UNIVERSITY OF CAMBRIDGE
Faculty of Economics

Institute for New Economic Thinking

Cambridge-INET Institute

Working Paper Series No: 2015/08

NETWORKS IN THE LABORATORY

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March 2015

Abstract

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Keywords: experiments, social networks, network games, markets, coordination, public goods, cooperation, social learning, communication, trading.

JEL: C91, C92, D85, L14, Z13.

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§Prepared for *The Oxford Handbook on the Economics of Networks*, edited by Yann Bramoullé, Andrea Galeotti, and Brian Rogers, Oxford University Press. We thank Matt Leister for helpful comments and suggestions.

1 Introduction

Social networks are an important determinant of individual behavior and aggregate outcomes in a variety of social and economic phenomena. Their study has been a central theme in the sociology literature leading to a large body of theoretical and survey-based empirical findings that document their role in different domains[1]. In contrast, economics has been largely oblivious to the role of social networks, until two decades ago when the early research on strategic network formation first developed[2]. Theoretical work on social networks has witnessed an exponential growth ever since: economists have analyzed the role of networks in the context of different games, as well as their importance in markets and a variety of areas in economics including labor, development, international trade, and finance[3].

Empirical research on social networks has lagged significantly behind the theory, and we still lack empirical validation for the bulk of the theoretical findings accumulated in the last two decades. The core reason for this lag is the challenges involved in the causal identification of the impact of network structure on behavior. A first hurdle is that observational data on social networks is usually unavailable or incomplete, and it remains challenging to identify the impact of network structure by proxying or imputing the network. Even when complete cross-sectional data is available, most social networks are constantly evolving leading to severe endogeneity issues. Finally, longitudinal datasets which include full information on the network are very rare, but even in these cases identification remains problematic[4].

The experimental methodology allows the causal identification of the network structure by controlling for cofounding factors such as preferences and information. It enables the researcher to exogenously impose a network of interactions among a group of subjects, and then vary it in a different treatment to isolate the effect of the structure of the network on individual behavior and group level outcomes. Recently there has been a rapid growth of experimental research on social networks, which is proving to be an invaluable tool to validate existing theoretical findings. Moreover, experiments are revealing how individuals actually use network information. They are generating behavioral data that relates network structure to choices which can serve as an input for novel theoretical developments. The purpose of this chapter is to survey the literature on laboratory and online experiments on

[1]See Wasserman [1994] for a slightly outdated but comprehensive review.

[2]Jackson and Wolinsky [1996] and Bala and Goyal [2000] are the seminal papers on network formation. As is often the case, there have been pioneers whose work preceded the systematic study of social networks in economics including Myerson [1977], Kirman [1983] and Montgomery [1991].

[3]See Goyal [2007] and Jackson [2008] for comprehensive reviews.

[4]See Manski [2000] for a slightly outdated treatment, and Chapter XX in the Handbook by Boucher and Fortin.

networks, and identify important directions for future research[5].

The next section focuses on experimental investigations of how network structure influences behavior in a variety of games, which abstract away from prices and market interactions. One channel for incorporating network structure into a game is by making players' payoffs depend on the neighbors in the network. Sections 2.1-2.3 focus on this channel and review experimental work on different types of games played on networks including coordination, prisoner's dilemma, and games with strategic substitutes and complements. A second channel is for the network to determine the information players have to make choices. Sections 2.4 and 2.5 focus on this channel by reviewing experimental work on strategic communication and learning in a network context. In reality, full information about the social network is rarely available to the researchers as well as the individuals embedded in the network. While the former is mainly a challenge for researchers using observational data, the latter is a primary concern for theorists who need guidance on what are the realistic assumptions to be made about a player's information regarding the network, in order to construct models that generate behaviorally valid predictions. Section 2.6 reviews experimental studies of games on networks that vary the information subjects have about the network, and it discusses how they can generate valuable input for further theoretical work.

Section 3 reviews a more recent strand of the literature which explores the role of networks in markets. In many decentralized markets there are constraints on who can trade with whom, and networks are a natural tool to capture these buyer-seller relations and/or intermediation services. Section 3.1 reviews experimental work in which the network determines the trading opportunities available to market participants. A second function of social networks is to provide information in markets where it is not available through prices or some external mechanism. Section 3.2 reviews experimental work on how social networks can be used to circulate information about traders' reputations. This information allows market participants to punish cheaters in environments with weak or non-existent formal institutions to enforce contracts, and incomplete information about past transactions, thereby determining who has an informational advantage in the market.

We conclude this chapter in section 4 by taking a holistic view of the current landscape of research on networks in economics. We identify directions for further experimental research that we deem important for several contexts in which social networks matter to determine individual behavior and aggregate outcomes.

[5]We exclude experiments that test strategic network formation models, which are reviewed in Kosfeld [2004]. Chapter XX of the Handbook by Breza discusses field experiments.

2 Games on networks

This section discusses experimental research on games on networks. We organize it according to the different contexts in which network structure has an impact on behavior: coordination, provision of local public goods, cooperation, communication and information exchange, and social learning. The last part discusses evidence on how the information individuals have about the network matters to determine how network structure affects behavior in these contexts.

2.1 Coordination and strategic complementarities

A primary purpose of social connections is to help us coordinate our choices to generate mutual benefits. For instance, we would like to pick the same phone messaging app to be able to communicate for free with our friends or acquaintances and avoid the charges from the provider. In other contexts, individuals care not only about choosing the same action but also on the intensity of the actions because there are strategic complementarities between an individual and her neighbors' actions. For example, the value a user obtains from visiting and contributing to an online review blog (e.g. yelp, tripadvisor) is increasing in the amount of information provided by other users. These situations are described by games with strategic complements, and the function of the network is to determine these strategic complementarities among specific individuals[6].

A canonical example of games with strategic complements is coordination games with Pareto-ranked equilibria. To fix ideas, consider the two-player two-action coordination game in Table 1. If $a > c$, $d > b$ then (a, a) and (d, d) are the pure-strategy Nash equilibria, and if $d > a$ then the latter is efficient or payoff dominant. However, if $(a-c)^2 > (d-b)^2$ then the (a, a) equilibrium is risk dominant à la Harsanyi and Selten [1988]. The experimental literature has extensively studied this type of coordination game even without the consideration of networks[7]. A major finding is that coordination failure is a common phenomenon in the laboratory[8].

The theoretical literature has expanded the scope of coordination problems by considering

[6]Chapter XX of the Handbook by Bramoulle and Kranton discusses the theoretical work on network games

[7]See Ochs [1995] for a comprehensive survey. Seminal experimental studies are Van Huyck et al. [1990, 1991] using order-statistic coordination games and Cooper et al. [1990] using variants of coordination games.

[8]Devetag and Ortmann [2007] provide a critical review of the literature and identify the major determinants affecting the success/failure of coordination in the laboratory. For instance, payoff structure matters in the sense of how attractive the secure strategy is and how risky the other actions are. Also, the group size can affect the incidence of coordination failure and success.

Table 1: Two-player coordination game.

	X	Y
X	(a,a)	(b,c)
Y	(c,b)	(d,d)

Assume $a > c$, $d > b$, $d > a$ and $(a-c)^2 > (d-b)^2$ throughout.

a variety of local interaction structures and their impact on coordination. Each individual in the population plays the baseline coordination game playing a single action with all his neighbors in the network. The individual's utility depends on his own action as well as on the actions played by the neighbors. Ellison [1993] and Morris [2000] prove that, in an evolutionary learning framework, players converge to the risk-dominant equilibrium in some stylized structures of local interaction such as circles and lattice.

A handful of experimental studies has investigated the role of local interaction structure in coordination problems. Keser et al. [1998] reports an experimental study on the effects of local interaction on coordination. They consider a finite repetition of a three-player game in which an individual plays the game in Table 1 with payoffs $a = 80$, $b = 60$, $c = 10$ and $d = 90$. A player has to use a common strategy with each of the other two players and gets the minimum of the payoffs that his strategy gains from the two plays. There are two treatments that vary the network structure: a complete network of 3 players and a circle network of 8 players. In the latter network, the player plays the coordination game with his two neighbors, while he is neither informed of the global structure of the network nor the size of the network. Subjects in the complete network converge quickly to coordinate on the payoff-dominant (d, d) equilibrium, while those in the circle network coordinate on the risk-dominant (a, a) equilibrium.

Berninghaus et al. [2002] investigate a game with the same payoffs as Keser et al. [1998] but they extend the experimental set-up by enriching the size and structure of interaction and the payoff function. Specifically, they include local interaction in a lattice as well as in a circle with 2 neighbors and 4 neighbors. They also allow the payoff function to depend on the minimum as well as the average of the payoffs from local interactions. Berninghaus et al. [2002] find that while the payoff-dominant d action is an experimental regularity in the complete network, the risk-dominant action a is chosen more often in the circle network and the lattice. While the results of Keser et al. [1998] and Berninghaus et al. [2002] provide nice evidence on network effects on coordination, they keep constant the number of neighbors of each player but not the overall network size, making comparisons across network treatments problematic.

