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NETWORKS IN ECONOMICS

A PERSPECTIVE ON THE LITERATURE

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ABSTRACT
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A Perspective on the Literature

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February 5, 2015

Abstract

It is instructive to view the study of networks in economics as a shift in paradigm, in the sense of Kuhn (1962). This perspective helps us locate the innovation that networks bring to economics, appreciate different strands of the research, assess the current state of the subject and identify the challenges.

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1 Introduction

The study of networks is one of the most dynamic fields of research in economics today. Research in networks is regularly published in the top journals of the profession. The best university presses bring out research monographs on networks written by economists. Researchers in networks win prizes and are awarded prestigious grants from research funding bodies. Some of the best graduate students in economics choose to work on networks. Governments, non-governmental organizations and private companies all express an interest in the findings of the networks research community.

When the editors of this handbook invited me to write a perspective piece, I felt that it was a good moment to pause, stand back and take stock.

In this paper, I will argue that at the start of the 1990's, the introduction of networks in economics marked a major break with existing practice. Today in 2014, half way through the third decade of its life, the study of networks has come of age. It is now 'normal science' in the sense of Kuhn (1962).

I start by drawing out the ways in which networks constitute a radical departure from standard models in economics, as seen in the 1980's. This will be illustrated with a case study: the research on social learning, before and after the introduction of networks. The case study will draw attention to a major methodological innovation: locating individuals within a general framework of social connections. The analysis yields a number of insights that relate social structure to individual behavior, learning dynamics, diffusion and welfare.

The second step in my argument shows how initial breakthroughs lead to the investigation of major new questions. The crucial role of social structure motivated a study of the origins of networks: where do they come from and what do they look like? This is a question that was not viewed as especially important or interesting prior to the research on social learning. I present a case study on the theory of network formation to sketch its key ingredients and its main insights. A distinctive feature of the research on network formation is a very wide range of applications. I illustrate the scope of the theory of network formation by showing that it provides an elegant resolution to two long standing puzzles in the social sciences: one, racial homophily patterns in friendship, and two, the law of the few in social communication.

I then argue that as the research on behavior in fixed networks and on network formation has matured it has taken on progressively more ambitious themes. This sets the stage for a discussion of the nature of research in networks today. I will argue that this work now encompasses the classical notions of preferences, individual choice, strategic behavior, competition and prices. As a result, networks are now becoming central to improving our understanding of macro economic volatility and cycles, patterns of international trade, contagion and risk in financial and social systems, resilience of infrastructure and supply chains, economic development, unemployment and inequality, and a host of other important phenomena. The present handbook offers a panoramic view of the tremendous vitality of this research.

By way of conclusion, I discuss some tensions between traditional models in economics and models in networks and how these tensions shape current research practice.

2 Networks in economics: a significant departure

This section develops the first step in the argument. I show that networks mark a radical departure and go beyond the traditional model in economics, as practiced in the late 1980's. The theoretical framework of economics was then organized around concepts for the study of interaction in small groups (game theory) and interaction among large groups (competitive markets and general equilibrium). A number of phenomena appear to arise in between these two extremes. By way of illustration and for concreteness, I take up and discuss the case of learning and diffusion. The received models in the 1980's appeared to be inadequate both from the viewpoint of introspection and also failed to account for the empirical patterns. This led to the first attempts at modeling decision making by individuals embedded in a social network. I sketch the main ingredients of these first set of models and then show how they depart from received models. I discuss the main insights and relate them to subsequent developments in the field.

The diffusion of new ideas, opinions, products and technologies is key to understanding social change, growth and economic development. Traditionally, economists have focused on a combination of individual heterogeneity and unknown profitability to explain patterns in diffusion; a prominent early contribution is Grilliches (1957).[1] Through the 1970's and 1980's the study of information imperfections and asymmetries occupied centre stage in economics. As information has economic value, it was natural to ask if starting from incomplete or imperfect information, individuals would 'acquire' information and 'learn' the 'optimal' action. In an early paper, Rothschild (1974) showed that a patient and dynamic optimizing agent will stop learning and hence will get locked into a sub-optimal action, with positive probability. This observation was followed by a large and technically sophisticated literature on single

[1]For a brief summary of the state of the literature in the 1980's, see Feder, Just and Zilberman (1985).

agent learning that continued through the 1980's and well into the 1990's. Alongside this work, there emerged a parallel line of work on multi-agent learning: do individuals learn rational expectations and do individuals learn to play Nash equilibrium (Fudenberg and Levine, 1998; Evans and Honkapohja, 2001)?

The research focused on the single individual or on groups where interaction was uniform and homogenous. However, the early work of Lazarsfeld, Berelson, and Gaudet (1948), Katz and Lazersfeld (1955), Coleman (1966), Granovetter (1973, 1974) and Ryan and Gross (1943) in sociology, Hagerstrand (1967) in economic geography, and Rogers (1983) in communications, points to a world that lies somewhere in between these two extremes: individuals, be they farmers or consumers or doctors, typically interact with only a small subset of the group. These small subsets – the neighborhoods – are stable and overlap in rich and complicated ways with the neighborhoods of others. The implicit argument in Coleman (1966) and Hagerstand (1968) is that these connections are the conduit through which information and influence flow and this shapes the diffusion of new ideas and practices.

