THE ECONOMICS OF NETWORKS: THEORY AND EMPIRICS

ISBN 90 5170 973 0

Cover design: Crasborn Graphic Designers bno, Valkenburg a.d. Geul

This book is no. **384** of the Tinbergen Institute Research Series, established through cooperation between Thela Thesis and the Tinbergen Institute. A list of books which already appeared in the series can be found in the back.

The Economics of Networks: Theory and Empirics

De Economie van Netwerken:
Theorie en Empirie

PROEFSCHRIFT

ter verkrijging van de graad van doctor aan de
Erasmus Universiteit Rotterdam
op gezag van de rector magnificus
Prof.dr. S.W.J. Lamberts
en volgens besluit van het College voor Promoties.

De openbare verdediging zal plaatsvinden op
21 december 2006 om 11.00 uur door

Marco Juri van der Leij

geboren te Delft

Promotiecommissie

Promotor:	Prof.dr. S. Goyal
Overige leden:	Prof.dr. M.C.W. Janssen Prof.dr. J.L. Moraga-González Prof.dr. T.A.B. Snijders
Copromotor:	Dr. M. Fafchamps

Voor opa en oma

Acknowledgements

About five years ago I started my endeavor to write a Ph.D. dissertation. Thinking back of how I was then and how I am now, it amazes me how much I have learned. Five years ago, I was quite a good undergraduate student in Econometrics with the intention of becoming a good theoretical economist as well. As a field of specialization I was thinking of Network Industries. Nowadays, I indeed feel comfortable doing 'theory', but I have also taken up and improved my econometric skills. Moreover, instead of doing research on Network Industries, I am currently doing 'cutting edge' research at the frontier of a new exciting research area, the 'Economics of Networks'.

A crucial turning point in this period was in December 2002, when Sanjeev Goyal, my Ph.D. advisor, and José Luis Moraga-González asked me to join a new research project. The objective of this project was to investigate whether the world of economists is indeed a small world, as posed by a theory of Watts & Strogatz (1998). I decided to join them, and since then I have learned so much about the nature of networks through discussions, presentations, trials and errors and many hours behind the computer. Eventually, all the effort resulted in a publication in the prestigious *Journal of Political Economy* as a short version of Chapter 2 of this dissertation.

It is clear that José Luis and, in particular, Sanjeev were crucial in making me the researcher that I currently am. Sanjeev has always tried to push, teach and stimulate me to become a better academic economist. He has also introduced me to his personal network. I am still clueless at times why he puts so much time and effort in helping me, but in the end I am extremely grateful that he does. To be honest, I cannot imagine that I could have had a better Ph.D. advisor than Sanjeev.

Sometimes Sanjeev could be pretty harsh, even though I knew it was for my own good. Nonetheless, in those times it was comforting to have José Luis as a counterforce. José Luis, always friendly and nice, would listen and advise me, be it on research or teaching or anything else. Although we have had less contact since he moved to Groningen, José Luis played an important role in the last 5 years.

In 2004, Sanjeev and I started a research project with Marcel Fafchamps. This project evolved and eventually Marcel became my co-advisor, in particular to assist me with the empirical content of the dissertation. Since then, I have learned and I am still learning from Marcel's experience in applied empirical research.

Many others have contributed to this dissertation by stimulating my thoughts and my intellectual development. First, I would like to mention Andrea Galeotti, who started his Ph.D. under Sanjeev Goyal a year before me, and who has been and still is a great colleague. Whereas Andrea was more senior than I was, after his departure I was the more senior student at the Tinbergen Institute. In that position I tried to stimulate and

I also benefited from the discussions with Sandra Phlippen and Mariëlle Non, who are currently the only Ph.D. students at Erasmus School of Economics working in the field of Network Economics. Also senior to me and very supportive and stimulating to work with were the faculty of the Department of Economics and the Econometric Institute. I am particularly grateful to Philip Hans Franses and Richard Paap with whom I am still collaborating on an econometric research project. I would also like to thank all the other students and staff members of the Tinbergen Institute, in particular Klaas Staal, with whom I shared an office for a couple of years.

I am also grateful for the contacts I obtained with people at other universities. Thanks to the participation in the Tinbergen Ph.D. council I regularly visited the Tinbergen Institute in Amsterdam to meet my fellow councilors and other TI students and researchers. I am particularly grateful to Sebi Buhai. We decided to collaborate on a research project, and Chapter 5 is the result. I also very much enjoyed and benefited from my long and short visits to the University of Essex, where everyone, and in particular, Michele Belot and Carlos Carillo-Tudela were very friendly and kind. In Essex I also became well acquainted with Fernando Vega-Redondo, who crucially motivated and helped me to join the University of Alicante after my Ph.D. defense.

A particularly stimulating environment was the 'Network Reading Group'. I have participated in this group for a couple of years, first at CREED in Amsterdam, where I benefited from discussions with Ernesto Reuben, Aljaž Ule, Arno Riedl and others, and later at USE in Utrecht, where I continued the discussion with Bastian Westbrock, Rense Corten, Stephanie Rosenkranz, Vincent Buskens, Jurjen Kamphorst and others. Both in Amsterdam and Utrecht I enjoyed talking to Ana Babus and Willemien Kets about networks as well as other things. Knowing that they would attend the reading group was a great stimulus for me to participate for such a long period.

I hereby would like to thank the inner thesis committee, Sanjeev, Jose Luis, Maarten Janssen en Tom Snijders for reading and commenting on my thesis. I would also like to thank the Econometric Institute, the Tinbergen Institute and the Vereniging Trustfonds Erasmus Universiteit Rotterdam for funding my academic visits and conference participations. I am also grateful to my parents for their unconditional support.

Finally, there is one person who contributed to this dissertation more than anyone else. My gratitude to her is infinite.

Contents

Chapter 1

Introduction

> "I read somewhere that everybody on this planet is separated by only six other people. Six degrees of separation between us and everyone else on this planet. The President of the United States, a gondolier in Venice, just fill in the names. I find it extremely comforting that we're so close. I also find it like Chinese water torture, that we're so close because you have to find the right six people to make the right connection... I am bound, you are bound, to everyone on this planet by a trail of six people." (Ouisa Kittredge in *Six Degrees of Separation*)[1]

The fact that we are all connected, constrained and influenced by our fellow humans in this world has fascinated mankind and it has inspired playwrights and movie makers. Social networks have also captured the attention of scientists. Not only sociologists have a primary interest in social networks, but also mathematicians, physicists, biologists, anthropologists, computer scientists, and management scientists have analyzed social networks from different perspectives.

And what about economists? Intuitively it seems that networks should be a major focus of the "study of choice and decision-making in a world with limited resources".[2] Doesn't someone's social network constrain her resources? Don't we make rational decisions on whom to contact and whom to get acquainted to? The quote above suggests so, and so does the term 'networking'. Firms have even set up services to organize and plot one's social network in order to facilitate contacts with new people.[3] However, economists are just starting to analyze the economic aspects of social networks.[4] Before the 1990s, economists typically assumed that social (market) interaction is anonymous and the social network is irrelevant. This approach is justified as long as models of anonymous interaction are able to provide good explanations for economic phenomena of interest. The

[1] The quote was taken from `http://www.imdb.com/title/tt0108149`. The movie script was adapted from the stage play 'Six Degrees of Separation' written by John Guare.

[2] Definition of economics as given by Economics Glossary at `http://www.mcwdn.org/ECONOMICS/EcoGlossary.html`.

[3] For example, see `http://www.visiblepath.com/`.

[4] The subfield of network economics is now quickly expanding, and becoming more established in economics. To illustrate this, in the EconLit database of economic journals 18 articles had the word 'network' in their title between 1974 and 1983. This number increased to 1127 articles between 1994 and 2003 (Galeotti, 2005b).

introduction of networks in economic models would then only lead to a higher complexity without offering further insights. In other words, interest in networks by economists is only justified if it gives us insights into economic phenomena that are impossible or implausible to explain without introducing networks.

Until 20 years ago, only few economists had been convinced that there were a lot of insights to gain from a network approach. This has gradually changed after a few influential publications in sociology that raised the interest in social networks, not only in sociology but also in economics.

In 1985 Mark Granovetter wrote ‘Economic Action and Social Structure: The Problem of Embeddedness’. Granovetter argued that all economic actions are embedded in social networks, and that many puzzling market situations can easily be understood if we take into account this embeddedness in social structure. He illustrated how the concept of embeddedness could enrich economic research by criticizing the ‘new institutional economics’ approach of Williamson (1975). Williamson argued that markets were undesirable in cases where buyers or sellers had to incur high transaction costs. In such cases, vertical integration of the buyer’s and seller’s firms would be preferable. Granovetter notes that many complex transactions with high transaction costs are sustained in buyer-seller markets. The key to understand this is the fact that buyers and sellers are embedded in a network of long-term business relations. Buyers and sellers do not want to lose the trust that they have build up in their market relations, because the abuse of transaction power would then lead to the loss of other market transactions as well. Further, Granovetter argues that it would be naive to think that buyers and sellers would align their economic interests if they are working in a vertically integrated firm.

It is important to note that Granovetter did not suggest to abandon the typical economic assumption of rational, self-interested behavior. On the contrary, Granovetter argued that seemingly irrational behavior can be rationalized once we take into account the social relations agents are embedded in. Thus the problem of economics was not the simplistic assumption of rationality, but the “neglect of social structure”. Granovetter thus suggests a theoretical approach that still involves the paradigm of rational action, and also takes into account the social relations agents are embedded in.[5]

1.1 On the economics of networks

Since the 1990s interest in networks has gradually increased. This has led to new economic models of network formation and network interaction. This thesis contributes to this quickly developing subfield in economics by analyzing economic aspects in three different types of networks; a network of collaborating scientists; a network of job contacts; and a network of transportation.

When we analyze the role of networks in economics, it is useful to structure the analysis around the following three questions:

1. What structural properties does the network have?

[5] In a similar vain James Coleman (1988) introduces and describes the function of ‘social capital’. See Sobel (2002) for a nice discussion of the social capital metaphor.

2. How does the network structure influence economic decision-making?

3. What role do economic incentives play in the formation of the network structure?

Question 1 is of an empirical nature. The objective of this question is to give us 'stylized facts' about the structure of networks. These stylized facts provide us guidelines for questions 2 and 3, which lead to a better understanding of the relation between networks and economic decision-making. While question 2 explores the causal relation of networks on economic decision-making, question 3 explores the reverse. The analysis of questions 2 and 3 may then lead to predictions on the network structure that can be tested empirically, thus they lead us back to question 1. Hence, an analysis based on the above questions leads to an analytical cycle, which in turn leads to a regular improvement of our understanding of the role of networks in economics.

The answers to the three questions above depend on the network type considered and on the economic context. However, scientists have also looked at commonalities between the different networks and economic settings. In this section we therefore consider the three questions from a general point of view.

1.1.1 Network structure

Although sociologists have a long tradition in the analysis of social networks, other sciences showed little interest in the structure of networks. Perhaps the reason for this limited interest was the difficulty to obtain network data. Typical sociological data sets are limited to a few tens or a few hundreds of observations. These data sets are well suited to analyze micro-properties of networks, that is, at the dyad or triad level (subsets of two or three persons). However, the disadvantage of these data sets is that it is very difficult to get a 'helicopter view' of the interconnections between different local networks, which together form a giant network themselves.

This has changed with the advent of the information and communication revolution. Electronic databases containing thousands of records have recently appeared, for example electronic bibliographies. From these databases data on the relations between thousands of individuals can be obtained. Further, advances in computer technology have made it possible to store and to analyze these large networks.

The arrival of new large data sets has created a boom in the analysis of network structures, mostly in physics, and has led to a better understanding of the macro-properties of networks. Many large networks, such as the WorldWideWeb (Albert, Jeong and Barabási, 1999), the internet, the electricity power grid, e-mail networks, film actor networks, and coauthorship networks, have now been analyzed.[6]

These networks typically have the following properties (Newman, 2003): small network distances, high clustering, and an unequal distribution of links. We now discuss these three properties.

Small network distances. The network distance between A and B is measured by the number of actors that separate A and B. Thus if there is a direct link between A and B,

[6] See Newman (2003) for an overview.

then the network distance is 1; if A and B are indirectly connected through a common 'friend' C, then the distance is 2, etcetera. The quote of 'six degrees of separation' suggests that the network distance between any two individuals in the world is, on average, six. Many people think that this is an urban myth, but in fact, it is based on evidence from a series of experiments carried out by Stanley Milgram (1967). Subjects living in distant states in the U.S., such as Kansas, were asked to forward a letter with the objective to reach target persons in Massachusetts. The subjects were only allowed to forward the letter to a person acquainted on a first-name basis with the request to forward the letter to one of her acquaintances, and so on, until the targets were reached. Eventually, about a quarter of the letters reached the targets and the average number of intermediate subjects on the chain was approximately six.[7]

At first sight, this short distance seems hard to believe, but it is easily understood by the following thought experiment. Suppose that everyone in the world has only 21 acquaintances. This means that an arbitrary individual A has 21 acquaintances at distance one. These 21 individuals each have 20 other acquaintances, and if A and these 21 individuals do not have acquaintances in common, then A has $21 \times 20 = 420$ persons at distance two. These 420 persons have each 20 other acquaintances leading to at most $420 \times 20 = 8,400$ individuals at distance three from A. Continuing this way of reasoning, then there are at most $168,000$ individuals at distance four, $3,360,000$ at distance five, $67,200,000$ at distance six, and $1,342,000,000$ at distance seven. Thus this thought experiment shows that the number of connected individuals within distance d grows exponentially with d, and, conversely, the average distance grows logarithmically with the size of the population, leading to 'small distances' for large networks.

It has now been confirmed that many large networks indeed follow this logarithmic rule. That is, the average network distance is in the order of $\log n$, where n is the number of nodes in the network.[8] Networks with this property are said to exhibit a 'small world effect'.

Clustering. The calculations in the above thought experiment give an upperbound to the number of individuals within a particular distance d. This upperbound is not reached if individuals have many of their acquaintances in common, or in the parlance of networks, if the network is *highly clustered*. To understand this, consider the following extreme example. Suppose A lives in a sect that consists of 22 members. All sect members are acquainted to each other and to no one outside the sect. Clearly A has 21 acquaintances, and these individuals have 21 acquaintances themselves. However, since everyone in the group has *all* their acquaintances in common, the number of individuals within distance d of A does not grow at all with d. That is, a chain letter starting at A will just keep on circulating within the group without ever leaving it.

This example illustrates a feature of networks with high clustering. Links in highly clustered networks are unlikely to connect new people. Therefore, highly clustered links

[7] This experiment has recently been repeated on a much larger scale using e-mail messages by Dodds et al. (2003). They find that the average chain length is indeed around six.

[8] In fact, in many instances the network distance increases even slower than $\log n$. This is probably due to the inequality in the link distribution. A mathematical proof in the case of scale-free random graphs is given by Bollobás and Riordan (2004).

do not help in reducing distances. This remark would suggest that high clustering of acquaintances contradicts short distances. It is then perhaps surprising that it is typically found that real networks are highly clustered *and* have short distances (Newman, 2003).

The apparent paradox of networks that have both high clustering and short distances was scientifically puzzling. This puzzle was solved by an insight from Watts and Strogatz (1998). They showed that, starting from a highly clustered spatial network with corresponding large distances, the introduction of only a small amount of random ties that bridges large geographical distances reduces the network distances dramatically while the level of clustering remains high. Thus in the example above, if only one of the sect members has a connection outside the sect, then clustering in the sect is still very high, while the connection of one single individual in the sect opens up indirect connections for *all* sect members to the outside world.

To conclude, Watts and Strogatz (1998) show that the empirical findings of short distances and high clustering do not contradict each other. They can easily be understood by introducing a small amount of randomness in a highly structured model.

Unequal distribution of links. A striking feature of many networks is the extreme inequality in the distribution of links across individuals. For example, Albert, Jeong and Barabási (1999) analyzed web pages of the Notre Dame university website. They found that, while 82 percent of the pages received less than 4 links from other webpages, a few pages received more than 1000 links. In Chapter 2 we report that economists had, in the 1990s, less than two coauthors on average. However, a few economists had many more, even more than 50 coauthors. An overview of the inequality in other networks can be found in Newman (2003).

While one should always expect some amount of heterogeneity among individuals, and hence some amount of inequality, the inequality in the distribution of links is very large, much larger than the inequality observed in the distribution of other human characteristics, such as age, length, weight or IQ. In fact, the inequality in the distribution of links is so large that it is hard to understand. Many network models, such as the Watts-Strogatz model above, do not generate such a large unequal distribution of links. Nonetheless, the fact that such an inequality is observed in so many networks suggests that there lies a general principle behind the formation of networks.

A plausible principle is given by Barabási and Albert (1999). They suggest a model in which a new node enters the network in each period and initiates links to existing nodes in the network. Importantly, the link formation is not entirely random. Instead, Barabási and Albert assume that the probability for a node to receive a link is proportionally increasing in the number of links a node already has. In other words, a node with 10 links has a 10 times higher chance of attracting new links than a node with only one link. Barabási and Albert call this *preferential attachment*.

In a process of preferential attachment, 'rich' individuals, that is, rich in links, are much more likely to become even 'richer'. Not surprisingly, this process therefore creates a profound inequality in the degree distribution. The model of Barabási and Albert therefore gives a good explanation for inequality in the degree distribution.[9]

1.1.2 Network effects

Network relations matter in a wide variety of settings. For instance, job seekers often hear about job vacancies from friends. Scientists hear about new papers from colleagues. Burglars learn the best burglary techniques from their peers. Therefore, one might expect persons in different network positions to behave differently. This raises two important questions. First, how does someone's strategic behavior exactly depend on her network position? Second, considering the society as a whole, how does social welfare depend on the network structure, that is, is society better off in a world with more links and/or shorter distances?

These questions have motivated economists to analyze games of local network effects. In these games the players are assumed to be embedded in a network. The strategy of a player is an effort or investment level. A player's payoff is increasing with her own effort, but it also depends on the effort levels of their direct neighbors in the network. An extensive analysis of this type of games is given by Galeotti et al. (2006). We discuss their paper below.

Galeotti et al. (2006) take a general approach, allowing many different payoff functions and different information structures into their model. With respect to information structure, on the one hand, Galeotti et al. consider the possibility that players exactly know everyone's position in the network. That is, everyone knows who is related to whom. This assumption is unrealistic, though. Therefore Galeotti et al. also consider the case where players know very little about the network. In that case players know who the neighbors are, but they do not know the neighbors' neighbors.

With respect to the payoff function Galeotti et al. make the following classifications. First, a network game is said to exhibit *positive externalities* if a player's payoff is increasing with the effort level of her neighbors. On the other hand, a network game exhibits *negative externalities* if the payoff is decreasing with the effort level of the neighbors. Most network applications consider network games with positive network externalities. In particular, in applications where agents obtain information from their friends the network game exhibits positive network externalities. In our discussion we focus on this type of network games.

An important classification of network games is the classification of games that exhibit local strategic complements and games that exhibit local strategic substitutes. In a network game of *local strategic complements*, the marginal payoff of a player's own effort *increases* with the effort of the neighbors. On the other hand, in a game of strategic substitutes, the marginal payoff *decreases* with the effort of the neighbors. We first discuss the results of Galeotti et al. (2006) for games of local strategic complements and then for games of local strategic substitutes.

[9] The original preferential attachment model does not generate high clustering, though. However, there are new models that are able to generate both short distances, high clustering and unequal degree distribution. A good example is Jackson and Rogers (2005).

Local strategic complements. In a game that exhibits local strategic complements, the incentives to put effort increases with the neighbors' effort levels. An application is in crime networks (Calvó-Armengol and Zenou, 2004). Clearly there is no legalized institution that teaches you how to become a criminal. Criminals learn criminal techniques from their friends. However, it is only possible to learn these techniques from friends if these friends have a lot of criminal experience themselves. An ordinary person without any criminal connections would be unable to learn criminal techniques and, therefore, has fewer incentives to become a criminal himself. On the other hand, someone growing up in a criminal neighborhood has all the opportunities to obtain criminal know-how and, therefore, has more incentives to become a criminal himself.

In a network game with local strategic complements, Galeotti et al. (2006) obtain the following results. First, if players have incomplete information about the network structure, then players with many links choose a higher effort level and obtain a higher payoff than players with few links. Thus, in the crime network application, players with many friends take part in more criminal activities and they obtain the highest criminal payoffs. If players have complete information on the network structure, then the situation is more complicated and the effort levels then depend on the whole network structure. However, in the case of linear-quadratic payoff functions, Ballester, Calvó-Armengol and Zenou (2006) show that the effort levels are proportional to the Bonacich centrality measure, a popular measure of how central persons are in a network.

The second result is that the creation of new network relations increases the effort levels of the players. Hence, effort levels are higher when the network is denser. This also implies that, in a dense network, social welfare is higher. In the crime network application this implies that 'dense' neighborhoods, in which each player has many links, are likely to be more criminal than 'sparse' neighborhoods. These criminals in dense neighborhoods also obtain higher criminal payoffs.

Local strategic substitutes. In a game of local strategic substitutes the incentives to put effort *decreases* with the effort levels of the neighbors. This occurs when players have to invest in order to produce a local public good, a good that is non-rival and non-excludable along geographical or social links (Bramoullé and Kranton, 2006). In such cases, players have incentives to free-ride on the efforts of others. For social network analysis, the most relevant case is the case where obtaining information autonomously is very costly, while it is very difficult to exclude information from neighbors. An example of such a game is in consumer search networks (Galeotti, 2005a). Consumers can actively search for price quotes by visiting shops. However, they can also simply ask friends who have already searched for prices. Thus consumers have incentives to free-ride on the search efforts of their friends.

Bramoullé and Kranton (2006) analyze a network game with local public goods in which players have complete information about the network structure. Galeotti et al. (2006) provide a more general analysis of games with local strategic substitutes. They obtain the following results. First, if players have incomplete information about the network structure, then players with many links have low effort levels, but obtain the highest payoffs. We illustrate the intuition behind this result in the context of consumer search. A consumer with many friends is likely to have a friend who searched for prices himself. Therefore, well connected consumers have few incentives to search themselves, but instead, they can simply ask for price information from their friends. In contrast, an isolated consumer cannot obtain price information unless he goes and searches for prices by himself.

If players know the complete network structure, then they can condition their effort levels on the whole network structure. Unfortunately, Bramoullé and Kranton (2006) show that in this case there is no clear monotonic relation between some network statistic and effort levels or payoffs. There can be many equilibria, some in which the central player free rides and some in which a central player does all the effort.

The second set of results for network games of local strategic substitutes concerns the effect on effort levels when links are added to the network. The network is quite complicated, so Galeotti et al. (2006) have to restrict themselves to special payoff functions. However, both their analysis of binary games with incomplete information and best-shot games with complete information suggest that the addition of new links reduces the individual and aggregate effort levels. This becomes visible by discussing two polar cases of network structure. In the empty network everyone has to put effort on their own and nobody is able to free-ride. On the other hand, in the complete network, where everyone is linked to everyone, only one player has to put effort and all other players are able to free ride on the effort of this single player. However, the effects of the addition of new links on social welfare is ambiguous.

To summarize, the discussion above shows that network effects crucially depend on the nature of the game, that is, whether the strategies of players are local strategic complements or substitutes.

1.1.3 Network formation

In the previous section we have summarized papers, which argue that the payoffs of individuals depend on their position in the network. But if the payoff depends on the network position, then individuals also have an incentive to improve their network position in order to obtain higher payoffs. Hence, a social network should not be seen as static. Instead, a network is shaped by the strategies of individuals.