Cassar [2007] experimentally studies the coordination game with payoffs $a = 1$, $b = 4$, $c = -1$ and $d = 5$. She considers the three network structures in Figure 1 chosen to typify (a) local, (b) random, and (c) small world types of networks. The networks keep constant relevant characteristics of the group such as the number of players and the total number of connections. She finds that 70% of subjects prefer the payoff-dominant d to the risk-dominant a action. Despite the high frequency of successful coordination, there are notable differences across networks. The small-world network achieves the highest level of coordination on the efficient outcome, while the random network has the lowest level of coordination. Also, the convergence rate of coordination differs across networks. Coordination on the payoff-dominant equilibrium occurs faster in the small world network than in the random network.

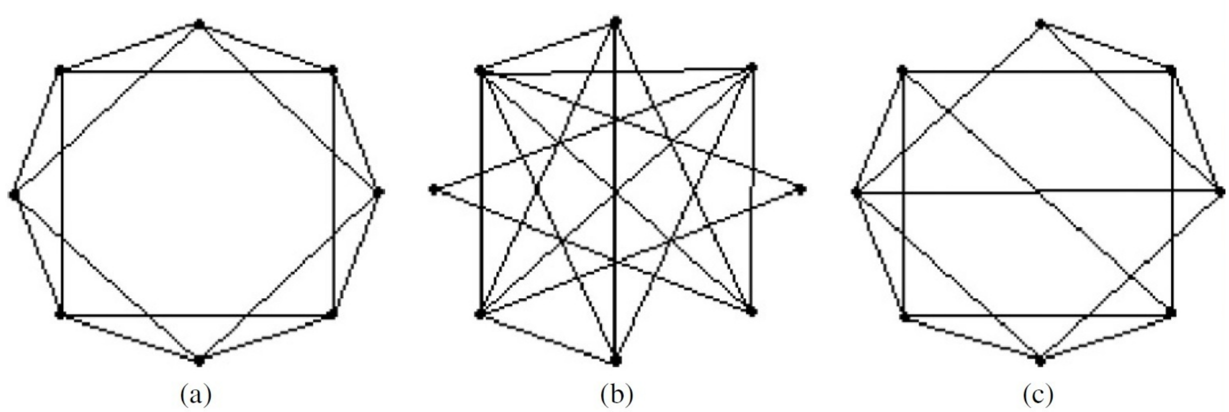

Figure 1: (a) Local, (b) random, and (c) small world type of networks examined in Cassar [2007].

The findings in Cassar [2007] on the relatively high incidence of the payoff-dominant d action seem at odds with those in Keser et al. [1998] and in Berninghaus et al. [2002]. Frey et al. [2012] examine a coordination game with payoffs $a = 780$, $b = 660$, $c = 120$ and $d = 900$ on 10 different network structures of 6 nodes, including the complete, star, line, circle and bipartite-type of networks. In agreement with Cassar [2007] they find convergence to the payoff-dominant outcome in almost all cases. They also find no significant difference across network structures. The conflicting evidence on convergence to the payoff or the risk-dominant outcome across the studies may result from the difference in relative attractiveness/riskiness of the payoff-dominant action between the designs, and it can only be resolved with further experimentation.

A common drawback shared by the above studies is the focus on small networks of at most 8 nodes, while in many contexts we are interested in coordination in large groups.

Kearns et al. [2009] examine experimentally a simple coordination game in which groups of 36 subjects have 1 minute to coordinate either on blue or red, which are chosen to frame the experiment in the context of a presidential election in the US[9]. The treatments were the assigned strength of preference for a color and the network structure. In all treatments subjects can only see their neighbors with their respective choices, but not the overall network. They find that coordination is more frequent in networks with a fat-tailed degree distribution compared to random networks. Moreover, a minority of well-connected subjects can make the whole network coordinate on their common preferred choice. In a follow-up study, Judd et al. [2010] examine a richer coordination problem: groups of 36 subjects have 3 minutes to coordinate on one colour out of a set of 9 choices. They run 6 network treatments which systematically vary the level of cliquishness, i.e the extent of tight-knittedness of equally sized subgroups in the network. The intuitive result is that consensus is decreasing in the level of cliquishness.

Coordination games are a special case of the class of games with strategic complementarities in which a player's benefit from an action is increasing in the actions of her neighbors. In a seminal contribution, Ballester et al. [2006] analyze a game of strategic complements on any network. The model belongs to a class of games of strategic complements in which individuals have linear best replies. It offers a way of decomposing the payoff interdependence into a global and a local interaction component. The global interaction effect is uniform across all players and reflects a strategic substitutability in players' choices, whereas the local interaction effect varies across pairs of players and captures strategic complementarity in players' decisions. They show that there is a unique Nash equilibrium as long as the complementarity effects are lower than a threshold determined by the largest eigenvalue of the adjacency matrix of the network. The key result is the closed-form characterization of this equilibrium, which shows that a player's action is proportional to a (transformation of a) network centrality metric first defined by Bonacich [1987]. In equilibrium a player's action increases in her connectedness, her neighbors' connectedness, her neighbors' neighbors connectedness, and so on. This result provides a tractable, rich and intuitive relation between equilibrium play and network position.

Gallo and Yan [2015b] examine experimentally the Ballester et al. [2006] game of strategic complements on four different networks: circle and wheel networks with 9 nodes, a 15-node network with two completely connected clusters joined by a single node, and the 21-node network in Figure 2. A notable result of the experiment is that subjects depart from Nash

[9]Chapter XX of the Handbook by Aral also reviews this study as well as other large experiments with a particular focus on web-based experiments.

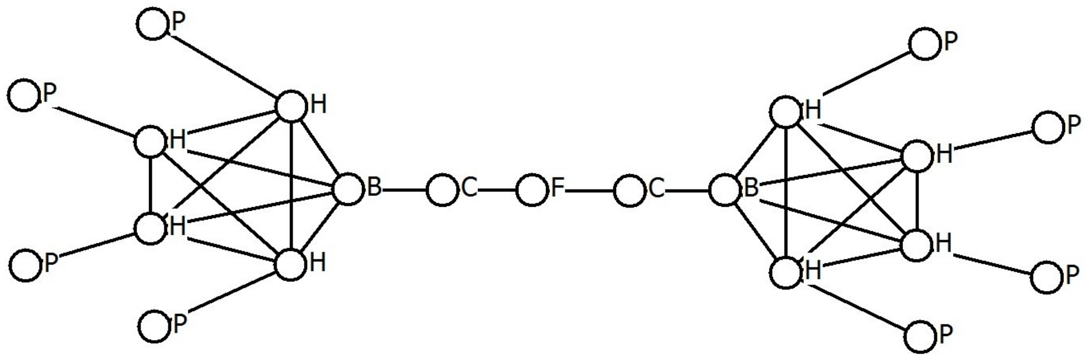

Figure 2: 21-node network in Gallo and Yan [2015b]. Given the calibration in the experiment, the equilibrium predictions for subjects' efforts are $e(B) = 78$, $e(H) = 77$, $e(C) = 38$, $e(F) = 33$ and $e(P) = 33$.

equilibrium and coordinate on a more efficient outcome in the symmetric circle network, but on average they converge to the (inefficient) equilibrium predictions in the asymmetric networks. This is a demanding test of the equilibrium predictions in the Ballester et al. [2006] model, so the convergence on average is evidence of the behavioral validity of the theory. Looking more closely into subjects' behavior, Gallo and Yan [2015b] found that subjects appear not to incorporate the network interactions fully into their decisions and tend to base their choices on the local structure of the network as captured by the degree. For example, in the network in Figure 2 play according to Bonacich would predict that the ranking of subjects' efforts is $e(C) > e(F) = e(P)$, while play according to degree would predict $e(C) = e(F) > e(P)$. The results show that degree is a highly significant predictor of subjects' play on nodes F, P and C while Bonacich centrality is not. The boundedly rational rule of only focusing on local network information may make sense in large, complex, and asymmetric networks. Whether human subjects adopt such a simple, boundedly rational rule of decision making in a complex network is an interesting question. A fuller investigation of this question will require one to use much larger networks than Gallo and Yan [2015b] used, with a careful selection of parameters of the games in order to drive a wedge between equilibrium choices fully reflecting the global structure of networks and choices made via such a bounded rational rule.

In all the studies reviewed in this section, the network structure is exogenously imposed by the experimenter. However, in reality coordination is facilitated by the fact that we actively choose our connections. Riedl et al. [2011] examine experimentally a weakest-link game played in two groups of 8 and 24 nodes, which we can think of as complete networks. They compare these treatments to an identical set-up in which groups of 8 and 24 subjects can choose their connections endogenously. There is a clear difference in the dynamics of play irrespective of group size: subjects converge to the inefficient risk-dominant equilibrium in the complete network, but they overwhelmingly converge to the efficient payoff-dominant equilibrium when they can pick their connections. The resulting networks in the treatments with endogenous connections converge to the complete networks, but in the early rounds subjects can use the ability to exclude low contributors as a punishment mechanism to ensure convergence to the efficient equilibrium. This study shows that the inclusion of a network formation stage has a clear effect on behavior, and further experimental work in this vein is desirable both in coordination and other types of games as we will see in the next sections.

