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NETWORKS AND MARKETS

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Abstract

Networks influence human behavior and well being, and realizing this, individuals make conscious efforts to shape their own networks. Over the past decade, economists have combined these ideas with concepts from game theory, oligopoly, general equilibrium, and information economics to develop a general framework of analysis. The ensuing research has deepened our understanding of classical questions in economics and opened up entirely new lines of enquiry.

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1 Introduction

Our life takes place at the intersection of the global and the local: we function in a world dominated by large firms and international markets, but we also inhabit small and overlapping neighborhoods of friends and family, colleagues and collaborators. Game theory is well suited for the study of behavior in small exclusive groups while general equilibrium theory provides a sophisticated approach to the understanding of large anonymous systems. Networks offer us a framework that combines local interactions within large interconnected populations. In doing so, they fill an important gap in the toolkit of economists.

The key methodological innovation of the early research on networks in the 1990's was the introduction of graph theory alongside purposeful agents. Two ideas were central: the study of how the network architecture shapes human behavior and the study of how purposeful individuals form links and thereby create networks. Over the past decade, economists have developed models that include networks, alongside the familiar notions of strategy, information, prices and competition. These models are now being applied to address an increasingly ambitious range of questions in economics. I see here a close analogy with the spread of game theory in economics, during the 1980's and 1990's, in one applied field after another.[1]

I begin by developing notation and basic concepts on networks in Section 2.

Section 3 outlines a framework that combines individual choice, networks and markets, while section 4 introduces the elements of an economic theory of network formation.[2]

The rest of the paper is devoted to a discussion of economic applications. There has been very rapid growth in research in this field over the last decade. In my presentation, I will favour lines of work that explicitly combine network ideas with familiar models of markets.

Section 5 deals with macroeconomic fluctuations. An understanding of their origins remains a fundamental question in economics. The dominant view is that aggregate fluctuations cannot be caused by sector specific shocks as we would expect that there are many such shocks taking place, and that they would cancel each other out. This section develops a model in which profit maximizing firms are located on nodes and the links reflect production linkages across sectors. Production decisions of firms are coordinated through prices in competitive

[1] For an overview of the early work on networks, see the previous invited lecture on networks, delivered at the 2005 Econometric Society World Congress (Jackson, 2006). The present paper focuses on developments in the theory of networks; for a survey of empirical work, see the companion piece by de Paulo (2016).

[2] For a more systematic and extensive exploration of these two general themes (the effects of networks on behavior and on how individuals create networks), see Goyal (2016). Easley and Kleinberg (2010) offers a general introduction to networks; Bramoulle, Galeotti and Rogers (2016) provides an overview of recent research on the economics of networks.

markets. I show how sector specific shocks may be amplified by the network structure – viz. the existence of general purpose technologies – to generate aggregate fluctuations.

Sections 6 and 7 turn to the study of trading and market power. In section 6, I study direct trade between buyers and sellers (with no resale). In the real world, buyers typically trade only with a subset of sellers. By contrast, in the standard Walrasian model, all agents can trade with each other at a common price. The first goal is to understand how this 'incompleteness' of direct trading relations affects economic activity. I study price formation in a network of buyers and sellers. The analysis provides an elegant network foundation for Walrasian competitive outcome: local trading relations must mirror the global buyer/seller surplus. The analysis also tells us how network structure shapes the distribution of earnings. As individuals are aware of the network in shaping their earnings, they seek to form links to create the 'right' networks. I show that linking activity among traders is rich in externalities. The discussion then moves on to conditions under which trading networks thus created are efficient.

Section 7 studies intermediation, a defining feature of the modern economy. Intermediation is prominent in agriculture, in transport and communication, in international trade, and in finance. I begin with a study of pricing games on intermediation networks and discuss how the pricing protocol and the network jointly shape pricing and define market power. The discussion highlights the role of critical nodes – nodes that lie on all paths in a network – in shaping behavior. I then turn to link formation by individuals who seek to extract intermediation rents. The analysis once again highlights the role of externalities and provides a theoretical foundation for the empirically salient core-periphery networks.

Section 8 takes up the role of social networks in labor, product and financial markets. Information asymmetries are an important feature of these markets. I begin with the empirical observation that a large fraction of jobs at all levels of the economy are obtained through social connections. This leads me to study the role of networks in shaping wages, unemployment and inequality. I then turn to product markets: social connections shape tastes and provide access to information. This motivates the introduction of social networks in traditional models of advertising and pricing. The analysis allows me to study the ways in which governments and firms can use social networks to further their own goals. The section ends with a brief discussion on social networks in financial markets.

Section 9 takes up transport networks. The state and private firms set up a variety of transport networks and then price access to these networks. Traditionally, research has focused on pricing issues. The discussion here focuses on network design issues. I begin with the monopoly problem: what is the best way to design a network to transport passengers across a collection of cities? This sets the stage for a discussion of competition between two networks. Hub-spoke networks economize on linking costs and on path length: they are salient both under monopoly and in the duopoly setting.

Section 10 discusses the nature of the firm. It is customary to partition economic activity between firms (based on hierarchy) and markets (based on anonymous arms length relations). In practice, economic activity often takes place outside markets and hierarchy; prominent examples are research alliances and capacity sharing. I discuss behavior of firms in these two contexts and then explore incentives to form networks. The discussion brings out the importance of the two-way flow of influence: networks are shaped by competitive forces in markets, but the formation of networks also significantly alters the functioning of the 'market'.

In section 11, I turn to the dynamic interaction between social networks and markets. Markets are traditionally associated with the erosion of social relations, but empirical work also provides us with notable instances where markets strengthen social interaction. I present a framework where individuals can choose exchange through networks *and* in (frictionless) anonymous markets. The analysis shows how social structure and the strategic relation between networks and markets – whether they are substitutes or complements – jointly shape individual choice, inequality and aggregate welfare.

Section 12 concludes.

2 Networks

I begin by introducing some notation and a few basic concepts about networks that will be used throughout the paper. For a general overview of graph theory, see Bollobas (1998); for introduction of network concepts to economics, see Goyal (2007), Jackson (2008) and Vega-Redondo (2007).

A network g comprises of a collection of nodes $N = \{1, 2, ...n\}$ with $n \geq 2$, and the links (g_{ij}), $i, j \in N$, between them. A node may be an individual, a firm, a project, a city or a country, or even a collection of such entities. A link between them signifies a relation. In some instances it is natural to think of the link as bidirectional; examples include friendship, research collaboration and defence alliance. In other instances, a link is unidirectional: examples include investment in a project, citation, a web link, listening to a speech or following a tweet.

Given a network g, $g + g_{ij}$ and $g - g_{ij}$ have the natural interpretation. In case $g_{ij} = 0$ in

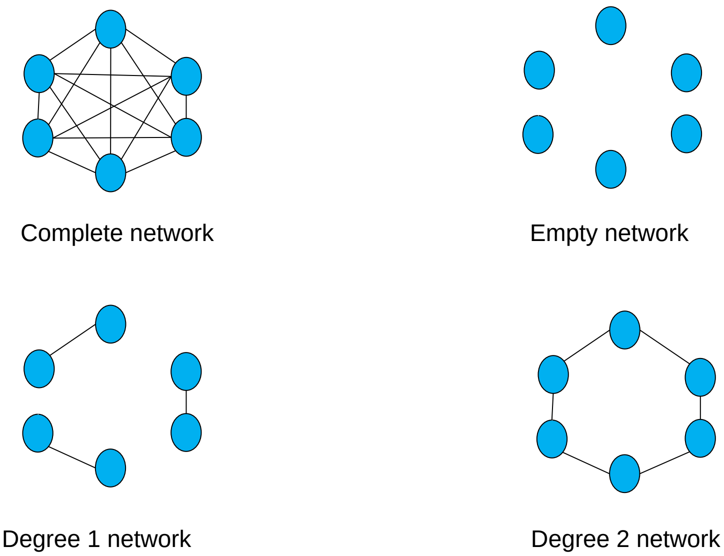

Figure 1: Regular networks

g, $g + g_{ij}$ adds the link $g_{ij} = 1$, while if $g_{ij} = 1$ in g then $g + g_{ij} = g$. Similarly, if $g_{ij} = 1$ in g, $g - g_{ij}$ deletes the link g_{ij}, while if $g_{ij} = 0$ in g, then $g - g_{ij} = g$. Let $N_i(g) = \{j | g_{ij} = 1\}$ denote the nodes with whom node i has a link; this set will be referred to as the *neighbors* of i. Let $\eta_i(g) = |N_i(g)|$ denote the number of connections/neighbors of node i in network g. Moreover, for any integer $d \geq 1$, let $\mathcal{N}_i^d(g)$ be the *d-neighborhood* of i in g: this is defined inductively, $\mathcal{N}_i^1(g) = N_i(g)$ and $\mathcal{N}^k(g) = \mathcal{N}_i^{k-1}(g) \cup (\cup_{j \in \mathcal{N}_i^{k-1}} N_j(g))$.

There is a path from i to j in g either if $g_{ij} = 1$ or there exist distinct nodes $j_1, \cdots, j_m$ different from i and j such that $g_{i,j_1} = g_{j_1,j_2} = ... = g_{j_m,j} = 1$. A component is a maximal collection of nodes such that there is a path between every pair of nodes. A network g is said to be connected if there exists one component, i.e., there is a path from any node i to every other node j.

Let $\mathbf{N}_1(g), \mathbf{N}_2(g), ..., \mathbf{N}_{n-1}(g)$ be a partition of nodes:: two nodes belong to the same group if and only if they have the same degree. A network is said to be *regular* if every node has the same number of links i.e., $\eta_i(g) = \eta \ \forall i \in N$ (and so all nodes belong to one group in the partition). The *complete* network, g^c, is a regular network in which $\eta = n - 1$, while the *empty* network, g^e, is a regular network in which $\eta = 0$. Figure 2 presents regular networks.

A *core-periphery* network contains two groups: the periphery,$\mathbf{N}_1(g)$, and the core, $\mathbf{N}_2(g)$. Nodes in the periphery have a link only with nodes in the core; nodes in the core are fully linked with each other and have links with a subset of nodes in the periphery. The star (or hub-spoke) network is a special case in which the core contains a single node. The *inter-linked star* or *multi-hub* network is a special case of the core-periphery network in which every node in the core is linked to all other nodes. Figure 2 presents core-periphery networks.

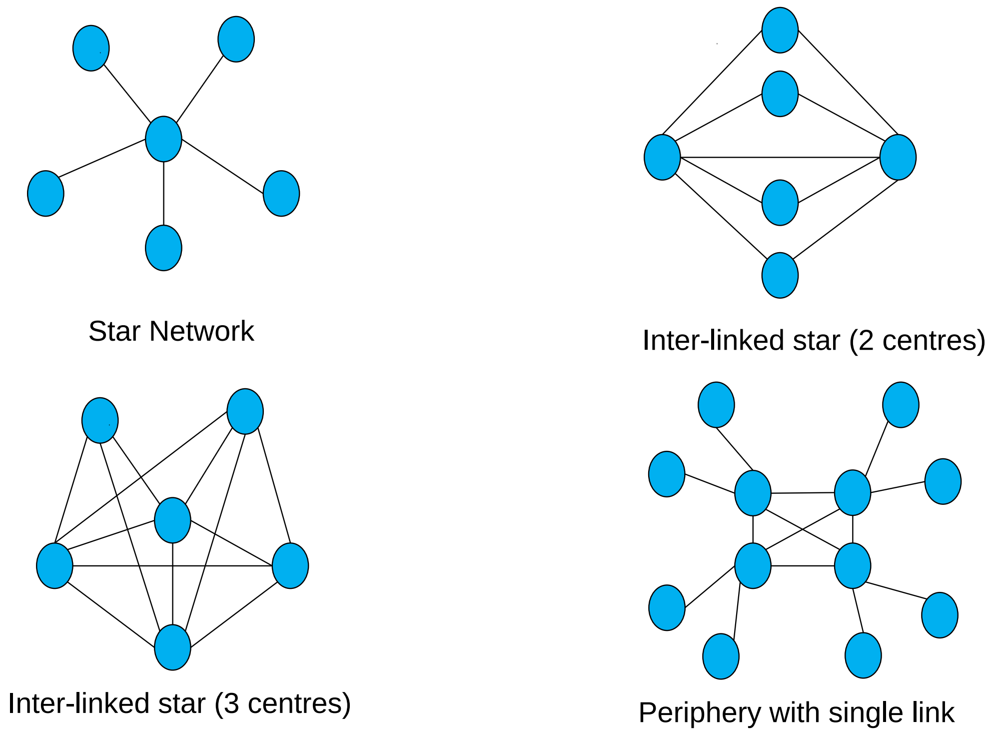

Figure 2: Core-periphery networks

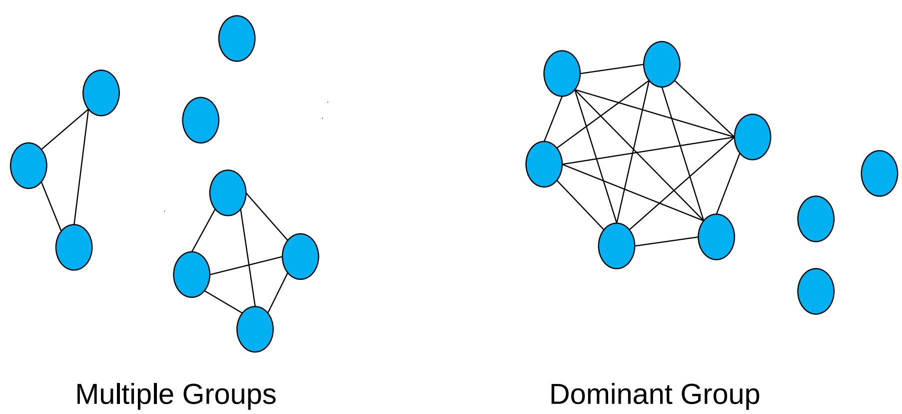

Figure 3: Exclusive group networks

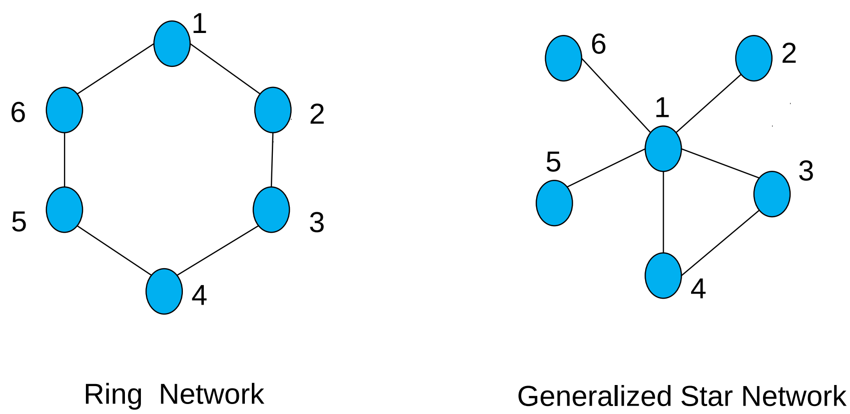

Figure 4: Differences in networks

Exclusive groups is an architecture with a group of isolated nodes $D_1(g)$ and $m \geq 1$ distinct groups of completely linked nodes, $D_2(g), .., D_{m+1}(g)$. Thus $\eta_i(g) = 0$, for $i \in D_1(g)$, while $\eta_j(g) = |D_x(g)| - 1$, for $j \in D_x(g)$, $x \in \{2, 3, ..., m+1\}$. A special case of this architecture is the *dominant group* network in which there is one complete component with $1 < k < n$ nodes while $n - k > 0$ nodes are isolated. Figure 2 illustrates exclusive group networks.