The natural questions are, firstly, what kind of network structures arise when individuals strive for a good network position. In particular, under what conditions are the links in the network unequally distributed? Secondly, are these arising network structures the best structures for society? These questions have been the focus of the economic theory of network formation.[10]

The answers to the above questions depend on the economic setting. It also matters if a relation can be forced unilaterally, or if mutual consent of the involved players is necessary. The above issues can be best described by discussing an extensively analyzed network model, the *connections model*. In this model the payoff of a player depends on the network as follows. A player i obtains δ benefits from her direct neighbors, δ^2 from individuals at distance 2, δ^3 from individuals at distance 3, etcetera. The cost of each

[10] Precursors of the network formation literature can be found in Boorman (1975) and Aumann and Myerson (1988). Dutta and Jackson (2003) contains a selection of influential papers from this literature. See also Jackson (2005) and Goyal (2005a) for an overview.

link is c. Thus players benefit from having short distances to other players, whereas too many links are costly.

Most of the literature has taken the view that a relation between two players i and j requires the consent of both players. Thus a relation between i and j will only be established if both i and j benefit from that link. Jackson and Wolinsky (1996) formalizes this view by introducing the following network concept. They define a network as *pairwise stable* if no pair of players has an incentive to create a link, while all existing links are supported by the players involved in that link. With this concept in hand they are able to analyze a general class of payoff functions.

In the connections model the typical stable network structures are a complete network (in which everyone links to everyone) when c is low, a *star* network when c is intermediate and an empty network (without links) when c is high. The result that the star network is pairwise stable for intermediate costs is also interesting in relation to the characteristics of actually observed networks. It illustrates that strategic network formation in the connections model leads to very unequal networks with short distances as observed in actual networks.[11]

With respect to the second question, the main result of Jackson and Wolinsky (1996) is that there is a general conflict between stability and efficiency in a network. Networks that generate the highest social value are very often not pairwise stable. In the connections model, Jackson and Wolinsky find a conflict between stability and efficiency for high c because while a star network would be efficient, only the empty network is pairwise stable. The reason is that a pair of players does not take into account the benefits their link has on third parties. A link reduces distances for *all* players, but only the two players directly involved in the link are able to decide on its formation.

Bala and Goyal (2000) analyze the connections model under the assumption that players form links *unilaterally*. This means that players do not require the consent of the other party to create a link. Bala and Goyal consider two versions of this model.

In the two-way flow model, the links are undirected. Here, one player initiates a link but both players involved obtain benefits from this link. An example of a two-way flow relation is a telephone call. One player makes the phone call and incurs the cost of calling, while both players benefit from the exchange of information during the telephone conversation. This model is similar to the model analyzed by Jackson and Wolinsky and the results are also quite similar. For $\delta = 1$ the star network or the empty network are equilibrium networks. Again there exists a conflict between stability and efficiency for moderately high c.

On the other hand, in the one-way flow model, the links are directed. That is, a player i obtains benefit from the players that she created a link with, but these neighbors do not obtain benefits from i. An application of this model is, for example, in spying activities between R&D firms. Firm A that spies at firm B obtains information about B's R&D

[11] In the standard connections model, the center of the star is the individual that obtains the *lowest* payoffs as she has to support many costly links while the peripheral players have to support only one link to obtain all the benefits. Goyal and Vega-Redondo (2004) consider a version of the connections model in which the benefit of an indirect connection is divided among all the critical players on the connection's path. In this model, the star network is stable and the star obtains high payoffs.

	Scientific Collaboration	Jobs	Transport
Q1: Network Structure	Chapters 2 & 3		
Q2: Network Effects		Chapter 5	
Q3: Network Formation	Chapter 4		Chapter 6

Table 1.1: Framework of the thesis

activities, while B does not obtain information in return (Billand and Bravard, 2004). In this version Bala and Goyal (2000) obtain the following finding. If $\delta = 1$, then the (strict) equilibrium network is the *wheel* network, a network in the shape of a circle. Note that this is a very equal network. Every player has only one link and no link is reprocicated. However, in this network the distance between players can be quite large. This illustrates that the emergence of inequality in the network crucially depends on the nature of the game.

1.2 Outline

This thesis is divided into three parts. *Part 1* considers coauthor networks, *Part 2* considers job contact networks and *Part 3* considers transport networks. The three questions mentioned before and the three types of networks suggest a matrix shown in Table 1.1. Each cell in the matrix contains by itself a broad range of questions, because different aspects of the network structure and different economic markets and situations can be considered. However, we do not intend to consider a complete analysis of all these questions. Instead, we consider specific issues for the three network types: a coauthor network, a job contact network, and a transport network.

We treat each chapter of this thesis as a small piece of a large scientific puzzle. Table 1.1 shows where each piece should be placed in the diagram. We now discuss the three types of networks and the individual chapters.

1.2.1 Coauthor networks

We start with a discussion of coauthor networks between economic researchers. When you take a look at a typical economic journal you would observe that some of the articles are written by a single author, while other articles are written by multiple authors. Thus many economists collaborate with eachother when they do research. All the collaboration relations between economists together form a collaboration or coauthor network. The nodes in this network are economists, and there exists a link between economists if they have written an article together.

The first question that naturally arises is why economists would like to collaborate in the first place. This question is particularly relevant, because there has been a striking trend towards more collaboration. Already in 1963 de Solla Price noted that the trend toward coauthorship "(...) is one of the most violent transitions that can be measured in recent trends of scientific manpower and literature",[12] and it should be noted that this

[12] The citation is taken from McDowell and Melvin (1983)

trend has continued since then. For example, in 1950, only 7 percent of the articles in the *American Economic Review*, the *Journal of Political Economy* and the *Quarterly Journal of Economics* was coauthored. This number has increased to 70 percent in 1994![13]

Several economists have analyzed the reasons for this increase in collaboration. An overview is given by Eisenhauer (1996) and Laband and Tollison (2000). McDowell and Melvin (1983) argue that an increase in the stock of knowledge has led to more specialization and collaboration. On the other hand, Hudson (1996) argues that technology has spurred coauthorship. Technological progress would make collaboration at a distance easier. Indeed, Hamermesh and Oster (2003) observe a larger increase in collaboration between economists from separate departments than that in collaboration within departments.

The increase in coauthorship is likely to be accompanied by a change in the structure of the collaboration network. In particular, the increase in collaboration between economists at distant departments must have made the 'world smaller', in terms of network distance between economists. This issue is the subject of Chapter 2.

In Chapter 2 we analyze the structure of the coauthor network of economists of three decades, the 1970s, 1980s and 1990s. We observe striking changes in these networks. While the network of the 1970s consists of larger and smaller 'islands', the network in the 1990s is much more integrated. In the 1990s, a 'giant component' exists in which everyone is directly or indirectly connected to everyone. This component comprises almost 40 percent of the network. Moreover, when we take a look at the average distance within the giant component, we observe that distances have become smaller despite the growth of the giant component. Therefore, we conclude that *economics is an emerging small world*.

Next, we take a closer look at the microstructure of the network. First, not surprisingly, we observe that economists tend to have more collaborators in the 1990s than in the 1970s. Second, the distribution of links in the network is very unequal. There are a few 'stars' in the network that have many coauthors. Third, the coauthors of these stars typically do not collaborate with each other. We then show that these stars are crucial for the integration of the network. Without these stars, the network would fall apart into very small islands. Therefore, we conclude that the world of economists is integrated by a set of interlinked stars.

Comparing our results to the generally observed properties of networks discussed in Section 1.1.1, we observe that high network clustering and inequality in the degree distribution are robust features of the coauthor network of economists. We also find small world properties, but, importantly, these small world properties are more profound in the 1990s than in the 1970s.

The analysis of Chapter 2 considers the links in a network as dichotomous, and hence, it does not take into account the strength of relations. Therefore, in Chapter 3 we take up an analysis of weighted networks. We measure the strength of a tie between i and j by the number of articles that i and j published together in a particular decade. Then we test an important sociological theory: Mark Granovetter's (1973) 'Strength of Weak Ties' theory.

[13]These numbers are taken from Figure 1 of Laband and Tollison (2000)

In his thesis, Mark Granovetter analyzed the role of social contacts in getting a job. Not surprisingly, he discovered that many job seekers find their new job with help of their social contacts. But, surprisingly, when Granovetter asked about the strength of the relation of these social contacts, he discovered that job seekers are more likely to hear about a suitable vacancy from weak ties (her acquaintances) than from strong ties (family or close friends).

In 'The strength of weak ties' (1973), Mark Granovetter formulated an explanation for his surprising finding. He hypothesized that close friends are likely to cluster in cliques, in which everyone knows everyone else. This social behavior has a disadvantage, because close friends are likely to have similar information and knowledge as the job seeker himself, while it is more important for a job seeker to obtain *new* information. Weak ties, that is, one's acquaintances, are more likely to provide such information, because weak ties are less clustered and, consequently, they often provide a 'bridge' to sources that are very different from one's own. Therefore, Granovetter hypothesizes that weak ties are more likely to reduce network distances between individuals than strong ties do.

Chapter 3 tests this theory, and we obtain the following result. While we find support for the hypothesis that strong ties are more likely to cluster together, we *reject* the hypothesis that weak ties are more important in reducing network distance. On the contrary, we find that *strong ties* are more important in reducing network distances, and hence, more critical for the connectedness of the network.

This is a surprising result and we try to find an explanation for this result. In Chapter 2 we discovered that the link distribution is very unequal, and that 'stars' are very important in connecting different subgroups in the network together. We show that the key to understand the rejection of the 'Strength of Weak Ties' theory is the observation that the ties between stars are usually stronger than the ties with peripheral players. It then follows directly that strong ties are more important in connecting different subgroups in the network, because strong ties often lead to stars.

The results in Chapter 3 thus show how important it is to take into account the inequality in the distribution of links. This structural property of the network is, however, ignored in the analysis of Granovetter (1973).

Our findings in Chapter 2 and 3 raise the following questions. First, what are the economic determinants of the network structure and observed change in the network? Second, what implications does the emergence of a small world between economists have on the generation of knowledge, the amount of competition between researchers and the amount of specialization into subfields?

The first question can be approached from different perspectives. In Chapter 4 we take the view that the collaboration network is only shaped by the incentives of economists to collaborate. These incentives depend on the quality of the researchers and the effort they put into their collaborations. Chapter 4 analyzes an incentives-based model with the above ingredients.

The analysis of Chapter 4 reveals the following. First, a decrease in communication costs or an increase in the rewards of collaboration facilitates more collaboration. This explains the increase in the number of links, and it contributes to the emergence of a small world. Second, an interlinked star structure is unlikely to arise when coauthors have to share the effort of writing an article. The reason is that high quality researchers do not have incentives to set up collaborations with low quality researchers when the costs of collaborating have to be shared. Instead, high quality researchers prefer to write with other high quality researchers and obtain a higher payoff.

We then identify two possible reasons why high quality researchers do collaborate with low quality researchers. One possibility is that the low quality researcher gains so much from collaborating with a high quality researcher that she is willing to take up *all* the costs of collaborating. Another possibility is that there are too few high quality economists around to collaborate with.

In Fafchamps, van der Leij and Goyal (2006) we take a different, empirical approach to the first question. We ask ourselves why two economists, i and j decide to start a research collaboration in year t. We argue that i and j have to become informed or familiar with each other before they start a collaboration, because it is too risky to start a collaboration with a complete stranger. We believe that economists discuss the research practices of their past collaborators with each other. Hence, information on potential collaborators is transmitted through the collaboration network. Therefore, i and j are more likely to start collaborating the lower the network distance between them. In our empirical analysis we indeed find evidence for this network effect. This evidence is very strong and robust, even after taking into account that economists working at the same department and the same field are more likely to collaborate.

The second question has yet to be analyzed. However, a bit of speculation is possible. An important concept in macroeconomics and economic growth is the 'knowledge spillover'. Knowledge and ideas cannot be made completely proprietary, but instead they disseminate to 'others', either scientific colleagues, R&D intensive firms or even nations. Jaffe, Trajtenberg and Henderson (1993) use patent data to show that there are indeed geographical knowledge spillovers. Moreover, Jasjit Singh (2005) shows that this knowledge dissemination also takes place in the network of research collaborators. It is then plausible that knowledge also flows through the network of coauthoring economists.

We therefore hypothesize that, with these spillovers, economists in good network positions benefit from their position. That is, the stars should be able to write better articles, because they benefit more from the knowledge spillovers. It is our intention to test this hypothesis in future research. However, it will be quite a challenge to detect this causal relation empirically, because the reverse relation also holds; high quality researchers are able to attract more funding, and therefore they are able to attract more collaborators and research assistants, and obtain a more central position in the network.

1.2.2 Job contact networks

Social networks are particularly important for job seekers. It is empirically well established that many job seekers, around 50 percent, find a job thanks to a social contact, see Rees (1966), Holzer (1988) or Granovetter (1995) for the United States, or Gregg and Wadsworth (1996) for the United Kingdom.[14] Given the relevance of social contacts in getting a job it is natural to ask how social networks affect labor market outcomes.

[14] See Montgomery (1991) for an overview.

In the analysis of the role of social networks in the labor market a distinction can be made between the use of job contacts by employers and the use of job contacts by job seekers. Employers often use the social contacts of their employees by asking them for referrals. The reason to rely on employee referrals to fill a vacancy is the difficulty to obtain useful information about applicants by formal means. Particularly in the case of job starters a C.V. does not give enough information about an applicant's specific job abilities, skills, motivation and mentality, and also interviews cannot provide complete information. Employers would like to be certain that a potential worker is indeed a good match for the firm. Of course, this is impossible, but applicants that are referred by good employees are often more reliable than applicants that directly apply without a referral. This perspective on the role of networks in the labor market is analyzed by Montgomery (1991). He notes that employers' reliance on employee referrals creates an adverse selection problem in the regular job market, since only bad workers are left. Therefore, employers are inclined to offer high wages to referred applicants and low wages to non-referred applicants.

The issue is different when we look at the role of networks from the job seekers' perspective. Job seekers do not seem to be too concerned about a lack of information on the right type of employer. According to Devine and Kiefer (1991) workers tend to search in markets where almost any job is acceptable, and they tend to accept any offer they receive directly. Instead, from the job seekers' perspective the main action is in the arrival rates of job offers. Since job contacts are very important to get information about job offers, it is plausible that the arrival rates of job offers are shaped by the job seekers' position in the social network and the structure of the social network as a whole.

Calvó-Armengol and Jackson (2004) provide an analysis on the role of social networks from the job seekers' perspective.[15] They consider a dynamic process in which individuals randomly lose their jobs and obtain information about new jobs. In each period, individuals hear about job vacancies by chance. These job vacancies offer identical wages and can be filled by anyone. If an individual is unemployed, then she applies for the job. On the other hand, if the individual is employed, then she passes the job information on to one of her unemployed friends.

Calvó-Armengol and Jackson (2004) show that this model is able to explain important empirical features of the labor market. First, in this process the unemployment rates of direct and indirect contacts are correlated. In other words, if a player loses his job, then it becomes more and more likely that the direct and indirect job contacts become unemployed as well. This can be understood by the observation that unemployed agents do not transmit any job information. They prefer to keep this valuable information for themselves. Hence, an unemployed person creates a hole in the job information network and this decreases the job opportunities of the unemployed person's neighbors.

The second feature of this model is that the chances of unemployed players to find a job decrease with the unemployment duration, a phenomenon called *duration dependence*. This feature can be understood as follows. The longer a player is unemployed, the higher the unemployment in the player's neighborhood becomes, and the fewer job information the player receives. Thus, the unemployment correlation across networks and time feeds

[15] This analysis is generalized in Calvó-Armengol and Jackson (2006).

back into the job opportunities of a player creating duration dependence. The third feature is that, not surprisingly, the employment opportunities depend on the network structure. This is true not only for individual players, but also for the aggregated unemployment level. Thus two networks with comparable size have different unemployment rates if the structures of the networks are different.

Calvó-Armengol and Jackson then extend their analysis to consider the causes of dropping out of the labor market. It is well-known that there is a profound difference in the drop-out rates between races in the United States. For example, Card and Krueger (1992) find that the drop-out rate for African-Americans is 2.5 to 3 times higher than that of whites. In their analysis Calvó-Armengol and Jackson argue that these differences can easily be understood if the networks and initial employment conditions differ across races. These initial employment conditions are magnified by the network effects.

From the above results, Calvó-Armengol and Jackson conclude that social networks are able to explain inequality between races. However, a couple of objections can be made to their model. First, their explanation of the difference in drop-out rates depend largely on the differences in the initial employment conditions.[16] Thus it appears that inequality in drop-out rates is almost fully explained by the assumption of inequality in initial employment conditions. The question about how these differences in initial conditions are created is not answered.

Chapter 5 addresses this issue by taking a slightly different approach. We are interested in the question whether social networks are able to explain occupational segregation, that is, the phenomenon that one group almost exclusively takes up one type of job. We also ask ourselves if social networks are able to explain employment and wage differences, even if all players start with the same initial conditions.

We assume that there exists a society that can be divided into two homogenous groups that do not differ in skills or productivity. These two groups could be men and women, for example, or natives and immigrants. At the beginning of their lives, each person has to make a choice about their career. We assume that each person can choose between two specializations; one leads to a career in job A and the other leads to a career in job B. An example could be the choice between a career in the medical sector, for example as a physician, or in the information technology sector as a programmer. Both choices require large investments in specialized training, and therefore, the choice for one career would make switching to another career very difficult.

When making a career decision, agents make expectations about their career opportunities. In particular, they make predictions about the probability of getting a job and expectations about the wage they would get. With respect to wages and employment probability, we make the following assumption. The wage is negatively related to the number of agents that choose a particular occupation. That is, if everyone chooses to become a computer engineer, then market forces should keep the wage of a computer engineer relatively low. It is therefore clear that at least some individuals choose a career in job A and some choose a career in job B.

[16]There is also a contagion effect that magnifies the initial employment differences. However, this contagion effect appears to be rather small.

With respect to the probability of getting a job we assume that this probability increases in the number of friends in the same occupation as the job seeker. This assumption should be seen as a simplification of the result in Calvó-Armengol and Jackson (2004) that people in a better network position obtain better jobs.

But how many friends does one expect to have? We assume that after the career decisions, job contacts are formed randomly, although more job contacts are formed within the player's own group. This assumption is based on empirical evidence that individuals tend to have more contacts with similar others. For example, Staiger (1990) finds that most men find a job through a male referral, and, correspondingly, most women through a female referral. This is even true for occupations and industries that are highly segregated. For example, in male-dominated occupations such as machine operators, 81 percent of the women who found their job through a referral, had a *female* reference.

In Chapter 5 we analyze a model using the above assumptions. We show that these assumptions lead to very strong occupational segregation. The intuition is as follows. Players have a slight preference to choose the same occupation as the majority of the player's group. The reason for this slight preference is the inbreeding bias in the social network and the fact that job contacts give vital job information. Following the group majority would enable players to create more friendships and thus have a higher probability to get a job. This slight preference to choose the same occupation as the majority in the group eventually drives a whole group to choose the same occupation.[17]

With the additional assumption that one occupation is higher valued than the other, we also show that our model is able to explain sustained differences in employment and wages. That is, agents are willing to give up a marginal career in the better paying job in order to have a higher probability of getting a job.

We now explain the differences between the analysis in Chapter 5 and the analysis in Calvó-Armengol and Jackson (2004). A crucial difference is that in the model analyzed in Chapter 5 the job contacts are formed *after* the crucial occupation decision is made. This implies that players have to make *expectations* about the job contact network they will form after their occupation decisions. In contrast, in Calvó-Armengol and Jackson (2004) the network structure is already determined when players make drop-out decisions. This difference is crucial. An empirical analysis should verify the relevance of the mechanism in Calvó-Armengol and Jackson and the mechanism in the model in Chapter 5.

1.2.3 Transportation Networks

While the coauthor networks and the job contact networks can be seen as parts of the social network, the transportation networks, that is, the railways, roads and airline routes, are of a completely different nature. One difference is, of course, the physical presence of railways and roads against the often informal and invisible character of social ties. Also the investment costs are often very different. The costs of roads and railways are typically in the billions of euros. However, one could argue that social relations can be very physical as well. Furthermore, airline connections do not require roads that need to be built and thus require smaller investments than, for example, railways. On the other hand, R&D contracts can involve large investments worth millions as well.

[17] This process is similar to the residential segregation process of Schelling (1978).

From an analytical point of view, there is a more essential difference. In a social network, the links are contacts or transactions between *players*. In a transportation network, the links are connections between *geographical locations*. Hence, the role of the economic players, in this case transportation firms, is very different. While players in a social network *are part of* the networks, players in a transportation network have or *own* the networks.

This difference creates an essential difference in the decision process of network formation. In a social network a player can only make decisions on the links in which she herself is involved. That is, a player i cannot force a tie between j and k. On the other hand, a transportation firm can invest in infrastructure between any two cities, from A to B, or from C to D. Thus the firm can completely *design* any network structure. As a consequence, the strategies considered for social network models and transportation network models are different. In a social network model, the strategy is to propose, communicate or form links with other players, and all strategies together form a network. On the other hand, in a transportation network model, the strategy is to *design a network*. The networks of all players together form an interconnected network themselves.

Network structure. Within transportation economics most attention has been given to the structure of airline networks. This is because a remarkable change in the structure of airline networks took place in the United States after the deregulation of the U.S. airline industry at the end of the 1970s.

Borenstein (1992) describes the evolution of the U.S. airline industry after the deregulation. He mentions that all large airline operators have formed 'hub-and-spoke' networks. These network structures, which might be called star networks as well, have a single hub that serves many spokes. The emergence of the hub-and-spoke networks has substituted some direct point-to-point connections. As a result, the major airlines nowadays offer fewer direct connections, but many more indirect connections than 30 years ago.

Network structures in other transportation modes have received less attention, probably because such a remarkable change as in the airline industry has never occurred. With the large investments necessary for railways and roads it is also more difficult for railway companies or governments to change the network structures.

Consequences for Airline Competition. With the change in network structure, there has been a change in the market structure as well. After the deregulation, many airline operators merged and market concentration increased (Borenstein, 1992). Despite this concentration, most fares decreased. However, the fares for trips from and to the hubs increased and airlines were able to make high profits on these hub-to-spoke trips (Borenstein, 1989).

Surprisingly these high mark-ups did not allow entry at the regional hub-to-spoke level. One explanation is the use of frequent-flyer programs and other marketing strategies that raise the switching costs for travelers (Borenstein, 1989). A different explanation is given by Hendricks, Piccione and Tan (1997). They argue that the hub-and-spoke network structure itself can deter market entry.

To understand this, note that in a hub-and-spoke network a link is crucial as part of many indirect connections, on top of one direct connection. This means that if an airline loses one direct connection, it loses many indirect connections as well. To illustrate this, suppose there are 26 cities named $A, B, \ldots, Z$, and suppose an airline has a hub at city A with spoke connections to $B, C, \ldots, Z$. If the connection AB is lost, then the airline loses the passengers traveling from B to C, to D, to E, etcetera, as well.

This complementarity between city-pair markets in a hub-and-spoke network makes entry very difficult. The hub-and-spoke network airline will try to do anything to retain a direct connection in order not to lose the complementary indirect connections, even if it would involve operating losses on the direct connection. It is then very difficult for a regional carrier to enter and compete in a hub-to-spoke market.

Network design. Before the deregulation of the U.S. airline industry, airlines were severely restricted in the choice of their connections. This changed with the deregulation such that the airlines were more or less free in their choice of network. Clearly the choice of almost all main operators was to install a hub-and-spoke network. The question is whether this choice was made in order to move towards more efficient networks, or that strategic interaction made these hub-and-spoke networks a strategic equilibrium outcome, but not necessarily an efficient outcome.

From an efficiency point of view, the main argument why hub-and-spoke networks are more efficient, is because the airline industry exhibits *economies of density* on their connections (Caves, Christiansen and Thretheway, 1984). This means that the average cost of maintaining a connection decreases if the number of passengers that take the connection increases. The reason is that larger airplanes with the same amount of pilots and staff can be used if there are more travelers. The hub-and-spoke network takes advantage of the economies of density, because this network design concentrates direct and many indirect travelers from a spoke city on a single connection to the hub. Thus, in the example above, all travelers from B to A, C, D, etcetera, take a flight from B to A, hence the density on this connection AB is very high. Thus the hub-and-spoke network makes full use of the economies of density, which makes it very efficient. This argument is formalized in Hendricks, Piccione and Tan (1995).

