the experiment. From left to right: regular network of degree 4 ($R4$), circle network ($C1$), star network (ST), and circle MPS network ($C2$), which is a mean-preserving spread of the circle network.

All the theoretical results presented in section 3 apply after the system has converged to a stable state. Thus, it is necessary to check that the trading markets have converged before comparing the outcomes across treatments. This leads us to our first hypothesis:

H1: Subjects assigned to the same group converge to demand the same number of vouchers at the end of the trading market, independently of the treatment they are assigned to.

The results of Theorem 2 and Corollary 1 allow us to formulate clear hypotheses on the differences in what subjects demand across treatments. In both treatments $R4$ and $C1$ subjects are symmetric in terms of the number of connections that they have. This means that every subject is crucial to determine the equilibrium split because every subject has the least number of connections in the network. However, a subject in $R4$ has double the number of connections of a subject in $C1$ so the $R4$ network first order stochastic dominates the $C1$ network and by Corollary 1 we

[13] See Appendix C for the exact wording, which is similar to the one used by Johnson et al. [2004] in a different experiment which involved a bargaining game between subjects and a computer.

hypothesize that subjects in $R4$ demand more vouchers after convergence. Similarly, any subject in $R4$ has more connections than the least connected subjects in ST and $C2$ so by Theorem 2 we hypothesize that subjects in $R4$ demand more vouchers after convergence. In summary, we have:

H2: Subjects in the $R4$ treatment demand more vouchers (after convergence) than subjects in the $C1$, $C2$ and ST treatments.

As mentioned above, subjects in $C1$ are symmetric in terms of the number of connections: everyone has two connections. The $C2$ network has the same total number of connections of the $C1$ network, but subjects are asymmetric in the number of connections they have. Thus, $C1$ second order stochastically dominates $C2$, and therefore by Corollary 1 we hypothesize that subjects in $C1$ demand more vouchers (after convergence) than subjects in $C2$. Similarly, all but one subjects in ST have only one connection so we hypothesize that subjects in $C1$ demand more vouchers (after convergence) than subjects in ST. In summary, we have:

H3: Subjects in the $C1$ treatment demand more vouchers (after convergence) than subjects in the $C2$ and ST treatments.

Finally, the ST and $C2$ networks have rather different structural properties. The $C2$ network has 3 types of subjects with one, two and three connections, and it has a higher total number of connections than the ST network. The ST network has a very uneven distributions of connections with one subject who is connected to everyone else and no other connection in the network. However, the result of Theorem 2 predicts that there should be no difference between the number of vouchers that subjects demand (after convergence) between the two treatments because in both networks the least connected subjects have the same number of connections (i.e. one):

H4: Subjects in the $C2$ and ST treatments demand the same number of vouchers (after convergence).

The statement of Theorem 2 also implies that after convergence there will be no difference across subjects in the same network with regard to the number of vouchers that each one of them demands. In other words, the overall structure of the network determines the split, but the structural position of each subject does not determine what that subject demands compared to others in a different structural position in the network. We can test this predictions in the ST and $C2$ treatments where subjects have asymmetric structural positions in the network. This leads to two further hypotheses:

H5: In the ST treatment, the subject at the center of the star network demands the same number of vouchers (after convergence) as the subjects assigned at the periphery.

H6: In the $C2$ treatment, the subjects demand the same number of vouchers (after convergence) independently of their position in the network.

Aside from the network structure, which is our main interest, Theorem 2 also makes the intuitive prediction that subjects who are less risk-averse should demand more vouchers. This leads to a further hypothesis to help to validate the theoretical results.

H7: In all treatments the subjects' risk aversion is inversely correlated with the number of vouchers they demand.

Table 1: Summary statistics and pairwise correlations for some of the main variables.[1]

	n	Mean	s.d.	1	2	3	4	5	6	7
1. Gender[1]	312	0.54	0.50	1.00						
2. Age	312	23.20	4.86	0.04	1.00					
3. Trust[2]	309	0.54	0.50	0.06	0.02	1.00				
4. Risk[3]	310	5.92	1.81	-0.21^{***}	-0.00	0.09	1.00			
5. HL[4]	274	4.19	2.82	-0.12	0.02	0.05	0.34^{***}	1.00		
6. Memory[5]	312	6.49	2.25	-0.14^{*}	-0.07	0.12	0.14^{*}	0.16^{*}	1.00	
7. Comp.	312	6.34	2.35	-0.21^{**}	-0.02	0.10	0.14^{*}	0.03	0.60^{***}	1.00
8. Social	312	6.35	2.06	0.15^{*}	-0.06	0.20^{***}	0.16^{**}	0.04	0.15^{*}	0.03

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. 1. Female= 1. 2. General trust question with 0 =“Need to be very careful” and 1 =“Most people can be trusted”; three participants did not answer the question. 3. General risk attitude question with $1-10$ scale where 1 =“not at all willing to take risks” and 10 =“very willing to take risks”; two participants did not answer the question. 4. Holt and Laury [2002]'s risk attitude test: 13 participants did not answer the question, 25 participants are excluded because they made at least one inconsistent choice (i.e. multiple switching points). 5. Variables 6, 7 and 8 are from general questions on participants' self-perception of their ability to (6) memorize and recall numerical information, (7) perform computations, and (8) spend a significant amount of their free time doing social activities with other people.

5 Experiment: Results

This section presents the results of the experiment. Section 5.1 describes the subject pool. Section 5.2 carries out a convergence analysis of subjects' decisions in all experimental sessions. Section 5.3 contains the analysis of the experimental data.

5.1 Sample description

The experimental data contains the decisions of 312 subjects. Each subject participated in one treatment so she played the game in one of the four network structures. We ran each treatment 13 times so we have 78 subjects that played the game on a given network structure and 13 independent observations per treatment. There are 50 rounds in each game so we have a total of $15,600$ demand decisions or observations. The experimental data was matched with the data from the questionnaire that subjects had to fill in at the end of the experiment.

Table 1 summarizes some of the most important variables in the sample and their pairwise correlation: 55.8% of the subjects were female, the average age was 23.2 years old and 55.7% believe that others can be trusted, which is higher than the average value from the World Values Survey (WVS) of the UK population. The level of trust is not correlated with gender or age.

After the questionnaire, subjects took a Holt and Laury [2002] risk attitude test. For each of 8 scenarios they had to pick between a certain win of £5 and a lottery with expected outcome x, where x varied from £15 for scenario 1 to £8 for scenario 8. A risk-neutral participant would be indifferent between the two choices at scenario 6 where the lottery gives £5 in expectation. The participants are on average risk-averse because the mean switching point is 4.27, which is equivalent to an expected lottery value of £11.73.[14] The results of the test have a highly significant

[14] This includes participants who always chose the certain option (62; coded as 0) and who always chose the lottery (18; coded as 9). If we exclude these participants, the mean switching point is 5.22, which is equivalent to an expected

positive correlation with the participants' self-perception of their attitude toward risk on a 1-10 scale. Female subjects are on average more risk-averse, although this is significant only for the self-reported measure of risk.

Subjects were also asked for their self-evaluation of their general ability at memorising and recalling numerical information (*memory*), performing computations without the aid of a calculator and without pen and paper (*computation*), and whether they spend a significant amount of their free time doing social activities with other people (*social*). *Memory* and *computation* have a highly significant positive correlation, and *memory* and *social* have a significant positive correlation. Females tend to report a worse *memory* on average, and *memory* has a significant positive correlation with both risk metrics. Females tend to report a worse *computation* ability on average, and *comnputation* is positively correlated with both risk metrics, although the correlation is only significant for the self-reported one. The tendency to be *social* has a significant positive correlation with the level of trust.

5.2 Convergence

The comparative statics predictions derived in section 3.2 apply once the system has converged to a stable state so the first step in the analysis of the experimental data is to show that $H1$ holds: the experimental markets reach a stable outcome. In the context of the experiment, I adopt the following definition of convergence:

Definition 8. A group converges to a convention x if

(i) at least 5 out of 6 subjects make the same demand x for at least 4 consecutive rounds, and

(ii) afterward it never occurs that more than 2 subjects do not demand x for more than 2 consecutive rounds.

A market has achieved "convergence" if requirement *(i)* applies: at least 5 out of 6 subjects make the same demand x for at least 4 consecutive rounds. I do not require that all 6 subjects make the same demand because this would not be consistent with our model in which agents are allowed to make mistakes and therefore may sometimes demand a different amount even after the process has converged. A market has achieved "stable convergence" if both requirements *(i)* and *(ii)* apply so that after convergence it never occurs that more than 2 subjects do not demand x for more than 2 consecutive rounds. Note that these definitions are significantly more demanding in comparison to other studies.[15] Table 2 summarizes the results.