The analysis of many actors located within complex networks strains the plausibility of delicate chains of strategic reasoning which are typical in game theory. Similarly, the 'local' interaction in social networks makes anonymous competitive equilibrium analysis implausible. This tension between the small and the large is fundamental to understanding behavior and it posed a challenge to the theory of the 1980's and motivated a major advance: a framework with multiple agents, making repeated choices and embodied in a stable social network. Early papers in this tradition include Bala and Goyal (1998, 2001) and Ellison and Fudenberg (1993).

I focus on Bala and Goyal (1998, 2001) as it presents a framework that combines a general model of networks with individual choice and learning dynamics. The key innovation is embedding rational individuals in a (directed) network. Individuals do not know the true value of different actions. So they experiment individually, use their own past experience, but they also use the experience of their friends and neighbors to guide their decision making. Moreover, their neighbors in turn use the experience of their friends, and so forth. In this way, information flows across the connections of a network. The interest is in understanding how the social structure shapes individual choice, belief dynamics and the diffusion of actions.[2]

Bala and Goyal (1998, 2001) develop a number of general results. Their first result draws out an important implication of network connections: if two individuals are directly or indirectly linked then, in the long run, they will learn from each other and make similar decisions

[2]For a survey of other early attempts to embed individual choice within social structure, see Kirman and Zimmerman (2001).

and earn the same amount. Thus local learning ensures that all agents in a *connected* society obtain the same utility, in the long run. Second, they show that highly connected *'hub'* players can hinder learning and the diffusion of desirable practices. Thus societies with influential 'hub' nodes may get locked into inferior practices. Third, they develop sufficient conditions on social structure – a combination of connectedness and local autonomy (that allows space and time for individual experimentation) – that guarantee convergence to the optimal action. Fourth, the simulations of the model generate patterns of diffusion through local spread that are consistent with observed empirical patterns.

Furthermore, the methodological innovations in the framework are worth noting. These papers introduced a number of concepts from graph theory – directed graphs, connectedness, inequalities in connectivity (hubs and spokes), and the combination of node heterogeneity and network structure. Second they located incomplete information, individual beliefs revision and dynamics of choice within a directed graph. This combination of individual choice and graphs is central to subsequent work on networks in economics.

These papers mark a radical departure with the traditional model in economics, as practiced in the 1980's. At that time, as pointed out above, economists focused their efforts at understanding single agent learning or public learning. The work in the early 1990's introduced graphs – with their attendant concepts. This permits the study of large social groups with overlapping neighborhoods. It goes beyond the established models for small groups as well as those that dealt with large groups. These early papers on social learning also foreshadow some of the tensions in the literature that shape current research practice. I briefly turn to this tension now.

The goal of the papers was to understand how Bayesian/fully rational individuals learn in a social network. The complications involved in making inferences about what neighbors observe and learn obliged the authors to make the assumption that an individual ignores the information about actions and experience of neighbors of neighbors possibly contained in the choice of action of the neighbor. This simplifying assumption reflects a tension that is a recurring theme in the research in networks. The tension arises from problems of tractability: models with fully rational agents and general network structures are difficult to analyze, especially in terms of deriving a clear relation between the network structure and individual behavior. It is also difficult to incorporate heterogeneity in a tractable way within a network model with fully rational agents.

As interest in social networks has grown, interest has moved to the study of a tighter characterization of how social networks shape learning. These questions pose difficult technical challenges and held up progress for a number of years; it is only now, in the last five years or so, that there has been a revival of interest in learning and diffusion in social networks. This new research has proceeded broadly along two lines: one strand of work has simplified the individual decision making ingredient of the model and focused attention on rich social networks and individual heterogeneities. The other strand maintains (and generalizes) the assumptions on individual beliefs and decision making but works within a special class of networks.

The potential of the first line of attack is well reflected in the papers that build on the DeGroot model (1974) of opinions and consensus; see DeMarzo, Vyanos and Zweibel (2003), Golub and Jackson (2010, 2012). In their recent work, Golub and Jackson (2010, 2012) provide a number of important results on this subject. In their 2010 paper, building on the work of DeMarzo, Vyanos and Zweibel (2003), they show that vanishing social influence is both necessary as well as sufficient in a context of naive learning to guarantee that complete learning obtains in a large society. This result nicely complements the analysis of incomplete learning in the Bala and Goyal (1998) framework, and it illustrates the value of moving to a simpler, reduced form, model of beliefs and choice. In their 2012 paper, Golub and Jackson study how the speed of learning in a society depends on homophily: the tendency of agents to associate disproportionately with those having similar traits. When agents' beliefs or behaviors are developed by averaging what they see among their neighbors, convergence to a consensus is slowed by the presence of homophily, but is not influenced by network density. The key contribution is a new measure of homophily based on the relative frequencies of interactions among different groups. These findings are very important in view of the presence of homophily in social relations (reported below in the network formation section).

The second strand of the literature maintains the assumption of Bayesian/rational decision makers: as the belief dynamics are generally non-linear, there are technical hurdles to a full understanding of the role of social networks in shaping learning and rates of convergence. This challenge has motivated an interesting program of research; recent contributions include Acemoglu et al (2011), Jhadbabaie, Molavi, and Tahbaz-Salehi (2013), Mossel, Sly and Tamuz (2015) and Mueller-Frank (2013), and others.