2.2 Public goods and strategic substitutes

The problem of the provision of public goods has a central role in different areas of the social sciences (e.g. Ostrom [1990]) including experimental research where there is a vast literature on experiments on public goods[10]. In the standard public goods game, subjects in a group have to decide how much of their initial endowment to contribute to a common pool. The sum of the contributions is scaled up by a common factor and distributed to all group members in equal shares independent of their contribution. A large number of studies has documented that subjects contribute significantly above Nash equilibrium in the one-shot version and the over-contribution pattern declines, but it does not converge to Nash, when the public goods game is repeated[11]. The tendency to contribute above the Nash prediction is often attributed to social preferences and, in particular, a form of conditional cooperation in which the contribution to the public good is positively correlated with individuals' beliefs about other members' contributions. Experimental research has also investigated how subjects in the lab respond to a variety of environmental and institutional factors such as production technology, payoff structures, punishment, communication, and so forth.

Several types of public goods are local in the sense that an individual's contribution benefits others who are nearby either geographically or in a social network. Examples include neighbors who benefit from a well-kept garden and non-excludable innovations which can be imitated by others who observe or learn about them. Bramoullé and Kranton [2007] analyze a public good game on a network in which links capture strategic substitutabilities between

[10] See, a bit outdated, Ledyard [1995] for a comprehensive review, and Chaudhuri [2011] for a recent survey.

[11] A series of early studies by Marwell and Ames [1981] show that contribution rates in the one-shot are in the $40-60\%$ range. See Fehr and Gächter [1999] for a study on a repeated public goods game.

an agent's and her neighbors' actions. They show that there is a large number of equilibria including specialized equilibria in which agents exert either no effort or provide the public good for all their neighborhood, distributed equilibria in which everyone exerts the same effort, and combinations of the two. Bramoullé and Kranton [2007] show that specialized equilibria are the only stable ones, and they relate the class of specialized equilibria to the graph theoretic concept of maximal independent sets, which allows one to check whether a specific action profile is a stable equilibrium just by checking if the set of specialists belongs to a maximal independent set of order 2[12].

Despite the nice correspondence between maximal independent sets and specialized equilibrium profiles, the size of the equilibrium set remains quite large. Experiments can therefore shed light on whether some of these equilibria are more salient and how saliency depends on the network structure. Rosenkranz and Weitzel [2012] examine experimentally the Bramoullé and Kranton [2007] local public good game on all six possible connected networks of four nodes. The first order finding is that the frequency of equilibrium play is very low even on these simple and small networks, although it is higher than what one would expect with completely random play. Moreover, local coordination occurs 6-7 times more frequently than equilibrium play. Rosenkranz and Weitzel [2012] observe low frequency of equilibrium convergence in networks with stable specialized equilibria, but whenever convergence occurs it is almost always to stable specialized equilibria. An intriguing result is that equilibrium coordination varies with network structure in a non-monotonic way, as it is highest in the complete and star networks, which are at opposite ends of the set of four node networks in terms of density and the spread of connectivity across nodes. Finally, subjects' actions are negatively correlated with their degree, which nicely mirrors the positive correlation found by Gallo and Yan [2015b] in the game of strategic complements on a network.

Galeotti and Goyal [2010] extend the Bramoullé and Kranton [2007] model by making the network endogenous. Agents play a network formation game à la Bala and Goyal [2000] as well as choosing a level of contribution to the local public good on the resulting network. The key result is that the introduction of a network formation stage drastically reduces the size of the equilibrium set: in every strict Nash equilibrium, the network has a core-periphery structure in which the agents at the core contribute while the agents at the periphery free ride. The introduction of a slight heterogeneity in the cost of providing the public good

[12] An *independent set* I of a network is a set of agents such that no two agents who belong to I are linked. An independent set is *maximal* when it is not a proper subset of any other independent set. A *maximal independent set of order* r is a maximal independent set I such that any individual not in I is connected to at least r individuals in I.

leads to a unique equilibrium, which is the star network with the central agent providing the public good and everyone else free riding. Moreover, the star network also maximizes welfare.

Goyal et al. [2014] test the predictions of the model for groups of four subjects. The baseline has homogeneous costs of providing the public good, and they compare this with a treatment in which one agent has a lower cost of providing the public good. The results provide only weak support for the theoretical prediction that the star network is the unique equilibrium. The low cost individual is more likely to be a well-connected hub compared to the high cost individuals, but the number of hubs is unchanged from the baseline, and the contribution to the public good of the low cost individual is lower than predicted by the theory. Moreover, the resulting network has an average connectivity of about 5 links, which is significantly higher than the 3 links in the star network.

Further experimental work on public good games on networks is necessary to validate the theory and shed light on the features of network structure which determine equilibrium. A promising starting point is a paper by Bramoullé et al. [2014] which provides a unified framework to analyze games of strategic complements and substitutes on networks, and nests the Bramoullé and Kranton [2007] and the symmetric case of the Ballester et al. [2006] models as special cases. The key result is the role of the lowest eigenvalue of the adjacency matrix of the network which captures how much the network amplifies the direct effects of one individual's actions on his neighbors' actions. This result can inform the design of experiments to test behavior in network games with the presence of both strategic complements and substitutes, which would constitute a bridge between the work by Rosenkranz and Weitzel [2012] and Gallo and Yan [2015b]. It can also inform the design of public good games on networks which are larger than the four node networks in Rosenkranz and Weitzel [2012] to explore the relation between structural features of the network and behavior in a richer setting[13].

2.3 Cooperation

The emergence and sustenance of cooperative behavior is a defining characteristic of human societies. Social scientists and evolutionary biologists have extensively investigated the determinants of cooperation using the prisoners' dilemma game as an abstract representation of the trade-offs involved in an individual's decision to cooperate with or defect on others.

[13]Suri and Watts [2011] report the results of a public good game played on networks of 24 nodes, but the choice of payoffs and the specific design they adopt makes it difficult to interpret their results in light of the Bramoullé et al. [2014] model.

In the simplest setting with two players interacting repeatedly, cooperation emerges if the players can condition their strategies on the other players' past behavior and the probability of another interaction is high enough[14]. An alternative mechanism for the emergence of cooperation is what is known as indirect reciprocity which operates when there are repeated encounters within a group and there is a reputation mechanism which allows a player to know someone's past choices with a high probability[15]. Cooperation is costly but leads to the reputation of being a cooperative individual, and therefore may increase the chances of being the recipient of cooperative behavior.

An extensive number of experiments have tested these theoretical predictions. Murnighan and Roth [1983], amongst others, show that repetition in the prisoner's dilemma game between two individuals leads to cooperative behavior which is increasing in the payoffs of the game as well as in the probability that the game will continue. Dal Bó and Fréchette [2011] validate these results and they show that cooperation may prevail in infinitely repeated games, but the conditions under which this occurs are more stringent than the subgame perfect conditions usually considered or even a condition based on risk dominance. In order to study indirect reciprocity, subjects play the game with randomly matched partners and they are informed about the partner's choices in previous rounds. There is plenty of evidence that subjects condition their behavior on the partner's past choices, and thus individuals who have cooperated in the past tend to receive more cooperation[16].

Different dimensions of social network structure play a role in the emergence of cooperative activity. As a first dimension, a crucial element for indirect reciprocity to emerge is the presence of a mechanism to share reputational information about third parties, and a natural channel to provide this information is communication through the social network. A second dimension is that in many instances cooperative activity is local, so the decision to cooperate or defect affects only an agent's neighbors in a geographical or social network rather than the whole society.

As the review in Chapter XX (ref to Nava's chapter) of this Handbook makes clear, there is no theoretical paper which provides a general characterization of a repeated prisoner's dilemma game on general network structures in the way that, e.g., Ballester et al. [2006] and Bramoullé and Kranton [2007] do for one-shot games of strategic complements and substitutes respectively. Haag and Lagunoff [2006] analyze the problem of a social planner who designs the optimal network for a group of individuals with heterogeneous discount

[14] See, e.g., Fudenberg and Maskin [1986] and Binmore and Samuelson [1992].
[15] See Nowak and Sigmund [2005] for a review.
[16] See, e.g., Wedekind and Milinski [2000], Milinski et al. [2002] and Seinen and Schram [2006].

factors. By restricting the attention to a specific type of trigger strategies, they show that greater social conflict may arise in more connected networks, and the optimal design exhibits a cooperative core and an uncooperative fringe when the individuals' discount factors are known to the planner. Several simulation-based studies[17] show that the structure of the social network has an effect on the level of cooperation, but they make specific behavioral assumptions on the agents' strategies which would need validation in experimental data. Chapter XX by Jackson (ref here) identifies the study of the interplay between network structure and cooperation as one of the promising areas for future theoretical work, and we believe experiments can be an invaluable tool to provide guidance on the features of the network structure that are behaviorally relevant as well as the strategies that subjects use in this context.