In 83% (43 out of 52) of the markets the subjects achieved convergence to the same demand with no significant difference across treatments in probability of convergence. On average they achieved convergence after 33 out of 50 rounds with no significant difference across treatments. There is significant variability in the number of rounds needed to achieve convergence across markets, but no significant difference across treatments.

The results are unchanged if one looks at the stricter requirement of stable convergence. Only 7% (3 out of 43) of the markets that achieve convergence do not achieve stable convergence, i.e. in

lottery value of £10.78, which still implies that participants are on average risk-averse.

[15] For instance, Rosenkranz and Weitzel [2012] define convergence as staying in the same equilibrium for at least three consecutive periods, and Goeree et al. [2009] define convergence as staying in the same equilibrium for at least one round.

Table 2: Frequency of convergence by treatment.

	(i) **Convergence**			*(i)* and *(ii)* **Stable convergence**		
Network treatment	*Number of markets*	*Mean round*	*Mean demand*	*Number of markets*	*Mean round*	*Mean demand*
$R4$	11/13	33.4	11.2	11/13	33.4	11.2
$C1$	11/13	34.6	11.0	11/13	34.6	11.0
ST	10/13	30.8	10.4	8/13	34	10.6
$C2$	11/13	32.8	10.5	10/13	33.2	10.5
Total	43/52	33.0	10.8	40/52	33.8	10.9

the large majority of markets once the subjects have converged to a demand they tend to continue asking the same demand. Two out of the three markets that do not stabilize are star network treatments. On average they achieve stable convergence after 33.8 rounds with no significant difference across treatments.

In summary, hypothesis $H1$ is validated in the majority of experimental markets: after 50 rounds the majority of groups converge to demand the same number of vouchers and do not change this demand, and this is independent of the network that they are assigned to.

5.3 Network structure and the market outcome

Before a full investigation of the dynamics of play, it is illustrative to inspect subjects' average demand across treatments. Table 3 shows the differences in subjects' average demands in the last 10 rounds of play between pairs of networks.[16]

Table 3: Impact of network structure on average buyer demand.

	Row minus column network		
	$C1$	ST	$C2$
$R4$	0.42	1.17^{**}	1.05^{*}
$C1$		0.75^{**}	0.63
ST			-0.12

Each entry indicates the difference in average demand in the last 10 rounds between subjects assigned to the treatment in the row and column network. Significance levels refer to Mann-Whitney tests on aggregated data at the session level for the last 10 rounds* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

There are significant differences across networks, which are in agreement with the theoretical predictions. As stated in $H2$, subjects in the $R4$ network converge to demand an average number of 11.5 vouchers, which is qualitatively higher than the average for the $C1$ network (= 0.42), and significantly higher than the averages for the ST (= 1.17) and $C2$ (= 1.05) networks. There is also a qualitative difference in the average number of vouchers demanded between the $C1$ and $C2$ networks (= 0.63) and a significant difference between the $C1$ and ST networks (= 0.75), which are in the direction predicted by $H3$. Finally, there is no difference between the ST and $C2$ treatments, as predicted by $H4$.

[16]The results and their significance levels are unchanged if we analyze the last 5 rounds.

Table 4: Impact of network structure on buyer demand.

Dep. var.: *demand*	(1)	(2)	(3)	(4)	(5)	(6)
*R*4		0.413	0.735**		0.495	1.047***
		(0.321)	(0.304)		(0.384)	(0.391)
*C*1	-0.413		0.321	-0.495		0.552*
	(0.321)		(0.258)	(0.384)		(0.329)
*C*2	-0.735**	-0.321		-1.047***	-0.552*	
	(0.304)	(0.258)		(0.391)	(0.329)	
ST	-0.845***	-0.431*	-0.110	-1.248***	-0.753**	-0.201
	(0.264)	(0.252)	(0.228)	(0.355)	(0.328)	(0.333)
Risk (Holt-Laury)	0.0438**	0.0438**	0.0438**	0.0495***	0.0495***	0.0495***
	(0.0185)	(0.0185)	(0.0185)	(0.0171)	(0.0171)	(0.0171)
Age	-0.0180*	-0.0180*	-0.0180*	-0.0207**	-0.0207**	-0.0207**
	(0.00973)	(0.00973)	(0.00973)	(0.0101)	(0.0101)	(0.0101)
Gender	-0.233**	-0.233**	-0.233**	-0.160	-0.160	-0.160
	(0.109)	(0.109)	(0.109)	(0.121)	(0.121)	(0.121)
Trust	0.0340	0.0340	0.0340	0.0153	0.0153	0.0153
	(0.0999)	(0.0999)	(0.0999)	(0.0900)	(0.0900)	(0.0900)
Memory	-0.0430	-0.0430	-0.0430	-0.0472	-0.0472	-0.0472
	(0.0364)	(0.0364)	(0.0364)	(0.0331)	(0.0331)	(0.0331)
Computations	0.0467	0.0467	0.0467	0.0454	0.0454	0.0454
	(0.0352)	(0.0352)	(0.0352)	(0.0304)	(0.0304)	(0.0304)
Social Activities	-0.0362	-0.0362	-0.0362	-0.0408	-0.0408	-0.0408
	(0.0233)	(0.0233)	(0.0233)	(0.0281)	(0.0281)	(0.0281)
Constant	11.1766***	10.7634***	10.4419***	12.2963***	11.8017***	11.2498***
	(0.3891)	(0.3837)	(0.3768)	(0.4851)	(0.4824)	(0.5119)
Observations	15600	15600	15600	5304	5304	5304
R^2	0.1245	0.1245	0.1245	0.2269	0.2269	0.2269
χ^2	79.18	79.18	79.18	75.18	75.18	75.18

GLS panel estimation with random effects per subject and standard errors clustered at the network level.
All specifications include trading round as a trend control and session fixed effects.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I investigate the validity of the hypotheses further by running a series of GLS panel estimations with subject's demand as the dependent variable and standard errors clustered at the group (i.e. network) level. I include random effects at the subject level, as well as controls for basic demographics (age, gender), attitudes toward risk as measured by the standard Holt-Laury test, and self-reported metrics of trust, memorizing ability, socialisability, and ability to perform numerical computations. In addition, I use the trading round as a trend control and also specify 15 session fixed effects.

Columns (1)-(3) in Table 4 analyze the whole sample of data so they include subjects' demands before convergence in markets that have reached a stable outcome and subjects' demands from markets that have not achieved convergence. Column (1) takes $R4$ as the control treatment, and it largely validates $H2$: subjects' demands in the $C2$ and ST networks are lower than in $R4$ and the differences are highly significant ($p < 0.01$). The difference between the $R4$ and $C1$ treatments is in the expected direction, but it is not statistically significant. Column (2) takes $C1$ as the control treatment, and it partially validates $H3$: subjects' demands in the $C2$ and ST networks are lower than in $C1$, but only the difference with ST is marginally significant ($p < 0.10$). Column (3) takes $C2$ as the control treatment, and it validates $H4$: there is no significant difference between subjects' demands in the $C2$ and ST networks.

Hypotheses $H2 - H4$ hold only after convergence, so a proper validation needs to limit the analysis to subjects' demands after the markets have converged. Columns (4)-(6) in Table 4 take a first step by limiting the data to the last 17 trading rounds of each market. I selected this cutoff point because the convergence analysis summarized in Table 2 shows that on average markets converges after 33 out of 50 rounds. However, this is a rough approximation because the variability in convergence time is high across markets. In contrast to the analysis with the whole data, the results now provide a validation of $H3$. Column (5) takes $C1$ as the control treatment, and it shows that, as expected, subjects' demands in the ST and $C2$ networks are significantly lower than in $C1$ at the 5% and 10% significance level respectively. Hypotheses $H2$ and $H4$ continue to be validated, as in the analysis that uses the whole sample. Column (4) takes $R4$ as the control treatment, and it shows that subjects' demands in the $C2$ and ST networks are lower than in $R4$ and the differences are highly significant ($p < 0.01$). The difference between the $R4$ and $C1$ treatments is in the expected direction, but it is not statistically significant. Column (6) takes $C2$ as the control treatment, and it shows that there is no significant difference between subjects' demands in the $C2$ and ST networks.