It is important to note that networks allow for a very rich range of possibilities in relationships, that go beyond degrees. To bring out this point in a simple way, consider a degree-2 regular connected network and a corresponding generalized star network with the same number of links.

Observe that as the nodes increase, 'distance' between the nodes is unbounded in the ring; distance is bounded above by 2 in the latter network. In the regular network, all nodes are essentially symmetric, while in the multi-hub network the hub nodes clearly have many more connections and are more 'central' than the other nodes. Finally, observe that in the ring, no pair of neighbors are linked, while in the latter network one pair of periphery nodes are linked (the frequency of 'connected' triads is measured by the 'clustering' coefficient).

3 Individual Choice, Networks and Markets

This section develops the elements of a framework for individual choice at the intersection of networks and markets. I will present three economic examples.

The first example concerns social learning and diffusion. The diffusion of new ideas and technologies in a society is a classical theme in the social sciences. In economics, the traditional models of diffusion examine the role of individual heterogeneity in explaining differential rates of adoption (Griliches (1957)). By contrast, there exists a long tradition of empirical work in sociology and related disciplines on the role of social connections in shaping adoption and individual behavior (Coleman (1966), Katz and Lazersfeld (1955), Rogers (1983), Ryan and Gross (1943)). Drawing on the early work of Bala and Goyal (1998, 2001), I present a model for the analysis of the dynamics of choice of technology among socially connected individuals.

Example 1 *Learning and Diffusion*

Individuals – e.g., farmers, consumers, doctors, firms – are located on nodes of a network and the links between the nodes reflect information flows between them. They choose between alternatives whose relative advantages are imperfectly known. Since rewards are uncertain, individuals use their own past experience and also gather information from their *neighbors*. The goal is to understand if information gathered from one neighbor spreads through connections to other neighbors and if everyone eventually adopts the optimal action.

There are two alternatives a_0 and a_1. Action a_0 yields 1 and 0 with equal probability. Action a_1 is an unknown technology. Its payoffs may be High or Low. In High state it yields 1 with probability 0.75 (and 0 with probability 0.25), and in Low state it yields 1 with probability 0.25 (and 0 with probability 0.75). So action a_0 is optimal in Low state and action a_1 is optimal in High state.

At the start, individual i believes that action a_1 is High with probability $\mu_i \in (0, 1)$ and Low with probability $1 - \mu_i$. Given the belief μ_i, the one period expected utility from action a_1 is given by

$$u(a_1, \mu_i) = \mu_i \pi_H + (1 - \mu_i)\pi_L. \tag{1}$$

An individual chooses an action to maximize (one-period) expected payoffs (I abstract from the information value of actions). So he chooses a_1 if $\mu_i > 1/2$ and a_0 if $\mu_i < 1/2$. At the end of the first period, every individual i observes the outcome of his own actions and those of his neighbors, $N_i(g)$ and then updates his prior μ_i, to arrive at the prior for period 2, μ_i'.[3] She then makes a decision in period 2, and so forth.

[3]In this example, a link is taken to directed: so, for instance, $g_{ij} = 1$ means that i observes j, but it does not say anything about whether j observes i. Formally, a directed link model allows for $g_{ij} \neq g_{ji}$. All the concepts introduced in section 2, for undirected networks, carry over in a natural way to directed networks.

Let the passing of time be denoted by $t = 1, 2, ...$ The goal is to understand how the network g, shapes the evolution of individual actions and beliefs $(a_{i,t}, \mu_{i,t})_{i \in N}$, over time.

Bala and Goyal (1998, 2001) first draw out a general implication of network connections: in a (strongly) connected society, all agents choose the same action and obtain the same utility, in the long run. They then examine the conditions on the network under which social learning ensures choice of the efficient action.

To fix ideas, suppose individuals are arranged around a circle and observe their immediate neighbors and in addition observe a common set of individuals (referred to as the 'Royal Family'). Bala and Goyal (1998) show that there is a strictly positive probability that everyone chooses action a_0 (even when a_1 is the optimal action), in the long run, *irrespective of the size of the population.* On the other hand, in a large society with only local neighbors (thus with no Royal Family), everyone chooses the optimal action with probability 1, in the long run. More generally, if there is an upper bound on the in-degree, then everyone will eventually choose the optimal action in a large (strongly) connected society. □

This example shows how concepts from graph theory (directed graphs, connectedness, heterogeneities in connections), taken together with results from statistical decision theory and probability theory illuminate the dynamics of diffusion. In recent years, the study of diffusion and social learning has attracted a great deal of interest, see e.g., Banerjee, Chandrashekhar Duflo, and Jackson (2013), Acemoglu, Dahleh and Ozdaglar (2011)), Gallo (2014), and Golub and Jackson (2010). For overviews of the research in this field, see Goyal (2012, 2016).

This example also draws attention to a very general finding in the research on networks: inequality in connections (reflected here in the presence of the highly connected Royal Family) can have large economic implications.

The second example combines choice, networks and markets within a common framework. The concept of neighbours plays a key role. An action that I take may raise or lower payoffs of neighbors: actions are said to create *positive externality* if an increase in their value raises the rewards of neighbours and they are said to create *negative externality* otherwise. If an increase in other's actions raises the marginal returns from own actions, the actions are *strategic complements*, while if an increase in other's actions lowers the marginal returns from own actions then we say that the actions are *strategic substitutes*. The effects of others' actions can have different effects depending on network location. So, for instance, actions of neighbors may generate positive effects while actions of non-neighbors may generate negative effects, and vice-versa. This draws attention to the rich and potentially complex interplay between action externalities and network location.

The goal is to understand how network location and structure shapes individual behavior and well being: do better connected individuals earn larger rewards as compared to poorly connected individuals? What is the best design of a network? For a general introduction to games on networks, see Goyal (2007).[4] I present an early model, taken from Goyal and Moraga-Gonzalez (2001), that introduces networks in an oligopolistic market.

Example 2 *Collaboration in Oligopoly*

Suppose demand is linear and given by $Q = 1 - p$. There are $n \geq 2$ firms. The initial marginal cost of production in a firm is $\bar{c} > 0$ and assume that $n\bar{c} < 1$. Each firm i chooses a level of research effort given by $s_i \in \mathbb{R}_+$. Collaboration between firms involves sharing of research efforts that lower costs of production. The marginal costs of production of a firm i, in an network g, facing a profile of efforts s, are given by:

$$c_i(s|g) = \bar{c} - (s_i + \sum_{j \in N_i(g)} s_j). \tag{2}$$

Note that $N_i(g)$ refers to the (undirected) neighbors. Let $\eta_i(g) = |N_i(g)|$. Research effort is costly: $Z(s_i) = \alpha s_i^2/2$, where $\alpha > 0$. Given costs $c = \{c_1, c_2, ...c_n\}$, firms choose quantities $(\{q_i\}_{i \in N})$, with $Q = \sum_{i \in N} q_i$. Using standard methods, it is possible to compute the Cournot equilibrium quantities for any cost profile c. Thus the payoffs of firm i, located in network g, and faced with a research profile s are:

$$\left[\frac{1 - \bar{c} + s_i[n - \eta_i] + \sum_{j \in N_i(g)} s_j[n - \eta_j(g)] - \sum_{l \in N \setminus \{i\} \cup N_i} s_l[1 + \eta_l(g)]}{n+1}\right]^2 - \frac{\alpha s_i^2(g)}{2}.$$

There is a positive externality across neighbors and negative externality across non-neighbors actions. Moreover, (due to the quadratic term) in the payoffs expression, actions of neighbors are strategic complements, while the actions of non-neighbors are strategic substitutes.

Goyal and Moraga-Gonzalez (2001) focus on regular networks (everyone has the same degree). They show that research effort is decreasing, production costs are initially declining and then increasing, and profits are initially increasing but eventually falling in degree.

[4]The study of games on networks remains an active field of research, see e.g., see Bramoulle and Kranton (2007), Ballester, Calvo-Armengol and Zenou (2006) and Galeotti, Goyal, Jackson, Vega-Redondo and Jackson (2010). For recent surveys of the research in this field, see Bramoulle and Kranton (2016) and Jackson and Zenou (2014).

They also consider the case where firms are local monopolists: in this situation, research efforts of neighbours and non-neighbours exhibit positive externalities and are strategic complements: consequently research efforts and profits are increasing in degree. □

Example 2 illustrates how concepts from game theory (strategic substitutes and complements), oligopoly theory, and concepts from the theory of graphs (increasing density of links) can be brought together to understand firm behavior in a textbook economic setting.

The third example takes up individuals embedded in communities who participate in competitive exchange markets. The example is drawn from Ghiglino and Goyal (2010).

Example 3 *Communities and Competitive Exchange*

Consider a pure exchange competitive economy with individuals located on nodes of an (undirected) network. There are two goods, x and y. Individuals have Cobb-Douglas preferences; the novel feature is that the good y is a relative consumption good. In particular, assume that utility of individual i, facing a consumption profile $(x_i, y_i)_{i \in N}$, is:

$$u_i(x_i, y_i, y_{-i}) = x_i^{\sigma}[y_i - \alpha\eta_i(y_i - \frac{1}{\eta_i}\sum_{j \in N_i(g)} y_j)]^{1-\sigma} \tag{3}$$

where $\sigma \in (0, 1)$ and α measures the strength of social comparisons, $N_i(g)$ refers to the set of neighbors, and η_i to the number of neighbors of i.

Let good x be the numeraire and sets its price equal to be 1. A general equilibrium is defined as a price p_y (for good y) that clears all markets given that individuals optimally allocate their budget across x and y. Our interest is in understanding how the structure of the network affects individual consumption and market prices.

Building on the work of Ballester, Calvo-Armengol, and Zenou (2006), the authors show that general equilibrium prices and consumption are a function of a single network statistic: (Bonacich) centrality. An individual's "centrality"' is given by the weighted sum of paths of different lengths to all others in a social network. Individual consumption is proportional to its node centrality and the relative price of good y is proportional to the average network centrality of all agents in the network. Adding links to a network pushes up centralities and this, in turn, pushes up the price of good y. □

This example shows how a key concept from social networks and graph theory – centrality – helps us understand prices and consumption in a textbook competitive economy.[5]

Centrality is a key concept in the literature on networks; the research over the past decade has shown that the relevant notion of centrality depends on the specific economic application. For an introduction to centrality in networks, see Goyal (2007) and Jackson (2008); for a survey of key player problems in economics, see Zenou (2016).

4 Linking and Network Formation

The finding that network structure can have large and systematic economic effects suggests that individuals will seek to form and dissolve links and create networks that are advantageous. At the very outset, it is worth emphasizing the novelty of the approach: the traditional approach in sociology and other social sciences focuses on the effects of social structure on behavior (Granovetter (1985), Smelser and Swedberg (2005)). In contrast, the economic approach to network formation locates the origins of networks in individual choice.

The beginnings of the theory of network formation can be traced to the work of Boorman (1975), Aumann and Myerson (1988) and Myerson (1977, 1991). In recent years, the theory of network formation has been a very active field of research. Broadly speaking there are two approaches: unilateral linking and bilateral linking.

The model of unilateral link formation 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. A link with another individual allows access, in part and in due course, to the benefits available to the latter via his own links. As links are created on an individual basis, the network formation process can be analyzed as a noncooperative game. Bala and Goyal (2000) assumed that the payoffs of individuals are increasing in the number of people accessed and declining in the number of links formed.

There are important practical examples of this type of link formation – investments in a project, loans/borrowing, hyper-links across web-pages, citations, (following links in) Twitter. But the principal appeal of this model is its simplicity.

The set of individuals is given by $N = \{1, ..., n\}$, where $n \geq 2$. The strategy of person

[5]I have focused on the case where the absolute difference in consumption of a good matters. In a recent paper, Immorlica, Kranton, Manea and Stoddard (2016) explore behavior of individuals who seek status – higher 'ranks' – in their neighborhood. For a general introduction to the role of the social comparisons, see Frank (1993).

$i \in N$ is $s_i = (s_{i,1}, ..., s_{i,i-1}, s_{i,i+1}, ..., s_{i,n})$ where $s_{i,j} \in \{0, 1\}$ for each $j \in N \backslash \{i\}$. Player i has a *link* with j if $s_{i,j} = 1$. A strategy profile for all players is denoted by $s = \{s_1, s_2, s_3, .., s_n\}$, with the set of all strategies being given by $\mathcal{S} = \prod_{i=1}^{n} \mathcal{S}_i$. There is an equivalence between the set of strategies and the set of all directed networks $\mathcal{G}$. So I use g to refer to a strategy profile and also to the directed network, thus created.