The paper by Cassar [2007] we already reviewed in section 2.1 was one of the first experimental studies to examine the prisoner's dilemma game in Table 2 with payoffs $c = 5$, $a = 4$, $d = 1$ and $b = 0$ played on the three networks in figure 1. Cooperation rates on all networks decrease to $20 - 30\%$ in the last rounds. There is some evidence that the cooperation rate is higher in the small world network compared to the local and random networks, and there is no difference between the local and random networks. Kirchkamp and Nagel [2007] report the results of a prisoner's dilemma game played on two different network structures of 18-20 subjects: regular networks of degree four and networks composed by two or three completely connected components. The first order finding is that there is no effect of network structure on cooperation levels. Gracia-Lázaro et al. [2012] confirm that network structure has no impact on cooperation in a large-scale lab experiment with subjects playing a prisoner's dilemma game with payoffs $c = 10$, $a = 7$, and $b = d = 0$ on two networks of more than 600 subjects each with a regular and fat-tailed degree distributions respectively[18].

Table 2: Two-player prisoner's dilemma game.

	Cooperate	*Defect*
Cooperate	(a,a)	(b,c)
Defect	(c,b)	(d,d)

Assume $c > a > d \geq b$ throughout.

[17] See, e.g., Ohtsuki et al. [2006] and Taylor et al. [2007].

[18] A recent contribution by Rand et al. [2014] finds an effect of network structure on cooperation by comparing several regular networks. The difference with previous studies may be driven by the particular payoffs chosen, the regularity of the networks or the specification of the game. This is an area that deserves further investigation.

In reality, individuals choose their partners and homophily is pervasive in social networks so we would expect cooperators to be more likely to be connected to other cooperators, which may generate a relation between cooperation and the structural properties of the network that is largely absent in experiments on fixed networks. Rand et al. [2011] examine experimentally a prisoner's dilemma game on an endogenous network with payoffs $c = 100$, $a = 50$, $d = 0$ and $b = -50$. In each round there is a first stage in which subjects can form or sever links followed by a prisoner's dilemma game played on the resulting network. The main treatment variable is the rate at which subjects can update the network: a baseline with a fixed network, a random mixing condition, and "viscous" and "fluid" conditions in which 10% and 30% of links can potentially be updated in each round respectively. They find that cooperation level in the fluid condition stays at about 60%, which is significantly higher than in any of the other conditions indicating that the ability to choose connections has a positive impact on the level of cooperation[19]. Jordan et al. [2013] show that this is because the possibility to form new connections with cooperative individuals encourages defectors to switch to cooperative behavior even if many of their neighbors are defecting.

An interesting question is whether there are some structural properties of the emerging networks that are associated with high cooperation. Unfortunately, most of the studies choose asymmetric payoffs which lead to the emergence of overconnected networks, because in absolute terms the losses of being connected to a defector are lower than the gains of being connected to a cooperator. An exception is Gallo and Yan [2015a] who examine a prisoner's dilemma game with symmetric payoffs $c = 5$, $a = 3$, $d = -3$ and $b = -5$ in a setting where subjects can form or sever links in the first stage of each round at no cost. They examine how variations in the information about the network and information about past actions of other subjects affect the emergence of cooperative activity[20]. They validate the findings in Rand et al. [2011] in a similar condition, and they show that the rate of cooperative activity is positively associated with the density and the level of clustering in the network.

2.4 Communication and information exchange

Communication and information exchange is common in many instances of social interaction. People exchange messages and information in order to avoid miscoordination and efficiency loss whenever a coordination problem is present. Game theorists model pure communication as "cheap talk": players' messages have neither direct payoff implications nor

[19] Wang et al. [2012] and Cuesta et al. [2015] confirm the validity of these findings in similar studies.
[20] See section 2.6 for further details.

are binding for actions (Crawford and Sobel [1982]). While theorists recognise the fact that cheap talk can play no role in strategic interaction because uninformative "babbling" equilibria always exist, they also provide conditions under which communication via cheap talk can signal players' intentions or private information to others and thus can improve upon how to play an underlying game. However, the problem of multiple equilibria is prevalent in cheap talk games and standard refinement arguments cannot help much in resolving the issue.

Experimental research on cheap talk models has shown that communication can be effective in guiding subjects' behavior and information in equilibrium selection.[21] As a precursor of the experimental literature of communication networks, Cooper et al. [1989, 1992] study the effect of (one-way vs. two-way) pre-play communication structure on coordination in several two-player coordination games. An overall finding is that one-way communication increases coordination in the Battle of the Sexes, whereas two-way communication is more effective in coordination on an efficient outcome in games with Pareto-ranked equilibria. The reason is that each of the communication structures plays a distinct role and has a differential impact in resolving strategic uncertainty.

While Cooper et al. [1989, 1992] are seminal in considering the effect of communication structure on coordination, their settings are limited in terms of the scope of the network structure. Choi and Lee [2014] extend them by considering a richer set of communication networks in a multi-player game. Specifically, they consider a four-player version of the Battle of the Sexes game in which the four players have a common interest to coordinate but each player has his own preferred outcome. Prior to playing the underlying game, the players engage in finite periods of pre-play communication. In addition to varying communication length, Choi and Lee [2014] investigate four networks of communication–the complete, star, kite, and line networks. The complete network represents a horizonal structure of communication in which all players communicate with each other, whereas the star network describes a vertical, centralized structure of communication in which one player takes the advantage of collecting information and influencing the group-level communication. The other two networks can be interpreted as representing communication structures lying in between, with less concentration of communication power on a single player. Because of the diversity in network positions in the setup, the experiment can address the effect of communication structure on equity of coordination outcomes as well as efficiency. Choi and Lee [2014] report substantial variations in both efficiency and equity across networks. Given

[21] For a survey see Crawford [1998].

the length of communication, the likelihood of efficient outcomes is highest in the complete network and lowest in the line network. Asymmetric networks tend to generate asymmetric coordination outcomes in favor of those who are better connected. However, the length of communication has an important influence on coordination outcomes. While increasing the length of communication improves the chance of coordination, it also makes the coordination outcome more equitable in the networks that produce asymmetric coordination outcomes.

The studies by Kearns et al. [2009] and Judd et al. [2010] we reviewed in section 2.1 can also be seen as having a cheap talk element prior to the play in a coordination game. In Kearns et al. [2009] subjects have one minute to change their choice between blue and red, but these choices can be reversed at no cost until the end of the minute so they can be interpreted as cheap talk about their final choice. Similarly, in Judd et al. [2010] they have three minutes and a choice among nine possible colors. Subjects differ in their preferences for the consensus color and are only informed about the current choices of their immediate neighbors. The results in Kearns et al. [2009] show that in networks generated using a preferential attachment process it is easier for subjects to reach global consensus than in random networks, and that the global consensus was frequently the preferred option of well-connected individuals.

Choi et al. [2011] explore the potential role of information networks in equilibrium selection in a dynamic game of public good provision. Networks are also used in describing various forms of observation structures of the history of play in dynamic games. The presence of asymmetric information about the play history can be an obstacle in achieving coordination. However, asymmetric information structure can make a certain outcome salient, as similar insights emerged from communication networks, and thus can make it easier for subjects to overcome coordination failure. Motivated by this idea, Choi et al. [2011] consider a simple dynamic game with three players in which players make voluntary contributions to the provision of a threshold-level public good over a finite number of periods. Players' contributions are irreversible and not refundable. The authors examine the empty network in which none of the players are informed of others' previous actions, and the complete network in which all players have full access to the history of play. In addition, they investigate a series of incomplete networks describing different asymmetric structures of information. While standard equilibrium analysis provides little guidance due to the multiplicity of equilibria, the experiments reveal that the degree to which subjects coordinate on efficient outcomes varies across different networks. Patterns emerging from the experimental data are overall consistent with two strategic incentives: those whose actions are observed may have an incentive to make contributions in early periods (strategic commitment) and those who can observe others' behavior delay their decisions (strategic delay). Asymmetries in the structure of information networks make these strategies salient.

Despite being still relatively small, the experimental literature on communication and information networks has already accumulated insightful evidence on the role of network structure in equilibrium selection and coordination outcomes. A first direction to explore in future research is the role of communication network structure in multi-player coordination games with Pareto-ranked equilibria. In such underlying games, Peski [2010] proposes the concept of ordinal generalized-risk dominance to generalize Harsanyi and Selten [1988]'s risk dominance notion. An open question is whether there is a relation between the structure of the communication network and the selection of the efficient over the generalized-risk dominant equilibrium. A second direction is an experimental test of the predictions in Hagenbach and Koessler [2010] and Galeotti et al. [2013], who extend the Crawford and Sobel [1982] cheap talk model to a network setting. Some key predictions of these models rely on the assumption that individuals' decisions to communicate depend on how many other individuals the recipient listens to, i.e. her in-degree. This requires individuals to take into account the network structure beyond their neighborhood and make inferences based on this information, which may not hold experimentally as section 2.6 will elaborate on. The relation between the in-degree distribution of the equilibrium communication network and the ranking of equilibria in terms of their efficiency is another example of a theoretical prediction that warrants an experimental investigation.