Columns (7)-(9) in Table 5 restrict the analysis to the markets that have achieved a stable convergence and to subjects' demands in these markets after they have converged. This is the most relevant data to test $H2$-$H4$, although now the panel is unbalanced because markets achieve convergence at different times. Column (8) takes $R4$ as the control treatment, and it fully validates $H2$: subjects' demands in the $C1$, $C2$ and ST networks are all lower than in $R4$ and the differences are highly significant ($p < 0.01$) for all treatments. Column (7) takes $C1$ as the control treatment, and it largely validates $H3$: subjects' demands in the $C2$ networks are lower than in $R4$ and the difference is highly significant ($p < 0.01$). The difference between the $C1$ and ST treatments is in the expected direction, but it is not statistically significant. Column (9) takes $C2$ as the control treatment, and it fully validates $H4$: there is no difference between the $C2$ and ST networks. In general, the results of the experiment lend support to the theoretical predictions on how subjects' demands change depending on the underlying communication network of the group they belong to.

A further prediction of the theoretical analysis is that after convergence a subject's demand

Table 5: Impact of overall network structure and individual network position on buyer demand

Dep. var.: *subject's demand*	(7)	(8)	(9)	(10)	(11)
*R*4	1.449***		2.580***		
	(0.434)		(0.480)		
*C*1		-1.449***	1.131***		
		(0.434)	(0.385)		
*C*2	-1.131***	-2.580***			
	(0.385)	(0.480)			
ST	-0.513	-1.961***	0.618		
	(0.339)	(0.400)	(0.403)		
ST center				0.00815	
				(0.111)	
*C*2 *degree* 1					0.0441
					(0.182)
*C*2 *degree* 3					0.126
					(0.205)
Risk (Holt-Laury)	0.0203	0.0203	0.0203	0.0263	0.0196
	(0.0215)	(0.0215)	(0.0215)	(0.0223)	(0.0301)
Age	-0.0102	-0.0102	-0.0102	-0.0322*	0.00149
	(0.0107)	(0.0107)	(0.0107)	(0.0179)	(0.0166)
Gender	-0.0912	-0.0912	-0.0912	0.0903	-0.230
	(0.102)	(0.102)	(0.102)	(0.131)	(0.234)
Trust	-0.140	-0.140	-0.140	-0.500***	0.160**
	(0.109)	(0.109)	(0.109)	(0.0969)	(0.0781)
Social Activities	-0.0516**	-0.0516**	-0.0516**	0.0454	-0.00466
	(0.0205)	(0.0205)	(0.0205)	(0.0405)	(0.0377)
Constant	11.5192***	13.3009***	10.3879***	9.7539***	8.4396***
	(0.5020)	(0.5715)	(0.5561)	(0.4126)	(0.3934)
Observations	2568	2568	2568	3900	3900
R^2	0.3924	0.3924	0.3924	0.2450	0.4081

GLS panel estimation with random effects per subject and standard errors clustered at the network level.
All specifications include trading round as a trend control and session fixed effects.
All specifications include the *Memory* and *Computations* controls which are always insignificant, and they are therefore omitted in the table to save space.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

is independent of the subject's position in the network, i.e. only the overall network structure matters. It is not possible to test this prediction in the $R4$ and $C1$ networks in which all positions in the network are equivalent, but one can test it with hypotheses $H5$ and $H6$ for the ST and $C2$ networks respectively. Column (10) in Table 5 restricts the analysis to the ST treatment, and it tests $H5$ by introducing the *ST center* variable, which is equal to 1 if the subject is positioned at the center of the star network and it is 0 otherwise. The results validate $H5$: the *ST center* variable is insignificant so the position of subjects in the star network is not a determinant of their demand. Column (11) in Table 5 restricts the analysis to the $C2$ treatment, and it tests $H6$ by introducing the *C2 degree 1* and *C2 degree 3* variables, which are equal to 1 if the subject is in a position with 1 and 3 connections respectively, and they are equal to 0 otherwise. The results validate $H6$: the *C2 degree 1* and *C2 degree 3* variables are both insignificant so the position of subjects in the circle with spokes network is not a determinant of their demand.

The final hypothesis $H7$ states that the more risk-loving subjects are the higher is their demand. I included in all regressions the *Risk (Holt-Laury)* variable which we obtain by making subjects fill in a standard Holt-Laury risk questionnaire, as described in section 4. The variable is coded such that higher values correspond to subjects that are more risk-loving. As expected, it is positive in all regressions and highly significant ($p < 0.01$) in specifications (1)-(3) that include the whole data.

6 A unique network of buyers and sellers

In the set-up of the model analyzed so far, buyers and sellers belong to separate groups. However, there are many contexts in which this is not the case and both buyers and sellers are part of the same community. Would the results of the model continue to hold in these contexts? This section investigates how the results in section 3 change if buyers and sellers belong to the same communication network. Section 6.1 illustrates the changes to the model and derives the bargaining solution, section 6.2 discusses the implications for the desirable communication structure for the members of a group, and section 6.3 carries out the comparative statics analysis.

6.1 Set-up and bargaining solution

There are two main changes to the set-up of the model that are required to describe a context where buyers and sellers are part of the same communication network. First, consider the information arrival process. Assume agent $b \in B$ is picked to play the game at time $t+1$: in the $\Delta t = 1$ time period she receives information from other buyers in B *and* other sellers in S about past bargaining rounds. As before, the expected total amount of information b receives before each bargaining round is equal to $\sum_{j \in L_b(g)} E[P(s_{bj})] = E[P(s_b)] = \sum_{j \in L_b(g)} g_{bj} = z_b(g)$. The only difference is that here $z_b(g) = \sum_{j \in B,S} g_{bj}$: b's sample comes from both buyers and sellers. The expected realizations of the Poisson processes define a *weighted, undirected network* of buyers *and* sellers, which is represented by a symmetric matrix $[g_{ij}]^{n \times n}$.

Second, consider the elements $\mathbf{s}$ of the state space $\mathbf{S}$ of the Markov process. Here, $\mathbf{s} = \{\mathbf{v}_1, ..., \mathbf{v}_{2n}\}$, i.e. for each agent i there are two vectors $\mathbf{v}_i$ and $\mathbf{v}_{2i}$ of size m. If $i = 1, ..., n$ then $\mathbf{v}_i = \{y^i_{k-m+1}, ..., y^i_k\}$, i.e. if $i \in B$ then the entries of $\mathbf{v}_i$ are the last m demands made by sellers in bargaining rounds involving i, and if $i \in S$ then the entries of $\mathbf{v}_i$ are i's last m demands. Similarly, if $i = n+1, ..., 2n$ then $\mathbf{v}_i = \{x^i_{k-m+1}, ..., x^i_k\}$. Assume that when a buyer $b \in B$ is picked to play the game, she receives a sample of information from her neighborhood about past demands made by *sellers*, i.e. the demands in the sample come from $\mathbf{v}_1, ..., \mathbf{v}_n$. Similarly, when a seller $s \in S$ is picked to play the game, the demands in the sample come from $\mathbf{v}_{n+1}, ..., \mathbf{v}_{2n}$.

The unique stable division is unchanged from the case of separate communication networks of buyers and sellers.

Theorem 3. *There exists a unique stable division $(x^*, 1-x^*)$. It is the one that maximizes the following product:*

$$u^{z_b^{min}}(x) v^{z_s^{min}}(1-x)$$

In other words, it is the asymmetric Nash bargaining solution with weights $z_b^{min}(g)$ and $z_s^{min}(g)$.

Lemma 2 is unchanged and therefore the proof of Theorem 3 follows the same argument as the proof of Theorem 2, and it is therefore omitted. The size of the information sample of the least informed member(s) of a group is the key determinant of the deal the group obtains in equilibrium. Whether this information comes from members of the same group or of the other group is inconsequential for the split of the pie. As in Theorem 2, the buyers with the minimum weighted degree will be the least informed and therefore they will be more susceptible to respond to mistakes from the sellers. Over time, this susceptibility weakens the bargaining position of the whole group of buyers, leading to the establishment of the conventional split that maximizes the product in (4).

6.2 Core-periphery networks

The introduction of communication across groups does not change the ANB solution. However, the desirable architecture for the group of buyers in this setting is not the same as in section 3.3 because here the sellers are part of the network. The corollary below shows that the desirable communication structures for the buyers are *core-periphery networks* where the buyers are at the core and the sellers at the periphery. For expository purposes this section restricts the analysis to unweighted networks. However, the proof of the statement of Corollary 4 in the appendix is for the general case of weighted networks.

First of all, we need to give a formal definition of core-periphery networks.

Definition 9. A *semi-bipartite network* $g(H)$ is a network with a subset of agents $H \subset N$, with $|H| \leq |N|/2$, such that $d_i(g) = 1$ for all $i \in H$ and if $i, j \in H$ then $g_{ij} = 0$.