Abusing terminology slightly, I shall say that $N_i^d(g) = \{j \in N | g_{i,j} = 1\}$ is the set of players with whom player i forms a link; let $n_i^d(g) = |N_i^d(g)|$. In the directed network g, let $\mathcal{N}_i(g) = \{k \mid i \xrightarrow{g} k\}$ be the set of individuals to whom i has a directed path. I follow the convention that a player accesses herself, and so the number of players accessed by player i in network g, is given by $n_i(g) \equiv |\mathcal{N}_i(g)| + 1$.

Example 4 *One-way and two-way flow models*

Consider a setting of information sharing. The model reflects the idea that more information is valuable, that a link with another person allows access to information that this person in turn accesses from her links, and that links are costly to form. In the one-way flow model, given a strategy profile g, the payoff of player i is

$$\Pi_i(g) = \phi(n_i(g), \eta_i^d(g)). \tag{4}$$

The function ϕ is strictly increasing in the first argument and strictly declining in the second argument. I interpret $n_i(g)$ as the "benefit" that player i receives from the network, while $\eta_i^d(g)$ measures the "cost" associated with maintaining her links. This is known as the one-way model.

The two-way flow model describes a network formation game in which links are unilaterally formed but where the benefits flow in both directions. Define $\hat{\eta}_i(g)$ as the number of people accessed by i in the undirected graph induced by g.

In the two-way flow model, the payoff to player i under strategy profile g is

$$\hat{\Pi}_i(g) = \phi(\hat{n}_i(g), \eta_i^d(g)). \tag{5}$$

The function ϕ is increasing in the first and decreasing in the second argument. □

Following the convention in this literature, let welfare in a network be given by the sum of individual payoffs. Denoting $W(g)$ as welfare in network g, it follows that

$$W(g) = \sum_{i \in N} u_i(g). \tag{6}$$

A network g is said to be efficient if $W(g) \geq W(g')$, for all $g' \in \mathcal{G}$.

Bala and Goyal (2000) develop a characterization of the architecture of equilibrium networks. They show that the network externalities in the linking process imply that equilibrium networks are either (strongly) connected or empty. Moreover, equilibrium networks have simple architectures: star (hub-spoke) networks (in the two-way flow model) and the cycle (in the one-way flow model). They also find that externalities have major effects: equilibrium networks are typically inefficient and the welfare costs can be very large.

I turn next to two-sided or bilateral link formation. A link between two players requires the approval of both the players involved. This is a good description of friendships, co-authorships, collaborations between firms, and free trade agreements between nations.

Following Myerson (1991) suppose that all players announce a set of *intended* links. An intended link is a binary variable, $s_{i,j} \in \{0, 1\}$ where $s_{i,j} = 1$ ($s_{i,j} = 0$) means that player i intends to (does not intend to) form a link with player j. Define $g_{i,j} = \min\{s_{i,j}, s_{j,i}\}$. Every strategy profile $s = \{s_1, s_2, ..., s_n\}$ therefore induces a corresponding *undirected* network $g(s)$. Define $\Pi_i : \mathcal{S} \rightarrow \mathcal{R}$ as the payoff function of a player i in network g.

What is the architecture of networks that are 'stable' and what are their welfare properties. Jackson and Wolinsky (1996) introduce the concept of pairwise stability.

Definition 1 *A network g is pairwise stable if:*

1. *For every $g_{i,j} = 1$, $\Pi_i(g) \geq \Pi_i(g - g_{i,j})$ and $\Pi_j(g) \geq \Pi_j(g - g_{i,j})$*

2. *For $g_{i,j} = 0$, $\Pi_i(g + g_{i,j}) > \Pi_i(g) \implies \Pi_j(g + g_{i,j}) < \Pi_j(g)$.*

Pairwise stability looks at the attractiveness of links in a network g, *one at a time*. The *first* condition requires that every link that is present must be (weakly) profitable for the players involved in the link. The *second* condition requires that for every link which is 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.

Jackson and Wolinsky (1996) develop a number of interesting economic examples. They also establish a general tension between pairwise stable and efficient networks. The theory of network formation remains a vibrant field of research; for overviews of this work, see Goyal

(2007), Jackson (2008), Bloch and Dutta (2012) Chandrashekhar (2016), Choi, Gallo and Kariv (2016).

5 Macroeconomic Fluctuations

Modern economies exhibit significant fluctuations that have large scale welfare implications. An understanding of their origins remains a fundamental question in economics. The dominant view is that large scale aggregate fluctuations cannot be caused by local/sector specific shocks: the reason is that in a complex large economy, one would expect that there are many shocks taking place and that they would cancel each other out. Long and Plosser (1983) and Acemoglu, Carvalho, Ozdaglar and Talbrezi (2012) provide a framework to illustrate how local sector specific shocks may be amplified by the production network structure to generate large scale aggregate fluctuations. Therefore, understanding the empirical structure can deepen our understanding of the origins of aggregate fluctuations and thereby help the design of appropriately targeted policies.[6]

By way of motivation, consider the 2011 earthquake in Japan: this set in motion the ensuing tsunami and led to the meltdown problems at the nuclear plant in Fukushima, Japan. These three events resulted in the destruction of human and physical capital, but they were amplified by the disruption of national and global supply chains.

> *When the linkage structure in the economy is dominated by a small number of hubs supplying inputs to many different firms or sectors, aggregate fluctuations may arise for two related, but distinct, reasons. First, fluctuations in these hub-like production units can propagate throughout the economy and affect aggregate performance, much in the same way as a shutdown at a major airport has a disruptive impact on scheduled flights throughout a country. ... the presence of these hubs provides shortcuts through which these supply chain networks become easily navigable.* (Carvalho (2014, page 24)).

Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012) study a production economy. There are n distinct firms, each specializing in a different good. These goods are a final good for consumption by the consumer but they also serve potentially as inputs in the production of other goods. For simplicity suppose that the consumer values all goods equally, and that

[6]For an early study of the implications of local network based complementarities on aggregate growth patterns, see Durlauf (1993).

she supplies labour inelastically and that she spends the wage income on consumption of the n goods. The output of sector i is given by:

$$x_i = (z_i l_i)^{1-a} (\prod_{i=1}^{n} x_{ij}^{\omega_{ij}})^a. \tag{7}$$

where x_{ij} is the input from sector j to sector i. The amount of labor hired by sector i is given by l_i , while $(1-a)$ is the share of labor in production. The sector specific productivity shock is captured by the term z_i. It is natural to start with the assumption that these productivity shocks are independent across producers of goods in the economy. The coefficients a and the ω_{ij} reflect the technological relations in the economy. Putting together the nodes and the technological relations then gives us the production network of the economy. Price taking firms (in the sectors) seek to maximize profits. The authors study the general equilibrium of this production economy.

The analysis in Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012) yields

Observation 1 *In equilibrium, (the logarithm of) aggregate value added, y, is a weighted sum of the (logarithm of) sector level productivity shocks, ϵ_i:*

$$y = \sum_{i=1}^{n} v_i \epsilon_i \tag{8}$$

where the weights, v_i, are given by the Leontief inverse matrix, and represent reflect the centrality of a sector in the production network, and $\epsilon_i = \log z_i$. This sets the stage for a study of how network topology affects the propagation of sector specific shocks.

I take up three networks to illustrate how network structure matters; see Figure 5. Consider first the simplest baseline case: an empty network with no intermediate input trade in the economy. So all sectors only use labour for production. In this economy, shocks to any given sector will not affect any other sector: there is no amplification of micro-level volatility.

Next consider a supply chain with 6 nodes, where inputs flow unidirectionally from a well-defined upstream sector through intermediate stages to a final downstream sector. In network parlance, this is a tree or line structure with a single source. Productivity fluctuations at the most upstream source, sector 1, now have a first-round effect on its immediate downstream customer, sector 2; a smaller, second-round effect on sector 3 and so forth. The presence of these indirect effects means that the production network amplifies the shock to sector 1.

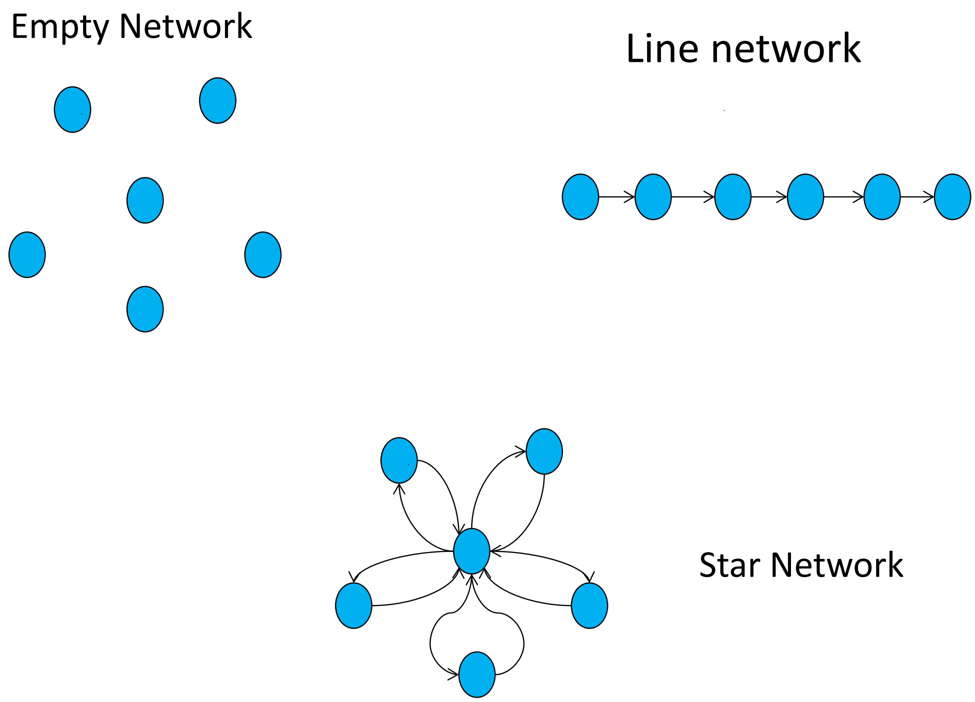

Figure 5: Simple Production Networks

Finally, consider the (directed) hub-spoke network with a single general purpose technology. The hub is used as the sole intermediate input in all other sectors and each of these sectors is necessary for the general purpose technology. The general purpose technology reflects features of real world sectors such as real estate and construction, finance, energy and information technology. It can be shown that this network generates the highest volatility. There are two reasons for this. One, fluctuations in the hub sector now have a large first order impact on every sector in the economy and two, the hub brings all sectors close to each other and therefore raises the power of second order effects.

This observation reinforces an important finding in Example 1 (in section 2 above): the key role of highly connected hubs in shaping aggregate outcomes.

To close the circle, I note some facts about the production network of the US economy: this is a relatively sparse graph that contains a small collection of highly connected hub sectors – the general purpose technologies – making the production economy a typical 'small world' (Acemoglu et al. (2012), Blochl, Theis, Vega-Redondo and Fisher (2011)). Thus sector specific shocks can potentially be amplified by the network structure to generate large aggregate shocks. The study of network amplification is a major field of research currently: for a survey of some of the general themes, see Acemoglu, Ozdaglar and Tahbaz-Salehi (2016). In a related line of work, global supply chains have motivated the study of the role of production networks in international trade (Antras (2015), Costinot, Vogel and Wang (2012)).

In the discussion above, it was assumed that firms are price takers and the network is exogenously given. In real world markets, firms often have stable relationships with small subsets of the market. A deeper understanding of price formation and market power in networks is thus clearly important in these settings. The study of market power is also a first step in developing a theory of the how the production economy itself evolves over time. The next section takes up the theory of price formation in networks.

6 Exchange and Market Power

In the standard Walrasian model, individuals – be they consumers, producers or traders – are anonymous, they can all trade with each other and this trade takes place at a common price. Empirically, individuals have clear identities and develop durable and personal relations of exchange, and there are definite limitations on who can trade with whom. Moreover, the terms of trade – between the buyers and sellers for the same good – often differ and these differences are related to the structure of relationships among the individuals (Uzzi (1996), Kirman and Vignes (1991)). There is thus a need to move beyond the Walrasian framework and develop a systematic understanding of exchange networks: their antecedents and their implications for pricing, allocation of surplus and aggregate efficiency.

I start with a simple two sided market comprising of buyers (numbering B) and sellers (numbering S). Each seller has a single indivisible good (which she values at 0) and every buyer has a known valuation for the good (which he values at 1). The trading relationships are represented by a bipartite network. A network in which all sellers can trade with all buyers (and vice-versa) is a special case of this setting. Suppose that an auctioneer announces prices with the aim of equating demand and supply. A price of p between a pair of traders means the buyer's payoff is $1 - p$ while the seller makes p. It is easy to see that if $B > S$ then the equilibrium price must be 1, while if $B < S$ then the price must be 0. Thus there is a single price for all trade and the outcome is efficient. I will denote this as the Walrasian benchmark.

I now turn to the more general networks where some buyers and sellers cannot trade with each other. Our interest is in the role of the network and so I use a price formation protocol that is close to the centralized Walrasian auctioneer. Following Corominas-Bosch (2004), I consider a model of price formation through bargaining. The bargaining process proceeds as follows: In period 1 and all subsequent odd periods, sellers make offers, which are observed by the connected buyers. Buyers who wish to trade at the prices they see, propose a price. Given these offers and counter-offers, a maximal matching is picked (this is a matching that maximizes the number of trades). Those who have an agreed trade, exchange at the agreed price and leave the market (without replacement). In round 2, and all subsequent even numbered rounds, buyers make offers, and connected sellers respond. Suppose all traders discount the future at rate $\delta \in [0, 1]$. This completes the description of a game on a network.[7] Our aim is to understand how network structure affects prices and the efficiency of trading.

There are broadly three types of outcomes: a buyer gets most of the surplus (p close to 0), a seller gets most of the surplus (p close to 1), and traders split the surplus (price close to 1/2). If two buyers are linked to a single seller then p is equal to 1; traders in disjoint pairs agree on a price $p = 1/1 + \delta$, as in the original Stahl-Rubinstein bilateral bargaining model. I now turn to more general networks.