Hendricks, Piccione and Tan (1999) extend their former analysis to a duopoly setting, and analyze if strategic interaction between two large airline operators supports or deters the emergence of hub-and-spoke networks. They find that two airline operators with *pure* hub-and-spoke networks cannot coexist if price competition is very strong. However, two airlines can coexist in some cases if they both do not have pure hub-and-spoke networks. These non-hub-and-spoke networks can be stable, while the networks are not efficient. This suggests that strategic interaction is not the cause of the emergence of hub-and-spoke networks. In fact, it might be the case that it is more efficient and welfare enhancing if airline networks become even more star-like than they currently are.

In their papers, Hendricks, Piccione and Tan ignore the spatial structure of transport networks. That is, they assume that all cities are at equal distances, whereas they are obviously not in the real world. Another issue that Hendricks, Piccione and Tan ignore is that airline routes may face competition from other transport modes. In particular, in Europe and Japan, a network of high-speed train connections is emerging. These high-speed train operators also have the desire to openly compete with the airline industry.

It seems that competition between different transport modes is largely ignored by transportation economists. In Chapter 6 we therefore consider a model of competing transport modes. We analyze how competition from a slow transport mode influences network decisions of a fast transport mode.

The model in Chapter 6 is very simple and should be seen as a starting point of a more complete analysis. We consider a model where everyone lives and works on a circular city. All individuals have to travel from home to work. There are two transport modes, slow and fast. The slow transport mode is directly accessible. On the other hand, the fast transport mode has only two stations and one connection. The decision on the 'network' here involves the location of the two fast transport stations on the circle.

We show that the fast mode operator has an incentive to *cluster* the stations when there is strong competition from the slow mode transport. That is, if the slow mode is quite fast, then the fast mode operator offers only a very short trip. In that case the stations are very close to each other. On the other hand, if the slow mode is extremely slow and thus not competitive, then the fast mode connection operates a service from one side of the circle to the other side of the circle.

The intuition behind this result is as follows. The fast-mode monopolist has to make a trade off. The value for travelers taking the fast transport mode connection instead of slow mode transport is larger if the fast mode operator offers longer trips. This gives an incentive to the fast mode operator to increase the distance between the stations, and this incentive becomes stronger if the fast mode is much faster than the slow mode. On the other hand, if the stations are close to each other, then the hinterland of the stations is much larger. Demand for travel mainly originates from the hinterland. Moreover, the hinterland becomes more important if the slow mode becomes more competitive. It then follows that the fast mode operator clusters the two stations when slow mode is very competitive.

The analysis in Chapter 6 illustrates the importance of an analysis that takes into account competition from other transport modes. However, the model in Chapter 6 is rather stylized. In particular, we do not consider network design decisions with many possible stations. Such an extended analysis would shed more light on the emergence and stability of hub-and-spoke network structure.

Part I

Coauthor networks

Chapter 2

Economics: an emerging small world

2.1 Introduction

It has now become a common place to argue that due to a series of technological and economic developments – such as the deregulation of airlines and telecommunications, the rise of facsimile technology and the internet– it is becoming cheaper for individuals to form and maintain more distant ties. This in turn, it is claimed, has reduced the 'distance' between people and has made the world 'smaller'.[1] This chapter carries out an empirical examination of this argument by examining how the economists' world has evolved over time during the period 1970-2000.

The notion of globalization or a small world is a broad one and applies to a wide range of social and economic activities. The first step in the analysis is therefore to define the scope of the enquiry. We shall consider economists who publish in journals between 1970 and 2000. We split this period into three ten year intervals, 1970-1979, 1980-1989, and 1990-1999. Every publishing author is a node in the network, and two nodes are linked if they have published a paper or more together in the period under study. We thus have three coauthorship networks (a network corresponding to each decade) and we will examine whether these networks have become more integrated over time. The second step in the study is to make the notion of distance and growing integration precise. We shall say that economists who coauthor a paper are at a distance 1 from each other, while economists who do not write with each other but have a common coauthor are at a distance 2 from each other, and so on. All economists who are either directly or indirectly linked with each other are said to belong to the same component and we shall refer to the largest group of interconnected economists as the giant component.[2] We shall interpret a larger size of the giant component and a shorter average distance between economists in the giant component as evidence of growing integration.

Our first finding is that the number of economists has more than doubled in the period from 1970 to 2000. This finding is consistent with the growth in the number of

[0]This chapter is based on a long version of Goyal, Van der Leij and Moraga-González (2006).

[1]The popularity of terms such as 'globalization', the 'death of distance', and 'global village' is one indication of this widespread feeling; recent references include Cairncross (2001), Castells (1996) and McLuhan (1994).

[2]The network terminology as well as the criteria for a small world are formally presented in Section 2.2.

fields/specializations and in the corresponding set of field journals during this period and it leads us to expect that the world has probably become less integrated. However, we find that in the 1970s the largest group of interconnected economists comprised only about 15 percent of the population while in the 1990s there was one huge group of interconnected economists with about 40 percent of the total population. The numbers are worth mentioning here: in the 1970s the giant component contained about 5,200 economists while in the 1990s it contained more than 33,000 members! We turn next to average distances between economists in the giant component. The average number of coauthors is very low; for instance, in the 1990s, a member of the giant component worked with only 3 other economists on average. Given the size of the giant component this leads us to expect that the average distance between economists must be large. However, we find that the average distance is small and that it has fallen over time, despite the growth in the size of the giant component. These findings lead us to say that economics is *an emerging small world*.

What is it about the distribution and arrangement of links among economists that makes this world small? A stable feature of this world is that average distances between economists are small and we first develop an explanation for this. We observe that the distribution of links is very unequal in each of the three periods under study. For example, the average number of collaborators in the whole 1990´s network was 1.672 while the maximally connected economist had more than 50 collaborators. Moreover, we find that the most connected authors had many more links than their cohorts and also that they had very low overlaps among their coauthors as compared to the average person in the network. These features lead us to use the term 'stars' for the most connected economists. We then study the role of these well-connected nodes in integrating the network. In the 1990s over 40 percent of the nodes were in the giant component but a deletion of the 5 percent most connected nodes leaves less than 1 percent of the nodes in the giant component, thus completely fragmenting the network. These observations put together lead us to say that *the world of economics is spanned by a set of interlinked stars* and that this is the principal explanation for the small average distances noted above.

In the popular press as well as in academic literature several authors have argued that the formation of more distant links have led to greater integration in the terms defined above.[3] To examine this issue, we look at the role of different variables – such as the average number of collaborators, the inequality in the degree distribution and the relative importance of distant collaboration – in explaining the main aggregate changes mentioned above. Our main finding is that an increase in the average number of collaborators for all quantiles of the degree distribution (and not the formation of more distant links *per se* nor changes in the inequality of distribution of links) is the crucial factor in explaining the massive growth of the giant component and the fall in average distances we have witnessed over time.

This chapter is related in different ways to strands of research in economics and physics. We now place our findings in context. There is a large body of research which argues

[3]See e.g., Castells (1996) on the formation of global networks and the crises in local communities.

that social interaction structure affects individual behavior and economic performance.[4] Given this research there is a pressing need for an empirical study that investigates what the interaction structure of *real world* social groups is, and how it is evolving over time. To the best of our knowledge this chapter is the first attempt in economics at empirically studying the structure of large evolving social networks. Our analysis identifies the stable features of a real world network and clarifies the nature of basic changes that have occurred in this network over time.

This chapter can also be seen as contributing to the literature on economics research. Recent work on this subject includes Ellison (2002) and Laband and Tollison (2000), among others. In particular, the increase in coauthorship has been noted and the reasons for it have been explored in Hudson (1996), while the role of informal intellectual collaboration is explored in Laband and Tollison (2000). A variety of arguments – such as increasing specialization and the falling costs of communication among others – have been proposed to explain increasing coauthorship among economists. Hamermesh and Oster (2002) present evidence which suggests that collaboration among distant authors has increased over the years. The novel feature of this chapter is the finding of an emerging small world and the study of the relative importance of two factors – increasing collaboration and more distant coauthorship – in explaining this phenomenon. In this connection, we would like to mention a recent article by Rosenblat and Mobius (2004). While the focus of their article is quite different their article also has a brief discussion of the effects of lower costs of communication on social distance. They argue that the formation of more distant connections per se explains the fall in average distance between economists. This is in conflict with our findings reported above. We discuss their work in detail after presenting our findings, in Section 2.3.

The empirical properties of large networks have been investigated extensively by physicists in recent years.[5] To the best of our knowledge this chapter is the first to study the properties of a network over an extended period of time (thirty years) with a view to understanding the stable and changing features of the network; earlier studies have focused on short periods of time (the maximum period of time covered seems to be 8 years, see Albert and Barabási (2002)). This difference in time horizon allows us to witness the emergence of the small world property in economics. The present chapter also appears to be the first study of economics collaboration networks; existing work focuses on the natural sciences, medical sciences and mathematics. This is interesting since networks in other subjects exhibit different properties. For example, the relative size of the largest interconnected group of authors and the average number of coauthors seem to be very different in economics as compared to physics or medical sciences.

---

[4]There is now a vast literature on the role of interaction structures in economics. A variety of terms such as local interaction, network effects, peer group effects, have been used. See e.g., Bala and Goyal (1998), Ellison and Fudenberg (1993) on social learning, Morris (2000) on norms of coordination, Eshel, Samuelson and Shaked (1998) on norms of cooperation, Burt (1994) on social networks and individual performance, Glaeser, Sacerdote and Scheinkman (1996) on local interaction and crime, Hägerstrand (1969) and Coleman (1966) on technological diffusion, and Munshi (2003) on migration.

[5]For surveys of this work see Albert and Barabási (2002), Dorogovtsev and Mendes (2002) and Newman (2001). For early work on the small world phenomena see Milgram (1967); for a survey of work in sociology see Kochen (1989). Jackson and Rogers (2005) is a recent economics paper on the formation of complex networks.

The rest of this chapter is organized as follows. Section 2.2 presents basic notation and definitions. Section 2.3 contains our analysis, while Section 2.4 concludes.

2.2 Networks

We start by setting down some basic notation which is useful to discuss network features precisely. Let $N = \{1, 2, ..., n\}$ be the set of nodes in a network. We shall refer to n as the *order* of the network. We shall be looking at undirected links in this chapter, and for two persons/nodes $i, j \in N$, we shall define $g_{i,j} \in \{0, 1\}$ as a link between them, with $g_{i,j} = 1$ signifying a link and $g_{i,j} = 0$ signifying the absence of a link. If two persons have published a paper together then they are said to have a link between them; if they have published no papers together then they have no link. Thus the information on authors and papers allows us to construct a network of collaboration. We shall say that there is a path between i and j either if $g_{i,j} = 1$ or if there is a set of distinct intermediate coauthors $j_1, j_2 ... j_n$, such that $g_{i,j_1} = g_{j_1,j_2} = ... = g_{j_n,j} = 1$. The collection of all links will be denoted by g. The set of nodes and the links between them will be referred to as a network and denoted by $G(N, g)$. Let $\mathcal{N}_i(G) = \{j \in N : g_{i,j} = 1\}$, be the set of nodes with whom i has a link in network G. Let $\eta_i(G) = |\mathcal{N}_i(G)|$ be the degree of node i in network G, and define $\eta(g) = \sum_{i \in N} \eta_i(G)/n$ as the average degree in a network G.

In case $\eta_1 = \ldots = \eta_n = \eta$ we will refer to η as the degree of the network. In general the degree is not constant across nodes/individuals and we are interested in the inequality in the distribution of degree across nodes. To measure this inequality we will compute Lorenz curves of the degree distribution and Gini coefficients. Suppose the set of nodes $S \subset N$ is ordered, such that $i < j$ if and only if $\eta_i < \eta_j$ for $i, j \in S$, and denote $n_s = |S|$ as the number of nodes in S and $L_S(h) = \sum_{i=1}^{h} \eta_i$ as the number of links in possession of the h least linked nodes. Then the Lorenz curve for S is given by connecting the points

$$(h/n_s, L_S(h)/L_S(n_s)) \in [0, 1]^2.$$

for $h = 0, \ldots, n_s$. The Lorenz curve measures the fraction of links that are in possession of the x percent least linked nodes. Note that perfect equality, that is a constant degree across nodes in S, implies that the Lorenz curve follows the 45 degree diagonal.

The Gini coefficient G_S measures the area between the Lorenz curve and the 45 degree diagonal. That is

$$G_S = 1 - \frac{1}{n_s} \sum_{h=1}^{n_s} \frac{L_S(h) + L_S(h-1)}{L_S(n_s)}.$$

An alternative way to write this is in terms of the relative mean difference:

$$G_S = \frac{\sum_{i=1}^{n_s} \sum_{j=1}^{i-1} (\eta_i - \eta_j)}{(n_s - 1) L_S(n_s)}.$$

We note that the Gini coefficient equals 0 in case of perfect equality and 1 in case of perfect inequality, that is when only one individual forms all the links in the network (an impossibility in graphs with two-sided links). A higher value of the Gini coefficient is interpreted as greater inequality in the degree distribution.

Two persons belong to the same component if and only if there exists a path between them. The path relation therefore defines a partition of the network into components. For a network G the partition will be denoted as $P(G) = \{C_1, ..., C_m\}$ with $m \geq 1$. In case $m = 1$ we have a connected network and in case $m = n$ we have the empty network. The components can be ordered in terms of their size, and we shall say that the network has a *giant component* if the largest component fills a relatively large part of the graph and all other components are small, typically of order $\mathcal{O}(\log n)$. We denote the size of the giant component as $n_{gc}(G)$.

The geodesic distance between two nodes i and j in network G is the length of the shortest path between them, and will be denoted by $d(i, j; G)$. If there is no path between i and j in a network G then we shall set $d(i, j; G) = \infty$. In case G is connected, the average distance between nodes of a network G is given by

$$d(G) = \frac{\sum_{i \in N} \sum_{j \in N} d(i, j; G)}{n(n-1)}$$

If G is not connected then the average distance is formally speaking infinite. In our data the network is not connected and so to study distances we shall use the average distance in the giant component as a proxy for the average distance in the network. The maximum distance between any pair of nodes in a network G is referred to as the diameter of the network and it is given by

$$D(G) = \max_{i,j \in N} d(i, j; G)$$

The clustering coefficient of a network G is a measure of the correlation between links of different individuals. The level of clustering in an individual i's neighborhood is given by

$$C_i(G) = \frac{\sum_{l \in N_i(G)} \sum_{k \in N_i(G)} g_{l,k}}{\eta_i(\eta_i - 1)}$$

for all $i \in N' \equiv \{i \in N : \ \eta_i \geq 2\}$, This ratio tells us the percentage of a person's coauthors who are coauthors of each other. The clustering coefficient for the network G can be obtained by averaging across all persons in a network. We shall use an averaging scheme which gives more weight to authors with a higher degree. This leads us to the following definition for the clustering coefficient:

$$C(G) = \frac{\sum_{i \in N'} \sum_{l \in N_i} \sum_{k \in N_i} g_{l,k}}{\sum_{i \in N'} \eta_i(\eta_i - 1)}$$

A star network is a network where one node, referred to as the center node, is linked to all other nodes in the graph while all these other nodes are only linked to the center node. In some networks, there is no single center of the network, but there is a small number of extremely well connected nodes and the partners of each of these nodes have almost no other connections. We shall, somewhat informally, refer to these well connected nodes as 'stars'.

We shall say that a network G exhibits small world properties if it satisfies the following conditions:

Table 2.1: Coverage of EconLit: Basic statistics

	1970s	1980s	1990s
Books	5	5302	16156
Book Review	0	0	1029
Collective Volume Articles	0	35422	96307
Dissertation	0	2649	9649
Journal Article	62518	95033	156601
Working Paper	41	12215	23446

1. The number of nodes is very large as compared to the average number of links, $n >> \eta(G)$.

2. The network is integrated; the giant component exists and covers a large share of the population.

3. The average distance between nodes in the giant component is small, $d(G)$ is of order $\ln n$.

4. Clustering is high, $C(G) >> \eta(G)/n$.

This definition is a modified version of the notion of small world presented in Watts (1999).

2.3 Empirical Patterns

We study the world of economists who published in journals which are included in the list of EconLit. We cover all journal papers that appear in a 10 year window and we look at three such windows: 1970-1979, 1980-1989 and 1990-1999. The list of journal articles includes all papers in conference proceedings, as well as short papers and notes. We do not cover working papers and work published in books. The main reason for not covering working papers is that this can potentially lead us into double counting. The main reason for restricting attention to journal articles is that the EconLit database covers books only from the 1980s and this would sharply restrict the time frame of our study. Table 2.1 provides an overview of the coverage of our data. Tables 2.2 and 2.3 give us data on the number of EconLit journals and the number of articles published in these journals over this period. The number of journals has grown from 196 in 1970 to 687 in 1999 while the number of journal articles in EconLit has grown from 62,569 in the 1970s to 156,454 in the 1990s. In Table 2.3 we can also see that the number of pages per article has increased from 12.85 to 16.49 and that less and less papers have a single author. This trend was highlighted in Ellison (2002a).

The list of journals that appear in EconLit is clearly partial and somehow arbitrary. To check the robustness of our findings, we also consider an alternative set of data. We

Table 2.2: Number of journals in EconLit: 1970-1999

Years	Number of Journals	Number of Journals in TI List
1970	196	46
1971	198	48
1972	198	47
1973	209	53
1974	203	55
1975	200	56
1976	220	58
1977	227	61
1978	242	64
1979	248	65
1980	256	67
1981	264	67
1982	262	68
1983	285	74
1984	304	79
1985	311	81
1986	318	86
1987	317	87
1988	324	90
1989	340	95
1990	353	98
1991	368	101
1992	425	104
1993	439	106
1994	491	107
1995	535	109
1996	590	110
1997	624	111
1998	656	112
1999	687	113

Table 2.3: Summary statistics for articles in EconLit.

dataset	All journals			TI list		
period	70's	80's	90's	70's	80's	90's
total papers	62569	95027	156454	26802	38133	52469
mean pages per paper	12.85	14.45	16.49	12.17	13.76	16.29
standard deviation	(9.94)	(10.27)	(10.59)	(8.69)	(8.40)	(9.08)
Authors per paper: Distribution						
single-authored	.753	.678	.578	.716	.616	.504
two authors	.210	.256	.309	.244	.311	.371
three authors	.031	.055	.090	.035	.064	.104
four or more authors	.005	.011	.023	.005	.009	.020

use the list of journals of the Tinbergen Institute Amsterdam-Rotterdam (hereafter TI list) to do this. This list of journals is used by the Tinbergen Institute to assess the research output of faculty members at 3 Dutch Universities (University of Amsterdam, Erasmus University Rotterdam and Free University Amsterdam). The Institute currently lists 133 journals in economics and related fields (econometrics, accounting, marketing, and operations research), of which 113 are covered by EconLit in 2000. Appendix B of this chapter presents the list of these journals and Table 2.2 shows the growth of this set over the 1970-2000 period. We observe that out of the 113 journals in 2000, only 46 were covered by EconLit in 1970! While some of the new journals are general interest journals, it is fair to say that most of the increase comes from the expansion in the number of field journals. We interpret this as evidence of a broadening as well as a deepening in the subject matter that is covered by economics. Table 2.3 also shows summary statistics for the TI list data set. Not surprisingly we see an increase in the number of papers, the number of pages per paper and the number of coauthored papers.

We thus have six data sets: 3 for the set of all journals covered in EconLit and 3 for the set of TI journals, and we construct a network for each data set. We first find the nodes in the network by extracting the different author names that appear in the data. As in Newman (2001) we distinguish different authors by their last name and the initials of all their first names. Consequently, authors with the same last name and different initials are considered different nodes. We note that a single author may sometimes be represented by two nodes because of misspellings in the data or because of a non-consistent use of middle names. On the other hand, two different authors might appear as one node in the network if their surname and initials are identical.[6] Further, for papers with more than three authors EconLit reports only the first author and the extension *et alia*, and, hence, the other authors are not known. We therefore exclude articles with four or more authors

[6]We have considered a more sophisticated alternative name extraction procedure and the main findings are robust; details of this procedure and the results are given in Appendix A of this chapter.

from our network analysis.[7] We then construct the whole coauthorship network by adding links between those authors that have coauthored a paper. We note that we do not weight the links, that is, we do not distinguish between more or less prolific relationships.

In what follows we present two types of results. The first set refers to the macro-statistics of the network; comparing these results against the criteria for smallness of the world mentioned above will enable us to examine whether the economics world is small or not; the second group of results pertains to the micro-structure of the collaboration network and they will be useful to investigate the sources of smallness in economics.

2.3.1 Aggregate patterns and the small world hypothesis

We now examine five aggregate statistics of the network that relate to our definition of "small world": the order of the network, the average number of links, the existence and size of a giant component, the average distance between the nodes in the giant component, and the clustering coefficient.

We start with an examination of the order of the network, i.e., the number of publishing economists. Table 2.4 tells us that the profession has grown substantially in this period: the number of authors has grown from 33,770 in the 1970s to 81,217 in the 1990s. The data based on the TI list is consistent with this trend: the number of authors has increased from 14,051 in the 1970s to 28,736 in the 1990s. Our first finding is therefore the following: *the number of journal publishing economists has grown substantially – more than doubling – over the period 1970 to 2000.*

We take up the average number of links next. In all the data we have assembled we observe the following: the average degree of the networks is very low in the period 1970 to 2000. For the set of all journals in EconLit, Table 2.4 tells us that the average degree was .894 in the 1970s, 1.244 in the 1980s and 1.672 in the 1990s. This number covers all publishing economists and it is useful to also examine the per capita number of collaborators among people who are in the giant component. Table 2.4 shows us that the per capita number of collaborators was 2.48 in the 1970s, 2.77 in the 1980s, and 3.06 in the 1990s. These numbers are consistent with the data based on the TI list of journals. Putting these numbers together with the number of total authors, yields us our next finding: *the average number of collaborators is very small relative to the total number of authors.*

We next discuss the existence and size of a giant component. Table 2.4 tells us that in the 1970s the largest component contained 5,253 nodes, which constituted about 15.6 percent of the population. This largest component has expanded substantially over time and in the 1990s it contains 33,027 nodes, which is roughly 40 percent of all nodes. Correspondingly, there has been a sharp fall in the proportion of isolated nodes from almost 50 percent in the 1970s to about 30 percent in the 1990s. At the same time the second largest component has also declined in size: it had 122 members in the 1970s and only 30 members in the 1990s. This trend is consistent with evidence based on the data corresponding to the TI list of journals. These observations lead to our next finding:

[7]Using other sources of information and the world wide web, we collected the missing names for the journals in the TI list. The results are given in Appendix A of this chapter. Including these articles did not alter our findings qualitatively.

Table 2.4: Descriptive statistics for six networks based on articles in EconLit.

dataset	All journals			TI list		
period	70's	80's	90's	70's	80's	90's
total authors	33770	48608	81217	14051	19694	28736
size of giant component	5253	13808	33027	2775	7283	14368
as percentage	.156	.284	.407	.197	.370	.500
second largest component	122	30	30	74	32	31
isolated authors	16735	19315	24578	5859	5999	6156
as percentage	.496	.397	.303	.417	.305	.214
average degree	.894	1.244	1.672	1.058	1.467	1.896
standard deviation	(1.358)	(1.765)	(2.303)	(1.433)	(1.815)	(2.224)
clustering coefficient	.193	.182	.157	.188	.180	.167
Giant Component						
average degree	2.48	2.77	3.06	2.48	2.70	2.95
standard deviation	(2.09)	(2.40)	(2.93)	(2.05)	(2.25)	(2.61)
average distance	12.86	11.07	9.47	11.99	11.12	9.69
standard deviation	(4.03)	(3.03)	(2.23)	(4.02)	(3.07)	(2.35)
diameter	40	36	29	33	31	26

There has been a significant increase in the level of integration of the network over the period 1970 to 2000. In particular, the giant component has grown substantially; it covered 15 percent of the nodes in the 1970s and covers over 40 percent of the nodes in the 1990s.