The work of Acemoglu et al (2011) reflects the potential in this line of work. This paper builds on the pioneering work of Banerjee (1992) and Bikhchandani, Hirshleifer (1993) and combines it with the theory of random graphs. There is a single sequence of privately informed individuals who take one action each. Before making his choice an individual gets to observe the actions of all the people who have made a choice earlier. The actions of his predecessors potentially reveal their private information. An individual can therefore use the information revealed via the actions of others along with his own private information to make decisions. The principal question is: do individuals eventually learn and choose the optimal action?

In their work, Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992) showed that there was a possibility of herding on the inefficient action. In their model all individuals observe everyone who has gone before them, before making a choice. Acemoglu et al (2011) relax this assumption. They propose that an individual draws a sample from the past individuals. The focus is on properties of the properties of sample. They show that learning is complete and the optimal action is chosen with probability 1 if the sample is 'expanding': expanding observations implies that the probability of an agent being observed goes to 0 as we move across time. This in turn means that there is a bound on the influence an individual can have in the long run. This is sufficient to ensure that privately generated information is not blocked out and that agents eventually choose the optimal action, in the long run.

The details of the arguments and the technical methods differ across the three papers discussed above – Bala and Goyal (1998), Golub and Jackson (2010) and Acemoglu et al. (2011) – but they point to a similar idea: in an information rich world social learning obtains when no single individual exercises social influence.

The initial motivation underlying the study of social learning in networks came from the empirical patterns on spatial and temporal diffusion of ideas, products and technologies. As the theoretical work has progressed, economists have examined the empirical implications of networks for learning and diffusion of networks. Important contributions to this line of work include Conley and Udry (2010) and Banerjee et al (2013). For a survey on the role of networks in economic development, see Munshi (2014).

Conley and and Udry (2010) investigate the role of social learning in the diffusion of a new agricultural technology in Ghana. The novelty of their work is a detailed description of each individual farmer's information neighborhood. They find evidence that farmers adjust their inputs to align with those of their information neighbors who were particularly successful in previous periods. As a check on the interpretation of these social learning effects they also study input choices for another crop, of known technology: there are no social learning effects in the latter case.

Banerjee et al. (2013) study the diffusion of micro-finance in Indian villages. They exogenously vary the 'injection points' of information across villages and ask how differences in network characteristics of the initial seeding nodes affects eventual adoption of micro-finance. Their main finding is that micro-finance is significantly higher when the injection points have higher eigenvector centrality. The authors also estimate a model of information diffusion and adoption using detailed data on demographic and network variables. These papers mark a departure from the earlier tradition of empirical work in its explicit treatment of network architecture. It also implicitly hints at the substantial advances in data availability and computing power. Big data is a broad scale technological change and this empirical work reflects an important point of contact with economics.

By way of summary, this case study brings out three general points. The first is methodological: around the early 1990's we see the first set of models that incorporate individual choice and network structure within a common framework. This marks a major advance in the conceptual framework and it brings the concepts and the insights of graph theory and networks into the mainstream of economics. This expansion also points to problems of tractability that shape future research. The second is the collection of analytical results: the role of social structure, in particular the role of hubs in shaping learning and creating blockages and lock-ins. These results motivate a large and flourishing current research programme on how structure shapes behavior; a prominent instance of this is the large body of work on games on networks.[3] The third point is the move toward the study of large data sets on networks and of dynamics of behavior on these networks. This hints to the impact of big data on research in economics; we will return to this point again in subsequent sections. Finally, the case study highlights how an economic approach combines with networks to deliver insights in areas that were previously the reserve of sociologists and geographers.[4]

3 The origins of networks

The finding that the social structure has large effects on individual behavior and well-being motivates an examination of the structure of social networks and very quickly leads to a study of their origins. This section develops the second part of the argument – the emergence of entirely new research questions – and presents a case study of the theory of network formation.

At the very outset, it is worth emphasizing the novelty of the approach: the traditional approach in sociology and related social sciences focuses on the effects of social structure on

[3]For early work in this field, see Goyal and Moraga (2001), Bramoulle and Kranton (2007) and Ballester, Calvo-Armenogol and Zenou (2006); for surveys of this work see Goyal (2007) and Jackson and Zenou (2014).

[4]One of the distinctive aspects of research on networks in economics is that it is concurrent with a very broad interest in networks across the social and the information sciences. For a discussion of the distinctiveness of the economic approach and the many points of contact and overlap between the different disciplines, see Goyal (2007).

behavior (Granovetter (1985), Smelser and Swedberg (2005)). The economic approach to network formation locates the origins of networks in individual choice. It therefore puts the traditional approach firmly on its head!

The second and equally interesting point to note is that a 'framework', once in place, begins to formulate entirely new questions, questions which would have appeared meaningless or without any great interest prior to its emergence. The new questions on network formation deepen the original investigations – on the effects of networks on individual behavior and learning dynamics – and they expand and reshape the research programme in a profound way.

The key innovation is the idea that the social (and economic) structure itself is created through purposeful individual activity. This is a powerful idea and it has had far reaching effects: it has deepened our understanding of classical questions in economics and the other social sciences and it has motivated altogether new lines of enquiry.

The beginnings of the theory of network formation can be traced to the work of Boorman (1975), Aumann and Myerson (1988) and Myerson (1991). The general framework and a systematic theory of network formation was first presented in Bala and Goyal (2000) and in Jackson and Wolinsky (1996). The two papers present complementary approaches to the process of network formation. Over the past two decades, this has been a very active field of research; one of its great successes has been a wide and expanding range of applications. As the applications have progressed, empirical analysis and experimental investigations have also gathered momentum.