Definition 10. Consider the set G of undirected, unweighted networks with n nodes. A *core-periphery* network is a connected and semi-bipartite network $g(H)$. The agents in $N \backslash H$ form the *core*, which is a quasi-regular network $g_{d,s}$, and the agents in H form the *periphery.*

The key characteristic of core-periphery networks is that they divide a society into two classes of individuals: on the one hand an elite of core individuals who are well-connected with each other, and on the other hand a group of peripheral individuals that are dependent on the elite and poorly connected with each other. It is intuitively clear why it would be desirable for the buyers to be at the core, the following corollary formalizes this intuition.

Corollary 4. *Consider the set G of all possible communication structures for a group of n agents comprising n_B buyers and $n_S < n_B$ sellers, and where the total number of links is $L \leq \frac{n_B}{2}(n_B - 1)$. Let $d = \left\lfloor \frac{2L+n_s-1}{n_B} \right\rfloor$ and let $s \in \mathbb{R}_+$ be the strength of each link. The networks which maximize the* *share buyers obtain in equilibrium are core-periphery networks where buyers form a quasi-regular network $g_{d,s}$ at the core and sellers are at the periphery. The same statement holds with the roles of buyers and sellers reversed.*

At the periphery sellers have the lowest number of links needed for the network to be connected, and at the same time they take the least number of links away from the buyers. The sellers' information sample is as small as possible: it is equal to the strength s of one link. On the other hand, at the core buyers maximize the number of links of the least connected buyer(s) given the available budget L. By forming a quasi-regular network at the core, the buyers' information sample is as large as possible, as shown in Corollary 3.

The proof in Appendix A is more general than the statement above and it characterizes the subset of weighted networks that maximize the share of a group. There are three main steps in the proof. First, for the sellers to get the smallest possible share there must be at least one seller s_0 with only one weak link. Second, the sellers $s \in S \backslash s_0$ should have at least the lowest number of links needed for the network to be connected while at the same time take the least number of links away from the buyers. Thus each seller, apart from s_0, is connected by one strong link to a buyer. Third, following the argument of Corollary 3, the buyers should form a regular network with strong links to maximize the smallest weighted degree among all the buyers. The remaining links can be assigned at random (as long as none of them links to s_0) so the core is a quasi-regular network of buyers and each seller has only one or a few links.

6.3 Comparative statics and the 50-50 split

When buyers and sellers share the same communication network, any change in the social network structure affects both buyers *and* sellers, and therefore the comparative statics will differ from the case of separate networks. The following is the equivalent statement to Corollary 1 in the modified set-up where buyers and sellers belong to the same communication network.

Corollary 5. *Let $(x^*, 1 - x^*)$ be the ANB for sets of agents B and S that communicate through a network g with degree distribution $p(z)$.*

(i) If $p'(z)$ is a variance-preserving FOSD shift of $p(z)$ then $x'^* = x^*$.

(ii) Assume that the least weighted degree for the sellers is (weakly) larger than the mean degree, i.e. $z_s^{min}(g) \geq \mu[p(z)]$. If $p''(z)$ is a mean-preserving SOSD shift of $p(z)$ then $x''^* \geq x^*$.

The same statement holds reversing the roles of buyers and sellers.

A shift to a *denser* communication network, without any changes in the variance of the distribution, leaves the equilibrium *ANB* unchanged. This is because the weighted degrees of the least connected buyers and sellers will change in absolute value, but not in relative value to each other. On the other hand, a shift to a *more homogeneous* communication network, holding constant the mean of the degree distribution, changes the equilibrium because it affects the relative values of the least connected buyers and sellers. Specifically, as the network becomes more homogeneous the difference between the shares of the two groups narrows down.

Corollary 5 further highlights how the introduction of a network to model information flows leads to new insights that are not accessible to a model without the network. As the statements of theorems 2 and 3 make clear, the fact that buyers and sellers belong to separate or the same communication network has no impact on the long-term equilibrium division making these two cases indistinguishable. However, the introduction of the network allows a comparative statics analysis that highlights how changes in the network affect the equilibrium division. The comparative statics clearly differs if buyers and sellers belong to the same network, and this leads to the insight of Corollary 5 that a shift in the distribution of connections that decreases the variability in number of connections across agents narrows down the difference in the shares that buyers and sellers obtain.

The model predicts that societies with more homogeneous social groups would have more equitable divisions. The limit network after a sufficient number of $SOSD$ shifts is a regular weighted network: if all the agents have the same utility function, then the equilibrium division in a regular weighted network is the *50-50* split.

Corollary 6. *Let g be a regular weighted network and let all agents have the same utility function, then 50-50 is the unique stable division.*

In the extreme case of a regular weighted communication network the equilibrium division is *50-50*, which suggests that this well-observed phenomenon may be more prevalent in societies with a very flat and non-hierarchical social structure. The mechanism that leads to the emergence of the *50-50* division in this model differs from other mechanisms previously advanced in the literature. Schelling [1960] advanced the idea that *50-50* is a prominent focal point, whose salience is exploited by two bargainers to coordinate on an efficient division. In Young [1993a]'s framework the *50-50* division emerges in societies where there are some individuals that exchange roles and, at different times, can be both buyers and sellers. On the other hand, in this model the driving force leading to the emergence of the *50-50* division is the homogeneity of the social structure of the society that buyers and sellers are embedded in.

7 Indirect communication

The basic set-up of the model only allows for direct communication between agents in the same group. In other words, imagine that there are 3 buyers b, b' and b'' such that $g_{bb'} = g_{b'b''} = 1$ and $g_{bb''} = 0$. The set-up analyzed so far allows agent b to receive information from b' about demands made by sellers in past bargaining rounds involving b', but not to receive information from b' about demands made by sellers in past transactions involving b'' despite the fact that b' may have just received that information.

This section presents an extension of the basic model which allows for this type of indirect communication, i.e. information traveling more than one step in the network. It shows that all the results are robust to the introduction of indirect communication and that they generalize in a straightforward way by replacing degree with the concept of *decay r-centrality*. The proofs are omitted given that only minor changes are required to adapt the proofs in Appendix A.

It is necessary to first introduce some new notation. A *path* $p(i, j; g)$ between i and j in a graph g is a sequence of links $p(i, j; g) = \{g_{ii_1}, g_{i_1 i_2}, ..., g_{i_p j}\}$ such that $g_{kl} > 0$ for all $g_{kl} \in p(i, j; g)$. The *length* of a path is $|p(i, j; g)|$, and if there is no path between i and j then the length is infinite. The *geodesic distance* $D(i, j; g)$ between i and j in g is the minimum number of links that need to be used along some network path to connect i and j. If there is no such path, then $D(i, j; g) = \infty$.

Define by $g^r_{ij} = \min\{g_{kl} \mid g_{kl} \in p(i, j; g), |p(i, j; g)| = D(i, j; g) = r\}$ the *information bottleneck* between i and j, and note that this is equal to g_{ij} if i and j are directly connected. The *r-neighborhood* of i in g is $L^r_i(g) = \{j \in N | D(i, j; g) \leq r\}$, where $r \in \mathbb{N}_+$ and clearly the case of $r = 1$

is simply the neighborhood. Let $\delta \in (0,1)$ be a discount factor that captures how much information decays as it travels through the network. The definition of *decay r-centrality* is the following:

Definition 11. The *decay r-centrality* of i in g is $C_i(r,g) \equiv \sum_{j\in L_i^r(g)} g_{ij}^r \delta^{D(i,j;g)-1}$

This centrality metric captures how much information an agent i receives from other agents who are at a distance less than or equal to r in the network. A difference with the basic framework is in the process of information arrival because now agents receive information from their extended neighborhood up to a distance r. Formally, in the $\Delta t = 1$ time interval, the probability $P(s_{bj}(\Delta t = 1) = k)$ that b receives a sample $s_{bj}(\Delta t = 1)$ of k past bargains from agent j is equal to:

$$P(s_{bj}(\Delta t = 1) = k) = \frac{e^{-g_{bj}^r \delta^{D(i,j;g)-1}} (g_{bj}^r \delta^{D(i,j;g)-1})^k}{k!}$$

where $g_{bj}^r \delta^{D(i,j;g)-1}$ is the rate of arrival of information to b from j. By standard properties of Poisson processes, the expected amount of information b receives from j before each bargaining round is $E[P(s_{bj})] = g_{bj}^r \delta^{D(i,j;g)-1}$. It is straightforward to see that the expected total amount of information b receives before each bargaining round is equal to b's decay r-centrality:

$$\sum_{j\in L_b^r(g)} E[P(s_{bj})] = E[P(s_b)] = \sum_{j\in L_b^r(g)} g_{bj}^r \delta^{D(i,j;g)-1} = C_b(r,g)$$

The definition of the Markov process and the other components of the set-up of the model are unchanged.