2.5 Social learning

In many social and economic situations individuals learn from others by observing their decisions and/or learning about their beliefs on an underlying unknown state of the world. Economists use the umbrella term social learning to describe this phenomenon. A general message from the economics literature on social learning is the emergence of cascades that lead everyone in the society to converge to the same behavior. There may be inefficient information aggregation and convergence to a sub-optimal outcome despite the fact that individuals maximize their own utility given beliefs formed in a Bayesian fashion.

The classical social learning model, introduced by Banerjee [1992] and Bikhchandani et al. [1992], and extended by Smith and Sørensen [2000], analyzes a sequence of agents making successive, once-in-a-lifetime decisions under incomplete and asymmetric information. That is, agents are uncertain about the underlying decision-relevant event, and the information about it is shared asymmetrically among them. The typical conclusion is that, despite the asymmetry of information, eventually every agent imitates her predecessor, even though she would have chosen a different action on the basis of her own information alone. In this sense, agents rationally 'ignore' their own information and 'follow the herd'. Furthermore, since actions aggregate information poorly, herds often adopt an action that is suboptimal relative to the total information available to agents. This is an important result that helps us understand the basis for (possibly inefficient) uniformity of social behavior. Following Anderson and Holt [1997], a number of papers[22] investigate social learning experimentally and demonstrate that herd behavior can be replicated in the laboratory.

In practice, individuals are located in complex social networks and learn mainly from observing the decisions of their neighbors and/or learning their beliefs about the underlying state of the world. The classical model of social learning can be seen as the very special case of a directed line network, in which information flows and/or observations about others' decisions only happens once for each agent and in one direction from the beginning to the end of the line. The theoretical literature has explored the impact of social network structure on two different types of social learning: observational learning in which a link between two individuals represents their ability to observe each other's actions, and communication learning in which a link between two individuals indicates that they can (truthfully) share their beliefs about the underlying state of the world[23].

Bala and Goyal [1998] and Gale and Kariv [2003] are the first theoretical models of observational social learning on networks. The key methodological difference in their approach is whether agents are fully Bayesian or there are exogenously imposed limitations in the agents' ability to make Bayesian inference on the network. Bala and Goyal [1998] assume a boundedly rational form of Bayesian updating in which agents only take into account actions and outcomes of neighbors' actions, and ignore any information that may be inferred by the sequence of neighbors' actions. Instead, Gale and Kariv [2003] investigate a fully Bayesian set-up in which agents are able to make inferences about non-neighbors' actions from their observation of neighbors' actions and their knowledge of the overall social network[24]. A general result is the convergence to an equilibrium in which all agents play the same action. Moreover, this action is the optimal action as long as one imposes some restrictions on the

[22] Selected contributions include Hung and Plott [2001], Kübler and Weizsäcker [2004], Çelen and Kariv [2004], Goeree et al. [2007] and Weizsäcker [2010].

[23] Chapter XX of the Handbook by Golub and Sadler reviews learning in networks, and Chapter XX by Breza surveys studies of social learning using field data.

[24] Other more recent contributions in this vein include Acemoglu et al. [2011] and Mueller-Frank [2013]

network structure.[25]

Choi et al. [2005, 2012] and Choi [2012] have undertaken an experimental investigation of learning in three-person, directed networks and focus on using the theoretical framework of Gale and Kariv [2003] to interpret the data generated by the experiments. The experiment design utilizes three networks–the complete, the star, and the circle network– along with variations in the structure of private information about the unknown state of the world. In each period, players simultaneously choose which state is more likely to have occurred at the beginning. This guess is made on the basis of the individual's private signal and the history of the play of their neighbors. As the game continues, the inference problem becomes more demanding because it requires a player to form higher order beliefs. Since noises in experimental data are inevitable, Choi et al. [2012] extend the Bayesian model to allow for the possibility of subjects making mistakes. This was done by adopting the model of Quantal Response Equilibrium of McKelvey and Palfrey [1995, 1998]. While the Bayesian model overall performs well, there are instances of networks and information structures in which the Bayesian model has a limitation in interpreting the data. Also, the heterogeneity of individual behavior in the data is hardly ignorable.

Choi [2012] develops a method for estimating a mixture model of heterogeneous rules of learning in networks. His approach is based on the observation that the sequence of tasks of learning constitutes a 'cognitive hierarchy,' which in turn suggests a natural hierarchy of cognitive types. Each cognitive type corresponds to the number of periods in which a player processes new information: starting from the lowest type who randomly guesses the state of nature, the next lowest type would only process his private signal but make no use of information obtained from the observations of his neighbors' decisions; the next lowest type would process his signal in period 1 and make an inference about his neighbors' signals from their decisions in the first period, but could not make any higher order inferences from then on, and so on. The estimation results show that this structural approach does a very good job of interpreting subjects' behavior and accommodating the heterogeneity of individual behavior in the data.

In contrast to the observational learning literature, the prevalent approach in theoretical work on communication learning on networks has been the assumption of boundedly rational learning. The most widely used rule was first proposed by DeGroot [1974]: each agent updates her beliefs by taking a weighted average of her neighbors' beliefs with the weight determined by the strength of the link in the communication network. DeMarzo et al. [2003]

[25] Mueller-Frank [2014] shows that convergence may also fail if there is one fully Bayesian agent in a society of non-Bayesian agents due to the ability of the fully Bayesian agent to influence the consensus.

formulate a model in which agents receive signals at time 0, they truthfully communicate their belief to their neighbors at each time period, and they update their beliefs by using DeGroot [1974]'s rule. They show that in the long-run all agents would converge to the same belief about the underlying state of the world, and the influence of each agent in determining the limit belief is tied to the agent's position in the communication network. This means that there will not be convergence to an unbiased aggregation of the initial signals except for the very special case in which the informativeness of each initial signal is exactly aligned with the influence of the recipient in the network[26]. Acemoglu et al. [2014] analyze a Bayesian communication learning model by assuming that agents can tag information, and they show that the presence of "information hubs" is a sufficient condition for asymptotic learning.

The predictive power of models based on the DeGroot [1974] set-up hinges on the specific assumption of bounded rationality in the updating rule, which is ultimately an issue that can only be resolved empirically. The experimental method can be particularly helpful in shedding light on this question as it would be very challenging to identify the updating rule in observational data. Corazzini et al. [2012] examine experimentally how individuals learn in two networks of 4 nodes: a circle with directed links arranged in a clockwise pattern so that each individual has one incoming and one outgoing link, and a hub-type network obtained from the circle network by adding two links so that the choices of one subject are observed by all the others. In the first round each subject receives an integer signal drawn from a commonly known distribution, and in each one of 12 rounds she has to guess the mean of the 4 signals after learning her neighbors' guesses in the previous round. The predicted outcomes for Bayesian and DeGroot-type updating are the same in the circle, but they differ in the hub network: Bayesian updating gives each subject's signal the same weight, while DeGroot-type gives a clear ranking in the importance of signals depending on the network position of the subject who received the signal. The results clearly show that in the hub network subjects give different weights to signals in broad agreement with the predictions of the DeGroot dynamics. The authors also propose a generalized updating rule in which individuals give weight to individuals who are listened to, as well as listen to many others, which nests DeGroot as a special case, and they show that it gives a good fit to the data.

A drawback of the Corazzini et al. [2012]'s set-up is that they only investigate one network in which there is a difference between the outcomes of the Bayesian and DeGroot learning, making it difficult to generalize their findings. In a recent working paper, Grimm and Mengel [2014] report an experimental study testing the predictive power of Bayesian and

[26]Other more recent contributions using the DeGroot [1974] rule include Golub and Jackson [2010], Acemoglu et al. [2010], and Gallo [2014b].

DeGroot-type learning in 5 different networks with 7 nodes. They find that subjects make decisions consistent with Degroot-type updating in $80 - 98\%$ of the cases in which the predictions of the two models differ for specific positions in the network. However, the dynamics of convergence to a limit belief suggests that subjects may be using rules-of-thumb that are more sophisticated than simple DeGroot, and the authors propose an alternative non-Bayesian model of learning that extends the DeGroot model by allowing individuals to adjust the weight placed on their previous behavior according to their clustering coefficient, which captures the proportion of an individual's neighbors who are connected to each other. This adjusted model of non-Bayesian learning appears to perform better than the DeGroot model.[27]

A major theme in the literature of learning in social networks is understanding which model of updating best describes individuals' decisions, and, consequently, group outcomes. Bayesian updating is a natural benchmark case, but it has the drawback of not being very tractable and it requires individuals to exercise increasingly demanding inferences from the observation of neighbors' behavior. DeGroot-type updating provides sharp predictions, but it makes ad hoc assumptions on the specific type of bounded rationality that individuals have when they process information. Further experimental research is required to identify the type of bounded rationality, which would be invaluable input for further theoretical work. A first step forward would be to identify which dimensions of information about the network the participants use in their updating, which is a topic we will discuss further in sections 2.6 and 4. A second step would be to investigate how this updating varies with the size and complexity of the network as the largest network explored so far has only 7 individuals. Finally, there are econometric issues that require careful consideration: subjects in an experiment tend to make mistakes and display significant individual-level heterogeneity of learning behavior, which makes a clean identification strategy more challenging.