The Marriage Theorem (Hall (1935)) provides us with conditions for a perfect matching: where all traders can in principle trade. It says that there exists a matching that covers a set of buyers B if and only if every subset of buyers in B is connected to a set of sellers of equal or larger cardinality.

The key to understanding trading in these networks is the idea of 'local' market dominance. Following Manea (2016a) let us say that a node i is under-demanded if there exists a maximal matching in which it is unmatched. Let U be the set of under-demanded nodes. Correspondingly, the set of over-demanded nodes $\mathcal{O}$ consists of nodes that do not belong to U and have at least one link to an under-demanded node. The set of perfectly matched nodes is simply the complement of the set of under-demanded and over-demanded nodes.

Corominas-Bosch (2004) exploits the Gallai-Edmonds Decomposition Theorem to establish the following striking result.

Observation 2 *Fix a network g. For every δ there exists a sub-game perfect equilibrium, in which under-demanded and over-demanded traders earn respectively* 0 *and* 1*. Sellers in the perfectly matched set earn $z = 1/1 + \delta$, while buyers get $1 - z$.*

In this model all trade occurs in the first period and so the outcome is efficient. However, the terms of trade can differ widely, depending on local market conditions.

[7]The bargaining protocol in Polanski (2007) also has a centralized structure though it differs in some details. The analysis there also exploits the Gallai-Edmonds decomposition and the results of the two papers are closely related.

The idea behind this result is simple: consider the profile in which all over-demanded sellers propose 1 and all buyers accept it. Suppose that a buyer rejects this proposal. Then in equilibrium the trade will take place among the remaining buyers and sellers in the sub-graph. So the buyer will be disconnected from all sellers in the original sub-graph. So his only hope is a possible payoff from connections across in other sub-graphs. But the decomposition theorem tells us that this buyer is only linked to sellers in other over-demanded sets. In such a sub-graph, sellers propose 1 and the buyers linked to them agree to the proposal. So the buyer cannot hope to earn anything positive by deviation. Given Observation 2, it follows that if $S > B$, then G will support the competitive outcome if and only if every seller is under-demanded. Likewise, if $S < B$, then G will support the competitive outcome if and only if every seller is over-demanded. Finally, if $S = B$, then G will support the competitive outcome if and only if all traders are perfectly matched.

This paper provides an elegant micro-foundation for the Walrasian benchmark: in particular, it tells us that the law of one price obtains only when all local markets reflect the global balance of buyer vs sellers. So, in a 'market' with surplus sellers there may be an outcome in which subsets of sellers make large sums of money because they are 'locally' in a buyer surplus market. In a follow up paper, Charness, Corominas-Bosch and Frechette (2007) show that the behavior of experimental subjects in a laboratory conforms to the predictions of the model.

In the Corominas-Bosch (2004) and Polanski (2007) models, the price formation process is centralized: a single price is announced to all linked traders at the same time. In recent work, Abreu and Manea (2012a, 2012b) study a model with decentralized matching: in every period a single pair of linked traders is picked to bargain. They show that decentralized trading has significant effects: bargaining may end in disagreement, a pair of traders may refuse to trade at one stage but agree to trade at a subsequent point. Moreover, decentralization creates the possibility of inefficient Markov perfect equilibrium.[8]

I have taken the network as given so far, but given the trading outcome on any network, we can now take a step back and ask what sort of networks would form if buyers and sellers can build links with each other. Consider the Corominas-Bosch (2004) model and suppose a link is two-sided and entails a cost $c > 0$ for each trader. As links are costly, the efficient network will entail a maximal set of disjoint pairs. Jackson (2008) shows that if $c < 1/2$ and the discount factor is close to 1, then pairwise stable networks coincide with efficient networks.

[8] The models of bargaining I have discussed all assume that traders who agree leave and are not replaced. For a study of bargaining in networks where traders are replaced, see Manea (2011).

This simple model provides us a benchmark to assess the role of networks in shaping bargaining. The study of bargaining in networks remains an active field of research; for a recent survey, see Manea (2016a).

I now turn to the two alternative price formation protocols – posted prices and auctions.

Lever-Guzman (2011) considers the setting of a market with price setting firms. The firms and consumers are located in a bi-partite network (as in the Corominas-Bosch model). Consumers' reservation utility is 1 and is known to firms. Every firm sets a single price and the network is commonly known. This describes a game on a network, with prices set by sellers and consumer decisions on purchases. The goal is to understand how the network shapes pricing and the allocation of surplus.

It is easy to see that if all consumers have two or more links with firms then a firm knows that a consumer can always compare two prices and the competitive (Bertrand) price is the natural outcome. If, on the other hand, there is a consumer who has only one link then the firm who has this captive consumer can always make a profit of 1 by setting a price of 1. If this firm also has consumers with multiple links then there is a tension in the pricing strategy: a high price may lead to a loss of the other consumers. This suggests that in general networks, firms will use mixed strategies in prices. The same intuitions arise in search theory; a well known early paper on price dispersion is Burdett and Judd (1983).

I now turn to auctions on networks and discuss the work of Kranton and Minehart (2001). There are two stages. In stage 1, buyers unilaterally choose to form costly links with sellers. These links enable buyers to procure goods or inputs. Buyers trade-off expected gains from trade against costs of link formation.[9] 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, somewhat surprisingly, that an efficient allocation mechanism (ex-post competitive environment) is sufficient to align the buyers' incentives to form ties with the social incentives. The following simple example illustrates the role of the link formation protocol – unilateral vs two-sided – in shaping the efficiency of networks.

Example 5 *Role of Linking Protocol*

There are two stages. In stage 1, players choose to form links. The links determine potential

[9] 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).

trade patterns. In stage 2, buyers simultaneously make bids to the seller. The winner is determined using a second price auction. Assume that the valuations of the buyers are uniformly distributed on the unit interval.

To fix ideas consider the simple case with 2 buyers and 1 seller. It is easy to see that in the single link network, the buyer will bid 0. In the two links network, buyers will submit valuations equal to their valuation, and so the expected price is the expected value of the second highest valuation. It maybe checked that the expected valuation of the winner is 2/3 (which is also the total value of surplus generated), while the expected price is equal to 1/3. Each buyer expects to earn 1/6, together they expect to earn 1/3, the seller expects to earn 1/3.

What are the incentives of the traders to form a network? I first characterize the efficient networks: observe that expected social value of one buyer is 1/2 while the expected social value of selling to two buyers is 2/3. This immediately implies that empty network is efficient if $c > 1/2$, the single link network is efficient if $1/6 < c < 1/2$, and the two link network is efficient if $c < 1/6$.

Consider the case of unilateral links formed by buyers. Observe that the network is an equilibrium if no buyer has an incentive to form a link: simple computations reveal that if the cost of a link $c > 1/2$ then the empty network is an equilibrium. Next consider the single link network: if a buyer has formed a link then for him to retain it $c < 1/2$. On the other hand, for the second buyer not to form a link it must be the case that returns are less than cost of link, i.e., if $c > 1/6$. I have thus shown that a single link network is an equilibrium if $1/6 < c < 1/2$. Similarly, a comparison of expected payoffs from linking reveals that the two link network is an equilibrium if $c < 1/6$.

Jackson (2008) shows that the linking protocol matters: with two-sided linking, efficient networks are generally not pairwise stable except for very high and very low costs of linking. $\square$

This discussion brings out two general points. The first is that the network structure and price formation mechanism both shape the efficiency of trading and the allocation of surplus. The second is that the link formation protocol has a decisive impact on the architecture of networks and the efficiency of the trading system. For a systematic exploration on inefficiencies in bilateral trading networks, see Elliott (2015) and Elliott and Nava (2015). Finally, the existing work assumes that traders know the network. For a general treatment of games with incomplete network knowledge, see Galeotti, Goyal, Jackson, Vega-Redondo and Yariv (2010).

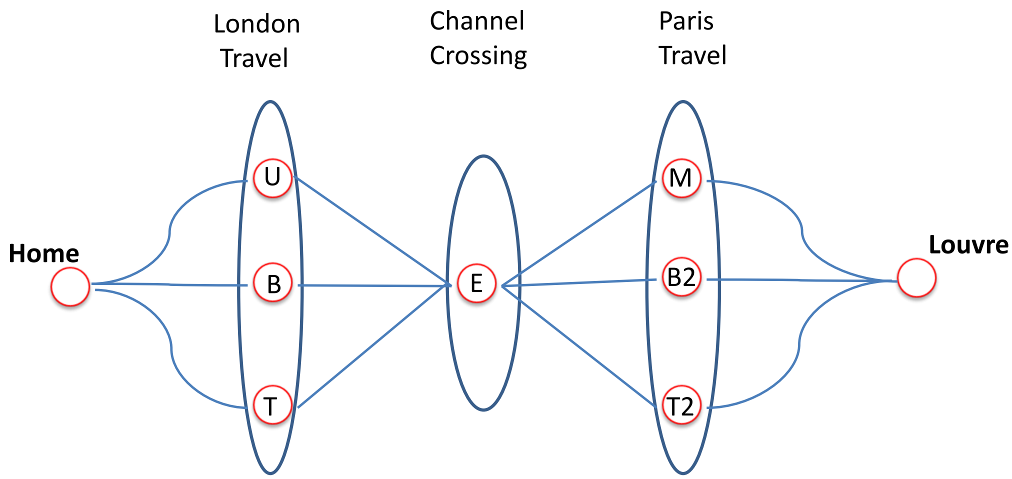

Figure 6: Transport Network: London to Paris

7 Intermediaries

I have so far considered direct ties between sellers and final buyers. Supply, service and trading chains are a defining feature of the modern economy. They are prominent in agriculture, in transport and communication networks, in international trade, and in finance. The routing of economic activity, the allocation of surplus and the efficiency of the system depend on the prices set by these different intermediaries. This section discusses recent research on price formation in networks of intermediaries.[10]

I begin with a simple model of posted prices, taken from Choi, Galeotti and Goyal (2016). By way of motivation, let us consider a tourist who wishes to travel by train from London to see the Louvre in Paris. The first leg of the journey is from home to St. Pancras Station. There are a number of different taxi companies, bus services and the Underground. Once at St. Pancras Station, the only service provider to Paris Nord Station is Eurostar. Upon arriving at Paris Nord, there are a number of alternatives (bus, Metro and taxi) to get to the Louvre. The network consists of alternative paths each constituted of local transport alternatives in London and in Paris and the Eurostar Company. Each of the service providers sets a price. The traveler picks the cheapest 'path'. Figure 7 represents this example.

[10]In an early paper, Nava (2015) studies a model where traders choose how much *quantity* to buy and sell from neighbors. He finds that intermediation arises endogenously in equilibrium: traders buy in order to resell to others. Prices strictly increase along any intermediation chain. Efficiency is attained only in large economies and only when intermediation is negligible.

This example suggests the following model: there is a source node, $\mathcal{S}$, and a destination node, $\mathcal{D}$. A path between the two is a sequence of interconnected nodes, each occupied by an intermediary. The source node and the destination node and all the paths between them together define a network. The passage of goods (or people) from source to destination generates surplus. Let us suppose that the value is known and for simplicity set it equal to 1. Intermediaries (who have zero cost) simultaneously *post a price*; the prices determine a total cost for every path between $\mathcal{S}$ and $\mathcal{D}$. The tourist moves along a least cost path; so an intermediary earns payoffs only if she is located on it. This completes the description of a game on a network.

The aim is to understand how the network structure of intermediation shapes the prices and the allocation of surplus across traders.

To build some intuition let us consider two simple networks. The first network has two paths between $\mathcal{S}$ and $\mathcal{D}$, each with a distinct node. The two intermediaries compete in price: this is a simple game of strategic complements. Standard arguments – a la Bertrand – tell us that the firms will set a price equal to 0. The second network contains a single line with two nodes between $\mathcal{S}$ and $\mathcal{D}$. The two intermediaries are now engaged in bilateral Nash Bargaining and the strategies are strategic substitutes (assuming that the sum of demands must equal the value of surplus). As in the standard model, there are a number of possible outcomes. These examples illustrate how classical models of price formation and competition constitute special cases of our framework and also show how networks and the strategic structure are intimately related.

Moving on to general networks, a node is said to be *critical* if it lies on all paths between $\mathcal{S}$ and $\mathcal{D}$. Choi, Galeotti and Goyal (2016) develop a full characterization of equilibrium pricing. This result shows that critical traders are sufficient but not necessary for surplus extraction. The lack of necessity arises due to possible coordination failures along chains of traders that enhance the market power of non-critical traders. These coordination problems give rise to multiple equilibria. Standard refinements do not resolve the multiplicity problem, and so the authors take the model to the laboratory. The experiments establish that subjects avoid coordination problems. As a result, trade always takes place, and non-critical traders make very little profits. Summarizing the theory and the experiments yields.

Observation 3 *When value from exchange is common knowledge, the presence of critical traders in both necessary and sufficient for full surplus extraction by intermediaries. Subjects in the laboratory typically coordinate successfully and trading outcomes are efficient.*

In the benchmark setting with full information the number of critical intermediaries does not have an important impact on pricing and trading outcomes. However, in markets with multiple vertically related firms, double marginalization is a major concern for policy and regulation; see e.g., Lerner (1934), Tirole (1994) and Spulber (1999). This motivates an extension of the benchmark model to a setting where value is uncertain. Suppose to fix ideas that value is uniformly distributed on the unit interval. This defines a new game on a network: the strategies remain as before but the payoffs are altered due to the incomplete information on valuations.

Consider the same two network examples as above. In the two path case, nothing essential changes: prices are still set at 0. But in the line network with two nodes, there is an outcome where both intermediaries set a price equal to 1/3, so there is no trade with probability 2/3. It is easy to see that with three intermediaries the price will be 1/4 and so the probability of no trade is 3/4. Thus individual prices are falling, aggregate price is rising and the probability of trade is falling in the number of critical traders. Using a combination of theory and experiments, Choi, Galeotti and Goyal (2016) generalize this insight to cover networks in general.