We now turn to the distance between the nodes in the network. As is the norm we set the distance between nodes in the different components to infinity and we use the average distance between nodes in the giant component as a proxy for our measure of average distance in the network. We find that this average distance was 12.86 in the 1970s, 11.07 in the 1980s, and 9.47 in the 1990s. This tells us that average distance has been very small throughout the period under study and moreover that it has declined, by approximately 25 percent, in spite of the tremendous growth in the giant component. We also note that this fall in average distance has been accompanied with a significant fall in the standard deviation in the distances between nodes from 4.03 in the 1970s to 2.23 in the 1990s. This pattern is consistent with the trends observed in the data on journals in the TI list. This leads to our next finding: *The giant component has become significantly "smaller" in terms of distances.*[8]

We next move to the level of overlap between coauthorship, which is measured by the clustering coefficient in the network. Table 2.4 shows that clustering coefficient for the network as a whole was .193 in the 1970s, .182 in the 1980s and .157 in the 1990s for the network of all EconLit journal articles, and .188 in the 1970s, .180 in the 1980s and .167 in the 1990s when we only consider articles in the TI list of journals. A comparison of these clustering levels with those that arise under a random process of generation (see Table 2.5) of links leads to our next result: *the clustering coefficient for the network is very high throughout the period under study.*[9]

When we set these findings against the criteria for a network to display small world properties, we find that throughout the period 1970-2000 the collaboration networks satisfy properties (1), (3) and (4), i.e. the average degree of the networks under consideration is tiny relative to the number of nodes, clustering is high, and distance within the giant component is small. As to criterion (2), we note that the coverage of the giant component was relatively modest in the 1970s but in the 1990s it covered over 40 percent of the nodes. That is, a giant component has emerged and thus in the 1990s the collaboration network satisfies all four criteria. Furthermore, we see a decline of average distances within the giant component. This leads us to conclude that *economics is an emerging small world.*

[8] If we consider distances between all pairs of authors in a giant component as an i.i.d. sample, we can use two-sample t-statistics to test the hypotheses of equal average distance in the 1970s and 1980s giant components and in the 1980s and 1990s giant components. The t-statistic is -1589.2 for the comparison of the 1970s and 1980s giant components and -4919.0 for the 1980s and 1990s ones. In both cases the hypothesis of constant average distance is clearly rejected.

[9] This can be substantiated by means of the following thought experiment. Consider the numbers from the 1990s. There are 81,217 authors and on average a person has 1.672 coauthors; we can interpret this as saying that the probability of a link being formed is approximately .00002. In a random graph the probability of link formation is independent, so the clustering coefficient should be approximately equal to this number. However, the actual clustering coefficient is .157, which is more than 7,000 times the level predicted by this thought experiment. We note that papers with three coauthors increase the clustering coefficient. We also computed the clustering coefficient considering papers with two coauthors only, see Appendix A for details. We found the clustering coefficient to be around .015, still more than 700 times the level predicted by a random link model.

Table 2.5: Actual TI List networks against simulated Erdős-Renyi random networks.

period	70's	80's	90's
# simulations	1000	190	45
	Size of the giant component (in perc.)		
Actual network	.197	.370*	.500*
Average Simulation	.156	.577	.751
Std.Dev. Simulation	(.034)	(.004)	(.002)
.95-confidence	[.069, .206]	[.570, .585]	[.747, .756]
	Average distance within giant component		
Actual network	11.99*	11.12*	9.69*
Average Simulation	40.07	18.27	13.33
Std.Dev. Simulation	(6.13)	(.34)	(.09)
.95-confidence	[29.77, 53.22]	[17.62, 18.91]	[13.18, 13.49]
	Clustering coefficient		
Actual network	.188*	.180*	.167*
Average Simulation	8.3×10^{-5}	1.0×10^{-4}	8.4×10^{-5}
Std.Dev. Simulation	(1.8×10^{-4})	(1.1×10^{-4})	(5.6×10^{-5})
.95-confidence	$[0, 7.2] \times 10^{-4}$	$[0, 3.9] \times 10^{-4}$	$[0, 2.1] \times 10^{-4}$

Actual network is based on TI List data set. The size and average degree of the simulated networks is identical to the actual network. The .95-confidence interval is based on the .025-percentile and .975-percentile of the simulated data set. Percentiles are computed from simulated data by linear interpolation.
*) Actual network is outside the .95 confidence interval.

2.3.2 Micro-level statistics

What is it about the number and arrangement of links in the network that generates these aggregate features? Our approach to this question is founded on the idea that individual economists have a choice between writing papers by themselves or in collaboration with others, and that the network of collaboration we observe arises out of the decisions they make in this regard. Thus the crucial micro level data in this approach are the number of collaboration links that an individual forms and the patterns of linking across economists.

We start with the behavior of the average number of links. In all the data we have assembled we observe the following: the average degree of the networks is very low but it has grown significantly in the period 1970 to 2000. For the set of all journals in EconLit, Table 2.4 tells us that there is almost a doubling in the per capita number of links/collaborators from .894 in the 1970s to 1.672 in the 1990s. This number covers all publishing economists and it is useful to also examine the per capita number of collaborators among people who are in the giant component. Table 2.4 shows us that the per capita number of collaborators increased from 2.48 in the 1970s to 3.06 in the 1990s. This trend is also visible and clear cut in the TI list of Journals. This yields us our first finding on the micro statistics of the network: *the number of collaborators is very small but it has been increasing consistently through the 1970-2000.*[10]

When we put together these average number of collaborators numbers with the average distance numbers noted earlier, we are struck by the striking efficiency with which the links connect the world of economics. To get a sense of this we conduct the following thought experiment: suppose we start with a person i and move outward through his coauthors and their coauthors and so on. What is the maximum number of people we can reach if everyone has η coauthors and the furthest away person is at distance k? To maximize reach, the most efficient way to organize the network is to have no overlap among the coauthors. Even in this extreme form of organization i will reach only $\eta((\eta-1)^k-1)/(\eta-2)$ people.[11] So for example, if $\eta = 2.5$ and $k = 15$ then i would be able to access 2,184 people. Moreover, the corresponding average distance from these people to i would be 13.01. How does this compare with the actual networks we observe? In the network of the 1970s, we find that average degree in the giant component is 2.5 and the average distance is 12.86, but the size of the giant component is over 5,200, which is more than twice the number 2,184! This informal discussion tells us that it is difficult to square the numbers for average degree and average distance with a regular (symmetric) network structure. A similar argument also applies for (uniform) random graphs with a comparable average degree. We provide aggregate statistics for uniform random graphs in Table 2.5. This table shows that average distance is significantly higher in random graphs as compared to what we observe in the actual network. These observations motivate a closer examination of the distribution of coauthors and the arrangement of links.

[10] As in the case of the average distances in the giant component, we can use two-sample t-statistics to test the hypothesis that the average number of collaborators is constant over time. The t-statistic is 32.1 for the comparison of the 1970s and 1980s networks is 32.1, and 37.6 for the 1980s and 1990s networks. The hypothesis of constant average degree is clearly rejected.

[11] The number of people reached is $\eta \sum_{i=0}^{k-1} (\eta - 1)^i$, which simplifies to the expression above.

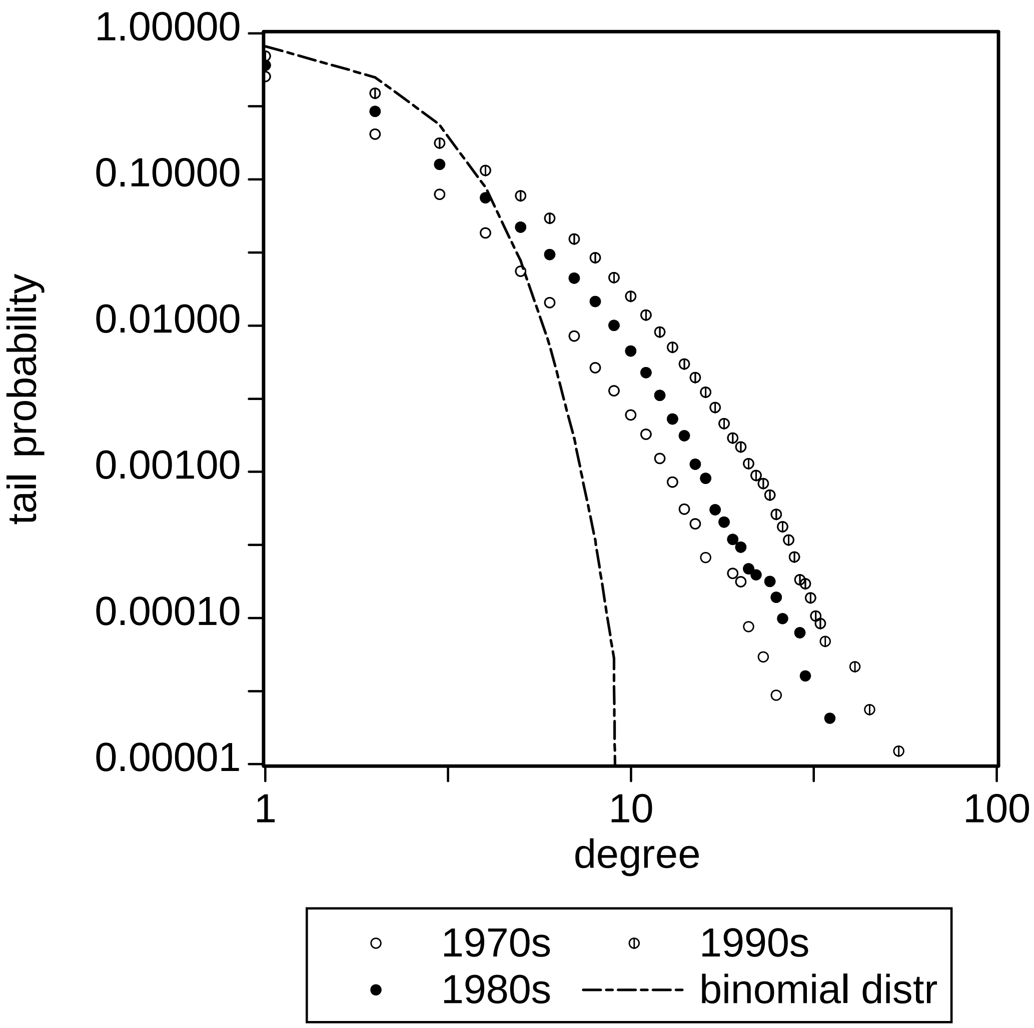


Figure 2.1: Pareto plot of the degree distribution.

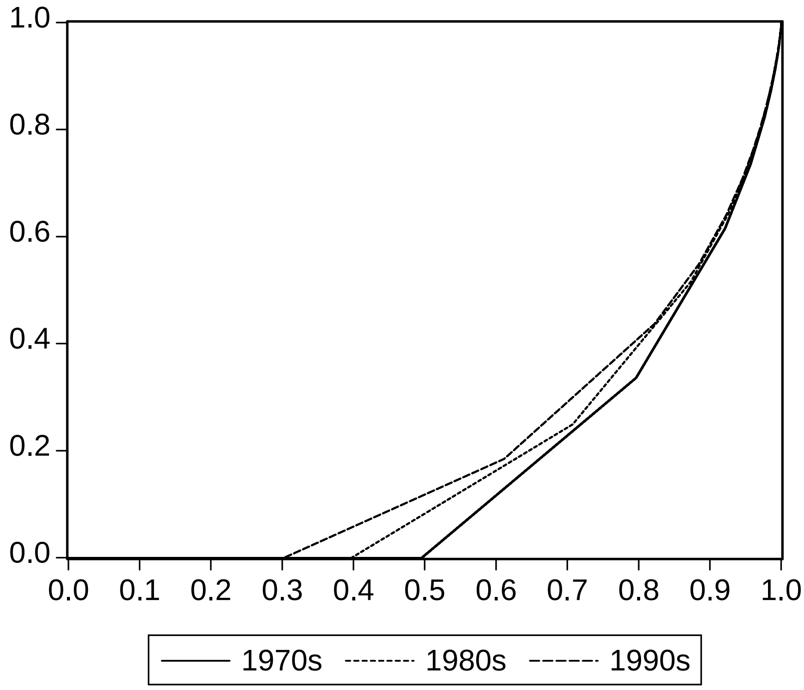


Figure 2.2: Lorenz curve of the degree distribution in the coauthorship network.

Figure 2.1 shows the Pareto plot for the distribution of links: this plot shows on a log-log scale the number of links per author k on the x-axis and the tail distribution, i.e., the fraction of authors for which $\eta_i \geq k$, on the y-axis. We start by noting that the Pareto plot of the degree distribution appears to converge to a straight line for high degree k. This suggests that at high quantiles the distribution converges to a Pareto or power-law distribution.[12] An important characteristic of such a distribution is the existence of a fat tail. Indeed, extreme degree values appear more frequently in the real data than in a binomial distribution fitted on the 1990s data set. While under the fitted binomial distribution it is unlikely that any author has more than 10 links, in reality we see that more than 1 percent of the authors have more than 10 links and some of them have 40 to 50 links. We explore the inequality in the degree distribution further by looking at the Lorenz curves. Figure 2.2 suggests that the 20 percent most-linked authors account for about 60 percent of all the links. These observations lead us to the following finding: *The distribution of links in the population of economists is very unequal and exhibits a fat tail.*

We now examine more closely the link pattern of the individuals who have very large degree in the network of collaboration. Table 2.6 tells us that in the 1970s the maximally connected person had 25 links and the 100 most linked persons had 12 links on average. Looking more closely at the most connected individual we see three very striking features: one, this person published 44 papers out of which 42 (i.e. 95 percent of them) were coauthored; two, he had 25 collaborators while the average number of collaborations

[12]A power-law distribution would take the form $f(k) = \alpha k^{-\beta}$, with $\alpha > 0$ and $\beta > 0$.

Table 2.6: Network statistics for the economists with the highest number of links.

Author	Papers	% Coauthored	Links	Distance 2	Clust.Coeff
		1970s			
tollison rd	44	0.955	25	57	0.053
heady eo	30	0.833	23	13	0.028
feldstein ms	73	0.288	21	40	0.024
schmitz a	23	0.870	20	29	0.042
smith vk	72	0.514	20	26	0.032
Average top 100	23.87	0.724	11.94	25.67	0.062
Average all	2.35	0.243	0.89		0.193
		1980s			
mccarl ba	36	0.889	35	97	0.022
thisse jf	34	0.971	30	80	0.055
lee cf	36	1.000	29	106	0.030
whalley j	52	0.808	29	44	0.022
schmitz a	26	0.846	26	118	0.058
Average top 100	28.42	0.827	16.36	49.80	0.062
Average all	2.65	0.315	1.24		0.182
		1990s			
thisse jf	66	0.970	54	244	0.022
lee j	58	0.586	45	158	0.019
sirmans cf	67	1.000	41	172	0.045
nijkamp p	67	0.940	41	57	0.034
michel p	48	0.938	34	169	0.036
Average top 100	37.69	0.849	25.31	99.40	0.043
Average all	2.82	0.409	1.67		0.157

Table 2.7: Error and attack tolerance of the network based on all articles in EconLit.

period	70's	80's	90's
Size of the giant component (in perc.)			
Whole network	.156	.284	.407
w/o random 2%	.149	.276	.398
w/o random 5%	.137	.263	.389
w/o top 2%	.002	.067	.256
w/o top 5%	.000	.001	.001
Average distance within giant component			
Whole network	12.86	11.07	9.47
w/o random 2%	12.88	11.17	9.58
w/o random 5%	12.89	11.21	9.68
w/o top 2%	9.26	29.80	19.00
w/o top 5%	2.64	5.71	8.91
Clustering coefficient			
Whole network	.193	.182	.157
w/o random 2%	.193	.183	.158
w/o random 5%	.192	.182	.157
w/o top 2%	.318	.280	.250
w/o top 5%	.440	.380	.344

per capita was less than 1; and three, the clustering coefficient for this person was only .05, which is much smaller than .193, the clustering coefficient of the network at large. Similarly, in the 1990s the most connected individual published 66 papers, of which 64 were coauthored (i.e. 97 percent of the total), had 54 collaborators (while the per capita number of collaborators was under 2) and a clustering coefficient of .02 (while the clustering coefficient of the network as a whole was .157). Thus the most connected individuals collaborated extensively and most of their coauthors did not collaborate with each other. These individuals can be viewed as 'stars' from the perspective of the network architecture. A closer inspection of Table 2.6 reveals that these three patterns are quite general and hold for the average of the 100 most linked individuals in the 1970s, 1980s and 1990s. This leads us to state: *There is a large number of 'stars' in the world of economics.*

We next examine the role of the stars in connecting different parts of the network. For this purpose we compared the consequences of randomly deleting 2 percent or 5 percent of the nodes on network connectivity and clustering with the consequences of deleting star nodes. We did this for the network based on all EconLit journals. Table 2.7 shows the results. We can see that a removal of 5 percent of the authors at random has almost no effect on the network connectivity and clustering. For the 1990s, we find that the size

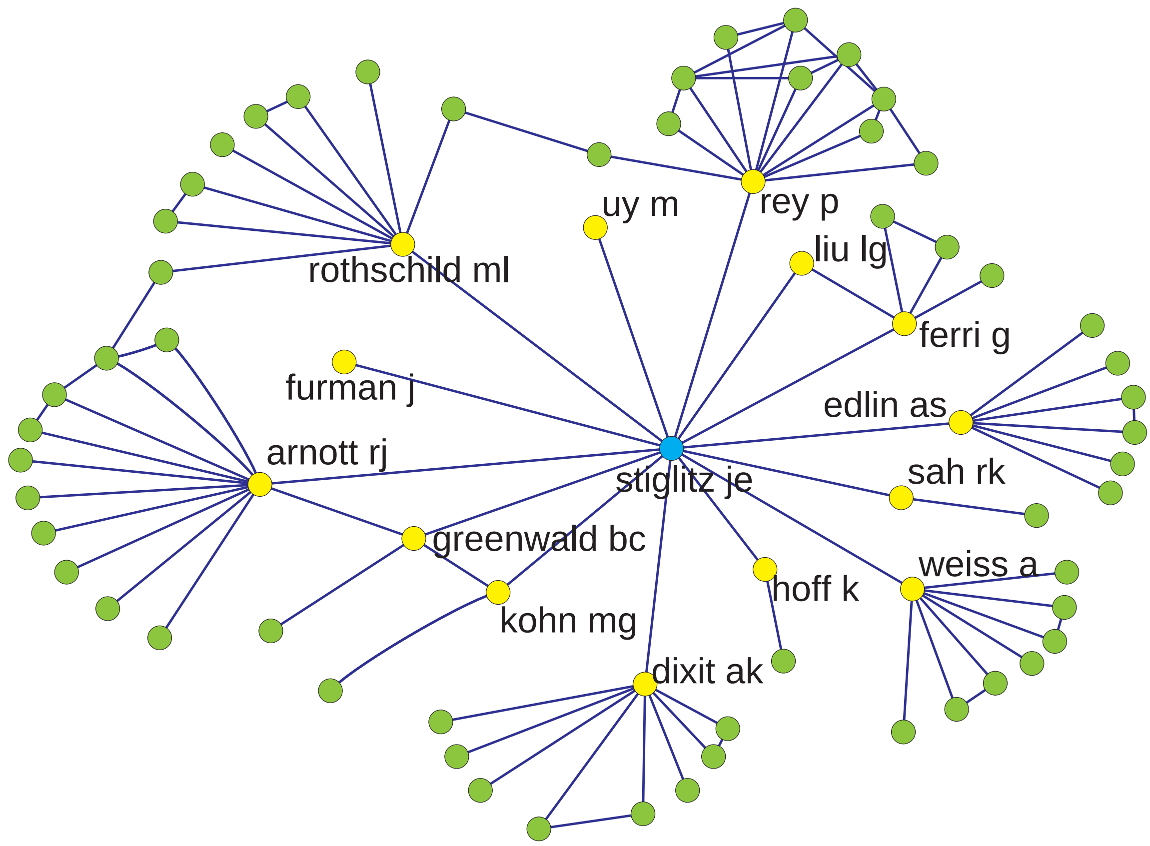


Figure 2.3: Local network of collaboration of Joseph E. Stiglitz in the 1990s.

Note: The figure shows all authors within distance 2 of J.E. Stiglitz as well as the links between them. The width denotes the strength of a tie. Some economists might appear twice or are missing due to the use of different initials or misspellings in EconLit. The figure was created by software program *Pajek*.

of the giant component goes down from .407 to .389, while the average distance within the giant component increases marginally from 9.47 to 9.68. By contrast, a removal of the 5 percent most connected nodes has a devastating effect on the network. The giant component breaks down almost completely. Moreover, the impact on clustering is very substantial: it increases from .157 to .344. This suggests that stars play the role of connectors and sharply reduce distance between different highly clustered parts of the world of economics. We therefore conclude that throughout the period under consideration *the economics world has been spanned by interlinked stars* an this is critical to understand the small average distance numbers noted in the previous section.

We would like to plot the networks for the periods of 1970s, 1980s and 1990s to get an overall picture of the networks. This has proven to be very difficult due to the large numbers of nodes involved. We have therefore tried to plot the local network around some prominent economists (Figures 2.3 and 2.4). These plots are fascinating and suggest a number of ideas; we would like to draw attention in particular to one striking feature of the networks: hierarchy. For instance, in the plot for Joseph Stiglitz (Figure 2.3) we

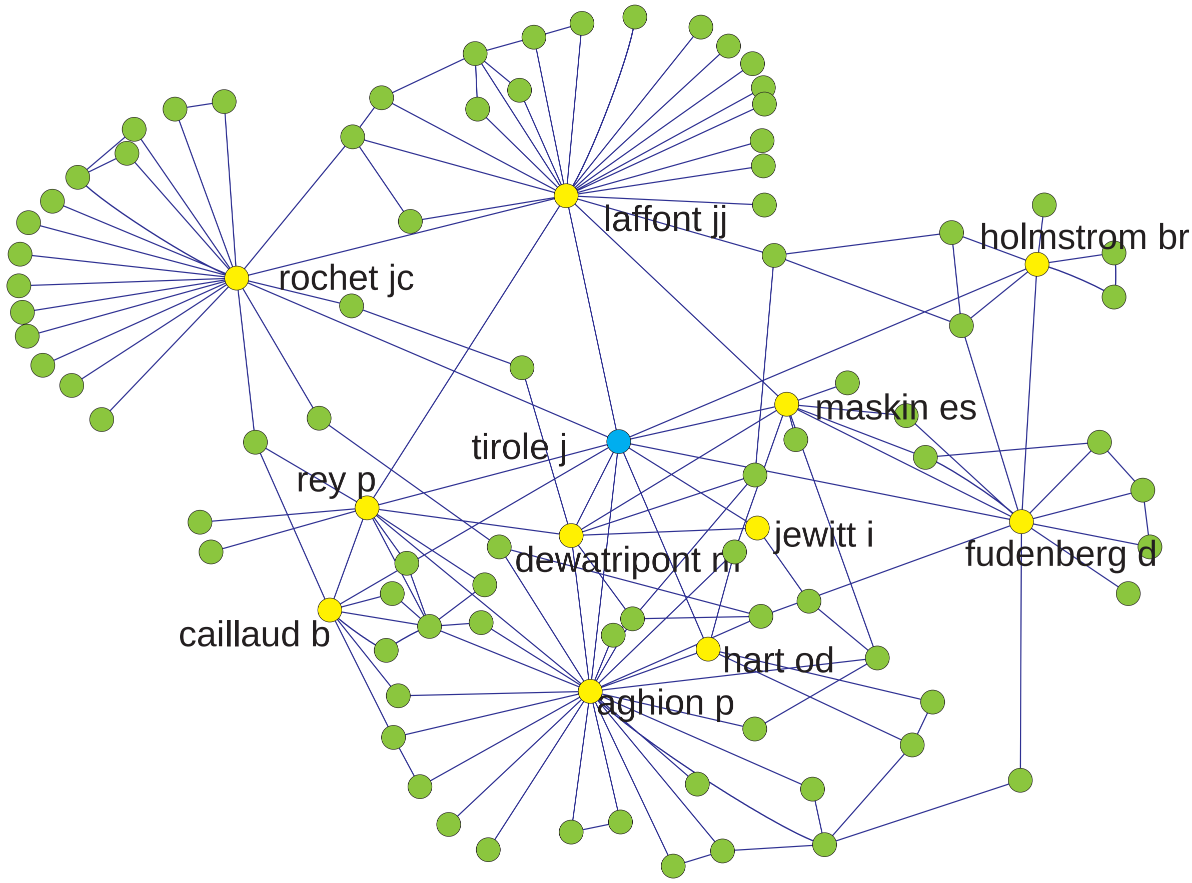


Figure 2.4: Local network of collaboration of Jean Tirole in the 1990s.