2.6 Incomplete information about the network

A common assumption of many theoretical and experimental studies that we have considered so far has been that individuals have complete information about the network structure. This is rarely the case when we consider applications as individuals would usually have access to information about local features of the network, e.g. their degree, and aggregate statistics

[27]Using a similar set-up, Mueller-Frank and Neri [2013] investigate networks of 5 and 7 nodes. They find that individuals' decisions do not satisfy three properties which are required by a class of non-Bayesian updating rules in order to achieve consensus, which may explain the lack of convergence to consensus in their experiment.

about the overall network structure, but no detailed information on the exact pattern of who is connected to whom. Even if the complete information about the network is available, a number of studies in social psychology show that the process of memorizing and recalling information about real social networks is affected by several biases[28], some of which have been confirmed in an experimental setting[29]. These biases may influence how individuals make decisions in network games, especially in contexts in which equilibrium play requires the knowledge of the network beyond the immediate neighborhood as in Bayesian learning in networks.

Galeotti et al. [2010] explore the role of incomplete information about the network in the context of games of strategic complements and substitutes, which we have reviewed in sections 2.1 and 2.2. In their set-up an agent knows her degree and the degree distribution of the whole network, but she does not have information on any other characteristic of the network including the identity of her neighbors. This is a rather severe form of incomplete information about the network, and an interpretation is that it applies to contexts in which an agent makes a decision before the specific identity of the neighbors is realized. Their model defines a game of incomplete information in which a player's type is her degree, and it nests the incomplete information versions of the Ballester et al. [2006] and Bramoullé and Kranton [2007] set-ups. Recall from sections 2.1 and 2.2 that in the complete information set-up the game with strategic complements has a unique equilibrium in which an agent's play depends on her Bonacich centrality, while the game with strategic substitutes has a multiplicity of equilibria. Galeotti et al. [2010] show that the introduction of incomplete information allows to prove the existence of monotone equilibria: actions are non-increasing (non-decreasing) in players' degrees under strategic substitutes (complements). Moreover, these are the unique symmetric equilibria if one puts some restrictions on the payoffs. This result is intuitive for the game of pure strategic complements, but in the case of strategic substitutes it reduces the equilibrium multiplicity present in the game with complete information, thereby significantly increasing the predictive power of the model.

Charness et al. [2014] test the predictions of the Galeotti et al. [2010] model in a series of experiments on a variety of networks with 5 nodes and a small set of networks with 20 nodes. Aside from the network structure, the two treatment variables are whether it is a game of strategic substitutes or complements, and the presence of complete or incomplete information about the network. They restrict their attention to active/inactive binary strategies which

[28] Examples include Krackhardt [1987, 1990], and Kumbasar et al. [1994].

[29] The only two experimental studies we are aware of in network cognition are Janicik and Larrick [2005] and Dessi et al. [2014].

implies that one of the binary actions leads to a secure outcome because a player receives a fixed payoff by choosing this action, regardless of her degree and the neighbors' decisions. In the incomplete information treatments with the small networks, subjects' play is in agreement with the predictions in Galeotti et al. [2010]: subjects use threshold strategies and the frequency of active players is monotonically increasing (decreasing) with connectivity for the case of complements (substitutes). Whenever incomplete information induces a unique equilibrium, subjects almost always make choices that are consistent with the equilibrium. In the context of strategic complements, Charness et al. [2014] find that when there are multiple equilibria, network properties are predictive of subjects' behavior and thus serve as an equilibrium selection tool. Specifically, connectivity and clustering influence the likelihood of activity: high connectivity and more clustering tend to increase coordination on the efficient equilibrium rather than the secure but less efficient one. They also find evidence that the introduction of uncertainty drives play to the most secure equilibrium.

The experiment by Charness et al. [2014] is a very good illustration of how the comparison of treatments with complete and incomplete information about the network can help in understanding the role of uncertainty about the network as well as shed light on other experimental results in the complete information set-up. In the context of strategic complements, the high frequency of equilibrium play when there is a unique equilibrium in the complete information setting is consistent with the results in Gallo and Yan [2015b] who find convergence on average to the equilibrium play on large networks when subjects have a large, non-binary set of actions at their disposal. The introduction of incomplete information about the network does not significantly alter the finding. In the context of strategic substitutes, the introduction of incomplete information helps to reduce the strategy space and acts as an equilibrium selection device both theoretically and experimentally: Charness et al. [2014] find high convergence to equilibria in contrast to the results in Rosenkranz and Weitzel [2012] who find low frequency of equilibrium play. An important caveat is that subjects in Rosenkranz and Weitzel [2012] have a large set of actions to select from, so an open question is whether the results in Charness et al. [2014] hold in a setting with non-binary actions.

Gallo and Yan [2015a] examine the role of incomplete information about the network in the context of the prisoner's dilemma game on an endogenous network which we reviewed in section 2.3. In each round of a repeated game, subjects first form costless links with other subjects and then play a prisoner's dilemma game on the resulting network. The authors vary the information that subjects have about the network as well as the information about others' previous actions. In the baseline, subjects only know the identity and previous five actions of their neighbors. The network information treatment adds information on the full network to the baseline, the reputation treatment adds information on the previous five actions by everyone to the baseline, and the final treatment has full information on the network and others' previous five actions. Mouse-movement tracking data shows that subjects make active use of the network information, but the availability of full information about the network has no effect on the aggregate level of cooperation which is solely driven by the availability of information on everyone's previous five actions. The availability of information about the network in addition to information on everyone's actions affects the distribution of cooperative activity: it allows cooperators to find each other and form their own separate community by excluding defectors to a separate community using the information about the network in the network formation process. Being part of the community of cooperators is highly beneficial, it allows a subject in the cooperative community to earn a payoff per round that is 23% higher than if she were in a community of defectors of equal size. These results also show that the choice made in other experimental studies of the prisoner's dilemma game on an endogenous network to only give subjects information about neighbors, rather than the whole network, is not without consequence.

Experimental designs that vary the information about the network available to subjects can also be useful to differentiate between competing models. The experiment by Grimm and Mengel [2014], which we already described in section 2.5, also varies information about network structure by allowing subjects to know only their own degrees in the network, or the degree distribution of the network as well as their own degree, or the complete structure of the network. The key insight is that fully Bayesian updating is responsive to the differential information about the network structure, but DeGroot-type updating is not, because it disregards the knowledge about the network structure beyond the neighbors in the belief updating process. As we have seen in section 2.5, subjects' decisions are very consistent with DeGroot updating. However, subjects make more correct guesses in some networks when they have more information about the network structure, which cannot be explained by DeGroot updating. Grimm and Mengel [2014] show that if subjects have complete information about the network then the weight they place on their belief is increasing in their clustering coefficient, which captures the extent to which their neighbors are connected with each other. In other words, subjects take into account correlations in neighbors' beliefs in a rudimentary way rather than ignoring them as assumed by DeGroot updating.

The variation of the information about the network available to participants reveals novel insights about the network games reviewed in sections 2.1, 2.2, 2.3 and 2.5. It sheds light on a range of issues including how equilibrium selection depends on the network, how agents update their beliefs using network information, and how decisions are distributed in the population. A fertile avenue for further research would be a systematic examination of what information about the network individuals make use of and how it matters in their decisions: the studies we have reviewed vary the network information in an ad hoc fashion which is not grounded in evidence of how individuals memorize, recall and use this type of information. We will explore further this theme in section 4.

3 Markets and Networks

This section discusses existing experimental research on markets and networks. We organize it by two distinct strands of the literature. In the first strand, networks are used as a tool of representing the trading relation among market participants. The second strand reviews a couple of studies that investigate the impacts of communication and information networks on trading behavior and market outcomes.

3.1 Trading frictions

The Walrasian theory of market equilibrium is a cornerstone of economics in understanding markets. It postulates that trade takes place on a centralized exchange mediated by a fictitious auctioneer. Competitive equilibrium in this frictionless economy has been a significant basis of understanding the workings of markets and economists' advice of public policy. Experimental research has also deepened our understanding on markets by investigating the properties of market institutions in a controlled environment. Starting from Chamberlin [1948] and Smith [1962, 1965], a large literature of market experiments has accumulated evidence that certain institutions in laboratory markets have remarkable properties of approximating an efficient allocation, predicted by the Walrasian theory, even with a small number of subjects[30]. One prominent such institution is the continuous double auction with a centralized process of trading.

In practice, there are many markets in which exchange is organized by decentralized trade and intermediation. In those environments, networks are a natural tool to represent the trading relationships among market participants. When the network is complete, every possible trading opportunity is present and therefore there is no constraint on trading

[30] See Sunder [1992] for a slightly outdated but comprehensive survey.

patterns. On the other hand, the incompleteness of the network signifies that some traders are unable to trade with each other. It implies either the pure loss of trading opportunities or the fact that an intermediation service is required for trading. When intermediation is costly, the incompleteness of the network becomes a source of trading frictions and a cause of inefficient allocation.