Now consider the unperturbed process, as in section 3.1. The following theorem is the equivalent version of Theorem 1 in this more general set-up: it shows that if information about the history of play is sufficiently incomplete then the unperturbed process converges to a convention, i.e. a $(x, 1-x)$ split as defined in Definition 3.

Theorem 4. *Let r be the maximum distance at which information travels in a group. Assume both g^B and g^S are connected and there is at least one pair of agents $\{i,j\}$ in each network such that $D_{ij}(g^B) > r$ and $D_{ij}(g^S) > r$. The bargaining process converges almost surely to a convention.*

First of all, note that if $r = 1$ then the statement above reduces to the statement of Theorem 1 as expected. Second, the intuition for the statement of the theorem is very similar to the special case of $r = 1$. As already mentioned, Theorem 1 in Young [1993b] proves that adaptive play converges almost surely to a convention in any weakly acyclic game with n agents as long as information is sufficiently incomplete. Here the incompleteness of information is given by the network structure: if the network is such that there are at least two agents who are at a distance larger than r then there will be agents who cannot sample some past rounds because they were played by agents in their group with whom they do not communicate.

Third, note that the subset of networks on which the process converges shrinks as r increases. If $r = 1$ then there will be convergence in any network that is not the complete network because it is sufficient that two agents are not connected to ensure that they have incomplete information about the past history. At the other extreme if $r \to \infty$ then the statement of the theorem has almost no bite because information about past plays is available to anyone in the network as long as the network is connected. This illustrates the importance of the network structure to deliver the incompleteness of information that is crucial to derive sufficient conditions for convergence to a convention.

As in the case of $r = 1$ analyzed in section 3, it is necessary to introduce perturbations in the system in order to obtain sharper equilibrium predictions that select one out of the large number of possible conventions. Define $B^r_{min} = \{j \in B \mid \lceil C_j(r, g^B)\rceil \leq \lceil C_b(r, g^B)\rceil, \forall b \in B\}$ to be the subset of buyers with the least decay r-centrality. Let $C_b^{min}(r, g^B) = \lceil C_j(r, g^B)\rceil$ for $j \in B^r_{min}$. Equivalent definitions apply to the sellers. The following theorem is the general version of Theorem 2 for the case of an arbitrary r.

Theorem 5. *There exists a unique stable division $(x^*, 1 - x^*)$. It is the one that maximizes the following product:*

$$u^{C_b^{min}}(x)v^{C_s^{min}}(1 - x) \tag{5}$$

In other words, it is the asymmetric Nash bargaining solution with weights $C_b^{min}(r, g^B)$ and $C_s^{min}(r, g^S)$.

Note that if $r = 1$ then decay r-centrality is the same as degree and therefore the statement of the theorem reduces to the one presented in section 3.2. The intuition is also very similar to the case of $r = 1$. The share a group obtains in equilibrium crucially depends on the communication network connecting the members of the group. Specifically, it hinges on the agents in the group with the smallest extended neighborhoods, in terms of the number and/or strength of the links connecting them to other agents up to the information radius r. The agents with the smallest extended neighborhoods will be the least informed when they have to bargain, and therefore they will be the most susceptible to respond to mistakes from the other side. In the long-run this susceptibility weakens the bargaining position of the whole group.

It is also possible to extend the results of the version of the model in section 6, where buyers and sellers belong to the same network, to allow for indirect communication among agents. The generalization of the results follows along the same lines as the generalization of the theorems for the version of the model with separate networks, and it is therefore left to the reader to explore it.

8 Conclusion

This paper has investigated the informational advantage an individual derives from being part of a group in a decentralized market where there is incomplete information about past transactions. The communication patterns within the group determine the information the individual has before a private bilateral transaction, and the outcome of the bargaining hinges on the accuracy of this information. In the long-run equilibrium every member of the group obtains the same share of the good in each transaction, and the group communication network critically determines the market outcome. More specifically, the equilibrium division depends on the number and the strength of the connections of the least connected individuals in each group. An immediate consequence of this result is that individuals belonging to a group with a high density and a low variability of connections across individuals fare better.

These theoretical predictions are validated in a lab experiment where the subjects are assigned to a group and they trade in an artificial market. The treatment variable is the communication network of the group the subjects are assigned to. The type of social relation that is investigated allows to sidestep the difficult task of credibly creating a social relation in the lab: creating a communication network is equivalent to designing a communication protocol among the workstations the subjects are assigned to. The creation of the network in the lab and the random assignment of subjects to different networks allows the unambiguous identification of the causal relation from network structure to the market outcome, which is usually unattainable with field data. The results of the experiment lend support to the theoretical predictions.

Network theorists have only recently started to examine models that investigate the role of network structure in determining market outcomes. In these models the mechanisms through which network structure affects market outcomes vary widely, reflecting the multiplicity of possible types of social interactions. This paper focused on the role of network structure as a carrier of market information. Hopefully this model may serve as a starting point for future theoretical and empirical work that aims at identifying the role of network structure using real market data.

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A Appendix: Proofs

This appendix contains all the proofs omitted in the main body of the paper. Hereafter let $\delta = 10^{-p}$ ($p \in \mathbb{Z}_+$) be the precision of the demands, and assume $x_t, y_t \in D$, where D is the set of all p-place decimal fractions that are feasible demands.

Proof of Lemma 1. Suppose the process is in state $\mathbf{x}$ at time t, and pick any two agents $b \in B$ and $s \in S$ to play the Nash demand game at time $t+1$. For any sample b receives from her neighborhood, the cumulative distribution $G(y)$ of previous demands by sellers is a probability mass function with value 1 at $1-x$. Thus, b's best reply is always to demand x. Following a similar argument, the seller s' best reply is always $1-x$. It follows that the state of the system at $t+1$ is the same as it was at t, and therefore $\mathbf{x}$ is an absorbing state of P. □

Proof of Theorem 1. The goal is to show that from any initial state $\mathbf{s}$ there is a positive probability p independent of t of reaching a convention within a finite number of steps. Select individuals b, b', b_0 such that $b \in L_{b'} \cap L_{b_0}$ and $g_{b'b_0} = 0$. Similarly, select individuals s, s', s_0 such that $s' \in L_s \cap L_{s_0}$ and $g_{ss_0} = 0$. Note that such individuals must exist because by assumption the networks are connected and they are not complete networks. Figure 2 in section 3 illustrates two networks of buyers and sellers with individuals b, b', b_0 and s, s', s_0. Note that in figure 2 agents b_0 and s_0 are labeled b'' and s'' respectively. Consider the following steps from t onwards.

(i) $[t, t+m]$: There is a positive probability that b and s (or agents like them[17]) will play the game in every period $t \in [t, t+m]$. Also, there is a positive probability that b and s will draw samples σ and σ' respectively. Let x and y be the best replies of b and s to these samples respectively. Then there is a positive probability of obtaining a run of (x, y) for m periods in succession such that $\mathbf{v}_b = (y, ..., y)$ and $\mathbf{v}_s = (x, ..., x)$.[18]

(ii) $[t+m+1, t+2m]$: There is a positive probability that b' and s' (or agents like them[19]) will play the game in every period $t \in [t+m+1, t+2m]$. There is a positive probability that they will sample from $\mathbf{v}_b = (y, ..., y)$ and $\mathbf{v}_s = (x, ..., x)$ respectively. Thus, there is a positive probability of obtaining a run of $(1-y, 1-x)$ for m periods in succession such that $\mathbf{v}_{b'} = (1-x, ..., 1-x)$ and $\mathbf{v}_{s'} = (1-y, ..., 1-y)$.

[17] An agent $b_i \in B$ that is "like" b is such that $b_i \in L_{b'} \cap L_{b_0}$. This condition allows b_i to potentially collect the same sample of information σ as b. Similarly, an agent s_i that is "like" s is such that $s_i \in L_{s' \setminus s_0}$, where $L_{s' \setminus s_0} = \{j \in N \mid j \in L_{s'}, j \notin L_{s_0}\}$.

[18] The argument here has been simplified on a number of dimensions for expository purposes: 1) it is not necessary that the same pair of agents plays in each of the m rounds, it is sufficient that they are "like" b or s (see footnote above); 2) it is not necessary that the m rounds are consecutive, as long as there is a finite time between them and they are still in the state $\mathbf{s}$ at the end of the third step below; 3) if different agents are involved in these rounds, then the state $\mathbf{s}$ of the system at the end of this step will not be such that there are two vectors $\mathbf{v}_b = (y, ..., y)$ and $\mathbf{v}_s = (x, ..., x)$, but such that there are m entries of vectors $\mathbf{v}_i \in \mathbf{s}$ equal to y and m entries of vectors $\mathbf{v}_j \in \mathbf{s}$ equal to x, with $i \in B$ and $j \in S$. The same observations apply to the second step below.