In this section I briefly sketch the building blocks and some of the main insights of the theory of network formation. I then illustrate the scope of the theory through a discussion of two classical questions in the social sciences.

I first take up the approach of **unilateral link formation**. This approach was introduced in Goyal (1993) and systematically studied in Bala and Goyal (2000). Consider a collection of individuals, each of whom can form a link with any subset of the remaining players. Link formation is unilateral: an individual can decide to form a link with another individual by paying for the link. It takes time and effort to sustain a link. A link with another individual allows access, in part and in due course, to the benefits available to the latter via his own links. Thus individual links generate externalities whose value depends on the level of decay/delay associated with indirect links. As links are created on an individual basis, the network formation process can be analyzed as a noncooperative game. The paper allows for general payoffs — increasing in number of people accessed and declining in number of links formed.

There are interesting practical examples of this type of link formation – hyper-links across web-pages, citations, 'following' relations on Twitter, and gifts. But the principal appeal of this model is its simplicity. This simplicity allows for a systematic study a number of central questions concerning social and economic networks.

Bala and Goyal (2000) provide a characterization of the architecture of equilibrium networks. The equilibrium networks have simple architectures: star (hub-spoke) networks and the cycle are salient. This prediction of great heterogeneity in connections and the presence of highly connected 'hub' nodes is an important theoretical contribution. In the star network, the central hub node will generally earn much larger payoffs as compared to the peripheral nodes. Thus, the theory provides a foundation for the idea that social structures may sustain great inequality. This part of the theory ties in closely and gains significance in the context of the earlier discussion on patterns of social learning in networks with highly connected hubs.

Bala and Goyal (2000) also introduce the study of dynamics of linking: at every point, individuals may revise their current links. Their main insight is that individual efforts to access benefits offered by others lead, rapidly, to the emergence of an equilibrium social network, under a variety of circumstances. This provides a foundation to the idea that certain social structures – including those that are very unequal – may be dynamically stable.

One virtue of the unilateral link formation model is that it allows us to combine graphs and the tools of non-cooperative game theory. This approach has subsequently been used in the study of a variety of economic problems. For a survey of this work, see Bloch and Dutta (2012) and Goyal (2007).

I turn next to **two-sided or bilateral link formation**. This approach was introduced and developed in Jackson and Wolinsky (1996). A link between two players requires the approval of both the players involved. This is the natural way to think about link formation in a number of social and economic contexts such as the formation of friendship ties, co-authorship, collaborations between firms, trading links between buyers and sellers, and free trade agreements between nations.

The simplest way to think of two sided link formation is to imagine an announcement game along the lines of the game sketched by Myerson (1991). Each player announces a set of *intended* links. A link between two individuals A and B is formed if both A and B announce an intention to create a link. In a context where links are two sided there are elements of "cooperation" involved in the formation of a link, and so solving such games calls for new concepts.

It is useful to begin the discussion with the familiar notion of Nash equilibrium as this will illustrate some of the conceptual issues that arise in the study of network formation with two-sided links. If every player announces that she wants to form no links then a best response is to announce no links. In other words, the 'empty' network is a Nash equilibrium for any network formation game. To overcome this type of coordination failure, Jackson and Wolinsky (1996) propose the concept of *pair-wise stable networks.*

A network is said to be pairwise stable if no individual wishes to delete a link and if no two unlinked individuals wish to form a link: Pairwise stability looks at the attractiveness of links in a network g, *one at a time*. Formally, every link present in a stable network must be profitable for the players involved in the link. For every link not present in the network it must be the case that if one player strictly gains from the link then the other player must be strictly worse off.

The second important contribution of the Jackson and Wolinsky (1996) paper was the result on a conflict between stability and efficiency. This highlights the pervasive externalities in linking activity and is a recurring theme in the subsequent research in this area.

The great attraction of pairwise stability is its simplicity. For any network it is relatively easy to check whether the two conditions are satisfied. The theoretical properties of this solution concept have been developed systematically and the solution concept has been widely applied; for a survey of this work, see Bloch and Dutta (2012) and Jackson (2008).

The network formation framework has motivated a vibrant theoretical, empirical and experimental literature. For book length overviews, see Goyal (2007) and Jackson (2008). For a recent overview on network formation models and applications, see the handbook on social economics edited by Bisin, Benhabib and Jackson (2012).

One of the great successes of this research has been an extensive set of economic applications. Examples of this work include formation of research collaboration networks (Goyal and Joshi, 2003), core and periphery in networks (Hojman and Szeidl, 2008), structural holes in trading networks (Goyal and Vega-Redondo, 2007), networks and coordination (Goyal and Vega-Redondo, 2005; Jackson and Watts, 2002), co-author networks (Jackson and Wolinsky, 1996), collusion networks (Belleflamme and Bloch, 2004), information networks (Galeotti and Goyal, 2010), peer networks (Cabrales, Calvo-Armengol and Zenou, 2011), labor market networks (Calvo-Armengol, 2004; Calvo-Armengol and Jackson, 2004), buyer-seller networks (Kranton and Minehart, 2001), risk-sharing networks (Ambrus, Mobius and Szeidl, 2014; Ambrus, Chandrashekhar and Elliott (2014), Bloch, Genicot and Ray, 2008; Bramoulle and Kranton, 2007), financial networks (Babus, 2008; Cabrales, Gottardi and Vega-Redondo, 2013; Farboodi, 2014), cyberattack and network design (Goyal and Vigier, 2014; Acemoglu, Malekian and Ozdaglar, 2014) and free-trade agreement networks (Goyal and Joshi, 2006; Furasawa and Konishi (2007)).