Note: The figure shows all authors within distance 2 of J. Tirole as well as the links between them. The width denotes the strength of a tie. Some economists might appear twice or are missing due to the use of different initials or misspellings in EconLit. The figure was created by software program *Pajek*.

find that he is linked to several persons who are themselves 'stars' in the sense discussed above. Furthermore, we observe that these star coauthors of Mr. Stiglitz typically do not work with each other and also that the coauthors of these persons typically do not work with each other, nor do they work with Mr. Stiglitz. Thus there seems to be a hierarchy of well connected persons. We find this structure remarkable as this hierarchy is mostly self-organizing. A similar structure can be observed in the plot for Jean Tirole (see Figure 2.4).

The discussion on micro-variables allows us to make two general points. The *first* point is about a stable feature of the network: interlinked stars span the network of collaboration and this helps explain the very low average distances observed throughout the period under study. The *second* point is about an important change: there has been a significant increase in the average degree of the network.

2.3.3 Explaining an emerging small world

There are two principal macro level changes in the structure of the economics network from which we conclude that a small world is emerging: one, the giant component is growing and two, average distance within the giant component is falling. Why is the world of economics becoming smaller over time? In this section we examine the relative importance of three possible explanations. One, an increase in the inequality in the distribution, two, the forming of more 'distant' links and three, an increase in the average number of coauthors.

The first possible explanation is that the inequality in the degree distribution is increasing in such a way that the star-like structure is becoming more prominent over time and this is making the economics world more integrated. To examine this hypothesis we explored the evolution of the inequality in the number of links per author by looking at Lorenz curves and Gini coefficients. Figure 2.2 shows Lorenz curves in the 1970s, 1980s and 1990s based on the data set that includes all EconLit journals. The plot reveals a decreasing trend in inequality over time. This observation is confirmed by the Gini coefficients reported in Table 2.8. However, this trend is mainly explained by a decrease in the number of isolated authors — from 50 percent in the 1970s to 30 percent in the 1990s— since it implies that more and more authors are involved in coauthoring. Interestingly, if we adjust for this participation effect by ignoring isolated authors, or by considering the giant component only, then Table 2.8 shows that the trend is reversed. As a result we conclude that *inequality in the distribution of links has increased within components and it has decreased when we consider the whole network.*

A second possible explanation is that (due to decrease in communication and traveling costs, collaboration across individuals located in different departments and countries has become easier) economists are replacing 'geographically' close ties by distant ones and this is making the world small. This is something we do not observe directly in our data but there is some empirical evidence which suggests that there has been an increase in distant collaborations in the last years. For example, Hamermesh and Oster (2002) find that in the 1970s only 5.6 percent of the collaborations were between authors working at different departments throughout the duration of the project. This number increased to 20.3 percent between 1992 and 1996. Similarly, Rosenblat and Mobius (2004) in a study

Table 2.8: Gini coefficients computed for several data sets.

period	70s	80s	90s
Whole network			
All journals	.659	.619	.585
TI List	.609	.559	.524
Network excluding isolated authors			
All journals	.324	.367	.404
TI List	.329	.366	.394
Giant component			
All journals	.381	.395	.420
TI List	.378	.385	.402

of 8 core economics journals[13] find that there has been a steady increase in collaboration among geographically distant authors, over the period 1980-2000. It seems reasonable to expect that the formation of more distant links can lead to a growth of the giant component as well as to a fall in the average distance within the giant component.

A third possible explanation for the small world is based on the observed trend of increasing collaboration. We have already noted that the average number of collaborators per author has increased over time. Moreover, the discussion above on the inequality in the degree distribution suggests that this increase in average degree has been somewhat evenly distributed in the population of economists. To check this, we look at the distribution of links in the collaboration network more closely.

Figure 2.1 shows the Pareto plot for the distribution of links. This graph shows that there is a first-order stochastic dominance relationship over time. The distribution of the 1980s first order stochastically dominates the distribution of the 1970s, while the 1990s degree distribution first order stochastically dominates the degree distribution of the 1980s. This leads us to argue that *the number of collaborators has increased for all quantiles of the degree distribution.* A higher average degree along with a somewhat fixed interlinked star architecture implies that the extra links bring economists, who may otherwise have been unconnected, together and this increases the size of the giant component and decreases the average distance within the giant component.[14]

[13]These journals are American Economic Review, Quarterly Journal of Economics, Journal of Political Economy, Econometrica, Review of Economic Studies, Review of Economics and Statistics, Rand Journal of Economics, and Brookings Papers on Economic Activity.

[14]We note that also in a uniform random graph the expected size of the giant component increases with average degree. Further, in a uniformly random graph average distance converges to $\ln n / \ln \eta$ for large n whenever $\eta > 1$ (see, e.g., Albert and Barabási, 2002).

These remarks lead us to examine the relative importance of these three factors in explaining the emergence of the small world. One way to address this issue is to regress the macro level variables on network size, average degree and the fraction of distant links; however, this procedure is not feasible since we only have 6 networks to compare. We therefore develop a method to compare networks after controlling for changes in number of nodes and average degree. The idea is that once we have controlled for changes in number of nodes and average degree then any macro-level changes we observe in the resulting network must be due to changes in distribution of degree along with changes in the arrangement of links. We implement this idea via a two-step procedure. To compare two networks, e.g. the 1980s network to the 1970s network, we first delete nodes *at random* from the 1980s network until the number of nodes is equal to the number of nodes in the 1970s network (i.e., 33,770 individuals). This step generates adjusted networks for the 1980s. We find that the average degree of these adjusted networks is lower than the average degree in the actual 1970s network. In the second step, to control for this difference, we then delete links *at random* from the 1970s network and the adjusted 1980s network to arrive at a common average degree for the two networks.

Since we control for the changes in size and degree, we can formulate the following hypothesis. If the increase in degree were the *main* factor leading to the emergence of a small world, we would expect that the networks adjusted by the above procedure are very similar. Alternatively, if other factors such as changes in the arrangement of links and in the degree distribution did matter a lot, then we would expect to observe a substantial increase in the size of the giant component as well as an important fall in average distances as we move from the 1970s to the 1980s adjusted networks, and from the 1980s to the 1990s adjusted networks.

To test this hypothesis we compare the 1970s and the 1980s adjusted networks, and the 1980s adjusted network to the 1990s one. We repeat the procedure 200 times and create a sample of 200 observations of adjusted networks, and for each network in the sample we compute the relevant statistics. Table 2.9 shows the means and the standard deviations of the main macro statistics based on this sample (note that the size and the average degree are fixed). Our *first* observation is that, on average in the sample of 200 simulations, the giant component comprised 12.9 percent of the population in the 1970s adjusted network, and 14.9 percent in the 1980s adjusted network. A test for constant size of the giant component is rejected with a two-sample t-statistic of 62.6. When we compare the 1980s adjusted network to the 1990s one we find that the size of the giant component in the 1980s network is 21.2 percent while it is 21.7 percent in the 1990s adjusted network. Testing for constant size in this case also leads to a rejection with a t-statistic of 17.4. Hence, the size of the giant component does increase, but only slightly compared to the increase of the giant component in the actual networks: as reported in Table 2.4, the giant component in the actual networks increased from 15 percent in the 1970s to 28 percent in the 1980s and to 41 percent in the 1990s! This analysis thus shows that changes in the arrangement of links and in the degree distribution have had a positive but relatively small effect on the size of the giant component.

Our *second* observation is about the average distance in the different networks. When we compare the 1970s and 1980s adjusted networks we find that average distance is 13.49 in the 1970s adjusted network and 13.77 in the 1980s adjusted network. Hence, after

Table 2.9: Simulation experiment to control for changes in size and degree in the networks based on all journals in EconLit.

dataset	All journals			
sample size	200	200	200	200
period	70's	80's	80's	90's
total authors	33770	33770	48608	48608
average degree	.80	.80	.95	.95
giant component (as perc.)	.129	.149	.212	.217
	(.003)	(.004)	(.002)	(.003)
isolated authors (as perc.)	.529	.532	.481	.482
	(.001)	(.002)	(.001)	(.002)
clustering coefficient	.173	.168	.140	.149
	(.002)	(.004)	(.002)	(.003)
Giant Component				
average degree	2.39	2.42	2.48	2.50
	(.01)	(.01)	(.01)	(.01)
average distance	13.49	13.77	12.57	12.12
	(.26)	(.47)	(.13)	(.21)
diameter	39	40	38	35
	(3.1)	(3.7)	(3.1)	(2.7)

Networks are adjusted by first deleting *nodes* randomly until a given order is reached; and then deleting *links* randomly until a given average degree is reached. The sample mean is given without parentheses. The sample standard deviation is given in parentheses.

Table 2.10: Simulation experiment to control for changes in size and degree in the networks based on the TI list.

dataset	TI list			
sample size	500	500	500	500
period	70's	80's	80's	90's
total authors	14051	14051	19694	19694
average degree	1.00	1.00	.1.25	1.25
giant component (as perc.)	.182	.204	.314	.313
	(.003)	(.007)	(.003)	(.005)
isolated authors (as perc.)	.436	.436	.360	.359
	(.001)	(.003)	(.001)	(.003)
clustering coefficient	.178	.173	.154	.161
	(.002)	(.005)	(.002)	(.004)
Giant Component				
average degree	2.43	2.41	2.52	2.53
	(.01)	(.02)	(.01)	(.01)
average distance	12.42	13.80	12.21	12.01
	(.26)	(.59)	(.14)	(.28)
diameter	35	39	36	34
	(3.3)	(3.9)	(2.9)	(3.0)

Networks are adjusted by first deleting *nodes* randomly until a given order is reached; and then deleting *links* randomly until a given average degree is reached. The sample mean is given without parentheses. The sample standard deviation is given in parentheses.

controlling for size and degree, we see a slight *increase* of 2.1 percent in average distance from the 1970s to the 1980s! This increase is significant according to a two-sample t-test with a t-statistic of 7.32. By contrast, in the comparison between the 1980s and 1990s, we find that the average distance in the 1980s adjusted network is 12.57 while it is 12.12 in the 1990s. Hence, we observe a modest 3.6 percent decrease in distances from the 1980s to the 1990s, which is significant with a two-sample t-statistic of -25.13. However, the average distance in the actual networks fell from 11.07 in the 1980s to 9.47 in the 1990s, a decrease of 14.5 percent. We thus conclude that changes in the degree distribution and/or the arrangement of links are not the main reason behind the fall in average distances within the giant component.

Summarizing: our analysis thus leads to the conclusion that *the increase in average degree for all quantiles of the degree distribution is the main driving force behind the emergence of a small world.*[15]

In a recent paper, Rosenblat and Mobius (2004) also examine changes in average distance in the giant component of an economics coauthor network (with 8 core economics journals) over the period 1970-2000. Their Table 6 suggests that it is the change in patterns of links that explains fully the fall in average distances. This is in conflict with our summary statement above. We now discuss their approach to understand the reasons for the conflicting conclusions.

There is a number of differences between the empirical work in this chapter and their paper. Perhaps the most important difference is in the scope of the enquiry: their analysis takes as a given the size of the giant component in the period under consideration.[16] By contrast, the main finding of our empirical analysis is that the size of the giant component has itself grown substantially over time. Indeed, this trend is robust and is to be observed in all the different collaboration networks we have studied. Changes in the size of the giant component are clearly very important for our claim that the economics world is becoming more integrated. We now explain how the changes in size of the giant component are also important in developing an explanation for falling distances within it.

Rosenblat and Mobius (2003) compare the collaboration network of 1975-1989 to the network of 1985-1999, and the network of 1970-1989 to the network of 1980-1999. They consider the giant component only and they observe that average degree in the giant component has increased from 2.52 in 1975-1989 to 2.72 in 1985-1999. They control for this change in average degree by deleting links according to the ratio $1 - C_1/C_2$, where C_1 is the average degree in the giant component between 1975-1989 and C_2 is the average degree in the giant component between 1985-1999. They find that average distances are lower in the giant component of the adjusted 1985-1999 network as compared to the actual 1975-1989 network. This leads them to argue that it is the change in the pattern of links that has led to a fall in average distances in the giant component.

[15]We also performed a similar experiment on the TI list data set. The results, which are reported in Table 2.10, lead to the same conclusions.

[16]In particular, they suppose that most economists belong to the giant component and that this feature of the network is a constant over time.

Table 2.11: Simulation experiments on the network based on all articles in *American Economic Review, Brookings Papers on Economic Activity, Econometrica, Quarterly Journal of Economics, RAND (prev. Bell) Journal of Economics, Review of Economic Statistics* and *Review of Economic Studies.*[a]

period	1975-1989	1985-1999	adj. 1[b]	adj. 2[c]
total authors	5530	5468	5468	5468
average degree	1.218	1.514	1.431	1.333
				(.017)
size of giant component	1147	1666	1577	1464
as percentage	.207	.305	.288	.268
			(.004)	(.008)
Giant component				
average degree	2.52	2.67	2.60	2.52
			(.01)	
average distance	10.39	9.49	9.77	10.19
			(.16)	(.23)
diameter	25	27	27.1	28.1
			(2.3)	(2.7)

[a] Authors names are distinguished by their last name and all first and middle initials. Adjusted networks are based on the average of 200 simulations. Standard deviation in the 200 replications is given in parentheses.

[b] Adjusted by removing $1 - C_1/C_2$ fraction of all links, where C_1 is the average degree in the giant component of the 1975-1989 network, and C_2 is the average degree in the giant component of the 1985-1999 network. (Method of Rosenblat and Mobius (2004).)

[c] Adjusted by removing links until the average degree in the giant component of the 1985-1999 network equals the average degree of the giant component in the 1975-1989 network.

We replicated their experiment and our results are reported in Tables 2.11 (see columns 1-3).[17] Our first observation is that the average distance in their giant component is 9.03 in the 1975-1989 network, much lower than the number we obtained (10.39). The same happens for the 1985-1999 network. Our second observation is that, using their method of adjusting the network, the average distance in the adjusted giant component (9.77) is higher than the average distance in the giant component of the actual 1985-1999 network (9.49). This is in contradiction to what they find. Finally, our third observation is that the average distance in the adjusted giant component (9.77) is lower than the average distance in the giant component of the actual 1970-1985 network (10.39). Thus after controlling for changes in degree using their methods, we observe that the arrangement of links seem to explain about 70 percent of the fall in average distances. This last finding is consistent with their finding that changes in the arrangement of links are the main explanatory variable behind the fall in average distances, but conflicts with our earlier summary statement above. We now examine the connection between average degree and average distance more closely.

An inspection of the Table 2.11 reveals that their method yields an adjusted network in which the average degree of the giant component is 2.60, which is (significantly) higher than the average degree in the giant component of the actual 1975-1989 network, which is 2.52. The reason for this discrepancy is as follows: implementing their procedure involves deleting links at random, which in a large enough network should yield the same average degree in the adjusted network as in the actual network. However, as links are deleted at random it is more likely that the authors with fewer links are disconnected from the giant component. As a result, the average degree of authors in the giant component of the adjusted network (2.60) is higher than what was aimed for (2.52). We claim that it is this difference in average degree which accounts for their results.

To show this, we simulate a sample of 200 observations of the 1985-1999 network by randomly deleting links until the average degree in the giant component is exactly identical to 2.52, the actual average degree in the 1975-1989 giant component. The results of the statistics based on this sample are reported in the fourth column of Table 2.11. We find that this leads to an average distance of 10.19 in the giant component, which is much higher than 9.49, the actual average distance for the period 1985-1999. Moreover, we note that this distance is significantly lower than 10.39, the average distance for the period 1975-1989, with a t-statistic of -12.60. This implies that factors other than the increase in average degree do explain a small part – about 22 percent – of the fall in average distance. As a result, we are led to the conclusion that the increase in average degree at all levels of the collaboration structure accounts for *most* of the change in average distance.

[17] We use a data set with the same 8 journals as Rosenblat and Mobius (2003). However, the data sets are not necessarily identical, as we have no information on the way the data issues mentioned in Section 2.3 are treated in the analysis of Rosenblat and Mobius. We treat the data issues in the 8 journal data set as follows; we ignore all papers with 4 or more authors and we distinguish authors by their last name and their initials. Further, we included the Bell Journal of Economics in the data set being the ancestor of the RAND Journal of Economics.

Table 2.12: Descriptive statistics for six networks based on articles in EconLit, considering only authors that published 5 or more papers.

dataset	All journals			TI list		
period	70's	80's	90's	70's	80's	90's
total authors	3864	6907	12396	1876	3117	4838
size of giant component	1406	3912	9279	800	2009	3795
as percentage	.364	.566	.749	.426	.645	.784
second largest component	18	9	16	18	21	7
isolated authors	1508	1947	2103	625	683	668
as percentage	.390	.282	.170	.333	.219	.138
average degree	1.261	1.862	2.716	1.407	1.987	2.618
standard deviation	(1.563)	(2.027)	(2.634)	(1.636)	(1.898)	(2.276)
clustering coefficient	.137	.144	.128	.130	.149	.133
Giant Component						
average degree	2.52	2.94	3.48	2.51	2.79	3.21
standard deviation	(1.75)	(2.05)	(2.60)	(1.79)	(1.85)	(2.20)
average distance	10.63	9.43	8.11	10.03	9.50	8.32
standard deviation	(3.67)	(2.67)	(1.98)	(3.78)	(2.89)	(2.23)
diameter	33	28	25	27	27	22

2.3.4 Data robustness

We now briefly discuss some aspects of the data that we use. We first note that the data sets we used included all authors that published a paper in a journal covered by EconLit. However, many authors published only one or two papers in their lives, and they cannot be considered to be actively engaged in economics research. As a first robustness check we therefore deleted all authors who published less than 5 papers in a decade. The macro-statistics for this network are presented in Table 2.12. The table shows that the results of an emerging world are robust with respect to this change. The only difference we observe is that the giant component is larger and the average distance is smaller compared to the entire network, as one would expect.

Another possible shortcoming of the above data for our purposes is the partial coverage of the EconLit list. We observe that this list has been growing over time and the data discussed above relate to this expanding world. This pattern creates the following possibility: in the 1970s the world of journals was actually very similar to the one we

Table 2.13: Network statistics for two networks based on articles in two fixed subsets of journals.

data set	Entire period[a]			Core journals[b]		
period	70's	80's	90's	70's	80's	90's
total authors	22960	27539	32773	3186	3387	3171
size of giant component	3076	5899	10054	237	608	779
as percentage	.134	.214	.307	.074	.180	.246
isolated authors	11260	11062	10572	1507	1143	701
as percentage	.490	.402	.323	.473	.337	.221
average degree	.885	1.134	1.386	.833	1.142	1.429
standard deviation	(1.312)	(1.508)	(1.695)	(1.095)	(1.279)	(1.405)
clustering coefficient	.198	.218	.216	.253	.259	.257
Giant Component						
average degree	2.45	2.62	2.70	2.45	2.45	2.55
standard deviation	(2.03)	(2.11)	(2.18)	(1.80)	(1.77)	(1.82)
average distance	12.15	12.63	12.33	7.94	11.92	11.02
standard deviation	(3.75)	(3.65)	(3.36)	(3.43)	(5.22)	(4.12)
diameter	29	37	34	22	33	29

[a] Network is based on articles in journals that appear in EconLit for the entire sample period from 1970 to 1999.

[b] Network is based on articles in *American Economic Review*, *Econometrica, Journal of Political Economy, Quarterly Journal of Economics* and *Review of Economic Studies.*

observe today but the EconLit data set does not capture this as it covered a small subset of journals and therefore excluded a large part of the journal publishing world. If this were true then the data above would be about the world of EconLit authors but would not be a good indicator of the world of journal publishing economists per se.

To get around this problem, we carry out two related robustness checks. We study the network of collaboration using only the subset of journals that appear in EconLit for the entire sample period. This is the route taken in Table 2.13. The number of authors has gone up significantly from 22,960 in the 1970s to 32,773 in the 1990s, about 43 percent. We now turn to the statistics on the pattern of connections. We note that the largest component has grown from 3,076 nodes in the 1970s, which was about 13 percent of all nodes, to 10,054 nodes in the 1990s, which is about 30 percent of all nodes. Likewise, the percentage of isolated authors has fallen from about 50 percent in the 1970s to about 32 percent in the 1990s. Thus the order of the network is increasing while the network is becoming more integrated. We note however that there is no trend in average distances in the giant component in the period under consideration. With regard to the micro statistics, Table 2.13 tells us that mean number of links per author has increased from 0.885 in the 1970s to 1.386 in the 1990s.

We finally consider a fixed set of five core journals, namely, *American Economic Review, Econometrica, Journal of Political Economy, Quarterly Journal of Economics* and *Review of Economic Studies*. Table 2.13 show the results we obtain. The size of the giant component has increased from 7 percent in the 1970s to 25 percent in the 1990s. Further, the number of per capita collaborators has increased from .833 in the 1970s to 1.429 in the 1990s and the clustering coefficient has remained high over time. There is no trend is average distance however.

The observations lead us to conclude that there is a significant increase in the size of the giant component as well as in the average degree of the network. This is consistent with our earlier observations. Further, average distances are small but there is no trend; the former is consistent with our earlier findings while the latter is not.

2.4 Concluding remarks

It has now become a common place to argue that due to a series of technological and economic developments – such as the rise of facsimile technology, the deregulation of airlines and telecommunications and the emergence of the internet– it is becoming cheaper for individuals to form and maintain more distant ties. This in turn, it is claimed, has reduced the 'distance' between people and made the world 'smaller'. This chapter has carried out an empirical examination of this argument.

We have studied the evolution of social distance among economists over a thirty year period. We have constructed coauthorship networks for the 1970s, 1980s and 1990s. Our first finding is that the network of economists is very large, that every economist maintains very few links on average and that the network of coauthors is highly clustered. Our second finding is that the size of the giant component has grown greatly and at the same time the average distance between economists in this component which has always been small has fallen. We interpret these findings as supportive of the hypothesis of an emerging small world. We have shown that economics is spanned by an interlinked set of stars and that this feature leads to small distances. We have then turned to an examination of the reasons for the growth in giant component and falling distances and we have found that an increase in the number of coauthors for all quantiles of the distribution of coauthorship is the main driving force behind these developments.

We have identified stable and changing features of the structure of coauthorship networks. It is important to understand if these structural features are conducive to the generation and diffusion of scientific knowledge. We hope to explore this issue in further work.

Appendix A: Data related issues

1. *Name extraction procedures*: In this chapter we identify distinct authors by comparing all initials. This procedure has the following potential problems. On the one hand, it will identify Anne Krueger and Alan Krueger both as A. Krueger; this results in collating two distinct authors into one author. On the other hand, James J. Heckman and James Heckman will be treated as different authors, which exaggerates the set of authors.

To address these concerns, we have also designed a more sophisticated algorithm to extract the authors' names. In this Appendix, we explain how the algorithm works. First, rather than taking the last name and only the initials of an author, it takes the last name as well as the full first name of an author. This procedure addresses the problem of distinguishing Alan Krueger from Anne Krueger.