A number of theoretical studies use networks to understand the effects of network structure on market outcomes in a variety of situations, including two-sided networked markets with bargaining (e.g., Kranton and Minehart [2003] and Corominas-Bosch [2004]), financial contagion (e.g., Allen and Gale [2000]), and intermediated trade (e.g. Condorelli and Galeotti [2012])[31]. A general takeaway from this body of work is that networks are a significant determinant of market efficiency and the division of trading surplus. Nevertheless, theory alone has limited predictive power and it is not very informative for policy due to the complexities of networks and the multiplicity of equilibria. Experimental research can complement these theoretical advances by shedding some light on equilibrium selection and the behavioral rules individuals adopt when facing the complexities of networks.

A first branch of the experimental literature examines two-sided networked markets. Charness et al. [2007] is an experimental test of the model by Corominas-Bosch [2004]. The market is described by a bipartite network of buyers and sellers, representing the limited set of trading opportunities, and by a protocol of sequential alternating bargaining over a shrinking value of a homogeneous and indivisible good. Corominas-Bosch [2004] provides a theoretical method of decomposing any network of buyers and sellers into relatively simple subgraphs, plus some extra links. A nice feature of the decomposition result is that any network is decomposed into a union of smaller networks, each one either a complete network in which the short side of the market induced by that network receives all the surplus, or an even network in which traders split the surplus nearly evenly. Charness et al. [2007] employ two separate simple networks–a three-person network, which is competitive, and a four-person network, which is even– and combinations of these two resulting in a variety of seven-person networks. They observe such a high degree of bargaining efficiency that 75% of the possible agreements are reached in the first round and the total payoffs received are 96% of the maximum attainable. The decomposition result predicts stark difference in bargaining outcomes, depending on how a link is added between two simple networks. The experimental

[31] Applications of networked markets are presented in Chapter XX (for financial contagion) and Chapter XX of the Handbook by Condorelli and Galeotti discusses the theoretical literature on strategic intermediation in networks. Chapter XX of the Handbook by Manea discusses the theoretical literature on buyer and seller networks.

data qualitatively validate the theoretical predictions.

Judd and Kearns [2008] also study experimentally bipartite exchange in large networked markets. The experiment examines a range of 36-person bipartite networks including regular and random networks as well as networks generated using a preferential attachment process, which means that the structure varies in terms of aggregate network properties such as the degree distribution. The main focus of the experiment is testing the predictions on the mapping of structural asymmetries in network topology into pricing behavior and efficient outcomes. They find that the level of efficiency is quite high across all network treatments and those with more links (and with more trading opportunities) obtain higher benefits from trading. Nevertheless, there is evidence of equality seeking or inequity aversion, despite that asymmetry in network positions results in unequal distribution of gains from trading.

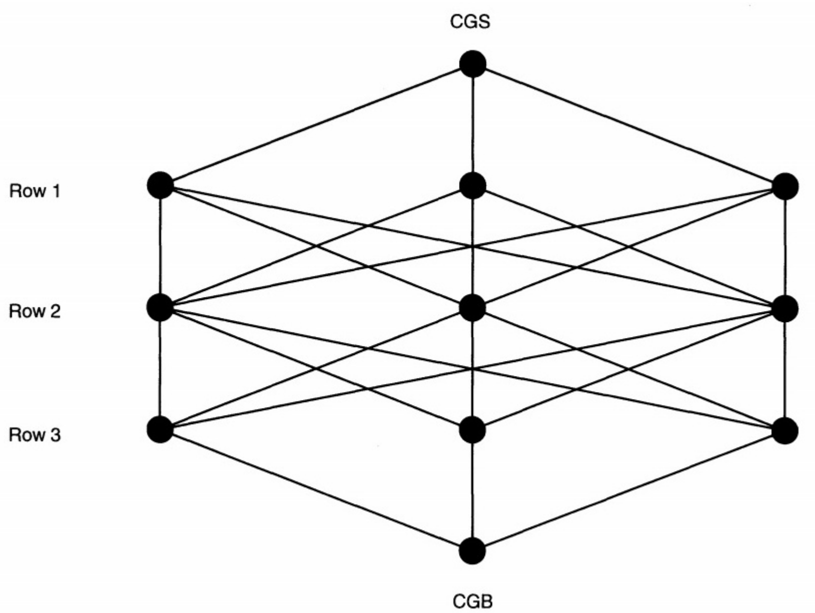

Figure 3: An example of a network in Gale and Kariv [2009].

A second branch of the experimental literature explores the impact of networked intermediation on efficiency and surplus division. Gale and Kariv [2009] study a simultaneous bid-ask model of trading in networks. A buyer and a seller need to trade a commodity or asset through a set of intermediaries. Traders are located on a rectangular network consisting of rows and columns of intermediaries. Figure 3 shows an example with three columns and three rows of intermediaries connecting the seller (CGS) at the top with the buyer (CGB) at the bottom. Trades are restricted to adjacent rows and links represent potential trading opportunities. Each intermediary simultaneously chooses a bid (the price at which he is willing to buy the asset) and an ask (the price at which he is willing to sell the asset). Each member of traders in a given row can trade with every member of traders in an adjacent row with whom he has a link. The variations of trading networks in the design of Gale and Kariv [2009] feature essentially Bertrand competition amongst horizontally positioned traders. Thus, from a given network, adding rows increases the amount of intermediation required to capture the surplus available, whereas adding columns increases the amount of competition. Due to Bertrand competition, in an efficient equilibrium the asset's transaction price is equal to its value after traversing the first row. Gale and Kariv [2009] report that the level of efficiency is very high and that the pricing behavior observed in the experiment converges to competitive equilibrium behavior in a variety of treatments. However, the rate of convergence varies depending on networks and other parameters of the design.

Choi et al. [2014] propose a static model of posted prices in networks and test its empirical relevance in the laboratory. In their model, there are a set of intermediaries lying between a buyer and a seller. The passage of a commodity from the seller to the buyer generates value. Intermediaries simultaneously set a price to get a share of this value. The model deals with both a trading situation of complete information where intermediaries know the value of exchange, and a situation of incomplete information where intermediaries choose a price prior to knowing the value of exchange. Trading occurs through a least cost path and an intermediary earns payoffs only if he is located on it. Choi et al. [2014] offers a complete characterization of Nash equilibria under both information cases. Theory allows both efficient and inefficient equilibria and predicts that node criticality[32] is a necessary condition for the extraction of intermediation rents. Due to the multiplicity of equilibria, theory alone cannot make sharp predictions on efficiency and surplus division.

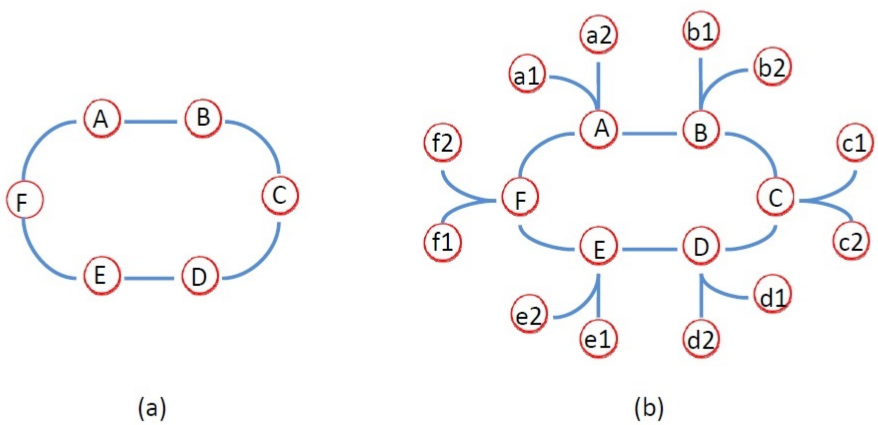

Figure 4: (a) Ring 6 and (b) ring with hubs and spokes in Choi et al. [2014].

[32]A node is critical if it lies on all paths between the buyer and the seller.

In the experimental part, Choi et al. [2014] examine several networks which vary in size and in absence/presence of critical nodes. Figure 4 show two networks with or without critical nodes: (a) ring 6 network and (b) ring with hubs and spokes. They also investigate variation of information on the value of exchange. The experimental data report a remarkably high level of efficiency across all networks in the benchmark model of complete information, in favor of an efficient equilibrium against an inefficient one. For instance, the efficient outcome occurs with probability 1 in the ring 6 network and with probability 0.95 in the ring with hubs and spokes. With regard to surplus division, the experimental results show that critical intermediaries set high prices and extract most of the surplus. As a result, intermediation costs are small in the ring 6 network (less than 15%) and are quite high in the ring with hubs and spokes (60% to over 95%). Thus, the model and the experiment taken together establish that the presence of critical intermediaries is both necessary and sufficient for large surplus extraction by intermediaries and that most of the intermediation rents accrue to critical intermediaries.

Experimental research on networked markets is an exciting research area. In experimental markets, one can control traders' preferences, technology, and private information, as well as network structure. It is practically impossible to achieve this level of control in observational market data. Because of such a methodological advantage, experiments on trading in networks can address issues that are hard to test using real market data.