I now discuss two applications of this approach that highlight its ability to address important open questions in the social sciences.

Homophily and Social Structure: An important strand of the research examines the effect of heterogeneity on social networks. This work asks how differences in costs and benefits of linking affect linking behavior and shape the overall social network. Early work in this field extended the basic network formation model and looked for equilibrium or pairwise stable networks (for an overview, see Goyal, 2007). In more recent years, interest has shifted to dynamic models of linking and the key element explored is *homophily.*

It is generally agreed that human relations exhibit *homophily*: individuals prefer to be friends with others like themselves. There is a long and distinguished literature on patterns of homophily in friendships. For an influential early discussion, see Lazarsfeld and Merton (1954); for a recent survey, see McPherson, Smith-Lovin and Cook (2001).

Three empirical regularities have been highlighted in this literature. One, larger groups tend to form more same-type ties and fewer other-type ties than small groups. Two, that larger groups form more ties per capita. Three, all groups exhibit an inbreeding bias: there are more friendships within a group relative to fraction in population (with the greatest bias being in middle-sized groups).

Currarini, Jackson and Pin (2009) develop a model of friendship formation that helps to explain these homophily patterns. Individuals have types and access type-dependent benefits from friendships. The innovation here is the model of friendships: individuals form friendships taking into account their preferences and the relative proportions of different types in the population. The authors examine the properties of a steady-state equilibrium of a matching process of friendship formation. They show that the three empirical regularities arise as properties of the steady state social relations if preferences exhibit biases.

The study of homophily and its consequences for inequality and segregation is a very active field of research currently; see e.g., Bramoulle et al. (2014).

The Law of the Few: The classical early work of Lazarsfeld, Berelson, and Gaudet (1948) and Katz and Lazersfeld (1955) investigated the impact of personal contacts and mass media on voting and consumer choice with regard to product brands, films, and fashion changes. They found that personal contacts play a dominant role in disseminating information which in turn shapes individuals decisions. In particular, they identified 20 percent of their sample of

4,000 individuals as the primary source of information for the rest. Moreover, there exist only minor differences between the observable characteristics of the influencers and the others. Recent empirical work on virtual social communities reveals a similar pattern of communication. How do we account for this pattern of specialization?

Galeotti and Goyal (2010) propose a model to study this question. This model combines the Bala and Goyal (2000) model of network formation with a model of local public goods developed by Bramoulle and Kranton (2007). They study a setting in which individuals choose to personally acquire information and to form connections with others to access the information these contacts acquire. Their main finding is that every (strict) equilibrium of the game exhibits the law of the few. The network has a core-periphery architecture; the players in the core acquire information personally, while the peripheral players acquire no information personally but form links and get all their information from the core players. The core group is small relative to number of individuals. They also show that a small heterogeneity in costs of acquiring information has strong effects: the individuals who have slightly lower costs of acquiring information constitute the core and acquire all the information. Thus strategic forces amplify small initial differences to create large differences in behavior and location in social structure.

A number of subsequent papers have explored models that combine behavior and formation of structure; see e.g., Baetz (2014) and Hiller (2013).

The theoretical research on network formation has been accompanied by a growing sophistication in empirical investigations on the structure and dynamics of networks. It is useful to view this work as dealing with small and large networks. Small networks may involve oligopolistic firms or countries (and range from a few nodes to a hundred nodes), while large networks involve scientists, individual consumers, or web pages (and may contain from hundreds of thousands to millions of nodes). The theoretical models in economics provide a good account for the stylized features of small and medium sized networks but these models do not account well for the complexities of large and massive networks. As computational power has grown the interest and ability to map very large networks has also grown. This gap between the successful theoretical game theoretic models and the properties of large empirical networks now presents a major challenge to the received theory.

Empirical contexts appear to be rich in heterogeneity and in dynamics: this suggests that individuals will have limited information on the identity of nodes and on the structure of the network. An early response to this complexity is a paper by Jackson and Rogers (2007).

They present a dynamic model of linking where newly born nodes use a combination of random linking and network based linking to form new networks. The linking follows plausible rules of thumb and individuals do not take into account the effects of their actions or the evolution of the network in making their choices. Nevertheless, the dynamics of linking generate a concrete set of predictions on network structure as a function of key parameters, such as the ratio of random versus network based linking. The model provides us with a mechanism that shapes network evolution. In this sense it is close to the models in physics and mathematics. However, as the micro structure is kept minimal – preferences, information and choice is not modeled explicitly – it is unclear how one can make use of the model for normative or for policy experimentation. There is thus a tension between the standard approach in economics and the need to account for large scale empirical networks.[5]

Empirical work also suggests that a relation between two individuals have different facets: a link may typically performs a variety of functions and that they are interrelated. Existing theoretical work on the other hand assumes that a network performs a single function and studies this role in isolation. Moving from single role networks to multiplex networks is an important challenge for future work.

To summarize, the theory of network formation provides an account for how individual action shapes social and economic structure. In founding a theory of social structure upon individual choice, it presents a major departure from earlier traditions in sociology and the other social sciences. The theory combines elements of the theory of games with probability theory and graph theory. It offers insights into a variety of real world phenomena, especially in the context of small and medium size networks. There, however, remains a tension between the stark predictions of the successful models of network formation and the complex properties of large and evolving networks.