[19] an agent $b_i \in B$ that is "like" b' is such that $b_i \in L_{b \setminus b_0}$. This condition allows b_i to potentially collect the same sample of information ρ as b'. Similarly, an agent s_i that is "like" s' is such that $s_i \in L_s \cap L_{s_0}$.

(iii) $[t+2m+1, t+3m]$: There is a positive probability that b_0 and s_0 will play the game in every period $t \in [t+2m+1, t+3m]$. There is a positive probability that b_0 will sample from $\mathbf{v}_b = (y, ..., y)$ and that s_0 will sample from $\mathbf{v}_{s'} = (1-y, ..., 1-y)$. Their best reply will then be $(1-y, y)$, so there is a positive probability of obtaining a run of $(1-y, y)$ for m periods in succession such that $\mathbf{v}_{b_0} = (y, ..., y)$ and $\mathbf{v}_{s_0} = (1-y, ..., 1-y)$.

(iv) $[t+3m+1, t+4m]$: There is a positive probability that agents $b_1 \in L_{b_0}$ and $s_1 \in L_{s_0}$ play the game for the next m periods. There is a positive probability that their samples come from $\mathbf{v}_{b_0}$ and $\mathbf{v}_{s_0}$ respectively. Their best reply will then be $(1-y, y)$, so there is a positive probability of obtaining a run of $(1-y, y)$ for m periods in succession such that $\mathbf{v}_{b_1} = (y, ..., y)$ and $\mathbf{v}_{s_1} = (1-y, ..., 1-y)$.

(v) $[t+4m+1, t+5m]$: There is a positive probability that agents $b_2 \in \bigcup_{k=0}^{k=1} L_{b_k}$ and $s_2 \in \bigcup_{k=0}^{k=1} L_{s_k}$, with $b_2 \neq b_0, b_1$ and $s_2 \neq s_0, s_1$ play the game for the next m periods. There is a positive probability that their samples come from $(\mathbf{v}_{b_0}, \mathbf{v}_{b_1})$ and $(\mathbf{v}_{s_0}, \mathbf{v}_{s_1})$ respectively. Their best reply will then be $(1-y, y)$, so there is a positive probability of obtaining a run of $(1-y, y)$ for m periods in succession such that $\mathbf{v}_{b_2} = (y, ..., y)$ and $\mathbf{v}_{s_2} = (1-y, ..., 1-y)$.

(vi) Now iterate the following step for $p = 3, ..., n_{max}-1$, where $n_{max} = \max\{n_B, n_S\}$.
$[t+(p+2)m+1, t+(p+3)m]$: There is a positive probability that agents $b_p \in \bigcup_{k=0}^{k=p-1} L_{b_k}$ and $s_p \in \bigcup_{k=0}^{k=p-1} L_{s_k}$, with $b_p \neq b_0, ..., b_{p-1}$ and $s_p \neq s_0, ..., s_{p-1}$ play the game for the next m periods. There is a positive probability that their samples come from $(\mathbf{v}_{b_0}, ..., \mathbf{v}_{b_{p-1}})$ and $(\mathbf{v}_{s_0}, ..., \mathbf{v}_{s_{p-1}})$ respectively. Their best reply will then be $(1-y, y)$, so there is a positive probability of obtaining a run of $(1-y, y)$ for m periods in succession such that $\mathbf{v}_{b_p} = (y, ..., y)$ and $\mathbf{v}_{s_p} = (1-y, ..., 1-y)$.

At time $t+(n_{max}+2)m$ the state of the system is such that $\mathbf{v}_i = (y, ..., y)\ \forall i \in B$ and $\mathbf{v}_j = (1-y, ..., 1-y)\ \forall j \in S$, i.e. the system has reached a convention. Thus, from any initial state $\mathbf{s}$ there is a positive probability of reaching a convention within $[n_{max}+2]m$ periods. Given that the number of states is finite, there is a positive probability p of reaching a convention within $[n_{max}+2]m$ periods, which concludes the proof. □

Proof of Lemma 2. Suppose that the process is at the convention $\mathbf{x} = (x, 1-x)$, where $x \in D^0 = \{x \in D : \delta \leq x \leq 1-\delta\}$. Obviously, to move from $\mathbf{x}$ to another convention $\mathbf{x}' = (x', 1-x')$ the agents need to make mistakes. Without loss of generality, assume that the sellers make the mistakes. Let π be a path of least resistance from $\mathbf{x}$ to $\mathbf{x}'$, and let $\mathbf{s}$ be the first state on this path. In order to get to $\mathbf{s}$, a buyer b_0 must have received a sample σ where by mistake some sellers have demanded a quantity that differs from $1-x$, such that b_0's best reply to σ is to demand a quantity $x' \neq x$. The buyers who require the minimum number of mistakes to switch best reply are the ones receiving the smallest sample. Recall that $B_{min} = \{j \in B \mid \lceil z_j \rceil \leq \lceil z_b \rceil, \forall b \in B\}$ is the subset of buyers with the least weighted degree. Let $z_b^{min} \equiv z_j$ for $j \in B_{min}$ and let $b_0 \in B_{min}$. Denote by p the number of mistakes by sellers in σ.

Consider the sample σ and construct a different sample σ' such that every entry of σ that differs from $1-x$ is replaced by $1-x'$, and every entry of σ equal to $1-x$ stays the same. Note that if b_0's best reply to σ was x', then her best reply to σ' must also be x'. By the mean-field assumption, σ' is composed by a total of z_b^{min} demands: p demands are equal to $1-x'$ and $z_b^{min}-p$ are equal to $1-x$.

Now, let us construct an alternative path π' from $\mathbf{x}$ to $\mathbf{x}'$ such that π' is also a path of least resistance with p mistakes. Start with the system at the convention $\mathbf{x}$ at time t. Consider the time t_1 when the md_{b_0} bargaining rounds played by buyers $b \in L_{b_0}$ happened after t. Let p of these md_{b_0} bargaining rounds be such that the seller involved made a mistake and demanded $1-x'$. There is a positive probability that b_0 plays with seller $s_0 \in S$ at time t_1 and receives a sample σ', and therefore she plays the best-reply demand x. Moreover, there is a positive probability that in the next $m-1$ rounds that b_0 and s_0 are picked to play, they again play with each other. Moreover, there is a positive probability that in each of these rounds b_0 receives the sample σ', which could still be available, and plays the best-reply demand x'. Thus, at some time $t_2 > t_1$, $\mathbf{v}_{s_0} = \{x', ..., x'\}$.

There is a positive probability that at time $t_3 > t_2$ agents b_0 and $s_1 \in L_{s_0}$ are picked to play, and that b_0 receives the sample σ' and s_1 receives his sample exclusively from $\mathbf{v}_{s_0}$.[20] Thus, b_0 will play the best-reply demand x' and s_1 will play the best-reply demand $1-x'$. Moreover, there is a positive probability that in the next $m-1$ rounds that b_0 and s_1 are picked to play, they again play with each other. Moreover, there is a positive probability that in each of these rounds they receive the same samples they got at t_3, which could still be available, and they play the best-reply demands x' and $1-x'$ respectively. Thus, at some time $t_4 > t_3$, $\mathbf{v}_{s_1} = \{x', ..., x'\}$ and $\mathbf{v}_{b_0} = \{1-x', ..., 1-x'\}$.

Following the same argument as the proof of theorem 1 above, it is clear that the process can now converge to the new convention $\mathbf{x}'$ without any further mistakes. Clearly, the same argument can be used to construct an alternative least-resistant path which starts with the buyers making q mistakes. In order to determine which least-resistant path requires the lowest number of mistakes, one has to compute these two numbers and choose the smallest. This leads us to consider four possible cases: two depending on whether the buyers or sellers make mistakes, and two depending on whether they ask a quantity higher or lower than what they get under the convention $\mathbf{x}$.

(i) Sellers make a mistaken demand $1-x' < 1-x$

Suppose sellers make p mistaken demands. Clearly, $p \leq z_b^{min}$, which is the sample size for the buyers with the smallest sample. As above, let $b_0 \in B_{min}$. Buyer b_0 therefore receives a sample of p mistaken demands $1-x'$ and $z_b^{min}-p$ conventional demands $1-x$. If b_0 demands $x' > x$ then she expects to obtain utility $u(x')$ with probability (p/z_b^{min}). On the other hand, b_0 demands $x < x'$ then she expects to obtain utility $u(x)$ for sure (because if the seller makes a mistake and demands $1-x'$ then $1-x'+x < 1$ and each agent gets their demand). Thus, b_0 switches to x' if

[20] Note that s_1 can receive his sample exclusively from $\mathbf{v}_{s_0}$ only if the size m of this vector is larger than z_{s_0}. This is guaranteed by the assumption made in section 3.2 that the individual memory $m \geq \max\{z_b, z_s\}$, where $b \in B$ and $s \in S$. Note that a lower bound would also be sufficient, what is necessary is that m is large enough.