The result on critical nodes is sharp but criticality may be seen as too demanding: a node that lies on most (but not all) paths has the same status as compared to a node that lies on only one path. Moreover, all critical paths have equal status in the model. It may be argued that location in the path – upstream or downstream – should matter. Related work with alternative pricing protocols develops these points. For auctions, see Kotowski and Leister (2014) and Gottardi and Goyal (2012); for bargaining, see Condorelli, Galeotti and Renou (2016), Gofman (2011), and Manea (2016b); for bid-and-ask prices, see Acemoglu and Ozdaglar (2007), Blume et al. (2007) and Gale and Kariv (2009).[11]

I begin with bargaining. Following Manea (2016b), consider the following intermediation game. A seller is endowed with a single unit of an indivisible good, which can be resold through linked intermediaries until it reaches one of several buyers. At every stage in the game, the current owner of the good selects a bargaining partner among his downstream neighbors in the network. The two traders negotiate the price of the good via a random proposer protocol. With probability p, the current owner makes an offer and the partner either accepts or turns down the offer. With probability $1 - p$ the downstream trader makes an offer. Irrespective of the offer originator, once an offer is rejected bargaining ends. The current owner has an

[11] For a comparison of outcomes under different pricing protocols, see Choi, Galeotti and Goyal (2016).

opportunity to select a new trader in the next stage. If an offer is accepted, then the two traders exchange the good at the agreed price. If the new owner is an intermediary, he has an opportunity to resell the good to downstream neighbors following the same protocol. The final buyer consumes the good upon purchase. Traders have a common discount factor $\delta \in (0, 1)$. The paper focuses on (Markov perfect) equilibria of this intermediation game.

To draw out the role of the network architecture, I focus on the simple setting where all traders have zero costs and all buyers have a common value $v > 0$. The following construction plays a key role in the analysis. Observe that any intermediary linked to two (or more) buyers will extract the full surplus of v, as traders become patient. This motivates the construction of the following layered graph. Start with the buyers, and add all intermediaries who are linked to at least two buyers, then add all intermediaries linked to at least two traders already present, and so on, until no more traders have two or more links to already present traders. This constitutes layer 0. Now consider traders left over: start with any trader who has one link with traders in layer 0, then add all intermediaries who have at least two links with intermediaries currently in layer 1 and proceed until there is no one with two or more links with traders in the emerging layer 1. Proceed recursively until all agents have been assigned to layers.

Manea (2016b) shows that, as $\delta \to 1$, the (Markov Perfect) equilibrium in any (acyclical) network can be characterized in terms of the resale values of different traders. These resale values are in turn defined by the different layers of the constructed multi-layered network.

To get a good sense of market power and behavior in the model it is useful to focus on a special class of networks, inspired by the example of travel from London to Paris (see Figure **??** above). A complete multipartite network has a single original seller and a single final buyer and there are L intermediating levels. Every node in a level is linked to every node in the adjacent levels above and below it. In this network, a node is critical if it is the unique member of a layer. Given the layer x, let k_x be the number of downstream layers that have critical traders. Let k be the number of 'critical' layers in the entire network. In the context of complete multipartite networks, the analysis in Manea (2016b) yields us:

Observation 4 *Fix a complete multipartite network and let $\delta \to 1$. In equilibrium, the reservation value of intermediary i in level x converges to $p^{k_x+1}v$. The payoff of the initial seller converges to $p^{k+1}v$ and payoff of the buyer converges to $(1-p)v$. The payoff of non-critical intermediaries converges to 0, while the payoff of critical trader at level x converges to $(1-p)p^{k_x+1}v$.*

Thus the market power of any trader depends on the number of layers in the induced graph and number of traders in each layer of the downstream graph.[12]

So far, I have assumed that all players know the value of the good. I now turn to settings with incomplete information on valuations/surplus. Condorelli, Galeotti and Renou (2016) study a setting where the good either has Low or High value to a trader. This valuation is independent of other's valuations and is private information. Trading proceeds as follows: the current owner makes a take-it-or-leave-it offer to a 'neighbor'. If the neighbor accepts then trade takes place, if not then he makes an offer to other neighbors. The process of bargaining gradually reveals information on the private valuations of traders. In equilibrium, High valuation traders always consume the product, while Low valuation traders seek out potential trading partners: the novelty here, relative to the earlier bilateral bargaining literature, is that search for a high valuation trader will involve possibly many other traders (in the network). A trader that lies on all paths between a trader i and the original seller – a suitably defined critical node – earns higher payoffs. For a general discount factor $\delta \in (0, 1)$, the analysis is intricate and trading exhibits complicated behavior: prices may be non-monotonic and trading inefficient. However, as $\delta \to 1$, trading is efficient: the traders manage to locate the High valuation trader (if one exists).

I turn next to auctions. Gottardi and Goyal (2012) and Kotowski and Leister (2014) study auctions in a network of intermediaries. I briefly describe the model and the main results from Kotowski and Leister (2014). There is a single source and possibly multiple eventual buyers (each of whom value the good at value $v > 0$). There are tiers of intermediaries between the original owner and buyers. In each tier, traders compete to provide intermediation services. The current owner conducts a second price auction among downstream traders to sell his good. The new owner does likewise until the good arrives at a buyer. The network is common knowledge but intermediaries have private information on their own costs. If the cost of trading is High then the intermediary drops out of the network.

Kotowski and Leister (2014) provide an elegant characterization of prices and profits. They show that behavior is defined by two network characteristics – number of layers and number of intermediaries in each layer – and the probability of High cost intermediaries. In the benchmark setting with two or more Low cost intermediaries in each layer the original owner will extract full surplus. Therefore, an intermediary earns rents only if it is the sole Low cost player in its layer, i.e., it is critical. With a greater probability of High cost, intermediate

[12] This application to complete multipartite networks is taken from Condorelli and Galeotti (2015).

layers can in principle earn rents, in the event that their competitors in the same layer have turned out to be high cost. However, this possibility has correspondingly negative effects on the resale value for upstream traders. The authors show that the resale value is increasing in the probability of being Low cost and in the number of traders in each layer.

This discussion illustrates the ways in which standard price formation protocols – posted prices, bargaining and auctions – may be used to study intermediation in networks. In all cases, critical traders appear to be central to shaping market power. The models also clarify how the pricing protocol and the timing (sequential versus simultaneous) of decision making interacts with networks and with private information. In the posted price model, all prices are set at the same time. If prices were set in sequence then upstream traders will extract more of the surplus, just as in the bargaining and in the auction models. The extent of this extraction will be mitigated by private information downstream.

Network formation: The discussion above shows that location within a network and the structure of the network have powerful effects on earnings. So it is only natural that traders will seek to shape their network. The model of posted prices discussed above brings out the role of critical nodes. Given the potentially large rewards of being critical, firms and individuals will make investments in connections to make themselves critical. However, these efforts will face counter-efforts from other nodes who would like to keep intermediation rents down. What is the outcome of these pressures? I address this question with the help of a network formation model taken from Goyal and Vega-Redondo (2007).

Consider a link announcement game. Every player $i \in N$ announces a set of (intended) links with others $s_i = (s_{i1}, ..., s_{in})$. A link between i and j is formed, $g_{ij} = 1$, if $s_{ij} = s_{ji} = 1$. Upon formation of a link, both players incur a cost $c > 0$. As before, $\mathcal{N}_i(g)$ is the set of players whom player i accesses in network g. For any $k \in \mathcal{N}_i(g)$, define $\mathcal{C}(j, k; g)$ as the set of players who are critical to connect j and k in network g and let $c(j, k; g) = |\mathcal{C}(j, k; g)|$. Then, for every strategy profile of intended links, $s = (s_1, s_2, ..., s_n)$, the (net) payoffs to player i are given by:

$$\Pi_i(s_i, s_{-i}) = \sum_{j \in \mathcal{N}_i(g)} \frac{1}{e(i, j; g) + 2} + \sum_{j,k \in N} \frac{I_{\{i \in \mathcal{C}(j,k)\}}}{e(j, k; g) + 2} - \eta_i^d(g)c, \tag{9}$$

where $I_{\{i \in \mathcal{C}(j,k)\}} \in \{0, 1\}$ stands for the indicator function specifying whether i is essential for j and k, and $\eta_i^d(g) \equiv |\{j \in N : j \neq i, g_{ij} = 1\}|$ refers to the number of players with whom player i has a link.

Goyal and Vega-Redondo (2007) show that equilibrium networks are either connected or empty. The attempt of traders to extract rents from intermediation pushes towards a star structure in which there is a single central node. However, the desire of traders to avoid paying rents pushes toward a competitive network like a ring – with no critical traders – in which no one earns any intermediation rents. Their analysis reveals that with coordinated bilateral linking, the second pressure dominates and the star emerges as the unique (non-empty) stable network. I state this as:

Observation 5 *For a wide range of linking costs the star network is the unique (non-empty) stable network. The ratio of payoffs of the hub trader and a periphery trader is unbounded, as the number of traders grows.*

The idea of location advantages in networks has a long and distinguished history in sociology, see e.g., Burt (1992). From an economic perspective, this work naturally motivates the question: can location advantages and large payoff differences be sustained among otherwise identical individuals? The above model shows that the strategic struggle for these advantages leads to a star architecture – where a single player becomes essential to connect every other pair of players – and that such a network is robust with respect to individual and bilateral attempts to alter the structure.

While this is a very sharp prediction, there are three features of the result that are potentially unsatisfactory. The first is that it requires many links from a single player: capacity constraints may render the star infeasible in applications. The second is that it exhibits an extreme form of market power and this will attract entry and probably a larger and more coordinated rewiring of links. The third is that nodes are homogenous and that paths are perfectly competitive.

7.1 Financial Intermediaries

In recent years, 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. 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. 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), and 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 who are connected to a few of the core banks. 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. I briefly discus this work.

van der Leij, Veld and Hommes (2016) extend the Goyal and Vega-Redondo (2007) model presented above by allowing for smoother competition between paths. Their first result is that a core-periphery network is not stable when agents are homogeneous. On the other hand, such a network arises naturally if there is heterogeneity – with respect to valuations – among individuals. The higher value banks constitute the core. In particular, their model can reproduce the observed core-periphery structure in the Dutch interbank market for reasonable parameter values.

Farboodi (2014) also explores the role of heterogeneity across nodes. There are banks that have links with depositors and banks that have links with potential investors. A link between two banks is a durable relationship. Links are unilateral: a link from X to Y constitutes a commitment from X to honor any loan demand from Y. 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 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 provide funding end up with too few connections. This creates excessive risk in the system at large.

In a recent paper, Wang (2015) explores the externalities in financial linking and the implications of contagion risk. In her model, firms form links by trading assets. Liquidation is costly. A link with a distressed firm percolates through the network: in a setting where contracts are not contingent on distant links, there is a externality generated by links. Her main insight is that when firms are highly dispersed in financial distress, the network features too many links with distressed firms and too few risk-sharing links among non-distressed firms. In an early paper, and using a more stylized model, Blume et al (2011) obtain a related result on over-connected networks in a setting where shocks spread through a system, but contracts are not contingent on third party links.[13]

[13]There is a large literature on financial contagion and systemic risk in networks, see e.g., Acemoglu, Ozdaglar and Tahbaz-Salehi (2015), Babus (2016), Cabrales, Gottardi and Vega-Redondo (2016), Elliott and

The discussion in this section brings out the importance of critical traders in shaping market power and the role of intermediation rents in the creation of trading and financial networks. The research also shows that profit motivated linking can lead to networks that sustain inefficiencies and exhibit systemic risk. The study of intermediation in networks remains a very active field of work; for recent work on related themes, see Galeotti and Goyal (2014) and Candogan, Bimpikis, Ehsani (2015).

8 Work, consumption and finance

This section studies the role of social networks in labor, product and financial markets.

8.1 Workers, unemployment and inequality

A significant fraction of all jobs are filled through the use of social networks (Granovetter 1974; Rees 1966; Cappellari and Tatsiramos 2010; Cingano and Rosolia 2012). There are two primary types of information for which contacts are used. First there is information on jobs: workers do not know which firms have vacancies while firms do not know the workers who are looking for a job. A second type of information concerns the ability of workers: a worker knows more about his own ability as compared to a potential employer. So firms seek information on quality and ability via personal contacts of their employees. This section examines the ways in which social networks affect the flow of information and thereby shape wages, unemployment and inequality.

Montgomery (1991) studies the adverse selection problem in labor markets. There are two periods. In each period a firm hires one worker. The output of a firm is equal to the ability of the worker in the firm. The ability of workers is private information. In period 1, firms pay wages equal to the (ex-ante) average ability of workers. During period 1, a firm learns the ability of its worker. At the start of period 2, it has a choice between asking the period 1 worker for the name of contact and offering a referral wage *or* simply posting a wage in the market. The key assumption is that there is a assortativity in social ties: so a High ability worker is more likely to have ties with other High ability workers. Competition between firms

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Hazel (2016), Elliott, Golub and Jackson (2014), Galeotti, Ghiglino and Goyal (2015). For a survey, see Acemoglu, Ozdaglar and Tahbaz-Salehi (2016).

The problem of network resilience also arises in communication, criminal and transport networks; for recent research on these topics, see Dziubinski and Goyal (2016), Baccra and Bar-Isaac (2008) and Goyal and Vigier (2014). For a survey of this line of work, see Dziubinski, Goyal and Vigier (2016).

means that wages equal expected ability of workers and, moreover, profits of firms are equal to zero (over the two periods).

Montgomery's (1991) analysis yields two insights. The *first* insight is that workers with more connections will earn a higher wage. The reason for this relation between connections and wages is simple: more connections implies a higher number of referral wage offers from firms and this translates in a higher accepted wage. The *second* insight is that an increase in the density of social connections raises the inequality in wages. This 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. These considerations may be summarized as:

Observation 6 *Consider the model of referrals. A firm uses a referral offer when its current employee is a high-ability worker but not otherwise. Referral wage offers are dispersed over an interval. As firms entice higher quality workers through the referral wages, the average quality in the market falls: so wages in the market are lower than ex-ante average quality. An increase in the density of social connections or in the assortativity of social ties leads to a rise in the (maximal) referred wage and a fall in the market wage.*

The Montgomery (1991) paper studies the role of social networks in resolving adverse selection problems in labour markets. I now turn to the role of social networks in facilitating the flow of information on jobs.