Sometimes an author's first name is not reported but only one or more initials. What does the algorithm do in these cases? Let us say that the name found is A. Krueger. Then the algorithm searches for all existing nodes in the database with the same last name and same initials. In case the algorithm finds only one such person, say Alan Krueger, then the publications of A. Krueger are assigned to Alan Krueger and the node A. Krueger is eliminated from the database. If, instead, the algorithm finds two or more nodes with the same last name and same initials, say Alan Krueger and Anne Krueger, then the algorithm doesn't alter anything and as a result A. Krueger, Alan Krueger and Anne Krueger are considered as different persons.

In a similar way, the algorithm addresses the problem of sporadic reporting of middle initials. If no middle initial is reported for a node, say James Heckman, then the algorithm searches for all persons with the same first and last name and a middle initial. If only one name with middle initial is found, say James J. Heckman, then the algorithm assigns the publications of James Heckman to James J. Heckman. Again, if the algorithm finds two or more nodes with the same first name and last name but different initials, say James A. Heckman and James J. Heckman, then these three names are considered as different authors.

We would like to report that we have analyzed the network data generated by this new procedure to extract authors' names. Table 2.14 presents the results. To ease the comparison with the earlier method of extracting names, we also report the network statistics of the paper in the Table. Our major findings with regard to an emerging small world also hold under this new name-extraction procedure. Actually, no remarkable changes are observed; perhaps the only visible change is that the new method identifies 2,000 authors less than the previous one in the 1990s, and that the size of the giant component is 3 procent smaller in this decade.

2. *Papers with 4 or more coauthors*: The analysis in the paper is based on data for papers with a maximum of 3 authors. This is because EconLit does not provide the names of all authors of a paper if the paper has been written by 4 or more persons. This raises the concern that if the number of papers with 4 or more coauthors is large then the results may be seriously affected. There are two ways to address this issue and we have implemented them in the following way.

Table 2.14: Network statistics obtained under the old and the new name-extraction procedures.

	New algorithm			Old algorithm		
decade	1970s	1980s	1990s	1970s	1980s	1990s
total authors	33768	48441	83209	33770	48608	81217
average degree	.890	1.237	1.611	.894	1.244	1.672
standard deviation of degree	1.359	1.779	2.209	1.358	1.765	2.303
size of giant component	5164	13358	31074	5253	13808	33027
—as percentage	.153	.276	.373	.156	.284	.407
second largest component	120	29	40	122	30	30
isolated authors	16846	19503	25881	16735	19315	24578
—as percentage	.499	.403	.311	.496	.397	.303
clustering coefficient	.193	.181	.169	.193	.182	.157
average distance in giant component	12.41	10.82	9.95	12.86	11.07	9.47
standard deviation distance in g.c.	3.81	2.98	2.46	4.03	3.03	2.23

First, we have examined the data obtained from articles with 1 or 2 authors only. The main network statistics for this data set are presented in Table 2.15. To ease the comparison with the statistics reported in the paper, the Table also incorporates the statistics for the data obtained from papers with a maximum of 3 authors. An inspection of this table reveals that the major patterns with regard to emerging small world –small and increasing average degree, increase in giant component, decrease in average distance and large clustering coefficient– also hold with these data. We now note that the magnitude of some figures changes substantially, in particular, restricting attention to articles with 1 or 2 authors leads to a sharp fall in the clustering coefficient. However, in spite of this decline, clustering coefficients are substantially higher than those to be expected in a random graph with corresponding average degree and size. We thus conclude that our main findings are robust to omitting articles with 3 coauthors. Since the number of papers with 3 authors is much larger (about 6.8 percent) than the number of papers with 4 or more coauthors (about 1.6 percent), this gives us confidence that the main findings will also obtain in the coauthor networks once we include all articles.

Second, we have tried to complete the data by collecting all missing names using sources of information other than EconLit. Collecting *all* missing information has turned out to be very difficult because some journals, like for example the Romanian *Studii si Cercetari Economice*, do not keep electronic records of old articles and our library has never collected them. As a result, we have restricted ourselves to collecting the missing names for articles published in a subset of journals. In particular, we have taken the Tinbergen Institute list of journals. This list, which we report in Appendix B, includes 133 journals and is used by the Tinbergen Institute to assess the research output of its

Table 2.15: Network statistics for data including articles with a maximum of 2 authors, and for data with a maximum of 3 authors.

	1 or 2 authors only			1, 2, or 3 coauthors		
decade	1970s	1980s	1990s	1970s	1980s	1990s
total authors	31754	44122	70106	33770	48608	81217
average degree	.660	.847	1.050	.894	1.244	1.672
standard deviation of degree	1.019	1.212	1.438	1.358	1.765	2.303
size of giant component	3130	8152	19338	5253	13808	33027
—as percentage	.099	.185	.276	.156	.284	.407
second largest component	42	27	33	122	30	30
isolated authors	17222	20233	19338	16735	19315	24578
—as percentage	.542	.459	.377	.496	.397	.303
clustering coefficient	.015	.018	.016	.193	.182	.157
average distance in giant component	14.01	13.01	11.99	12.86	11.07	9.47
standard deviation distance in g.c.	4.52	3.72	2.97	4.03	3.03	2.23

Table 2.16: Descriptive statistics for networks based on articles in TI List journals in EconLit.

dataset	all articles			articles with 3 or less authors		
period	70's	80's	90's	70's	80's	90's
total authors	14306	20238	30060	14051	19694	28736
average degree	1.156	1.618	2.321	1.058	1.467	1.896
standard deviation degree	1.581	2.006	2.972	1.433	1.815	2.224
size of giant component	3005	7912	16548	2775	7283	14368
—as percentage	.210	.391	.550	.197	.370	.500
second largest component	120	41	53	74	32	31
isolated authors	5818	5937	5903	5859	5999	6156
—as percentage	.407	.293	.196	.417	.305	.214
clustering coefficient	.289	.245	.333	.188	.180	.167
average distance in giant component	11.72	10.75	8.84	11.99	11.12	9.69
standard deviation distance in g.c.	3.79	2.94	2.08	4.02	3.07	2.35

fellows. In 2000 EconLit covered 113 of these journals. For this subset of journals, we have succeeded in collecting the missing names and completing the database. The results obtained with this data set are reported in Table 2.16. To ease the comparison, we also report the statistics for the data obtained from papers with a maximum of 3 authors. Again, the Table shows that the trends with regard to emerging small world also appear with the new data. As expected, the most dramatic change is the sharp increase in clustering coefficients, which reinforces our conclusions. In summary, we conclude that our results are robust to the inclusion of papers with 4 or more authors.

Appendix B: Tinbergen Institute List of Journals

Journals (AA): 1. American Economic Review 2. Econometrica 3. Journal of Political Economy 4. Quarterly Journal of Economics 5. Review of Economic Studies

Journals (A): 1. Accounting Review 2. Econometric Theory 3. Economic Journal 4. European Economic Review 5. Games and Economic Behavior 6. International Economic Review 7. Journal of Accounting and Economics 8. Journal of Business and Economic Statistics 9. Journal of Econometrics 10. Journal of Economic Literature 11. Journal of Economic Perspectives 12. Journal of Economic Theory 13. Journal of Environmental Economics and Management 14. Journal of Finance 15. Journal of Financial Economics 16. Journal of Health Economics 17. Journal of Human Resources 18. Journal of International Economics 19. Journal of Labor Economics 20. Journal of Marketing Research 21. Journal of Monetary Economics 22. Journal of Public Economics 23. Management Science(*) 24. Mathematics of Operations Research (*) 25. Operations Research (*) 26. Rand Journal of Economics / Bell Journal of Economics 27. Review of Economics and Statistics 28. Review of Financial Studies 29. World Bank Economic Review.

Journals (B): 1. Accounting and Business Research(*) 2. Accounting, Organizations and Society(*) 3. American Journal of Agricultural Economics 4. Applied Economics 5. Cambridge Journal of Economics 6. Canadian Journal of Economics 7. Contemporary Accounting Research(*) 8. Contemporary Economic Policy 9. Ecological Economics 10. Economic Development and Cultural Change 11. Economic Geography 12. Economic History Review 13. Economic Inquiry / Western Economic Journal 14. Economics Letters 15. Economic Policy 16. Economic Record 17. Economic Theory 18. Economica 19. Economics and Philosophy 20. Economist 21. Energy Economics 22. Environment and Planning A 23. Environmental and Resource Economics 24. European Journal of Operational Research(*) 25. Europe-Asia Studies(*) 26. Explorations in Economic History 27. Financial Management 28. Health Economics 29. Industrial and Labor Relations Review 30. Insurance: Mathematics and Economics 31. Interfaces(*) 32. International Journal of Forecasting 33. International Journal of Game Theory 34. International Journal of Industrial Organization 35. International Journal of Research in Marketing(*) 36. International Monetary Fund Staff Papers 37. International Review of Law and Economics 38. International Tax and Public Finance 39. Journal of Accounting Literature(*) 40. Journal of Accounting Research 41. Journal of Applied Econometrics 42. Journal of Applied Economics 43. Journal of Banking and Finance 44. Journal of Business 45. Journal of

Comparative Economics 46. Journal of Development Economics 47. Journal of Economic Behavior and Organization 48. Journal of Economic Dynamics and Control 49. Journal of Economic History 50. Journal of Economic Issues 51. Journal of Economic Psychology 52. Journal of Economics and Management Strategy 53. Journal of Evolutionary Economics 54. Journal of Financial and Quantitative Analysis 55. Journal of Financial Intermediation 56. Journal of Forecasting 57. Journal of Industrial Economics 58. Journal of Institutional and Theoretical Economics / Zeitschrift für die gesamte Staatswissenschaft 59. Journal of International Money and Finance 60. Journal of Law and Economics 61. Journal of Law, Economics and Organization 62. Journal of Macroeconomics 63. Journal of Mathematical Economics 64. Journal of Money, Credit and Banking 65. Journal of Population Economics 66. Journal of Post-Keynesian Economics 67. Journal of Risk and Uncertainty 68. Journal of the Operations Research Society(*) 69. Journal of Transport Economics and Policy 70. Journal of Urban Economics 71. Kyklos 72. Land Economics 73. Macroeconomic Dynamics 74. Marketing Science 75. Mathematical Finance 76. National Tax Journal 77. Operations Research Letters(*) 78. Organizational Behavior and Human Decision Processes(*) 79. Oxford Bulletin of Economics and Statistics / Bulletin of the Institute of Economics and Statistics 80. Oxford Economic Papers 81. Oxford Review of Economic Policy 82. Probability in the Engineering and Informational Sciences(*) 83. Public Choice 84. Queuing Systems(*) 85. Regional Science and Urban Economics 86 Reliability Engineering & System Safety(*) 87. Resource and Energy Economics / Resource and Energy 88. Review of Income and Wealth 89. Scandanavian Journal of Economics / Swedish Journal of Economics 90. Scottish Journal of Political Economy 91. Small Business Economics 92. Social Choice and Welfare 93. Southern Economic Journal 94. Theory and Decision 95. Transportation Research B - Methodological 96. Transportation Science(*) 97. Weltwirtschaftliches Archiv / Review of World Economics 98. World Development 99. World Economy

(*) Journal not covered by EconLit

Chapter 3

Strong ties in a small world

3.1 Introduction

This chapter examines the celebrated strength of weak ties hypothesis. In his seminal paper (Granovetter, 1973), Granovetter argued that weak ties in a social network (one's acquaintances) are more important for information dissemination than strong ties (one's close friends). Consequently, individuals and societies with few weak ties are disadvantaged. Not only do they receive news or important information later than others, but they are also less able to organize themselves.

In short, Granovetter's argument proceeds as follows: strong ties are *transitive*; this means that if two individuals have a common close friend, then it is unlikely that they are not related at all. Therefore, strong ties cover densely knitted networks, where a 'friend of my friend is also my friend'. On the other hand, weak ties are much less transitive, and therefore weak ties cover a larger but less dense area. Weak ties are more likely to be *bridges*: crucial ties that interconnect different subgroups in the social network. The suggested network structure implies that information from a strong tie is likely to be very similar to the information one already has. On the other hand, weak ties are more likely to open up information sources very different from one's own. Also, a society with few weak links is likely to be scattered into separate cliques with little communication between cliques. Granovetter's arguments may be viewed as an aspect of a more general theory of social structure: the idea that the social world is a collection of groups which are internally densely connected via strong links, and there are a few weak links connecting the groups.

Granovetter provides some evidence in support of his theory. He finds that in a survey of recent job changers living in a Boston suburb 27.8 percent of the respondents who found their new job through a contact said they rarely saw this contact, while only 16.7 percent of the respondents who found their new job through a contact indicated that they frequently saw their contact. Thus job seekers mainly receive information on job openings through weak ties. (Granovetter, 1973, 1995). However, this result does not seem to be robust. For example, in many East Asian countries it is found that job seekers depend heavily on *strong* ties in their job search (Bian and Ang, 1997).

[0]This chapter is based on Van der Leij and Goyal (2006).

In later surveys (Granovetter, 1983, 1995) Granovetter provides more empirical evidence. However, a closer look reveals that this empirical work typically focuses on the relation between strength of a tie and some social outcome of the actor involved, for example, employment, income, status. They usually do not test Granovetter's arguments relating to properties of the network structure. Thus, empirical research that directly tests the structural content of the strength of weak ties hypotheses using a large data set appears to be lacking.[1] There are two main reason for why previous researchers have focused on small network samples or indirect tests. First, data on large networks was not available, and, second, until recently computers lacked the computational power to tackle data sets of tens of thousands of actors. However, with the availability of large data sets and the advances in computing power, these problems can now be overcome.

In this chapter we use one such data set, a data set of coauthorship relations of economists publishing in scientific journals, to explore the validity of Granovetter's hypothesis. This data set contains about 150,000 articles from 120,000 economists collected over a 30 year period. This data set is, in particular, convenient due to its large coverage, and the fact that it allows us to define the existence and the strength of a tie objectively and unambiguously; a tie between authors A and B exists when they have published an article together, and the strength of their tie is measured by the number of articles A and B have jointly published.

We formalize the structural part of Granovetter's theory in terms of two testable statements: first, that strong ties are transitive; and, second, that weak ties are more important in reducing shortest path lengths between actors. Our principal findings with regard to these hypotheses are as follows: we find strong support for the first hypothesis that strong ties are transitive. However, we reject the hypothesis that weak ties are more important in reducing shortest path lengths.

These findings are surprising and lead us to explore more closely the distribution of strong and weak links in the network. The key finding here is that 1) the network is connected by a set of interlinked stars,[2] and 2) ties between actors with many ties are relatively stronger. These two properties help explain the relatively greater criticality of strong ties. To illustrate this we present examples of networks around specific individuals in our data set in Figure 3.1 and 3.2. These local networks suggest that strong ties often lie in the center of the coauthor network.

These findings put together suggest that the social world exhibits a core-periphery structure. A small subset of individuals constitutes the core: members of the core have a large number of links, while members in the periphery have few links. A person in the core maintains several links with other members of the core, and these links are strong. She also maintains a large number of links with members of the periphery and these links are weak. Figure 3.5 illustrates this network architecture.

These findings allow us to make a general point on social structure. The classical view has been that society consists of different communities with strong ties within and weak ties across communities. Our work provides evidence for the existence of societies which

[1] The two exceptions we located are Friedkin (1980) and Borgatti and Feld (1994); these papers are discussed in detail below. We note that these two studies also make use of a relatively small data set.

[2] A star in a node with a large number of links, these links lead to partner nodes which have few links and moreover the partner nodes are not linked to each other.

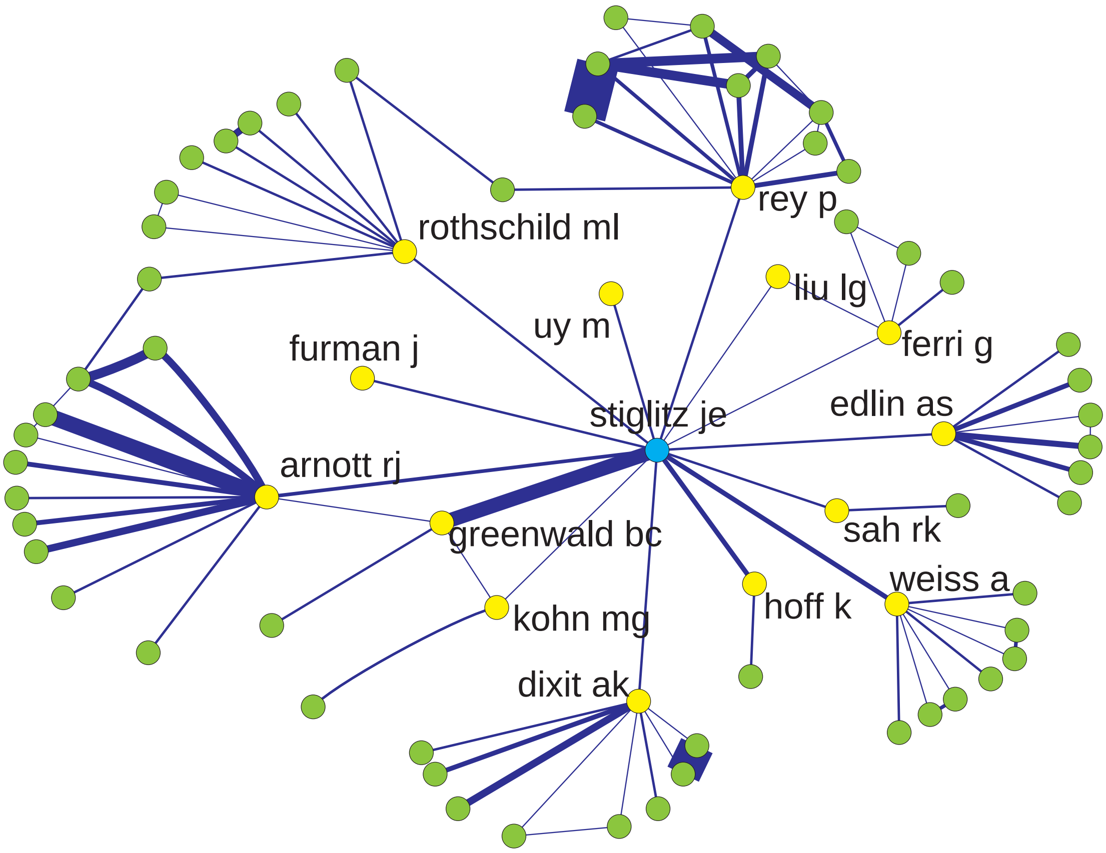


Figure 3.1: Local weighted network of collaboration of Joseph E. Stiglitz in the 1990s.

Note: The figure shows all authors within distance 2 of J.E. Stiglitz as well as the links between them. The width denotes the strength of a tie. Some economists might appear twice or are missing due to the use of different initials or misspellings in EconLit. The figure was created by software program *Pajek*.

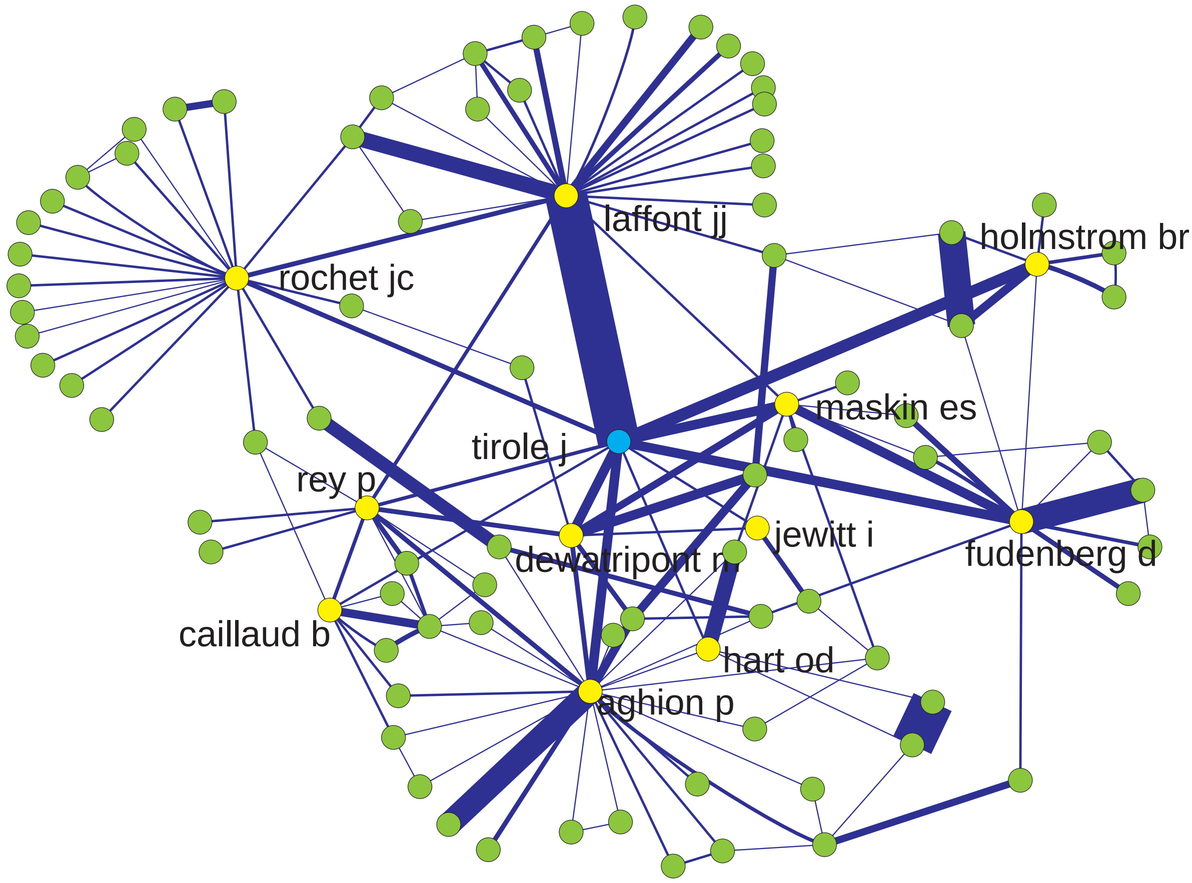


Figure 3.2: Local weighted network of collaboration of Jean Tirole in the 1990s.

Note: The figure shows all authors within distance 2 of J. Tirole as well as the links between them. The width denotes the strength of a tie. Some economists might appear twice or are missing due to the use of different initials or misspellings in EconLit. The figure was created by software program *Pajek*.

exhibit a core-periphery structure, with the strong ties being located in the core. In such societies, strong ties are more important for bridging the network than weak ties.

We place our findings in context now. There is a long tradition in the study of social structure which argues that a society consists of different communities with strong ties within communities and weak ties between them. The strength of weak ties theory proposed by Granovetter (1973) may be seen as a formalization of this tradition. These hypotheses are powerful and intuitively plausible and they have been the subject of a number of studies. The ideas underlying these hypotheses also find expression in a variety of spheres ranging from the study of personal identity in social philosophy (see e.g., Avineri and de Shalit, 1992; Taylor, 1989) to the diffusion of innovations via social communication (see e.g., Rogers, 1995). Our findings must be placed against this background and should be interpreted as making two general points: one, we identify two structural properties of networks under which the strength of weak ties hypotheses does not hold and two, we present empirical evidence from a particular network – the coauthor network – to show that there exist networks which exhibit these two properties. These findings point to a more general point concerning how societies may be structured.

This chapter builds on and extends the empirical findings on large networks. The structure of large social economic and technological networks has been the subject of extensive study in physics, and more recently has been also examined by economists and sociologists. The work in physics is surveyed by Barabási and Albert (1999), Albert and Barabási (2002), Dorogovtsev and Mendes (2002), Newman (2003) and Watts (1999); for work in economics see Goyal, van der Leij and Moraga-González (2006), and Jackson and Rogers (2006), while for recent work in sociology, see Moody (2004). The two views of the world we discussed above bear a close relation to two competing models in the complex networks literature. The view of highly clustered local neighborhoods with few random weak links between them is echoed in the 'small world' model of Watts and Strogatz (1998). On the other hand, the view of a very unequal network in which stars dominate is related to the scale-free networks emphasized by Barabási and Albert (1999). In this literature little attention has been paid to the strength of ties, and complex dynamic models of weighted networks are just recently emerging (Yook et al., 2001; Barrat et al., 2004a, 2004b; Newman, 2004). Our work points out an interesting and potentially important connection between classical hypotheses in sociology and key findings in the new work on complex networks.