4 The route to normal science: prices, competition and networks

At the start and through the 1990's, research on networks focused on behavior in given networks and on the theory of network formation. I would say that this research proceeded at

[5]Galeotti et al (2010) present one resolution to this tension. They assume that individuals have limited and local information of the complex network in which they are embedded. This leads them to develop a model of incomplete private information and examine how variations in the strategic structure of the game, the depth of network knowledge and the underlying network structure jointly shape behavior.

a 'pure' and 'general' level with relatively little connection to applications. But, by the end of the decade, economists working in networks began to address specific economic questions and, as they did so, they began to develop models that included competition, prices and markets. Indeed, the last decade has seen the emergence of a very rich and thriving research programme in which these standard economic concepts play a central role. In this respect, there is a close analogy with the spread of game theory during the 1980's and 1990's in one applied field after another in economics. We are beginning to see a similar trend with networks.

The aim of this section is to illustrate this development through a discussion of a few notable examples. I find it useful to distinguish between 'social' and 'economic' networks; while this distinction is a little artificial in some applications, it is helpful in organizing the discussion.

4.1 Economic Networks and Markets

In the classical Walrasian model it is assumed that individuals are anonymous, that they can all trade with each other and that this trade takes place at a common price. In real world markets buyers and sellers develop durable relations of exchange, these relations are personal and that there are definite limitations on who can trade with whom. Moreover, terms of trade differ across traders and that they depend on the network structure of relations; for empirical evidence see e.g., Uzzi (1993), Kirman and Vignes (1991), among others. These findings lead us to view markets as networks. We are then led to ask what are the incentives of buyers and sellers to form durable relations?

I start with a discussion of the **market as a network**. Kranton and Minehart (2001) consider a model with two stages. In stage 1, buyers unilaterally choose to form links with sellers. These links enable buyers to procure goods or inputs. Buyers trade-off expected gains from trade against costs of link formation.[6] In stage 2, the valuations of buyers are realized; they then engage in trade with sellers restricted by the network structure defined in the first stage. The trading in stage 2 takes place through a centralized auction where at each price efficient matches are determined.

The paper establishes two major results: networks arise as a mechanism to pool uncertainty in demand and trade it off with the costs of establishing bilateral ties. The analysis also reveals, somewhat surprisingly, that an efficient allocation mechanism (ex-post competitive

[6] For a related strand of the literature on buyer-seller networks with a different modeling approach – based on heuristic learning rules and random linking decisions – see Weisbuch, Kirman and Herreiner (2000).

environment) is sufficient to align the buyers' incentives to form ties with the social incentives. For a systematic recent study of inefficiencies in networked markets, see Elliott (2014).

The Kranton-Minehart (2010) model pertains to direct buyer-seller ties: the modern economy is characterized by extensive and complicated array of supply chains, that span industries and countries. A more recent strand of the literature studies pricing, contracting and competition in these supply chains (Choi, Galeotti and Goyal (2014), Gale and Kariv (2009), Goyal and Vega-Redondo (2007), Manea (2013), and Kotowoski and Leister (2012), and Nava (2014)). This work builds on the earlier tradition of games on networks. The study of supply chains is now also a major focus of study in macroeconomics: the interest here is in understanding how the network structure of production connections amplifies shocks and thereby generates more or less aggregate volatility (Acemoglu et al. (2012), Carvalho (2014)).

I now turn to the other standard model of markets: **oligopolistic competition.** The standard model of oligopoly assumes that firms non-cooperatively set prices (or quantities). Empirical work suggests that collaboration between firms is common. This collaboration takes a variety of forms, which include creation and sharing of knowledge about markets and technologies, the setting of market standards and the sharing of facilities (such as distribution channels or plane capacity). Typically, collaboration ties are bilateral and are embedded within a broader network of similar ties with other firms. Considerable asymmetries exist between the level of collaborative activity across firms, with some firms forming several ties whereas others are poorly linked (Powell 1990; Hagedoorn, 2002; Gulati, 2007). This empirical evidence motivates the study of the relation between oligopolistic market competition and collaboration networks.

Goyal and Joshi (2003) present a framework for the study of these issues. The two ingredients are a model of bilateral link formation and the standard textbook model of oligopoly. The innovation here is a general model of bilateral linking. Prior to competing in the market, firms can form pair-wise collaborative links with other firms. These pair-wise links involve a commitment of resources and lead to lower costs of production of the collaborating firms.

Goyal and Joshi (2003) show that incentives to form links are closely related to market competition: in a standard homogenous good model if competition is in prices, firms choose to form no links, while if competition is in quantities, then firms typically form dense but asymmetric networks of collaboration. Thus collaborations are used by firms to generate competitive advantage. Moreover, market competition shapes networks and these networks in turn define the competitiveness of firms in a market. This two-way flow of influence between markets and networks is central to understanding economic activity.

Collaboration networks in markets remains an active field of research; recent papers explore socially optimal networks and the scope of public policy (Koenig et al. (2014), Westbrock (2010)).