$p \geq z_b^{min} \frac{u(x)}{u(x')}$. The minimum p occurs with the largest possible $u(x')$, i.e. with $x' = 1 - \delta$, which is the largest possible mistake the sellers can make, so:

$$p = z_b^{min} \frac{u(x)}{u(1-\delta)} \tag{A.1}$$

(ii) Sellers make a mistaken demand $1 - x' > 1 - x$

Now suppose sellers make p mistaken demands, but they demand more than the conventional demand. Now, if b_0 demands $x' < x$ then she expects to obtain utility $u(x')$ for sure. On the other hand, if b_0 demands $x > x'$ then she expects to obtain utility $u(x)$ with probability $(z_b^{min} - p)/z_b^{min}$. Thus, b_0 switches to x' if $p \geq z_b^{min} \left(1 - \frac{u(x')}{u(x)}\right)$. The minimum p occurs with the largest possible $u(x')$, i.e. with $x' = x - \delta$, which is the largest possible mistake $x' < x$ the sellers can make, so:

$$p = z_b^{min} \left(1 - \frac{u(x-\delta)}{u(x)}\right) \tag{A.2}$$

(iii) Buyers make a mistaken demand $x' < x$

Following an argument similar to case *(i)*, the minimum number q of mistaken demands by buyers needed for the seller with the smallest sample to switch is equal to:

$$q = z_s^{min} \frac{v(1-x)}{v(1-\delta)} \tag{A.3}$$

(iv) Buyers make a mistaken demand $x' > x$

Following an argument similar to case *(ii)*, the minimum number q of mistaken demands by buyers needed for the seller with the smallest sample to switch is equal to:

$$q = z_s^{min} \left(1 - \frac{v(1-x-\delta)}{v(1-x)}\right) \tag{A.4}$$

Combining equations (A.1), (A.2), (A.3), and (A.4) it follows that the least number of mistakes necessary to move out of the convention $\mathbf{x}$ is $\lceil R(x) \rceil$, where $R(x)$ is equal to:

$$R(x) = \min \left\{ z_b^{min} \frac{u(x)}{u(1-\delta)}, z_b^{min} \left(1 - \frac{u(x-\delta)}{u(x)}\right), z_s^{min} \frac{v(1-x)}{v(1-\delta)}, z_s^{min} \left(1 - \frac{v(1-x-\delta)}{v(1-x)}\right) \right\}$$

It is straightforward to show that the first term is at least as large as the last one for all $x \in D^0$, so it can be ignored. Thus, the minimum resistance to move out of the $\mathbf{x}$ convention is $\lceil R(x) \rceil$, where $R(x)$ is given by (3). □

Proof of Theorem 2. Lemma 2 in Young [1993a] shows that a division $(x, 1-x)$ is generically stable if and only if x maximizes the function $R(x)$ in (3). Lemma 3 in Young [1993a] shows that as $\delta \to 0$, the maxima of the function $R(x)$ converge to the asymmetric Nash bargaining solution in (4). The proofs of the equivalent statements to lemmas 2 and 3 for this model are essentially the same as in Young [1993a], and they are therefore omitted here. □

Proof of Corollary 1. Let us look at *(i)* and *(ii)* separately.

(i) First, consider the case $i = B$. The goal is to compare the $(x^*, 1-x^*)$ ANB solution for agents that communicate through networks g^B and g^S, and the $(x'^*, 1-x'^*)$ ANB solution for agents that communicate through networks g'^B and g^S, where $p'_b(z)$ FOSD $p_b(z)$. The claim is that $x'^* \geq x^*$. From equation (3) we have:

$$R(x) = \min\left\{z_b^{min}(g^B)\left(1 - \frac{u(x-\delta)}{u(x)}\right), z_s^{min}(g^S)\frac{v(1-x)}{v(1-\delta)}, z_s^{min}(g^S)\left(1 - \frac{v(1-x-\delta)}{v(1-x)}\right)\right\} \leq$$
$$\leq \min\left\{z_b^{min}(g'^B)\left(1 - \frac{u(x-\delta)}{u(x)}\right), z_s^{min}(g^S)\frac{v(1-x)}{v(1-\delta)}, z_s^{min}(g^S)\left(1 - \frac{v(1-x-\delta)}{v(1-x)}\right)\right\} = R'(x)$$

because, by definition of $FOSD$, $z_b^{min}(g^B) \leq z_b^{min}(g'^B)$. Thus, the unique division $(x'^*, 1-x'^*)$ that maximizes $R'(x)$ is such that $x'^* \geq x^*$, where $(x^*, 1-x^*)$ is the unique division that maximizes $R(x)$. The case $i = S$ is similar, and it is therefore omitted.

(ii) Note that by definition of $SOSD$, $z_b^{min}(g^B) \leq z_b^{min}(g''^B)$. Replacing $z_b^{min}(g'^B)$ by $z_b^{min}(g''^B)$, the proof of this statement is the same as the proof of *(i)* above. □

Proof of Corollary 4. Let us prove a more general statement by characterizing the subset of networks $G_B \subset G$ that maximize buyers' share, where G is the set of all possible networks g such that the total number of links is L and the strength of each link is in the $[\underline{s}, \overline{s}]$ range.

Assume that $n_s \leq n_b$. First, in order to minimize sellers' share, there must be a seller s_0 such that $d_{s_0} = 1$ and $g_{s_0 b_0} = \underline{s}$, i.e. s_0 has only one weak link with one buyer b_0. Second, for the network to be connected each seller $s \in S \backslash s_0$ must have one link g_{si}, and, to maximize the number of links of buyers, let $i \in B$, $g_{si} = \overline{s}$ and assign the links so that there is no buyer who is connected to more than one seller. Third, by corollary 3, the networks that maximize the buyers' share are quasi-regular networks generated by $\overline{g}_{d,\overline{s}}$, where $d = \left\lfloor \frac{2L+n_S-1}{2} \right\rfloor$. Here, the addition of the $n_S - 1$ term takes into account the strong links buyers have with the sellers $s \in S \backslash s_0$. The only restriction on the construction of the quasi-regular network is that the links assigned at random are first assigned so that b_0 and each buyer who is not linked to any seller is assigned one link, and then the remaining links are assigned at random as long as none of them links with s_0.

A similar argument to the proof of corollary 3 shows that the existence of a network g which gives a weakly higher share to buyers and which is not in G_B would lead to a contradiction. Clearly the unweighted, core-periphery networks in the statement of corollary 4 belong to G_B. □

Proof of Corollary 3. Denote by G_Q the quasi-regular networks generated by regular networks in $\overline{g}_{d,a}$. The proof is by contradiction. Suppose there exists a network $g \in G$ such that $g \in G_B$ and $g \notin G_Q$. There are two possible cases:

(i) $g \in G_B$ and $G_Q \cap G_B = \emptyset$: If this is the case then $\min_{b\in B} z_b(g) > \min_{b\in B} z_b(\overline{g}_{d,a}) = \overline{s}d$, i.e. $\min_{b\in B} z_b(g) \geq \overline{s}d+\epsilon$. Given that the maximum link strength is $\overline{s}$, this implies that $\min_{b\in B} d_b(g) = \lfloor \frac{2L}{n_B} \rfloor + 1$ and the degree of all other buyers must be at least equal to this. But then the total minimum number of links is $\frac{n_B}{2} \min_{b\in B} d_b(g) > L$, which is a contradiction.

(ii) $g \in G_B$ and $G_Q \subset G_B$: If this is the case then either $\min_{b\in B} z_b(g) > \min_{b\in B} z_b(\overline{g}_{d,a})$ or $\min_{b\in B} z_b(g) = \min_{b\in B} z_b(\overline{g}_{d,a})$. The argument above shows that the former leads to a contradiction, so suppose that $\min_{b\in B} z_b(g) = \min_{b\in B} z_b(\overline{g}_{d,a}) = \overline{s}d$. Thus, $\min_{b\in B} d_b(g) = d$ and the degree of all other buyers must be at least equal to this. The minimum total number of links for this to hold is $d \cdot n_B/2$, which leaves a maximum of $L - d \cdot n_B/2 = L - \lfloor L \rfloor$ links to assign. But this means that g is a quasi-regular network, no matter how the remaining links are assigned and we have a contradiction. □

Proof of Theorem 5. Let us look at *(i)* and *(ii)* separately.