To the best of our knowledge there are two previous studies of the structural features of strength of weak ties hypothesis. We first discuss Friedkin's (1980) work. Friedkin's research is based on a survey of 136 faculty members in seven biological science departments of a single university. He defines a tie between A and B to be strong if A and B have discussed both their current research together, while a tie is weak if only either A or B's research has been discussed by the two. In his analysis Friedkin confirms the strength of weak ties theory on five hypotheses. However, the hypothesis that 'weak ties create more and shorter paths' is based on only a small simulation with 4 replications (Friedkin 1980, p.417, Hypothesis 4 and Footnote 6), and hence this test is very limited. In our analysis, this hypothesis is crucially rejected. This difference in results leads us to an investigation of general properties of networks under which the strength of weak ties may not hold.

Borgatti and Feld (1994) propose another test for the strength of weak ties theory based on the overlap and non-overlap of the neighborhoods of dyad members.[3] They apply their procedure to Zachary's (1977) Karate club data. For this particular data set they reject the hypothesis that the dyad members of weak ties have larger non-overlapping neighborhoods. This finding is echoed in our work. The contribution of this chapter lies in identifying a general set of network properties – inequality in connections and stronger ties between highly linked individuals – under which the strength of weak ties hypothesis is likely to fail.

The rest of the chapter is outlined as follows. In Section 3.2 we lay out the main hypotheses of Granovetter's paper. In Section 3.3 we present our main empirical results. Then in Section 3.4 we give an explanation for the conflicting results, focusing on two properties of networks: an unequal distribution of links and the relation of degree to the strength of the links. In Section 3.5 we show that these properties indeed account for the rejection of the 'strength of weak ties' theory. Section 3.6 concludes.

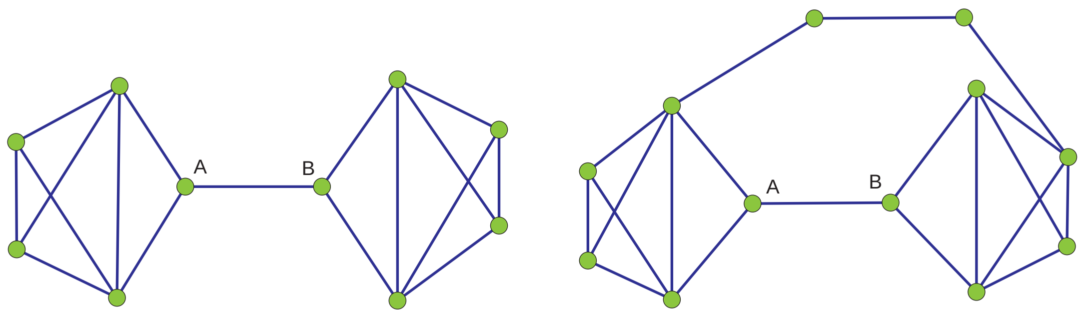
3.2 The strength of weak ties: main hypotheses

We first recapitulate the arguments of Granovetter's 'strength of weak ties' theory. The theory consists of a logical sequence of hypotheses on structural network features, starting with hypotheses on the microstructure of networks and leading to hypotheses on the macrostructure of networks. In our test we focus on two hypotheses, one on the micro-level and one on the macro-level, which capture the essence of the 'strength of weak ties' theory.

Intuitively the strength of a social tie is a "(...) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie." (Granovetter, 1973, p. 1361). Granovetter argues that the strength of a tie is directly related to the network structure. In particular, consider a triad of three individuals A, B and C in a social network in which AB and AC are tied. We call such a triad a connected triple. Now, consider the likelihood that there is also a tie between B and C. If that is the case, then the triad is called completed, and the connected triple is called transitive. Granovetter argues that triad completion is more likely if AB and AC are *strong*, because "(...) if C and B have no relationship, common strong ties to A will probably bring them into interaction and generate one" (Granovetter, 1973, p. 1362). Further, since AB and AC have a strong tie, B and C are likely to be similar to A and therefore similar to each other, and this facilitates the formation of a tie between B and C.

For the development of his theory Granovetter takes this argument to the extreme, in the following way; consider three individuals A, B and C in a social network. Suppose A-B and A-C have a strong tie, while the B-C tie does not exist. About such a triad structure, Granovetter says the following: "I will exaggerate in what follows by saying that this triad never occurs – that is, that the B-C tie is always present"(Granovetter, 1973, p. 1363). This leads to our first hypothesis.

[3] Their test procedure requires the full adjacency matrix of actors. This makes the procedure for our networks of more than 80,000 actors in the 1990s infeasible, and we therefore use a different approach.



(a) The tie between A and B is a bridge. (b) The tie between A and B is a local bridge of degree 6.

Figure 3.3: Two networks with a bridge and a local bridge.

Hypothesis 1A: The forbidden triad: *in a social network a situation where A has strong ties with B and C and B and C do not have a tie between them does not occur.*

A more plausible form of this hypothesis would simply require that the likelihood of triad completion should be much higher in case A-B and A-C are strong ties, as compared to when they are both weak ties. According to Granovetter: "(...) the triad which is most *unlikely* to occur, (...) is that in which A and B are strongly linked, A has a strong tie to some friend C, but the tie between C and B is absent."(Granovetter, 1973, p. 1363). This leads to the following version of hypothesis 1.

Hypothesis 1B: *For a set of three players with two links present, the probability of triad completion is much higher if the links are strong as compared to the case where the links are weak.*

The second step in the theory is then to relate Hypothesis 1A to the presence of shortest paths and bridges. These concepts are defined as follows; a *path* between i and j is a set of actors $i = i_0, i_1, \ldots, i_{z-1}, i_z = j$ for which i_{k-1} and i_k, $k = 1, \ldots, z$ are tied. Here z is the path length; recall that the distance between two nodes i and j in network g refers to the shortest path length between these nodes in network g. A *bridge* or *critical link* is then a tie in a network which provides the only path between some actors i and j. A *local bridge* is a tie between i and j in which the length of the shortest path between i and j other than the tie itself is larger than 2. Figure 3.3(a) and 3.3(b) illustrates a bridge and local bridge.

Granovetter then shows that if Hypothesis 1A is true and if every person has several strong ties, then *no strong tie is a (local) bridge*, or equivalently, all (local) bridges are weak ties. Since strong links are transitive, none of these links are likely to be critical. This does not apply to weak links, since many of the triads with weak links are likely not to be completed.

A weaker version of this statement leads to our second hypothesis. Granovetter says, "The significance of weak ties, then, would be that those which are local bridges create more, and shorter, paths. Any given tie may, hypothetically, be removed from a network; the number of path broken and the changes in average path length resulting between arbitrary pairs of points (with some limitation on length of path considered) can then be computed. " (Granovetter, 1973, p. 1366). Then the contention is that the removal of a weak tie would, on average, break more paths and increase average path length more than the removal of a strong tie. For computational reasons we concentrate on shortest paths, leading to the following hypothesis, separated into two parts.

Hypothesis 2A: *the removal of an arbitrary weak tie from the network would break more shortest paths between actors than the removal of an arbitrary strong tie.*

Hypothesis 2B: *the removal of an arbitrary weak tie from the network would increase average distance in the network more than the removal of an arbitrary strong tie.*

Hypothesis 2 closes Granovetter's theory as far as it concerns the structural network features.

In his original paper, Granovetter (1973) was also concerned with the implications of Hypothesis 2 for diffusion, social mobility, and political organization. These potential effects of networks are clearly important and have been the focus of extensive research in different disciplines. The present chapter will however be concerned with the structural aspects of the strength of weak ties.[4]

3.3 Testing the hypotheses

We test the hypotheses using data on coauthorship networks of economists publishing in scientific journals. The data is derived from EconLit, a bibliography covering economic journals, and it is split up in three decades, 1970-1979, 1980-1989 and 1990-1999. Each node is an economist.[5] Two economists are linked whenever they wrote an article together either as the only two authors, or together with a third author. Note that an article with three coauthors automatically results in a closed triad. EconLit does not provide full information on author names of articles with 4 or more authors, hence these articles are excluded from the analysis.[6]

We measure the strength of a tie by the number of articles over a decade of which the two associated economists were coauthors. Our measure of strength has the great merit that it does not rely on subjective interpretations of respondents. It is objective and easily and directly measurable. Furthermore, ties based on this measure are symmetric and positive. Granovetter's theory is expressed in terms of symmetric positive ties (Granovetter, 1973, footnote 2), and our measure is therefore directly applicable to the theory.

We now make some remarks on our interpretation of the coauthor network as a social network and the idea of using number of coauthored papers as a measure of strength of a

[4]For pioneering work on the effects of social networks on the diffusion of innovations, see Coleman (1966) and Hägerstrand (1969). For a survey of this work, see Rogers (1995).

[5]Author names appear in different forms, often without middle names or with only initials mentioned, and thus an extraction rule is necessary to match the different names to the correct author as best as possible. The rule we used can be obtained from the corresponding author.

[6]In economics, papers with 4 or more coauthors constitute about 1.6 percent of all papers, and we do not expect that including them in the analysis will alter any of our main findings.

tie between two authors. It seems to us that in the social sciences – where collaborative research typically involves one or two collaborators – it is very likely that the coauthors also know each other personally. Our second observation concerns the relation between number of coauthored papers strength of tie. At an intuitive level, it seems clear that coauthoring more papers is suggestive of more sustained interaction, and this is a good first measure of strength of tie. On the other hand, we are conscious that there is no direct causal relation between number of papers and strength of tie. This brings us to the more general point that is worth emphasizing. Our arguments identify structural features of a network under which the strength of weak ties hypothesis will not hold. The interpretation of the coauthor network as a social network is proposed by way of motivation. Thus, the formal validity of the general argument we are developing in the chapter depends on characteristics of a network structure and it does not depend on the interpretation of the coauthor network as a social network.

Second, our measure does not control for productivity differences between scientists. For someone who is used to write dozens of papers with her coauthors a tie based on only three publications might be considered weak, while the same tie might be considered strong for someone who has published four papers in a decade. Thus instead of having an *absolute* measure of strength, a *relative* measure (relative to the total production of the scientists involved in the tie) might be more appropriate. This is an important issue, and we return to this later in Sections 3.4 and 3.5.

Before proceeding with the tests we first provide some general properties of the coauthor network over the period 1970-2000. These are summarized in Table 3.1.[7] The coauthor network of economists has some characteristics which are common to many large networks and which have been explored extensively by physicists (Newman, 2003). That is, many economists (up to 40 percent of the total population of economists) are part of one large cluster of connected nodes, called the 'giant component', while the second largest cluster is extremely small relative to the size of the whole network. Further, average distance is remarkably small, and the fraction of connected triples that are transitive, known as the clustering coefficient, is much higher than one would expect in a random matching network. Further, when we focus on the trends in the properties we observe that average distance has become much smaller, while the giant component has become much larger. Thus, a *small world* is emerging in economics (for details of this study, see Goyal et al. 2006).

3.3.1 Testing hypothesis 1

We now turn to hypotheses 1A and 1B. First, we define a tie between A and B as a *weak tie* if the strength of the tie is smaller than some threshold, $c_S = \{2, 3, 5\}$, and a *strong tie* otherwise. Next, for each of the three networks we gather the set of ordered triples with actors A, B and C for which there is a tie between A and B and between A and C. We partition this set of triples ABC into three subsets in which:

1. both A and B, and A and C have a *weak* tie (weak-weak);

[7] The reported numbers differ slightly from the numbers reported in Chapter 2; this is due to differences in the rule that distinguishes author names. In this chapter we use the rule that is described in Appendix A of Chapter 2.

Table 3.1: Network statistics for coauthorship networks in economics, 1970s 1980s and 1990s.

period	1970s	1980s	1990s
number of nodes	33768	48441	83209
number of links	15020	29952	67018
number of papers	62227	93976	152868
average link degree	.890	1.237	1.611
std.dev. link degree	(1.359)	(1.779)	(2.209)
max link degree	24	36	51
average strength	1.265	1.336	1.354
std.dev. strength	(.877)	(.952)	(1.043)
max strength	26	25	39
size of giant component	5164	13358	31074
as percentage	.153	.276	.373
second largest component	120	29	40
isolated	16846	19503	25881
as percentage	.499	.403	.311
clustering coefficient	.193	.181	.169
degree correlation	.124	.151	.137
average distance	12.41	10.82	9.95
std.dev. distance	(3.81)	(2.98)	(2.46)
maximum distance (diameter)	35	37	30

Link degree of a node: number of links attached to the node. Strength of a link: number of papers coauthored by the two authors of a link. Size of giant component: size of the largest component, a subset of nodes for which there is a path between each pair of node in the subset. Second largest component: size of the largest component except the giant component. Isolated: number of nodes without any links. Clustering coefficient: fraction of connected triples that are transitive. Degree correlation: correlation coefficient between the link degrees of two neighboring nodes. Distance of a pair of nodes: shortest path length between the pair of nodes.

2. if A and B have a weak tie, then A and C have a strong tie (weak-strong);

3. both A and B, and A and C have a *strong* tie (strong-strong).

For these three subsets we compute the fraction of triples that are completed, that is, for which there is also a tie between B and C. Table 3.2 shows the results for the three data sets of the 1970s, 1980s and 1990s and strength thresholds of 2, 3 and 5.

From the table we directly observe that the strong hypothesis 1A is rejected as in all cases the fraction of transitive triples is below one half. Moreover, the numbers in Table 3.2 clearly suggest that the weak hypothesis 1B is true in the coauthor network. For instance take the definition that a link is strong if there are 5 or more papers involved. For the 1990s network, we find that triple completion occurs in (approximately) 16 percent of the cases where a weak-weak triple exists, while it occurs in almost 50 percent of the cases where a strong-strong triple exists. χ^2-tests suggest that these differences are statistically significant. Thus triples with two strong links are more likely to be transitive.

While the χ^2-test statistics are indicative, conclusions cannot be directly drawn from them. The problem is that these tests require independence of observations, while observations in our datasets of connected triples are far from independent. In fact, the triples in the network overlap each other. Hence, the same author names appear over and over again in different triples. For example there are 243931 connected triples in the network of the 1990s, allowing for 3×243931 different author names. However, only 45110 different author names appear in these triples.

In order to address the problem of 'overlapping triples' we perform a more rigorous analysis in the form of a logistic regression. We test whether for an ordered connected triple ABC the probability of a link between B and C is increasing in the strength of the ties AB and AC. More precisely, we estimate $\theta = \{\alpha, \beta_1, \beta_2\}$ in the following logistic regression:

$$\Pr\left(s_{BC} \geq 1 | s_{AB} \geq 1 \wedge s_{AC} \geq 1\right) = \Lambda\left(\alpha + \beta_1 \frac{\ln s_{AB} + \ln s_{AC}}{2} + \beta_2 \left|\ln s_{AB} - \ln s_{AC}\right|\right), \tag{3.1}$$

for each ordered connected triple ABC. Here $\Lambda(\cdot)$ is the logistic function and s_{PQ} is the strength of a tie between P and Q.

In order to obtain a data set with independent observations, we propose to thin the data set, that is, to perform a standard logistic regression on *random subsamples* from the set of all ordered connected triples ABC. The motivation for this method is that a fixed set of randomly chosen actors is unlikely to influence each other if the network becomes very large. For example, while in a class room of 30 students each actor might have some direct or indirect influence on their classmates, in a social network comprising the whole world one random actor in one part of the world is unlikely to have any dependence on a random actor in a different part of the world. Thus, if the size of a random subsample of ordered triples is large, but relatively very small compared to the size of the set of all ordered connected triples, then the observations in the subsample are close to independent while large-sample asymptotic results still hold. That is, estimators are consistent and the standard errors are correctly specified.

The proposed method has a drawback, however, since by taking a random subsample we do not make use of all the information in the data, and hence, we dramatically reduce

Table 3.2: Fraction of subsets of connected triples that are transitive in the coauthorship network for economists, 1970s, 1980s and 1990s.

period	1970s	1980s	1990s
observations	29515	83752	243931
Strong tie: ≥ 2 papers			
weak-weak	.209	.193	.177
weak-strong	.140	.138	.135
strong-strong	.300	.279	.257
χ^2-test	340.6	920.6	2046.8
p-value	.000	.000	.000
Strong tie: ≥ 3 papers			
weak-weak	.196	.176	.164
weak-strong	.160	.184	.171
strong-strong	.396	.355	.337
χ^2-test	152.8	322.6	974.5
p-value	.000	.000	.000
Strong tie: ≥ 5 papers			
weak-weak	.192	.176	.163
weak-strong	.211	.244	.232
strong-strong	.444	.425	.487
χ^2-test	21.3	224.6	890.4
p-value	.000	.000	.000
all	.193	.181	.169

Observations are connected triples. The set of connected triples is partitioned into three subsets. Weak-weak: connected triples consisting of two weak ties. Weak-strong: connected triples consisting of one weak and one strong tie. Strong-strong: connected triples consisting of two strong ties. All: all connected triples. χ^2-test: test statistic for χ^2-independence test (2 degrees of freedom).

Table 3.3: Estimation results of a logistic regression on the transitivity of connected triples.

variable	coefficient	.95-confidence	p-value
DUMMY70S	-1.459	(-2.086, -0.933)	0
DUMMY80S	-1.534	(-1.917, -1.179)	0
DUMMY90S	-1.613	(-1.866, -1.371)	0
AVGSTRENGTH	.751	(.095, 1.343)	.027
DIFFSTRENGTH	-.522	(-.996, -.056)	.027
loglikelihood	-455.19		

Results of regressions on 10000 random subsamples with each subsample 1000 observations. Each observation is a triple ABC for which A and B are tied and A and C are tied. The dependent variable, $TRANSITIVE$, is 1 if BC is also tied, and 0 otherwise. $AVGSTRENGTH = (X_{AB} + X_{AC})/2$ where X_{AB} is the natural logarithm of the number of papers A and B have written together. $DIFFSTRENGTH = |X_{AB} - X_{AC}|$. $DUMMY70S$, $DUMMY80S$, and $DUMMY90S$ are dummy variables to indicate whether the observations were drawn from the 1970s, 1980s or 1990s. *coefficient* is the average of the estimated coefficients in the 10000 regressions. *.95-confidence* is the .025- and .975-quantile of the coefficients estimated from the 10000 regressions. *p-value* is $1 - |2s - 1|$ where s is the fraction of estimated positive coefficients.

the power of the test. This implies that there is a trade off between efficiency and accuracy in the choice of the size of the subset. If the sample is too small, then the test has not enough power to give significant results, while if the sample is too large overlapping triples would distort the statistical results.

We apply this subsampling method on the combined data set of ordered connected triples ABC in the 1970s, 1980s and 1990s. This combined data set contains 357198 observations. We randomly take 1000 observations from this combined data set and we perform the logistic regression as in (3.1) in which we also include dummies for the three decades.[8] With this subsample size the power of the test is still quite high, while the overlap of triples is starkly reduced.[9] We repeat this procedure a 10000 times, and we report estimation results in Table 3.3.

Clearly, the variable $AVGSTRENGTH$ has a significantly positive coefficient ($p = .027$). Thus the stronger the ties AB and AC, the more likely it is that B and C are tied. To give some intuition of the numbers, if AB and AC are both based on one coauthored paper, then the estimated probability that there is a link BC is .189 in the 1970s, .177 in the 1980s, and .166 in the 1990s. If on the other hand AB and AC are both based on 10

[8] A Lagrange-Multiplier test on the alternative of separate logistic regressions for each decade is not rejected. The LM statistic is on average 4.37, while the .05-critical value is 9.49. Thus the use of a pooled regression with decade dummies is appropriate.

[9] In the 1000 connected triples typically more than 2700 different author names appear

papers, then the estimated probabilities increase to .572 in the 1970s, .553 in the 1980s, and .534 in the 1990s. Thus there is strong support for hypothesis 1B.

It is interesting to note that the variable $DIFFSTRENGTH$ is significantly negative. This means that a triple with one weak and one strong link is less likely to be transitive than a triple with two intermediate strength links, let alone with two strong links. To give a numerical example, if AB is based on 10 articles, but AC on only one article, then the estimated probability of a tie BC is .141 in the 1970s, .132 in the 1980s and .123 in the 1990s. Thus the hypothesis holds only for triads for which AB and AC are *both* strong. Note that this is in agreement with hypothesis 1B.

3.3.2 Testing hypothesis 2

We next look at testing hypothesis 2A. We perform a regression analysis on *link betweenness* of the links in the giant component. Link betweenness was introduced by Girvan and Newman (2002).[10] The formal definition is as follows. Let n be the number of nodes in the network, g the set of ties in the network and let $\mathcal{L}_{ij}$ be the set of shortest paths between i and j. Then the link betweenness of a link AB is

$$B_{AB} = \frac{2}{n(n-1)} \sum_{ij} \frac{1}{|\mathcal{L}_{ij}|} \sum_{L \in \mathcal{L}_{ij}} I_{AB \in L},$$

where $I_{AB\in L}$ is an indicator variable, which is 1 if $AB \in L$ and 0 otherwise. In short, link betweenness of a link AB measures the fraction of all pairs of actors i and j for which the link AB lies on a shortest path between i and j. If there are multiple shortest paths between i and j, then each shortest path contributes equally to the link betweenness of the links on these paths.

We can also rephrase the definition by saying that the link betweenness of a link AB measures the number of shortest paths in the network that would be broken if the link AB would be removed from that network. This formulation reveals that it is appropriate to use this measure in a test on hypothesis 2A.

Our test proceeds as follows. First, we extract the giant components from the networks of the 1970s, 80's and 90's, and for each tie in a giant component we compute link betweenness using the algorithm of Newman (2001). We then stack the observations on betweenness of links in the giant components of the three decades (72640 observations), and we randomly select a subsample of 1000 observations. For this subsample of ties we estimate the effect of the logarithm of strength on the logarithm of betweenness by means of an OLS regression in which we include three decade dummies.[11] We repeat this procedure a 1000 times. In Table 3.4 we report average estimation results.

The results in Table 3.4 are very surprising. The strength of a tie has significant positive relation with the tie's link betweenness. Thus *strong ties* have a higher link

[10] The concept of link betweenness is very similar to the concept of betweenness centrality (Freeman, 1977). While betweenness centrality measures the centrality of actors, link betweenness measures the centrality of the actor's ties.

[11] An LM test on the alternative of separate regressions for each decade is not rejected with an average LM statistic of 4.46, while the .05-critical value is 9.49.

Table 3.4: Estimation results of a regression on link betweenness

variable	coefficient	.95-confidence	p-value
DUMMY70S	-7.870	(-8.451, -7.345)	0
DUMMY80S	-8.954	(-9.313, -8.624)	0
DUMMY90S	-9.899	(-10.140, -9.666)	0
LNSTRENGTH	.480	(.108, .825)	.013
R^2	.060		

Results of regressions on 10000 random subsamples with each subsample 1000 observations. Each observation is a link AB in the giant component of either the 1970s, 1980s or 1990s network. The dependent variable is the natural logarithm of link betweenness of link AB. $LNSTRENGTH$ is the natural logarithm of the number of papers A and B have written together. $DUMMY70S$, $DUMMY80S$, and $DUMMY90S$ are dummy variables to indicate whether the observations were drawn from the 1970s, 1980s or 1990s. *coefficient* is the average of the estimated coefficients in the 10000 regressions. *.95-confidence* is the .025- and .975-quantile of the coefficients estimated from the 10000 regressions. *p-value* is $1 - |2s - 1|$ where s is the fraction of estimated positive coefficients.

betweenness, and these strong ties are crucial in connecting different actors in the network. In other words, hypothesis 2A is clearly rejected.