Calvo-Armengol and Jackson (2004) study a model of information transmission on job vacancies. Information about new jobs arrives to individuals. If they are unemployed they take up the job; if employed they pass on information to their unemployed friends and acquaintances. With positive probability an employed worker may lose his job. The process of job loss, the arrival of new job information, and the transmission of this information via the network defines a dynamic process. The outcome is the employment status of individuals. The interest is in understanding how the properties of the social network affect the employment prospects of different individuals.

Calvo-Armengol and Jackson (2004) develop three main insights. The *first* insight is that the employment status of two individuals in a connected network is positively correlated. If Mr A is employed then it is more likely that he will pass on information about jobs to his neighbors who in turn will pass on information if they are employed. Thus if Mr. A is employed then it is more likely that his neighbors are employed as well. The *second* insight is that the probability of an individual finding a job is declining with the duration of his unemployment. If Mr A has been unemployed for a long time then he must not have received information on jobs from others, and this is more likely if the neighbours are themselves unemployed. But this suggests that it is less likely that they will pass on new information concerning vacancies. Empirical research provides broad support for the positive correlation in employment rates of communities and neighborhoods and also shows that unemployment exhibits duration dependence. The *third* insight pertains to a multiplier effect on sustaining networks: a community with higher unemployment has lower incentives to keep connected. The loss in connections will however lower the employment rate, as information on jobs is not passed on. Thus small initial differences in unemployment rates can lead to a sequence of drop outs, which in turns can have large long run effects on the employment prospects of the group.

Observation 7 *The employment status of workers in a connected network is positively correlated. There is positive duration dependence of unemployment. There is a network multiplier in unemployment: communities with high unemployment have lower incentives to maintain links, the lack of connections raises unemployment rates.*

In Calvo-Armengol and Jackson (2004), prices and competition do not play a role, while in Montgomery (1991) there is no modeling of network topology. There is also no explicit model of network formation in these papers. In a recent paper, Galeotti and Merlino (2014) examine the relation between labor market conditions and the role of social networks in matching vacancies with job seekers. They allow for workers to invest in connections with a view to accessing information that other workers may have. The arguments in Calvo-Armegol and Jackson (2004) suggest that if the firing rate is very high then social connections are less attractive as people will not pass on job information. On the other hand, if the firing rates are very low then there is little value in information on new jobs. So linking is attractive only when there is a moderate 'separation' rate in the labor market. The authors build on this observation to show that the inverted-U relation between job separation rate and network investments determines an inverted-U relation between job separation rate and the probability that a worker finds a job through his social contacts. This prediction is consistent with data from the UK labor market.

There is a large literature on search and matching; in this literature search is random and workers are acting in isolation of each other (Rogerson, Shimer and Wright, 2005). As the networks approach to the study of labor markets matures it would be important to develop models that combine random and network based search. This would be a first step to understanding the relative empirical significance of networks and random search in shaping wages and unemployment.[14]

8.2 Advertising and Pricing

In the standard product market model a firm chooses prices, advertising strategy and quality taking as given heterogenous consumer preferences (Tirole, 1994). The background assumption is that individuals are anonymous and act in isolation of each other. Empirical work however suggests that friends, neighbors, and colleagues play an important role in shaping consumer choice. This social influence arises out of information sharing and also due to compatibility pressures. In the past, the practical use of such social influences for advertising or pricing was limited due to the absence of good data on networks. The availability of large amounts of data on online social networking along with the other advances in information technology have have led to an exciting new research programme on ways that firms and governments can harness the power of social networks to promote their goals. Practical interest has centered on questions such as: what are the relevant aspects of networks for marketing and competition? How much should a firm be willing to pay to acquire information about social networks?

Galeotti and Goyal (2009) study a simple model of large (directed) networks to study these questions. Their work distinguishes between the *level* and the *content* of social interaction. The level of interaction pertains to the number of people someone talks to (or the number of friends she has). Empirical work over the past decade has generated data on degree distributions across product categories as well as their relation to demographic characteristics of individuals which are traditionally used in design of influence strategies (Leskovec, Adamic, and Huberman (2007), and Keller, Fay, and Berry (2007)).

The content of social interaction reflects the way in which actions of others' affect individual incentives. In case of word of mouth communication about product quality and prices, the presence of a single informed neighbor leads to product awareness and possibly purchase. In case of choice of language a sufficient proportion of neighbors need to choose an action before an individual will switch to this action.

[14]See Galenianos (2014) for a model of search and social networks. The role of social networks in addressing information problems is also relevant for an understanding of migration patterns, see e.g., Munshi (2014) and Beaman (2016).

A first remark concerns the uses of network information: the use of such information reduces waste in advertising resources and generates greater sales. The effectiveness of social influence campaigns can be further increased by using more detailed information – such as the connections of different individuals in the social network. This leads naturally to a study of what is the right target in a network? Galeotti and Goyal (2009) find that that in the word of mouth context it is optimal to target individuals who are poorly connected. By contrast, in the proportional adoption externalities application, it is optimal to seed the most connected individuals (as they are unlikely to adopt via social influence)!

They also show that the effects of networks on profits turn on the content of the interaction. In the word of mouth context, an increase in connectivity enables greater spread of information: this increases sales and profits. On the other hand, if the product exhibits adoption externalities, an increase in connectivity makes it harder to satisfy the requirement that (say) all of them buy a product. Thus, an increase in social interaction in the presence of adoption externalities lowers profits. These considerations are summarized in

Observation 8 *The nature of optimal targets in networks depends on the content of social interaction: if interaction takes the form of word of mouth communication then poorly connected nodes constitute optimal targets, while in the adoption externality context highly connected nodes are the optimal targets. Greater connectivity raises profits in the case of word of mouth communication, but lowers profits in the case of adoption externalities.*

Galeotti and Goyal (2009) focus on the case with one firm, with one step spread of advertisement, and the firm only chooses advertising. Current research expands the scope of the analysis significantly to include multiple firms, dynamics of spreading information, see e.g., Fainmesser and Galeotti (2016), Goyal and Kearns (2012), and Campbell (2013). The use of social networks for the optimal diffusion of information remains an active field of research in economics.

In a related line of work, researchers have explored the use of optimal pricing in social networks. In the industrial organization literature, consumer value and hence, pricing, is conditional on the number of consumers who adopt different products (Farrell and Saloner (1986), Katz and Shapiro (1985)). Network externality often arises through the use of common products or services in personal interaction. So it is reasonable to suppose that the value of adopting a product to a consumer should depend on how many of her neighbors adopt the same product. This observation motivates the new strand of research on optimal pricing in networks.

Bloch and Querou (2013) and Candogan, Bimpikis and Ozdaglar (2012) study the problem of optimal monopoly pricing in social networks where agents care about consumption of their neighbors. Given a profile of prices $\mathbf{p} = (p_1, ..., p_n)$, and consumption profile $\mathbf{q} = (q_1, ..., q_n)$, an agent i's utility is given by

$$U_i(q_1, .., q_n) = a_i q_i - \frac{1}{2} b_i q_i^2 + q_i \sum_j g_{ij} q_j - p_i q_i \tag{10}$$

where g_{ij} measures the influence of i on j and $a_i > 0$ and $b_i > 0$. Observe that an increase in neighbor's consumption raises marginal utility of consumption.[15]

Given prices $\mathbf{p}$, under standard conditions there exists a unique consumption equilibrium. The analysis in Candogan, Bimpikis and Ozdaglar (2012) and Bloch and Querou (2013) yields

Observation 9 *Denote by G the adjacency matrix reflecting the social relations. The monopolist's optimal price vector satisfies*

$$\boldsymbol{p} = \boldsymbol{a} - \left[\Delta - \frac{G + G^T}{2}\right]^{-1} \frac{\boldsymbol{a} - c\boldsymbol{1}}{2}$$

where Δ is a diagonal matrix with terms $2b_i$ on the diagonal, $\mathbf{a}$ the vector of a_i's, c is the marginal cost of production and $\mathbf{1}$ is the vector of 1's.

Observe that if all influences are symmetric, $G = G^T$, and the monopoly sets a uniform price across the network. There are two forces at work: on the one hand, greater connectivity means greater utility and this pushes toward higher prices. On the other hand, greater connectivity also means greater externalities and this pushes towards lower prices to boost direct demand and hence the demand of neighbors. In the linear model under study, these two effects cancel out exactly. Observe that equilibrium consumptions do vary across nodes, and the authors show that they are proportional to the Katz-Bonacich centrality. Pricing in networks remains an active field of research; see Aoyagi (2015) for a model with competition among several firms.

The literature on social networks in product markets is motivated by practical concerns. The models incorporate asymmetric/incomplete information and network externalities. The analysis brings out the advantages of using networks to define optimal targets for advertising

[15] The specification here focuses on local externalities; it is possible to generalize this model to assign weights that decay in path length/distance. The case with no decay would then say that payoffs depend on membership of same component: this would correspond to the traditional formulation in the industrial organization literature, where payoffs depend only on group size (as in Katz and Shapiro (1985)).

and also in shaping optimal pricing: degree distributions and network centrality are the relevant network features. The analysis also highlights the ways in which networks can amplify small differences in resources between competing firms. While much progress has been made, it is clear that we have only a partial understanding of the interaction between consumer search and word of mouth communication interacts with firm advertising.[16]

8.3 Financial Markets

Financial markets are one context where the paradigm of competitive markets, and common prices that reveal information of all traders remains dominant. In recent years, empirical research has shown that social networks play a prominent role in shaping trading activity. I present a brief overview of this work.

Cohen, Frazzini and Malloy (2008) show that portfolio managers place larger bets on firms where they have social connected senior managers or board members; Interestingly, these investments also yield higher returns. Similarly, Hong, Kubik and Stein (2005) present evidence that US fund managers located in the same city commit to correlated investment decisions. 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. This empirical research motivates a formal analysis 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 and derive relations between trader behavior, prices and trading volume, and the network topology. For a general overview of networks in finance, see Allen and Babus (2009).

9 Transport Networks

Firms (and governments) create infrastructure and price access on these networks. Traditionally, interest has focused on pricing issues; for a survey, see Altman and Wynter (2002) and Laffont and Tirole (2001). Moreover, as transport networks compete for passengers and for revenue, it is natural to view network formation as a competitive process. This section discusses the elegant work of Hendricks, Piccione and Tan (1995, 1999) on airline networks.

[16]See Galeotti (2010) for a model of social networks with search and pricing in product markets.

Historically, airlines have been either publicly owned or heavily regulated. This has meant that both the routing as well as the pricing of services has been controlled in a variety of ways. In recent years, the airline market has been liberalized greatly in the US and Europe and also in other parts of the world. This has been accompanied by new entry and a significant fall in prices. Market concentration has gone up in direct flights but has come down in indirect flights. Airline networks increasingly exhibit a *hub-spoke* structure (with most flights being routed through a single city).

Following Hendricks, Piccione and Tan (1995), consider a single airline serving set of cities $N = 1, 2, \ldots, n$, $n \geq 3$. Travel is one-way (from city i to city j). People living in a city wish to travel to other cities. Let i, j index cities. A direct connection is a non-step flight from i to j. Operating the flight entails a variety of costs, such as check-in counters and ticketing. So suppose that one direct connection serves both routes i to j and j to i. For simplicity, suppose that there is a fixed cost of operating a direct link between any pair of cities, given by $F > 0$. The network of direct flights between the n cities is an (undirected) graph g. The profits of the airline is revenue minus fixed costs. The revenue (net of variable costs) is additively separable across city-market pairs. For each city pair, the revenue depends solely on the length of the path a traveler has to cross. Let $\pi(z)$ denote the revenue for a carrier when z is the length of path. It is reasonable to suppose that revenue is falling in path length. The analysis of Hendricks, Piccione and Tan (1995) is summarized in

Observation 10 *Suppose that revenue is falling in path length. Then there exist link cost levels F^* and F^{**}, such that for $F < F^*$ the complete network is optimal, for $F^* < F < F^{**}$ the hub-spoke network is optimal, and for $F^{**} < F$ the empty network is optimal.*

The proof builds on the trade-off between number of links versus path length: increasing direct flights is costly but raises revenue. The hub-spoke network balances the objectives perfectly: it contains the minimum number of links for any connected network and at the same time is also has short paths lengths (the maximum path length is 2). So if direct paths are attractive between two peripheral airports then, from separability, this must be true for all pairs of airports: the complete network with direct point-to-point flights between every pair of cities must be optimal.

In a subsequent paper, Hendricks, Piccione and Tan (1999) study competition between two airlines who choose flight networks. They develop a two-stage game in which two carriers simultaneously choose their networks and then compete for travelers. The carrier offering the shorter path between any city pair has a competitive advantage because length is costly for the traveler. They restrict attention to costs where a point to point network is unattractive, even for a monopolist. The paper studies the relationship between the severity of competition and the architecture of routing networks. In the setting of aggressive competition (e.g., Bertrand-like behavior), monopoly is an equilibrium outcome: a single carrier operates a hub-spoke network. Both airlines operating hub-spoke networks cannot be sustained in equilibrium. By contrast, in the setting of non-aggressive competition, there exists an equilibrium with competing hub-spoke networks (when the number of cities is not too small). Figure 7 represents the outcomes.