(i) The goal is to compare the $(x^*, 1-x^*)$ ANB solution for agents that communicate through network g, and the $(x'^*, 1-x'^*)$ ANB solution for agents that communicate through network g', where $p'(z)$ FOSD $p(z)$ and $Var[p(z)] = Var[p'(z)]$. The claim is that $x'^* = x^*$. By definition of a variance-preserving FOSD shift, we have that $z_i(g) = \varsigma z_i(g')$ for each $i \in N$, where $\varsigma > 1$ and $\varsigma \in \mathbb{R}_+$. The variance-preserving FOSD shift is therefore only a rescaling of $R(x)$ by a ς factor. Thus, the unique division $(x^*, 1-x^*)$ that maximizes $R(x)$ is also the unique division that maximizes $R'(x) = \varsigma R(x)$, i.e. $x^* = x'^*$.

(ii) First, assume that $z_s^{min}(g) > \mu[p(z)]$. By definition of a mean-preserving SOSD shift we have that $z_b^{min}(g'') > z_b^{min}(g)$. Moreover, $z_s^{min}(g'') < z_s^{min}(g)$ because of the definition of SOSD shift and the assumption that $z_s^{min}(g) > \mu[p(z)]$. Substituting these inequalities into the expression (3) for $R(x)$ it is straightforward to see that the unique division $(x''^*, 1-x''^*)$ that maximizes $R''(x)$ must be such that $x''^* \geq x^*$, where $(x^*, 1-x^*)$ is the unique division that maximizes $R(x)$. The case $z_b^{min}(g) > \mu[p(z)]$ is similar and it is therefore omitted. □

Proof of Corollary 6. Let all agents have the same utility $u(.)$. If g is a regular weighted network then $\beta \equiv z_b^{min}(g) = z_s^{min}(g) \equiv \sigma$. Substituting this into (4) one obtains that the unique stable division $(x^*, 1-x^*)$ is the one that maximizes $u(x)u(1-x)$, which is clearly $x^* = 0.5$. □

B Appendix: Instructions

Dear participants,

Welcome and thank you for participating to this experiment. Before we describe the experiment, we wish to inform you of a number of rules and practical details.

Important notes

- **Silence:** Please do remain quiet from now on until the end of the experiment. Those who do not respect the silence requirement will be asked to leave the experimental room.
- **No writing**: You are not allowed to use a pen or take notes during this experiment

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General rules

During this experiment you will be asked at times to take decisions that will affect your outcome and the outcome for other participants. It is important for you to know that your decisions will remain completely confidential.

Each person will be assigned fictitious initials: we will always use your fictitious initials and never your real name or any other information that might allow other participants to identify you.

If you have a question, please raise your hand.

Description of the experiment

In this experiment you will be a trader in a market. The seller that you will be trading with is played by the computer.

The figure below is an illustration of how the trading happens. In each trading round there are 17 vouchers at stake. You trade by inputting **your demand** using the keyboard and clicking on "Confirm." Note that this is **the amount of vouchers that you want to have for yourself.**

There are two potential outcomes:

1) If the sum of your demand and the seller's demand is less than or equal to 17 than you win the number of vouchers that you demanded
2) If the sum of your demand and the seller's demand is greater than 17 than you do not win any vouchers

For example, if you input "8" then you will win 8 vouchers if the seller's demand is equal to or less than 9, and you will win no vouchers if the seller's demand is greater than 9.

In general, if you make a high demand then you earn a high number of vouchers, but you run the risk of not getting any voucher if the seller is also making a high demand. On the other hand, if you make a low demand then you earn a low number of vouchers, but there is a low risk that you will earn nothing. The seller is in the same position as you are.

Vouchers at stake	Your demand
17	____

In order to test whether you understand how the trading works, we will now play a trial trading round in which we will tell you the demand that the seller will make before the trading. This trial has no impact on your earnings.

Now look at your screen. In the middle of the screen it should state the demand that the seller will make in the trial trading round. Now input the demand that maximizes the number of vouchers that you earn. You input the demand in the bottom-right corner of the screen by typing the number of vouchers that you want to demand for yourself and then by clicking "Confirm" with the left button of your mouse. Please input your demand now.

Everyone should have now finished the trial trading round. If your demand was not the optimal demand to make, you should see it written in the blank space where you input your demand. Note that in the experiment you can make a demand that is below the optimal demand and you will get the vouchers you demanded.

Please raise your hand if this has appeared on your screen so that the experimenter can come to your workstation and clarify any doubts about the trading procedure.

You belong to a group formed by 6 traders (including yourself). You are connected to some of the traders in your group and you can use the previous experience of the traders in your group to help you decide which demand to make.

The figure below is an illustration of how this information will appear on your screen. You have information about previous **demands made by the seller in transactions involving the traders you are connected to.** In the example below the seller demanded 8 vouchers in one previous transaction involving your friend A. T. In three previous transactions involving your friend F.G., the seller demanded 9, 11 and 7 vouchers.

Note that the information you receive from other traders has been randomly picked from the history of previous transactions, so the other traders have no role in picking this information. The amount of information you receive from each friend may vary across trading rounds. The order of display of the information is randomly generated.

Information from friends about **demands made by the seller** in previous rounds:

Friend	**Demand by the seller**		
A. T.	**8**		
F. G.	**9**	**11**	**7**

Vouchers at stake	Your demand
17	

Now we will show you a trading round by running through all the screenshots that you will see.

At the beginning of each trading round you will see the following screenshot:

Time left to make your demand: 15 sec

Information from friends about **demands made by the seller** in previous rounds:

Friend	**Demand by the seller**		
A. T.	**8**		
F. G.	**9**	**11**	**7**

Vouchers at stake	Your demand
17	

The first line in the top-left panel indicates the total time you have to make your demand. The time counter starts at 15 seconds and it is red: this indicates that it is active and it is counting down the seconds till the end of the trading round.

In the middle of the screen you have information about previous **demands made by the seller in transactions involving the traders you are connected to.**

After 5 seconds the time counter reaches 10 seconds left, and the option to input your demand will appear in the bottom right part of the screen. You can make your demand by using the keyboard to input a number between 0 and 17 and then clicking "Confirm."

Time left to make your demand: 10 sec

Information from friends about **demands made by the seller** in previous rounds:

Friend	**Demand by the seller**		
A. T.	**8**		
F. G.	**9**	**11**	**7**

Vouchers at stake	Your demand
17	____

Suppose that your demand is 8: after 5 seconds the following screenshot will appear if the sum of your demand and the seller's demand is less than or equal to 17:

In this round you have won **8** **vouchers**

Otherwise, if the sum of your demand and the seller's demand is more than 17, the following screenshot will appear:

In this round you have won **0** **vouchers** **because the sum of demands exceeds 17 vouchers**

Note that in case you fail to click on your demand within 10 seconds, the following screenshot will appear:

In this round you have won **0** **vouchers** **because you did not make any demand**

The seller

The role of the seller is played by the computer, which represents a seller who is trying to earn as many vouchers as possible in the trading.

Similarly to you, the computer makes demands based upon its previous experience of trading with people in your group. Specifically, the computer samples the recent history of demands made by the people in your group and then chooses a demand which maximizes the expected number of vouchers it can win (given the sample it received).

Note that the computer only uses previous experience on trading with people in your group to decide its demand for trading with you (and people in your group). The rule that the computer uses to determine its demand does not vary over the course of the experiment.

Market

You will participate in one trading session formed by 50 trading rounds. A trading session represents a "market." Prior to the beginning of the market, you are randomly assigned to a group formed by 6 traders (including yourself). There are 50 trading rounds in the market, so you trade with the seller 50 times. After the 50^{th} round a screenshot saying "The market is now closed" will indicate the end of the market.

Your earnings

At the end of the experiment 6 trading rounds will be selected at random to determine your earnings.

The exchange rate is 1 voucher = 11 pence

If we denote by **V= number of vouchers won in 6 randomly drawn trading rounds**, then your earnings at the end of experiment will be equal to:

Total earnings = 11p x V

Do you have any questions?

Trading

We will now start the market. We will pause the market after 3 trading rounds so that you have an opportunity to clarify any doubts after you have tried the trading procedure.

Note that in the first trading round you do not receive any information from your friends because nobody has done any trading in the market yet.

The initial 3 trading sessions of the trading market start NOW.

You have now had a chance to practise trading. Please raise your hand if you have any questions.

The market resumes NOW.