In the applications above, I have considered direct ties between buyers and sellers or between firms. I now turn to **intermediation**. The financial sector embodies intermediation in a pure form – that between the sources and the eventual users of savings. Traditional models of the banking sector generally pay little attention to the rich patterns of intermediation within the sector. Following the financial crises of 2008, there has been renewed interest in the role of interconnections among financial institutions as a source for the transmission and possible amplification of shocks. Consequently, a number of papers have documented the structure of the inter-bank lending network, see e.g., Bech and Atalay (2010), Afonso and Lagos (2012), Van Lelyveld I., and t' Veld (2012). The broad consensus is that this network has a core-periphery structure: there is a core of large banks that are densely interconnected, and a large number of smaller banks at the periphery. There is a net inflow of funds from the peripheral banks to the core banks. These empirical findings motivate the study of economic mechanisms underlying the formation of core-periphery financial networks.

In a recent paper, Farboodi (2014) develops a model of the financial sector in which banks choose to form endogenous intermediation links with each other. There are banks that have links with depositors and banks that have links with potential investors. A link between two banks is a durable relationships. Links are unilateral: a link from A to B constitutes a commitment from A to honor any loan demand from B. A bank has an incentive to form multiple links and be the intermediary between a source bank and a destination bank as it can then earn 'rents'. Farboodi (2014) shows that a core-periphery network endogenously emerges as an equilibrium outcome. An important result is that the network is inefficient as banks who lend to investors 'over-connect', exposing themselves to excessive counter-party risk, while (depositor linked) banks who mainly provide funding end up with too few connections. This creates excessive risk in the system at large.

This paper builds on the early work of Allen and Gale (2000) and Babus (2006) in financial networks and Goyal and Vega-Redondo (2007) in the theory of network formation. It is also part of the recent flurry of activity in the area of financial networks: other recent papers include Allen, Babus and Carletti (2012), Acemoglu, Ozdaglar and Tahbaz-Salehi (2015), Cabrales, Gottardi and Vega-Redondo (2012) and Elliott, Golub and Jackson (2014).

4.2 Social Networks and Markets

In this section, I discuss the interaction between social ties between individuals – examples include friendships, family ties, street neighborhoods, caste, race and religious affiliations – and markets. As a first approximation, these ties may be taken as given and external to the specific economic problem being studied.[7]

I start with a discussion of **social networks in product markets**. In the standard product market model a firm chooses prices, advertising strategy and quality taking as given heterogenous consumer preferences (Tirole (1994)). The role of friends, neighbors, and colleagues in shaping consumer choice has been brought out in a number of studies over the years. In the past, the practical use of such social influences for advertising or pricing was hampered by the lack of good data on them. The growth of the Internet and the large amounts of data on online social networking along with the other advances in information technology have made it considerably easier to gather data on social networks and have led to an explosion in interest on how firms and governments can harness the power of social networks to promote social and private goals. Practical interest has centered on questions such as: for which product categories are networks important and when are they unimportant; what are the relevant aspects of networks; how should a firm use social networks to promote its product; how much should a firm be willing to pay to acquire information about social networks and how should a firm compete with other firms on social networks.

Galeotti and Goyal (2009) study the optimal strategy of a firm that wishes to reach maximum number of consumers located in a social network. The firm chooses whom to target with advertisements, under the assumption that advertisements travel through connections. They show that the optimal strategy involves targeting more connected nodes in some cases and poorly connected nodes in other cases. The use of social networks always leads to higher sales and greater profits. However, an increase in the level and dispersion of social interaction can have non-monotonic effects on level of optimal strategy. Finally, they also show that the returns to investing in market research on social networks are greater in more unequal networks.

These results are obtained in a setting with one firm, with one step spread of advertisement,

[7]The effect of social networks on economic life is the subject matter of economic sociology; for an overview of this work, see Smelser and Swedberg (2005). There are overlaps between the work in sociology and research on networks in economics and a deeper engagement would be mutually beneficial. But a detailed discussion of the relations will not be attempted here, as it will take me too far afield. I make some general remarks on this issue in the appendix.

and with advertising strategy only. Current research extends and deepens the scope of the analysis significantly to include multiple firms, dynamics of spreading information, and to allow for pricing in addition to advertising choices (Fainmesser and Galeotti (2014), Goyal and Kearns (2012), and Campbell (2013)). The use of social networks for optimal diffusion of information remains a very active field of research in economics and in other social and information sciences.

In a related line of work, researchers have explored the use of targeted pricing strategy in social networks. In the standard network externalities literature pricing was conditional on the size of aggregate consumer base (Farrell and Saloner (1986), and Katz and Shapiro (1985)). Network externality often arises through the use of common products or services in personal interaction. So the value of adopting a product to a consumer would depend on how many of her neighbors adopt the same product. In other words, the value depends on adoption patterns in the local neighborhood. This motivates the study of optimal pricing that is sensitive to the network properties of individuals. In an important paper, Bloch and Querou (2013) analyze the problem of optimal monopoly pricing in social networks where agents care about consumption of their neighbors. They show that optimal prices are related to consumer centrality in the social network. This relation depends on the market structure (monopoly vs. oligopoly). They identify two situations where the monopolist does not discriminate between nodes in the network: linear monopoly with consumption externalities and local monopolies with price externalities. Aoyagi (2014) extends this work to allow for more general externalities and competition among several firms.