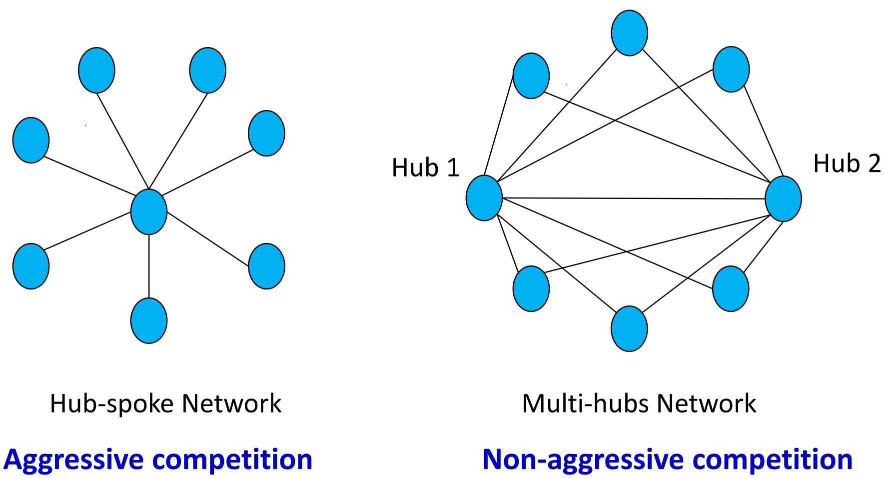

Figure 7: Airline Routing Networks

We have discussed competition between networks within the specific setting of demand for transport. But the problem is of more general interest. The next section takes up the networks in the context of the theory of the firm.

10 The nature of the firm

Following the early work of Coase (1937), and more recently that of Williamson (1975), it is customary to partition economic exchange as taking place in the 'market' (anonymous, arms-length) or within a firm (in a hierarchy). Empirical work, however, suggests that firms maintain a variety of durable relationships; research alliances and capacity sharing agreements are two prominent examples. Moreover, individuals in a firm maintain social relations with individuals in other firms and these social relations shape the behavior of the different firms.

These empirical observations have motivated the expression, 'network forms of organization' (Powell, 1990). I start by discussing research alliances and capacity sharing agreements in a static setting and then turn to the dynamics of inter-firm relations.

In some industries, firms procure standardized inputs from arm's length markets, in others firms vertically integrate and produce their own specialized inputs, and there are prominent examples in which firms maintain ties with a stable set of suppliers (Uzzi (1996)). What determines these patterns? The discussion elaborates on the circumstances in which networks of buyers and sellers performs better than vertically integrated markets or spot exchange markets.

Following Kranton and Minehart (2000), suppose that there is a set of buyers $B = \{b_1, b_2, ..., b_m\}$ and a set of sellers $S = \{s_1, s_2, ..., s_n\}$. Every buyer demands a single unit of an input. This input can come in two types: it can be a (normalized) zero-value *standard* input or a positive-value *specialized* input. The buyer can buy the *standard* input from a competitive fringe of input suppliers at a price normalized to zero. Alternatively, a buyer can vertically integrate and produce a *specialized* input itself, by investing in a *dedicated* asset, at a cost $\alpha_d > 0$. Finally, a buyer can create links with sellers of *specialized* inputs ("specialists"). Each link costs $c > 0$ to a buyer.

A buyer i has a random valuation v_i for a specialized input, with $v_i = z + \varepsilon_i$, where z and ε_i are random variables. Assume that z is a common shock to all buyers, with mean $\overline{z} > 0$. The variable ε_i is a buyer-specific shock which has mean 0. There are S *specialists* who can produce just one specialized input. A buyer who acquires the input from a seller needs to have a link with that seller. As mentioned above, building the link costs $c > 0$ to the buyer. A seller needs to invest $\alpha_f > 0$ in a *flexible* asset to be able to produce a specialized input. Assume $\alpha_f = \alpha_d = \alpha$ for simplicity. Once the investment is made, the seller can satisfy the needs of different buyers, i.e., the seller is a *flexible* specialist

An *industrial structure*, g, is formed by the investments of the buyers and the sellers. Networks involve buyers' specific investments and sellers' quasi-specific investments.

I start by looking at welfare maximizing industrial structures. Fix an industrial structure (or network) g and a vector $v = (v_1, v_2, ..., v_m)$ of (realized) buyers' valuations. Let $A(v, g)$ be an *allocation* of goods given buyers' valuations v and the industrial structure g. The economic surplus derived from an allocation of goods in an industrial structure g is $w(v, A(v, g))$. The allocation $A^*(v, g)$ is *efficient* if $w(v, A^*(v, g)) \geq w(v, A(v, g))$, for all feasible $A(v, g)$. For an industrial structure g, the expected surplus is $E_v[w(v, A^*(v,g))]$ and expected welfare is then

$$W(g) = E_v[w(v, A^*(v,g))] - \alpha \sum_{i=1}^{B} \delta_i(g) - c \sum_{i=1}^{B} l_i(g) - \alpha \sum_{j=1}^{S} \kappa_j(g) \tag{11}$$

where $\delta_i(g) = 1$ when buyer i is vertically integrated and equals zero otherwise, $l_i(g)$ is the number of links buyer i maintains, and $\kappa_j(g) = 1$ when seller j has invested in productive capacity and equals zero otherwise. We shall say that an industrial structure g is *efficient* if $W(g) \geq W(g')$ for all networks $g' \neq g$. Kranton and Minehart (2000) establish

Observation 11 *If buyers valuations are widely dispersed, productive capacity is expensive, and costs of linking are modest, then a network structure is efficient.*

I now turn to the question of whether buyers and sellers have the right incentives to form efficient network structures. Consider the following simple two-stage game. In the first stage, buyers choose unilaterally whether to invest in a dedicated asset (which costs them α), or to create links (which costs them c), or not to invest at all. Likewise, sellers choose whether to invest in a flexible asset (which costs them α) or not to invest at all. In the second stage, buyers' valuations are realized and production and exchange takes place. I look at the case where the exchange is competitive (modeled as in Kranton and Minehart, 2001), i.e., as having sellers holding simultaneously ascending-bid auctions and buyers bidding truthfully).

In a network, sellers simultaneously hold ascending-bid auctions. It is optimal for a buyer to remain in the auction of all his linked sellers until the price reaches his valuation. Anticipating *competitive* revenues, what are buyers' incentives to create links? Kranton and Minehart (2000) show that, given sellers' investments, a link contributes to the buyer the same amount as it contributes to social welfare. The conclusion here is that with this price formation protocol, buyers and sellers will form network industrial structure when it is efficient. (This is reminiscent of the results in Kranton and Minehart (2001) model of buyer and seller networks.)

I next turn to research alliances among firms. Firms increasingly choose to collaborate in research with other firms. This research collaboration takes a variety of forms and is aimed both at lowering costs of production as well as improving product quality and introducing entirely new products. Indeed, Hagedoorn (2002) argues that there has been a significant increase in the level of collaborative research among firms. Two features of this collaboration activity have been highlighted. The first feature is that firms enter into a number of relationships with non-overlapping sets of firms: in other words, the relations are non-exclusive. The second feature is that firms often collaborate with other firms within the same market, giving rise to a complex relation which combines cooperation and competition. Example 2 (presented in section 2), illustrated the effects of collaboration networks on firm research activity and profits. I now discuss the formation of research networks.

Following Goyal and Joshi (2003), suppose there are $N = (1, 2, 3, ..., n)$, with $n \geq 2$ firms. Consider a link announcement game along the lines of Myerson (1991). A link costs $F > 0$ to each firm and lowers their marginal costs of production by $c > 0$. The links constitute an alliance network that defines a vector of firm costs. The rewards from a link depend on market competition. Strong competition refers to the case where only the unique lowest cost firm makes profits (Bertrand competition with homogenous goods is an example). Moderate competition refers to the case where lower costs imply higher profits (examples include Cournot competition with homogenous goods and price competition with differentiated goods).

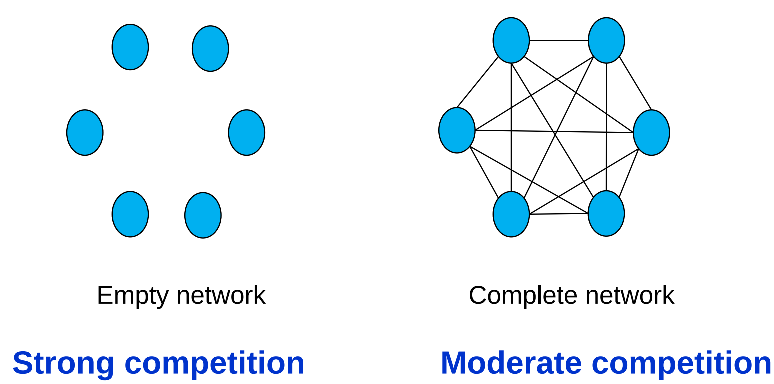

Figure 8: Stable Collaboration Networks

Goyal and Joshi (2003) show that markets and linking activity interact in interesting ways with potentially large welfare effects. They show that with strong competition, the empty network (with no links), is the unique pair-wise equilibrium. With moderate competition, the complete network (with all links present) is the unique pair-wise equilibrium. The intuition is as follows: In the case of strong competition, no two firms can hope to make money in a non-empty network. Anticipating this outcome, firms form no links. On the other hand, under moderate competition, if two firms form a link, both lower costs, and therefore increase their profits, at the expense of other firms. Thus any incomplete network is vulnerable to a profitable deviation. Figure 10 represent these outcomes. This is a simple result but it has an important message: there is a two way flow of influence between markets and networks. Markets shape incentives to create links, but these networks in turn define costs and therefore shape the nature of competition.

These differences in the network can have potentially large welfare effects. Define social surplus as the sum of firm profits and consumers surplus. Goyal and Joshi (2003) show that under strong competition the efficient network entails a core-periphery network (with two firms fully linked firms in the core), whereas with moderate competition the efficient network is complete. These observations are summarized in:

Observation 12 *Suppose the cost of a link, F, is small.*

1. *With strong competition, the empty network, (with no links), is the outcome. With moderate competition, the complete network is the outcome.*

2. *Under strong competition the efficient network is a core-periphery network (with two fully linked firms); under moderate competition the efficient network is complete.*

Thus efficient networks are formed under moderate competition, but there is a divergence between individual incentives and efficiency under strong competition. This suggests that moderate competition may attain greater efficiency, due to the endogeniety of networks.

So far, the focus has been on the setting with small costs of linking. I now briefly discuss large costs of linking. To make progress, consider the linear demand homogenous good Cournot model. It turns out that, in this model, the marginal returns may be written in a compact form as a function of own links and of the sum of all links amongst the other firms. In particular, marginal returns are increasing in own links and they are declining in the sum of links of others. This property of payoffs immediately implies that if two firms have links then they must be linked. Thus, any (equilibrium) network must consist of a set of firms in a complete component and a set of isolated firms. The empty network and the complete network are limit cases of this class of networks.

This result also reveals that highly connected firms have an incentive to subsidize links with isolated firms (who may not find it profitable to form a link). Goyal and Joshi (2003) show that when firms can make transfers, the star network and multiple-hub networks are stable. Figure 10 represents these networks. The reason for this increasing marginal returns from own links and falling marginal returns in links of others: the central firm in a star has high marginal returns from an additional link, while peripheral firms with a single link have low marginal returns. Simple computations reveal that in these networks, the central highly connected firm earn higher profits compared to the peripheral firms. The analysis of efficient network for large costs of linking is presented in Westbrock (2010).

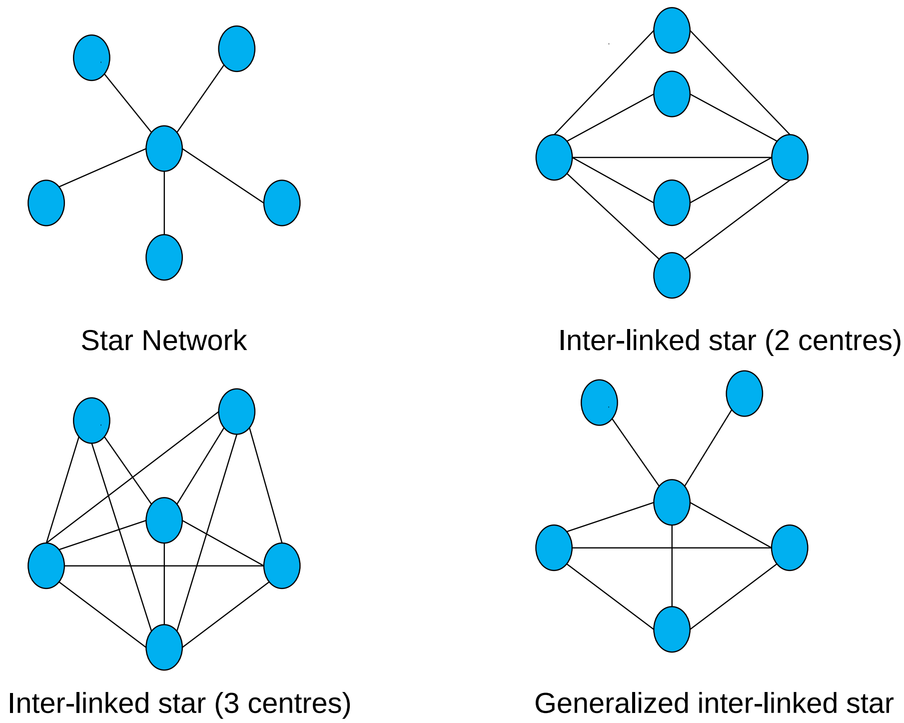

Figure 9: Stable Collaboration Networks with Transfers

More generally, given the increasing returns to own links, it follows that if a firm is linked to a firm with k links then it must also be linked to every firm with k or more links. This observation is central to the construction of nested graphs, that have been developed in the more recent work of Koenig, Tessone and Zenou (2014).

I have discussed models of networks and firms where information is symmetric. In actual practice, a firm is more likely to know about the knowledge and skills of other firms with whom it has had past collaborations. Similarly, individual firms are likely to have significant private knowledge about own efforts and skills. In the context of research and development, formal contracts will typically not be able to address these problems fully. So firms may prefer repeated collaboration with existing collaboration partners or with firms about whom they can get reliable information via existing and past common partners. In other words, the network structure of past collaborations may well play an important role in shaping the performance of existing collaborations as well as the pattern of new collaborations. These considerations constitute key elements in the argument on the social embeddedness of economic activity (Granovetter, 1985; Raub and Weesie 1990).[17]

Two questions have received attention: what types of firms enter into collaborative agreements and with whom? In a dynamic setting, there is the issue of how the existing pattern of collaboration links relates to the governance structure of a new collaboration partnership – do firms write a formal contract or are loose research sharing agreements? There is a large empirical literature on this question, see e.g., Kogut, Sham, and Walker (1994), Gulati (2007), Powell, Koput and Smith-Doerr (1996). The formal study of evolving relations in a network with asymmetric information, appears to be an open problem. For an early study of repeated games on fixed networks with exchange of information among players, see Haag and Lagunoff (2006). For a survey of the theory of repeated games on networks, see Nava (2016).