3.2 Information flows

Information plays a key role in the well-functioning of markets. As we have already seen in sections 2.4 and 2.5, social networks are a channel for information to flow among individuals and therefore the structural features of the communication network may be related to the outcomes that we observe in the market. Furthermore, the social network will create heterogeneities across individuals depending on their position in the network, which may result in some of them having an informational advantage. Here we focus on two functions of communication networks in markets. The first function is to monitor other market participants in a market environment in which contracts are not perfectly enforceable and therefore information about other individuals' conduct is critical to ensure that cheaters are punished. The second function is to provide information about the value of goods in markets where this information is not common knowledge through publicly displayed prices, but it is only shared privately by the participants in a market transaction.

The first function of communication networks in markets has received significant attention in the economic history and development literatures to explain the existence of active trading markets in contexts where there are no formal institutions to enforce contracts. For instance, Greif [1993] provides historical evidence that monitoring through communication networks allowed the Maghribis to become the main traders in the Mediterranean in the 13th century.

Cassar et al. [2010] reports the results of an experiment to examine the role of information networks in trading behavior in a multi-market situation where contracts are not perfectly enforceable. The market institution is a continuous double auction in which buyers and sellers are randomly assigned and their values and costs are heterogeneous. There are two markets running simultaneously: a "local" market where contracts are strictly enforced, and a "distant" market where cheating is possible with a seller delivering a lower-quality good and a buyer paying less than promised. In addition to the structure of the two markets, traders are fully connected with a subset of traders in the distant market via a clique network, which enables them to observe and thus monitor the past play of their network members' trading including all bids, asks, and transactions made by them. Thus, traders know whether and which members of their network cheated, and can build up their reputation within their network. The clique network further varies with regard to the composition of values and costs to create networks with potentially high trading surplus and networks with low trading surplus. The baseline treatment has no network so all trades in the distant market are anonymized. The results show that the presence of information networks significantly reduces cheating and increases efficiency, and that, due to the facilitation of monitoring within a network, networks lure high surplus traders out of the local market and into the distant market.

A second function of communication networks is to provide market information to traders in contexts where there is incomplete information because there are no publicly available prices and information about the value of goods is only circulated within social networks. For instance, Rauch and Trindade [2002] show that Chinese immigrant networks significantly increase international trade volumes, and this only happens for commodities whose prices are not publicly available, providing strong evidence that belonging to the network gives them an informational advantage. Gallo [2014a] extends the model in Young [1993] to capture this function of social networks in markets. In a decentralized market one buyer and one seller are randomly matched to play a Nash demand game in each time period, and, before playing the game, they receive information about past transactions through their social network. The process converges to a unique equilibrium where each buyer (seller) gets the same and the split between buyers and sellers depends on the degree of the least connected individual(s) in each network: the lower the degree of the least connected buyer (seller) the lower the share going to every buyer (seller). The 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.

Gallo [2014a] also reports the result of an experiment testing the predictions of the model. He examines four six-person networks of buyers which vary in density and distribution of connectivity: a regular network of degree 4, the circle, the star and a 4-node circle network with two spokes. Subjects are assigned to a specific position in a network, which is unchanged for all the 50 rounds of the experiment, and they are told they are traders in a market and they will be trading with a seller played by a computer. 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. The results of the experiment lend support to the theoretical predictions. Subjects in the regular network of degree 4, which has the highest density, converge to a significantly higher demand than subjects in other networks. Subjects in the star and circle with spokes networks, which are the only ones with a least connected node of degree 1, are undistinguishable and converge to a lower demand than the other two networks.

4 Future directions

The previous sections have reviewed the main work in the literature on network experiments and identified open questions within specific topics that would benefit from further research. In this section we take a more holistic view of the current landscape of research on networks in economics, and identify directions for further experimental research that are important for several areas where networks matter.

The nature of theoretical modelling in the network literature varies significantly depending on the size of the network. At one end of the spectrum there are models describing phenomena in small networks of a few nodes: the standard game theoretic approach applies well here as strategic considerations are paramount and the small set of players makes most problems tractable. At the other end of the spectrum there are models describing phenomena on large networks: the prevailing approach is to use different types of stochastic processes with no strategic element or a boundedly rational approach based on heuristics. Theoretical models for the intermediate size case adopt a mix of the game theoretic and stochastic approaches, and this is arguably the area where network structure has the most interesting effects and the literature is less developed. The social learning models we reviewed in section 2.5 provide a good illustration of this spectrum with fully Bayesian and DeGroot-type models being particularly relevant for describing behavior on small and large networks respectively, and a truly hybrid model between the two arguably still missing.

Up to now the experimental literature in economics has largely focused on small networks of at most a dozen nodes. This is a limitation to the general validity of the findings as some of the few experiments which have compared intermediate and small sized networks show interesting evidence of the importance of network size[33]. A practical reason to focus on small networks is to keep session sizes manageable as well as the fact that if the network is the unit of analysis then the number of independent data points is divided by the network size, which means that large network experiments would require a large subject pool. However, these practical considerations have been overcome by several researchers outside of economics[34], and a systematic study of how network structure affects behavior in intermediate and large sized networks is important to enrich our understanding of their impact on behavior.

A related direction for future experimental research is improving our understanding of how individuals learn, memorize and recall information about the network, and what heuristics and potential consequent biases are involved in this process. An extensive literature in cognitive psychology has documented how individuals use heuristics to handle demanding cognitive tasks and how these heuristics may lead to systematic biases[35]. This is particularly relevant for networks of intermediate and large size where the complexity and sheer number of potential network architectures mean that individuals cannot possibly have complete information about the network they are embedded in. Dessi et al. [2014] provide some evidence that individuals tend to underestimate the mean degree and overestimate (underestimate) the number of rare (frequent) degrees in a 15-node network using a graphical methodology to generate the network in the lab, and show that these biases are also present in two real networks mapped through surveys. However, the cognitive processes we use to memorize and recall network information and the resulting biases are still largely unexplored. As we have seen in section 2.6, the introduction of incomplete information about the network in theoretical models can provide novel insights, and experimental evidence on how to model

[33] Examples include Choi et al. [2014] and Gallo and Yan [2015b].

[34] Among the studies covered in this review, Judd and Kearns [2008], Judd et al. [2010] and Kearns et al. [2009] conduct experiments on networks of 30-50 individuals, and Gracia-Lázaro et al. [2012] has networks of more than one hundred nodes.

[35] See Tversky and Kahneman [1974] for some examples of this body of work. Kahneman [2011] gives a comprehensive account accessible to the general public.

incomplete information would be very valuable to avoid ad hoc assumptions and provide input to improve the behavioral validity and predictive power of the theory.

A prominent dimension of many social connections is their strength. The reduction of relations such as friendship, trust, the people we seek advice from and communication to a binary variable is rather coarse and fails to capture the important role that the strength of links plays in relating network structure to behavior. The results in several theoretical models that we have reviewed in section 2 apply to any weighted network, e.g. Ballester et al. [2006] and DeMarzo et al. [2003] amongst others. However, there is no paper we are aware of in the network experiments literature within and outside of economics which has investigated weighted networks. The creation of weighted networks in the lab presents its own challenges, but overcoming them would allow the exploration of a dimension of network structure which plays an important role in many contexts where network structure affects behavior.

In recent years there has been a growing number of experiments showing that culture matters for play in different games[36]. Social relations are intertwined with culture, and we would expect the relation between social network structure and behavior to be dependent on culture in several contexts. For instance, Currarini et al. [2009] show that the tendency for individuals to form relations with others who are like them along some dimension, or homophily, shapes the network structure and in turn this affects individual behavior (e.g. Golub and Jackson [2012]). McPherson et al. [2001] review evidence that homophily varies along different dimensions including ethnicity and culture, which suggests a relation between culture, the networks that form and the way they impact behavior. Ideally the investigation of the role of culture requires running an experiment with individuals in different geographical locations, which has become feasible only recently thanks to the development of web-based experiments[37]. The development and diffusion of web-based experiments opens up the opportunity of novel research on how culture and social networks jointly influence behavior.

Finally, in the introductory perspective on the literature in chapter XX, Goyal (REF) argues that the economics of networks is transitioning to a "normal science" through the application of network models to competition, prices and markets across different fields in economics. Some examples he gives of this transition include recent studies on the role of networks in product, financial and labor markets which contribute to the gradual integration of networks into the standard economics framework, and policy-makers' growing awareness of their importance. A case in point is the prominence of networks in the discussions among

[36] Examples include Henrich et al. [2001] and Jackson and Xing [2014].

[37] Examples of web-based network experiments include Rand et al. [2011] and Gallo and Yan [2015a].

academics, policy-makers and the general public in the aftermath of the 2008 financial crisis. A number of theory papers have been written on this topic since[38], but we believe that the inclusion in theoretical models of realistic assumptions about the behavior of market agents is critical for the application of theoretical results to policy. In an ongoing project, Choi et al. [2015] examine experimentally how market freeze depends on network structure and the information agents have about the network in a standard trading market with a continuous double-auction. The findings in this experiment may shed light on the behavior of individuals in this environment, which can then be fed into theoretical models to generate predictions that can be tested experimentally. Our hope is that this type of two-way dialogue between theoretical and experimental work will continue to grow to increase our understanding of the relevance of networks in economics and policy-making.

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[38] See Chapter XX of the Handbook for a review.

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