I turn next to the role of **social networks in financial markets**. This is one setting where the standard market model of anonymous traders and common prices that reveal information of traders has been very dominant. In recent years this standard view has been the subject of much attention, both empirically and theoretically. By way of motivation, I start with some empirical findings. Cohen, Frazzini and Malloy (2008) show that portfolio managers place larger bets on firms when they went to school with senior managers or a board member and perform significantly better on these holdings. Similarly, Hong, Kubik and Stein (2005) document that US fund managers located in the same city commit to correlated investment decisions. The authors argue that such correlated choices may be due to peer-to-peer communication or because fund managers in a given area base their decisions upon common sources of information. The empirical evidence motivates a more systematic study of the relation between information social networks and trader behavior and aggregate outcomes on volume and prices. Ozsoylev and Walden (2011) and Colla and Mele (2010) study asset pricing in markets where traders are located in information networks. They study trader behavior on a fixed network and derive a relation between equilibrium outcomes (on prices and trading volume) and the network topology.

I turn finally to the role of **social networks in labor markets**. Workers like jobs that suit their skills and location preferences, while firms are keen to hire workers who have the right ability for the job. However, workers do not know which firms have vacancies, and finding out the right job takes time and effort. Similarly, firms do not know which workers are looking for a job. Faced with this lack of information, workers look for job advertisements in newspapers and magazines. They also spread the word among their friends and acquaintances that they are looking for a job, and indeed there is substantial evidence that they often get information on job vacancies via their personal connections. A second type of information problem concerns the ability of workers: a person generally knows more about his own ability as compared to a potential employer. Indeed, this asymmetry in information leads workers to invest in signals of their quality (such as educational degrees, certificates and licenses), and it leads potential employers to ask for references and recommendation letters. Referrals – references and recommendation letters – are widely used in the process of matching workers and firms. A letter of reference is only valuable in so far as the employer can trust the writer of the letter; this suggests that the structure of personal connections is likely to play an important role in matching workers and firms.

These observations raise the question: how does the pattern of social contacts affect the flow of information about jobs? The flow of information across persons will influence how quickly workers are matched with jobs which will in turn shape the level of employment. The patterns of social connections will also determine who gets information and when; this in turn may determine who gets a job and who is left unemployed, which will in turn have a bearing on the distribution of earnings and overall inequality in a society. The study of social networks in labor markets has a distinguished and long history; for a survey of this work, see Granovetter (1974) and Goyal (2007). The older work has an empirical orientation. In recent years, economists have made significant progress in the theoretical analysis of this issue.

Calvo-Armengol and Jackson (2004) study a model of information transmission on job vacancies. Their analysis of this model yields three main insights. The *first* insight is that the employment status of individuals in a social network is positively correlated. Empirical work suggests that there is significant correlation in employment status within social communities or geographically contiguous city districts. The *second* insight is that the probability of finding a job is declining with the duration of unemployment. Duration dependence of unemployment has been widely documented. The reason that duration dependence arises in a context of social information sharing is that a longer spell of unemployment reveals that a person's social contacts are less likely to be employed, which in turn makes it less likely that they will pass on information concerning vacancies. The *third* insight is that small initial differences in employment across otherwise identical groups of individuals can have significant effects on the incentives to drop out of the labor market. However, if individuals drop out of the social network then this reduces the value to others of remaining in the network. Thus small initial differences can create a sequence of drop outs, which in turns can have long run effects on employment prospects of the group.

Montgomery (1991), studies the adverse selection problem in labor markets. The analysis of this model yields two key insights. The *first* insight of the analysis is that workers with more connections will earn a higher wage and that firms who hire through contacts (of their existing high quality workers) will earn higher profits. The reason for this relation between connections and wages is simple: more connections implies a higher number of referral wage offers from firms (on average) and this translates into a higher accepted wage (on average). The *second* insight is that an increase in the density of social connections raises the inequality in wages. This effect is a reflection of the lemons effect: an increase in social ties means that more high ability workers are hired via referrals, and this lowers the quality of workers who go into the open market, thereby pushing down their wage, relatively.

In Calvo-Armengol and Jackson (2003), prices and competition do not play a role, while in Montgomery (1991) there is no modeling of network topology. The integration of network topology with the usual ingredients of pricing and competition remains a challenging open problem.

5 Closing the circle

The study of networks is one of the most dynamic and exciting fields of research in contemporary economics. The research ranges across theory, experiments and empirics. The models address an increasingly wide and ambitious range of questions using mathematical models and statistical techniques that in turn draw on a variety of disciplines. In this paper, my aim has been to locate the innovation that networks bring to economics, to assess the current state of research and to point to current challenges.

I have argued that research on networks in economics started with theoretical innovation in the early 1990's. At the start, both the research on social learning and the research on network formation emerged in relative autonomy from applications and empirical work. When the results came in contact with substantive issues in economics this research gathered momentum. It generated new questions that built on the research and lent the programme greater significance. In the last decade the innovations have matured; now they combine with pre-existing concepts – such as competition, asymmetric information, and prices – to build an encompassing framework. In the words of Kuhn (1962), research on networks in economics has acquired the traits of 'normal' science.

I have also identified a persistent and growing tension between (much of) the theoretical research and the empirical findings on behavior and structure of large and complex networks. This tension should not come as a surprise: traditionally, economists have been successful at developing concepts for the study of interaction in small closed groups (game theory) and interaction among large groups (competitive markets and general equilibrium). A social network typically consists of a large number of individuals and any individual interacts only with a small subset of them. The analysis of many actors located within complex networks strains the plausibility of delicate chains of strategic reasoning which are typical in game theory. Similarly, the 'local' interaction in social networks makes anonymous competitive equilibrium analysis implausible. Thus networks fall between the 'small' and the 'large'. So, while much has been accomplished, I believe that this tension will continue to offer a fertile ground for new and exciting research in the years to come.

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