The second issue concerns the governance of network forms of organization. Empirical work has examined the nature of contracts and governance structures which define collaboration links between firms. This work suggests that collaboration agreements become less formal if partners are embedded in social networks of previous collaboration links (Gulati, 2007). This is suggestive of the growth of trust via participation of firms in a social network of collaborative links. We lack a formal model where the issue of contract form or complexity can be examined in relation to networks of trust.

11 The Great Transformation: shifting boundaries

The Great Transformation refers to the large scale changes in political, legal and social structure during the process of industrialization. The traditional view, following Polanyi (1944) is that economic activity was more embedded in social ties in pre-industrial then it is in modern societies. In recent years, this view has been contested by a distinguished group of scholars; for an influential statement, see Granovetter (1985).[18]

While these arguments are timely, it is worth noting that arguments on the relation between social ties and markets have older, and very distinguished, antecedents. There is, on the one hand, the classical *doux-commerce* stance, going back to the eighteenth century

[17]Scientific collaboration shares some features in common with research alliances among firms; for an empirical investigation of the role of networks in fostering co-authorship in economics, see Fafchamps, Goyal and van der Leij (2010) and Ductor, Fafchamps, Goyal and van der Leij (2014).

[18]The large literature on the role of social capital in economic and political performance must be mentioned here, Coleman (1988), Putnam (1993) and Dasgupta and Serageldin (1999).

(Montesquieu, 1748; Paine, 1792; Condorcet, 1795). It argues that markets create new opportunities for exchange, and these opportunities require that individuals cooperate with each other. Therefore, markets broaden the scope and hence reinforce social ties. Other scholars have argued that the expansion of markets are accompanied by wide ranging changes in attitudes and institutions, and these changes crowd out social ties (Polanyi (1944), Thompson (1971), Scott (1977); Sandel (2012). For eloquent accounts of this debate, see Hirschman (1977; 1982), and for a recent review of the debate, see Besley (2012). This argument takes the view that community-based economies, or *moral economies*, rest on norms of reciprocity and markets represent an outside option that undermine such norms. This section presents formal models and empirical evidence to assess the scope and validity of these arguments.

I start with the discussion of an early paper by Kranton (1996) that develops an elegant model to explore the scope of the second line of reasoning.[19] She takes the view that community based exchange involves reciprocity: I do you a favor today and you reciprocate in kind at a later date. Individuals who do not fulfill their obligations are punished by a termination of the favor exchange relationship; the seriousness of this punishment depends on the presence of alternatives. Thus the availability and size of a spot market where agents can anonymously exchange will affect the enforceability of reciprocal exchange. The size of the market is important because it shapes the costs of obtaining goods/services: thin markets raise the costs of search, while thick markets reduce them. The more individuals engage in reciprocal exchange, the less they need to rely on markets to obtain goods and services and vice-versa. Thus there is a negative externality from markets to reciprocal exchange. These arguments are summarized in

Observation 13 *Reciprocal-exchange and markets are substitutes and both constitute a self-sustaining system.*

What about welfare? The key issue here is substitutability of goods: in reciprocal relations individuals are obliged to accept whatever their partner provides. This restricts the range of goods. So if commodities are substitutable, reciprocal exchange is efficient while if goods are poor substitutes then markets are efficient. Putting together these points with the last observation above suggests the following reinforcement dynamics: starting from an initial situation in which most people are engaged in reciprocal exchange the system may well persist as no one wishes to enter the market due to the high search costs. On the other hand, if a

[19] For a recent study on the practice of bilateral favor exchange and its implications for the functioning of markets, see Bramoulle and Goyal (2016).

large fraction of the population is in the market (or if a national government opens up its economy to global markets) then reciprocal relations may gradually shrink and disappear.

The defining feature of the above model is that markets and community are mutually exclusive: one can grow only as the expense of the other. But the empirical evidence on this subject is mixed. I present two examples to illustrate this point.

Example 6 *Caste Networks and Globalization*

Munshi and Rosenzweig (2006) explore the impact of economic liberalization of the Indian economy in the 1990s. This led to a shift toward the corporate and finance sectors, which increased the returns to white-collar jobs, for which knowledge of English was necessary. The authors estimate that in the city of Mumbai, the premium to English education (compared to education in the local language, Marathi) went up by roughly 25%, over the 1990s. Crucially, the authors note that caste connections are (i) central for jobs search in the blue collar sector, but not in the white collar sector, and (ii) the networks are accessible to males but not the females.

Their main finding is about the effects of market liberalization on schooling. Boys adopted English language much less than their female counterparts: thus those with less access to the traditional network joined the market more. The gap in English education between girls of high and low castes shrank, but the gap for boys remained (roughly) intact. Moreover, participation in markets led to an erosion in the traditional networks. □

Example 7 *The Digital Provide: Mobile telephones and social connections*

The expansion of mobile telephony in developing countries and its potential for large development impact has been extensively commented upon (see e.g. Aker and Mbiti, 2010). Jensen (2007) studies the impact of mobile telephones on fishermen in Kerala, India in the 1990's. Prior to the introduction of cellphones, fishermen fished and sold their catch almost exclusively within their local catchment zone. The adoption of cellphones had a large and differential impact. Fishermen could now exchange information with buyers, friends and relatives, and auctioneers while at sea, therefore obtaining precious information about the demand in different fish markets. By 2001, more than 65% of all fishing boats in Kerala owned a cellphone. Adoption was significantly higher for fisherman with larger boats.

Fishermen raised their participation in the market along with more intensive use of social connections (in communication). Moreover, it was the larger boats with a more extensive set of connections that took greater advantage of the new opportunities. This had significant implications for welfare and inequality. □

These two empirical studies motivate a theoretical framework that includes both substitutes and complements relations between markets and networks and that that allows for heterogeneity in social connections.[20]

Following Gagnon and Goyal (2016), I consider a model where individuals located in a social structure choose a *network* action (x) and a *market* action (y). Payoffs to action x are increasing in the number of neighbours in the social structure who adopt the same action: this captures the local externalities in network activity. In contrast, market exchange is monetized, anonymous and short-term, and agents are price-takers: payoffs to action y are independent of the decisions of others. The actions x and y may be *complements* or *substitutes.*

The authors start with the observation that behavior in this setting is described in terms of a simple network property: the *q-core*. To develop some intuition for this notion note that the payoffs to x depend on the number of one's neighbors who adopt x; adoption decisions of neighbors are in turn a function of how many of their neighbors adopt x, and so forth. This leads naturally to the notion of a set of individuals who each have a threshold number of neighbors, whose neighbors in turn each have this threshold neighbors, and so forth. The *q-core* of a graph is the maximal set of individuals having strictly more than q links with other individuals belonging to this set. Figure 11 illustrates the derivation of the $4-$-core in a network, through the progressive elimination of nodes that have 4 or fewer links.

The characterization of behavior in terms of the q-core allows a study of a number of questions.

First, consider the issue of who participates in markets and what sorts of social structure facilitate market participation. Gagnon and Goyal (2016) show that in the substitutes case, it is the individuals outside the q-core who take part in market exchange; by contrast, in the case of complements, it is the individuals within the (appropriate) q-core who do so. Denser networks will have a larger q-core and so will witness lower market participation in case of substitutes and higher adoption with complements.

Next consider welfare (defined as the sum of payoffs of all individuals). The authors show that markets may lower aggregate welfare when the actions are substitutes but that they

[20]Informal insurance remains important in developing countries (see Townsend (1994), Ambrus, Mobius and Szeidl (2014) and Ambrus, Elliott and Chandrashekhar (2016)). The relationship between social networks and markets is central to an understanding of the take-up of formal insurance schemes (see Gagnon and Goyal (2016) and Mobarak and Rosenzweig (2012).

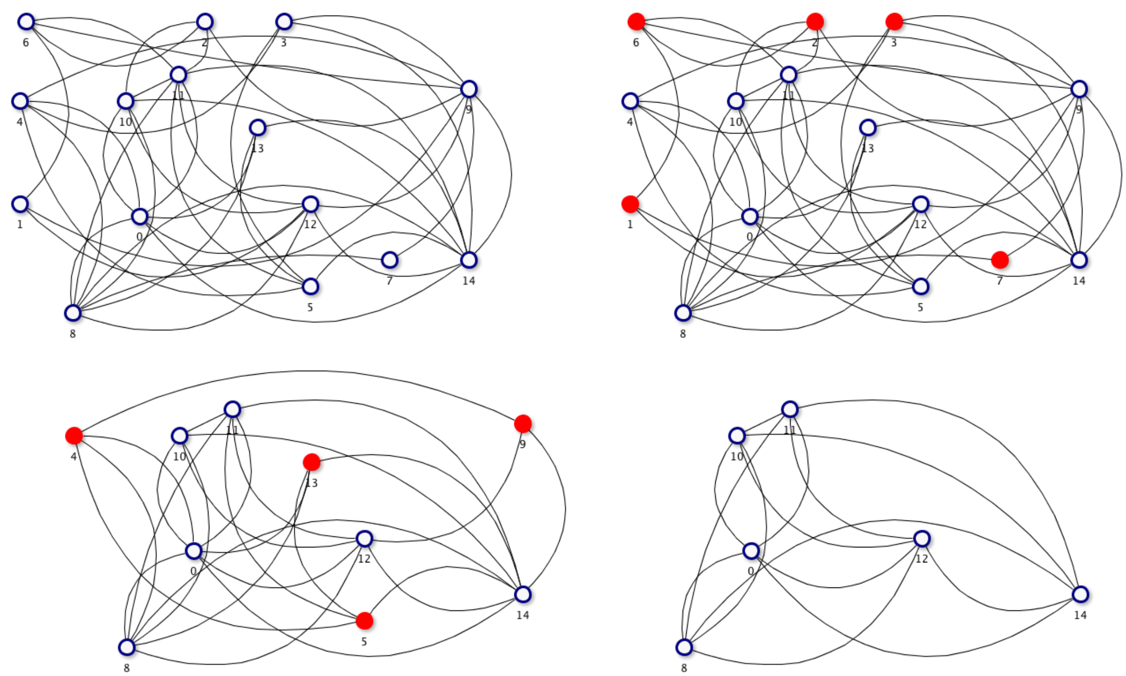

Figure 10: The 4-core

always raise it in the case of complements. The intuition is that when someone joins the market (chooses y) and "leaves the network" (drops x) she imposes a network externality on her neighbors who stay with x. This negative effect may outweigh the personal rewards of joining the market. In the complements case, market exchange raises marginal payoffs of network action and thus 'raises all boats'.

The analysis also yields a crisp prediction on inequality: markets typically raise inequality in case of complements but always lower inequality in the case of substitutes. The reason is that with complements the marginal returns are highest for the 'well connected' members of the social network. In the substitutes case, the market action offers an outside option to individuals who benefit the least from the network, and therefore has the potential to reduce inequality. These points are summarized in

Observation 14 1. *In the case of substitutes, members of the relevant q-core participate in the network activity and those outside it move to the market. The converse is true in case of complements.*

2. *Market participation is higher in a denser network in case of complements but lower in the case of substitutes.*

3. *Welfare is always raised by the emergence of a market in case of complements, but may fall in case of substitutes.*

4. *Markets typically increase inequality in the case of complements but lowers inequality in the case of substitutes.*

To close the circle, I now briefly return to the two empirical case studies discussed above and map them onto the model presented in Gagnon and Goyal (2016).

In the Caste Networks and Globalization setting, the action x refers to Marathi language while action y refers to English language schooling. The payoffs to x are correlated with participation in caste working class networks. The social connections mainly cover jobs for young men: so young men are well connected in large sub-castes; girls are poorly connected. The authors tell us that market liberalization raises returns to English. The model predicts that in response adoption of English should be higher for girls than for boys and that gender inequality should decrease. These predictions are consistent with the empirical patterns identified in Munshi and Rozenzweig (2006).

Turning to impact of mobile telephony, note that payoffs of fishermen are given by sales. The sales depend on information about prices in local fish markets. Let action x refer to "obtaining information", y refer to "owning a cell phone". Information sharing with social contacts becomes more profitable when combined with the purchase of a mobile phone. The model predicts that fishermen (with bigger boats and) with more contacts are more likely to adopt mobile telephony and that this will raise inequality. This is consistent with the empirical patterns identified in Jensen (2007).

More generally, these discussions suggest that the dynamics between markets and social networks exhibit interesting non-linearities. One technology can lead to the relative decline in one function of social networks, while a subsequent technology can lead to a revival of the same function (or the development of a new role for social networks).[21] I illustrate this point with a topical example.

Through much of human history, news was passed on through private communication. Indeed, the Royal Society was set up in London in 1660, in an attempt to formalize such private communication through weekly meetings. The growth of newspapers, television and radio through the 19^{th} and 20^{th} century gradually led to a decline in the role of social interaction in communication. It is possible that we are witnessing witnessing a reversal of this movement.

[21]For an overview of the impact of modern communication technologies on the relation between anonymous markets and social network based exchange, see Sundararajan (2016).

The explosive growth of online social networks is a defining feature of the last decade. The Reuters Institute for the Study of Journalism (RISJ) reports that more than half the population of many countries (e.g. Brazil, Spain, Italy and Finland) use Facebook for news purposes (RISJ, 2014). This rise of online news has proceeded in tandem with a sharp decline in traditional newspaper markets (Newman, 2009; Currah, 2009). For an entertaining account of the fall and rise of social networks as vehicles for communication of news, see Standage (2013).

12 Concluding remarks

The origins of a systematic study of networks in economics can be traced to the 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. As the theoretical findings came in contact with substantive issues in economics, research gathered momentum: networks now combine with the classical ideas of competition, prices and information to offer an encompassing framework for economic analysis.

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