A disadvantage of using link betweenness is that it only reveals the number of shortest paths that would be broken if a tie would be removed from the network; it does not tell us how much the distance between a random pair of actors increases. This motivates us to turn to hypothesis 2B; the removal of an arbitrary weak tie from the network would increase average distance in the network more than the removal of an arbitrary strong tie. Before we turn to our test procedure, it should be mentioned that the distance between two unconnected actors is undefined (or infinite), and therefore the average distance can only be computed for network *components*. Remember that a component is a cluster of actors in which all actors are directly or indirectly connected to each other.

Unfortunately, this raises the problem that the size of the component might change when a link is removed from the network, which affects average distance as well. We therefore look at the following aspects of hypothesis 2B. We only focus on the largest (giant) component in the network, and we say that hypothesis 2B is supported if the removal of an arbitrary weak link would both decrease the size of the giant component as well as increase the average distance within the component more than the removal of an arbitrary strong link.

To test this hypothesis we perform the following simulation on the coauthorship network of the 1970s, 1980s and 1990s. Let a tie based on two or more papers be a strong tie, and let a tie based on one paper be a weak tie. We randomly delete 50 *strong* ties from the giant component of the coauthor network, and we recompute the size of the giant component and the average distance within the giant component. Next, starting from the original network we delete 50 *weak* ties from the giant component, and we again compute the size of the giant component and the average distance within the giant component. We repeat this procedure m times, thus we create for each network two samples of m observations.[12] One sample measures the effect of deleting strong ties on the size of the giant component and the average distance, while the other sample measures the effect of deleting weak ties.

The test then boils down to comparing the mean (both for size of giant component and average distance) of the two samples in a one-sided heteroskedastic two-sample t-test. First, we test the null hypothesis that the sample mean for the size of the giant component in the two samples is identical against the alternative hypothesis that the sample mean in the first sample, in which we delete strong links, is larger than in the second. Next, we test the null hypothesis that the sample mean for average distance in the two samples is identical against the alternative hypothesis that the sample mean for average distance in the first sample is smaller.

Table 3.5 shows the results of these t-tests. We find that the removal of weak ties indeed decreases the size of the giant component more than the removal of strong ties. This is in support of Granovetter's strength of weak ties hypothesis. However, with respect to average distance we find an unexpected result. Not weak links, but strong links have a bigger impact on average distances in the giant components.

The above simulation results suggest that hypothesis 2B does not hold; although the removal of a weak tie has a bigger impact on the size of the giant component than the removal of a strong tie, the impact on average distance is smaller for the removal of a weak tie than for the removal of a strong tie. However, since the two effects are conflicting the simulation results are a bit unsatisfying, and we therefore perform more simulations on the 1970s network as a robustness check. In these simulations we increase the number of links that are removed from the network. While in the above simulations we measured the effect of randomly and simultaneously removing 50 links, in the following simulations we remove 100 up to 500 links at once. Since there are 542 strong links in the giant component of the 1970s, in these simulations we remove a considerable fraction of all strong ties in the 1970s network.

As before we delete k random weak links ($k = \{100, 200, 500\}$) from the giant component in the 1970s and we measure the size of the giant component and the average distance within the giant component. We then delete k random strong links from the giant component, and we again measure the size of the giant component and the average distance. We repeat this procedure m times, such that we have two samples of m observations; one in which we measure the effect of deleting weak ties on the size of the giant component and average distance, and one in which we measure the effect of deleting strong ties. We then perform one-sided heteroskedastic two-sample t-tests on the size of the giant component and average distance.

[12] We repeat the simulation 200 times for the 1970s and 1980s and network, and 100 times for the 1990s network. These simulations are very time consuming, and this restricted the number of simulations we could perform.

Table 3.5: Simulation results for the coauthorship network for economists, 1970s, 1980s and 1990s.

period	1970s	1980s	1990s
replications	200	200	100
Size of giant component			
actual	5164	13358	31074
after deleting 50 strong ties			
mean	5113.4	13333.2	31056.7
std.dev.	22.8	11.3	9.6
after deleting 50 weak ties			
mean	5106.4	13325.4	31049.9
std.dev.	22.8	16.3	9.9
one-sided t-test			
t-stat.	3.08	5.57	4.97
p-value	.001	.000	.000
Average distance			
actual	12.407	10.818	9.949
after deleting 50 strong ties			
mean	12.485	10.838	9.955
std.dev.	.062	.009	.003
after deleting 50 weak ties			
mean	12.444	10.828	9.952
std.dev.	.056	.016	.003
one-sided t-test			
t-stat.	6.88	7.74	6.61
p-value	1.000	1.000	1.000

Simulation compares the effect of randomly deleting 50 strong ties to randomly deleting 50 weak ties from the giant component. A strong tie is a tie based on 2 or more papers, and a weak tie is a tie based on 1 paper. One-sided t-test is a one-sided heteroskedastic two-sample t-test; the null hypothesis is equal mean for the sample after deleting weak ties and the sample after deleting strong ties. The alternative hypothesis for the size of the giant component is that the mean size of the giant component after randomly deleting 50 strong ties is larger than the mean size after randomly deleting 50 weak ties. The alternative hypothesis for average distance is that the mean average distance after deleting 50 strong ties is smaller than the mean average distance after deleting 50 weak ties.

Table 3.6: Simulation results for the coauthorship network for economists in the 1970s.

removed links k	100	200	500
replications	200	200	200
Size of giant component			
actual	5164	5164	5164
after deleting strong ties			
mean	5058.9	4950.5	4562.2
std.dev.	31.3	42.3	66.8
after deleting weak ties			
mean	5048.9	4927.5	4554.4
std.dev.	32.2	43.5	61.5
one-sided t-test			
t-stat.	3.14	5.36	1.20
p-value	.001	.000	.115
Average distance			
actual	12.407	12.407	12.407
after deleting 50 strong ties			
mean	12.565	12.733	13.254
std.dev.	.086	.119	.215
after deleting 50 weak ties			
mean	12.484	12.565	12.816
std.dev.	.080	.117	.174
one-sided t-test			
t-stat.	9370	14.30	22.38
p-value	1.000	1.000	1.000

Simulation compares the effect of randomly deleting k strong ties to randomly deleting k weak ties from the giant component of the 1970s. A strong tie is a tie based on 2 or more papers, and a weak tie is a tie based on 1 paper. One-sided t-test is a one-sided heteroskedastic two-sample t-test; the null hypothesis is equal mean for the sample after deleting weak ties and the sample after deleting strong ties. The alternative hypothesis for the size of the giant component is that the mean size of the giant component after randomly deleting k strong ties is larger than the mean size after randomly deleting k weak ties. The alternative hypothesis for average distance is that the mean average distance within the giant component after deleting k strong ties is smaller than the mean average distance after deleting k weak ties.

Table 3.6 shows the results from these simulations. We observe that the effect on the size of the giant component becomes insignificant when comparing the removal of 500 weak ties to the removal of 500 strong ties. On the other hand, the effect on average distance becomes more strongly significant when removing more ties at once. That is, the removal of 500 strong ties significantly increases the average distance more than the removal of 500 weak ties. Thus these supplementary simulations show that support for hypothesis 2B becomes weaker when considering the removal of 500 strong ties compared to the removal of 500 weak ties.

The above analysis shows that hypotheses 2A and 2B are not supported. Before we saw however that hypothesis 1B was supported. This seems a contradiction, and we therefore want to explain this apparent contradictory finding.

3.4 Explaining the rejection of Granovetter's theory

Under which measurable conditions on the network structure is Hypothesis 2A likely to be rejected? In this section we argue that there are two network properties that are crucial to understand the failure of hypothesis 2A. The first property is significant inequality in distribution of connections across individuals, and the second property is the existence of a positive correlation between strength of tie and the number of connections. We show that the coauthor network of economists has these two properties. Further, if we control for the effect of these properties, we show that there is a weak residual effect in support of Granovetters's theory. These findings provide evidence for our explanation of the rejection of hypothesis 2A in Section 3.3.

The first property is the existence of stars, that is, actors have a high number of links. These stars play the role of connectors in the network (Albert, Jeong and Barabási, 2000). That is, they connect different subgroups in the network that would be isolated if the stars were not there. Given their crucial role in the network, the stars have a high betweenness centrality, and the links between stars have high link betweenness.

The second property is that the links between stars are stronger than other links. Because of the central position of the stars in the network, this implies that the links with high link betweenness are typically *strong*. These two properties put together suggest that strong links connect individuals who have more links on average and this means that they lie on more shortest paths. This fact more than compensates for the clustering in strong links noted above and results in strong links having a greater criticality.

We explain the working of the above two properties by considering two types of network structures, the island network structure and the core-periphery network structure. In the island network both hypothesis 1 and 2 are true, while in the core-periphery network hypothesis 1 is supported, while hypothesis 2 is rejected. Figures 3.4 and 3.5 present the island structure and the core-periphery structure, respectively.

Consider first the network structure of Figure 3.4. There are three islands. Each island consists of four nodes, and all four nodes on an island are directly connected to each other with a strong tie. Furthermore, different islands are connected with exactly one weak tie. In a stylized way this network represents a view of the world which has been

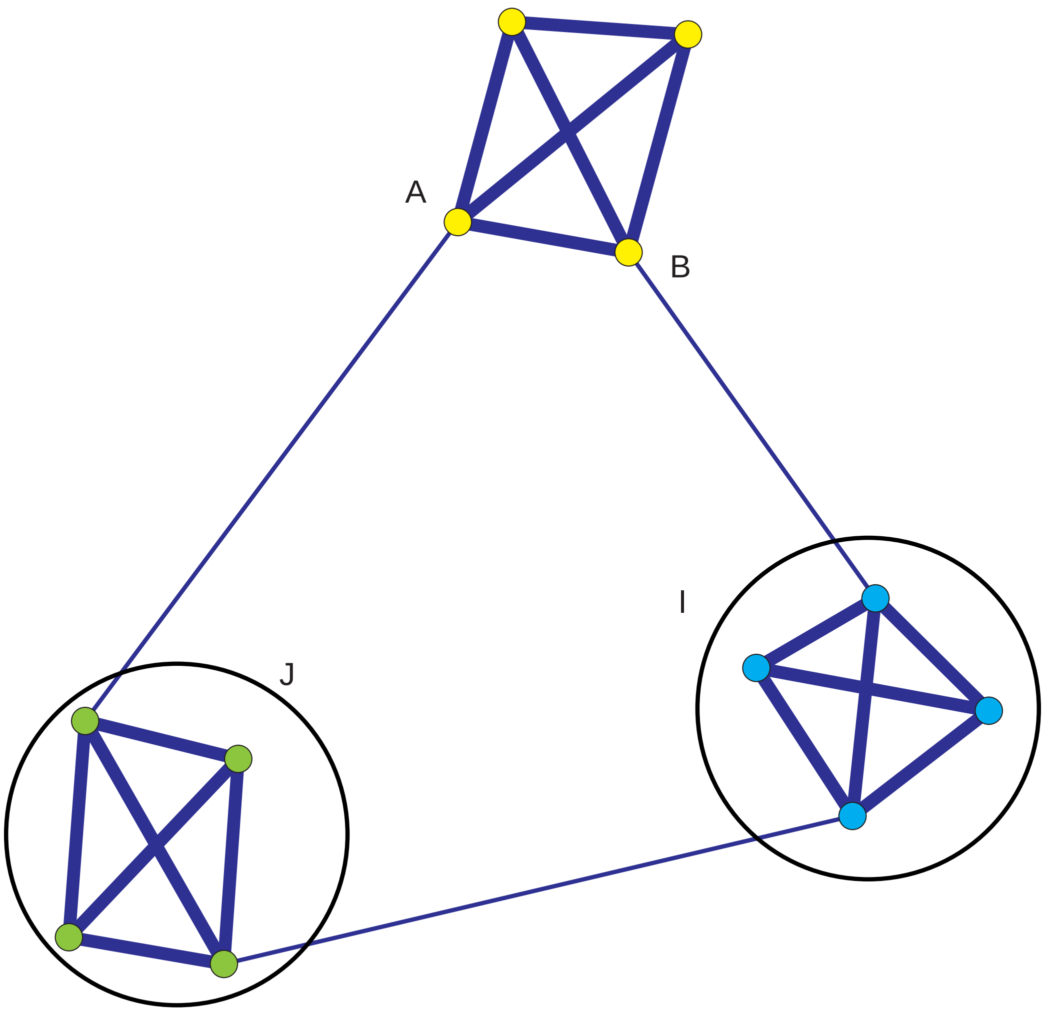


Figure 3.4: An island network.

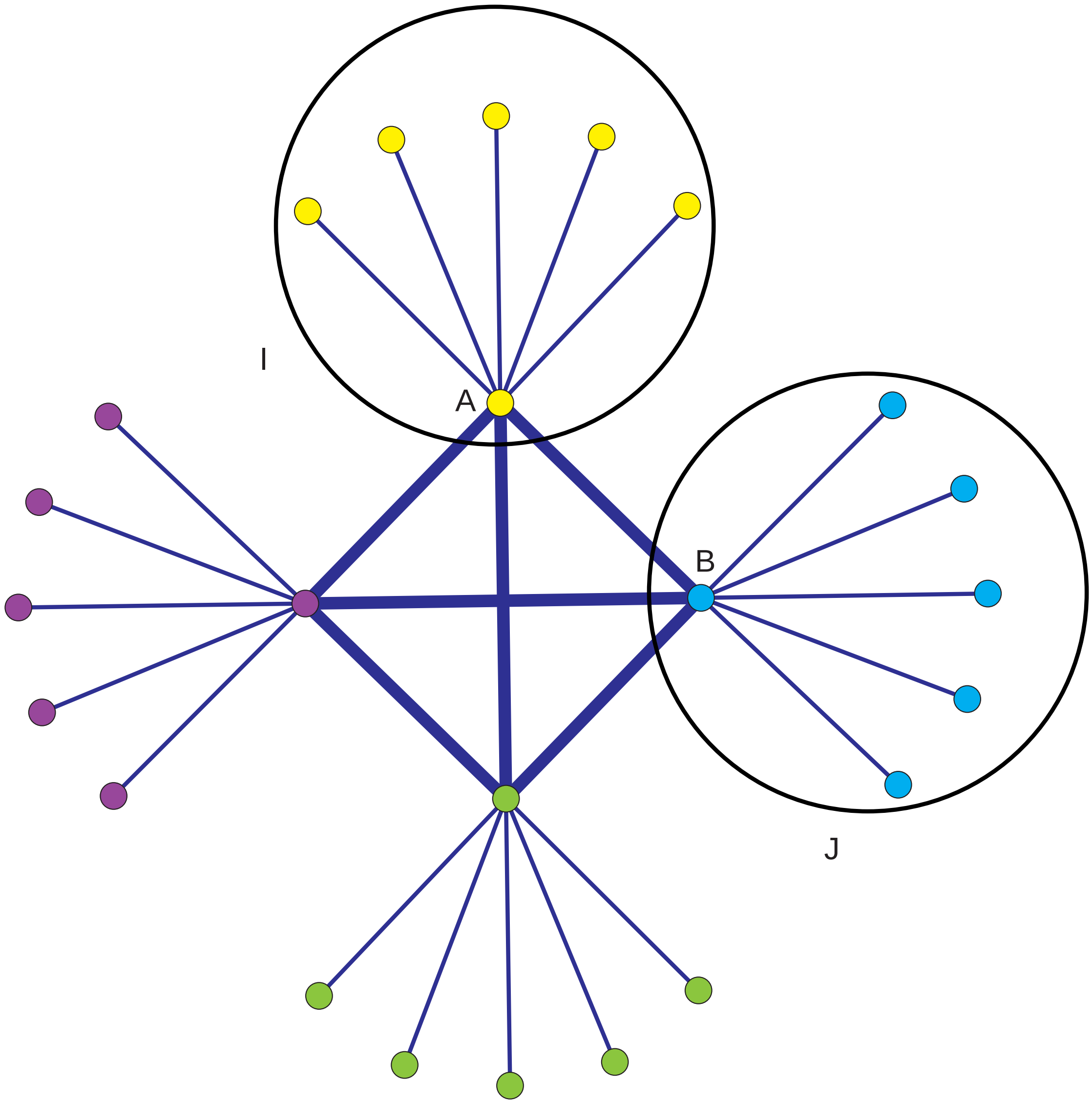


Figure 3.5: A core-periphery network.

often put forward when explaining the 'strength of weak ties' theory.[13] That is, the world consists of families or communities with very strong ties between family members. These families are connected through trade relations or occupational colleagueships. However, these interfamily ties are typically weaker than intrafamily ties. In fact, Granovetter puts forward this view of the world when he discusses the effects of weak ties on the ability of communities to organize themselves (Granovetter, 1973, pp. 1373–1376).

From Figure 3.4 it is easily seen that with such a view of the world, hypothesis 1 and 2 hold. First, hypothesis 1 is obviously true as the only connected triples with two strong ties are within an island, while triples with one or two weak ties involve nodes from different islands. As everyone within an island is directly connected, it must be that all connected triples with two strong ties are transitive. Second, the link betweenness of weak ties is higher then the link betweenness of strong ties. Weak ties directly connect two separate islands; $4 \times 4 = 16$ shortest paths depend on a weak tie. The strong tie, on the other hand, is only crucial for the connectedness of the actors involved in a strong tie. In Figure 3.4, the strong tie between A and B lies on the shortest path between A and B, between A and the actors of island I, and between B and the actors of island J; a total of $5 + 5 = 10$ shortest paths. Other strong ties have the same or lower link betweenness. Hence, in the island network weak ties have higher link betweenness than strong ties.

These computations suggest why Granovetter's 'strength of weak ties' theory typically holds in an island network structure. We now illustrate how the theory typically fails to hold for the core-periphery structure (as given in Figure 3.5). This network consists of a core of four actors, who are strongly connected in a clique. These actors have a number of ties with peripheral players. In Figure 3.5 each core actor is connected to five peripheral actors. The peripheral actors themselves have only a weak link to one of the core actors, and no link to other peripheral actors. We refer to this network structure as the core-periphery network structure. In contrast to the island network structure, the core-periphery network has a distinct hierarchy.

When we examine the two hypotheses of Section 3.2 in the context of the core-periphery structure, we observe the following. First, triples with two strong ties necessarily involve core actors only. Since the core is completely internally connected these triples are transitive. On the other hand, triples with a weak tie involve peripheral players, and these triples are typically not transitive. Hence, the first hypothesis holds. Second, in contrast to hypothesis 2A, *strong* ties have higher betweenness. In a core-periphery network a strong tie belongs to the shortest path of the two core actors *and* the peripheral 'clients' attached to the core actors. On the other hand, a weak tie only connects the peripheral player involved. So, in Figure 3.5, the link between A and B belongs to the shortest paths of all nodes between I and J, a total of $6 \times 6 = 36$ paths. A weak tie only belongs to the shortest paths that connect a peripheral player to the rest of the network; in Figure 3.5 23 paths. Hence, strong ties have a higher betweenness than weak ties in a core-periphery network. Thus hypothesis 2A is rejected.

To understand the failure of the 'strength of weak ties' theory in the core-periphery structure, we first note that in both Figure 3.4 and Figure 3.5 weak ties form (local) bridges. However, the importance of these bridges is very different in the two network

[13] See, for example, Figure 2 in Granovetter (1973, p. 1365) or Figure 1 in Friedkin (1980, p. 412).

structures. In the island network structure the bridges connect different *communities* to each other, while in the core-periphery network structure the bridges only connect a single peripheral player. Hence, we argue that the bridges are more 'crucial' in the island structure than in the core-periphery network structure.

3.5 The network structure of the coauthor network

We now show that the coauthor network has the two properties mentioned in Section 3.4, and that these two properties indeed explain the rejection of Hypothesis 2A in Section 3.3.

We first refer to our work in Chapter 2. In this chapter we showed that the coauthor network has a very unequal degree distribution. Most economists have only one or two links, but there is small fraction of *stars* with many, up to 50 links. Furthermore, we showed that the removal of these high degree 'stars' from the network is catastrophic for the cohesion of the coauthor network, while the removal of random nodes has only a small, gradual affect on the network cohesion (see also Albert et al., 2000). For example, the removal of 5 percent of the nodes with the highest degree from the coauthor network would result in a complete breakdown of the giant component. Hence, this work shows that high degree nodes are very important in connecting different parts of the network.

We now show that there exists a strong and positive correlation between strength and average degree. We perform the following regression on the links in the giant component of the coauthor networks of the 1970s, 1980s and 1990s. The dependent variable is the logarithm of strength of links, and the regressors are: 1) the average log degree of the two actors attached to a link and; 2) the difference between the log degrees of the two actors; 3) three decade dummies. We again take 10000 random subsamples of size 1000 and perform regressions on these 10000 subsamples. The estimation results of these regressions are shown in Table 3.7.

We observe that there is a positive relation between strength of links and average degree of the two coauthors, and a negative relation between strength of links and difference of degree between coauthors. Hence, if two actors A and B both have many links, then the link between them is expected to be strong.

To support our claim that it is indeed the two above observations that explain the rejection of hypothesis 2A, we repeat the regression of link betweenness on strength of a link; however, this time we add variables on average degree and difference in degree to the regression. Thus we control for the indirect effect that strong links are often between high degree nodes, and a link between these high degree nodes has a high link betweenness. If our explanation is valid, then we would expect the degree variables to be highly significant. Furthermore, our explanation for the rejection of Hypothesis 2A becomes irrelevant when we compare ties with the same degree of its actors. In that case, Granovetter's arguments should become more prominent again. Thus, after we control for the degree of the tie's actors, we should expect Hypothesis 2A to hold. That is, we should expect a negative coefficient for the strength variable.

We again stack observations on links in the giant components of the networks in the three decades and we again take 10000 random subsamples of 1000 observations. We then perform regressions on the subsamples with log betweenness as dependent variables and

Table 3.7: Estimation results of a regression on the strength of ties

variable	coefficient	.95-confidence	p-value
DUMMY70S	.0244	(-.0854, .1369)	.666
DUMMY80S	.0229	(-.0660, .1127)	.613
DUMMY90S	.0030	(-.0818, .0863)	.943
AVGDEGREE	.1827	(.1258, .2402)	0
DIFFDEGREE	-.0411	(-.0762, -.0048)	.027
R^2	.057		

Results of regressions on 10000 random subsamples with each subsample 1000 observations. Each observation is a link AB in the giant component of either the 1970s, 1980s or 1990s network. The dependent variable is the natural logarithm of the number of papers A and B have written together. $AVGDEGREE = (X_A + X_B)/2$ where X_A is the natural logarithm of the number of links A has. $DIFFDEGREE = |X_A - X_B|$. $DUMMY70S$, $DUMMY80S$, and $DUMMY90S$ are dummy variables to indicate whether the observations were drawn from the 1970s, 1980s or 1990s. *coefficient* is the average of the estimated coefficients in the 10000 regressions. *.95-confidence* is the .025- and .975-quantile of the coefficients estimated from the 10000 regressions. *p-value* is $1 - |2s - 1|$ where s is the fraction of estimated positive coefficients.

Table 3.8: Estimation results of a regression on link betweenness controlling for degree

variable	coefficient	.95-confidence	p-value
DUMMY70S	-11.160	(-11.985, -10.374)	0
DUMMY80S	-12.562	(-13.322, -11.810)	0
DUMMY90S	-13.807	(-14.588, -13.028)	0
LNSTRENGTH	-.084	(-.422, .227)	.631
AVGDEGREE	2.410	(2.096, 2.728)	0
DIFFDEGREE	.607	(.363, .857)	0
R^2	.270		

Results of regressions on 10000 random subsamples with each subsample 1000 observations. Each observation is a link AB in the giant component of either the 1970s, 1980s or 1990s network. The dependent variable is the natural logarithm of link betweenness of link AB. $LNSTRENGTH$ is the natural logarithm of the number of papers A and B have written together. $AVGDEGREE = (X_A + X_B)/2$ where X_A is the natural logarithm of the number of links A has. $DIFFDEGREE = |X_A - X_B|$. $DUMMY70S$, $DUMMY80S$, and $DUMMY90S$ are dummy variables to indicate whether the observations were drawn from the 1970s, 1980s or 1990s. *coefficient* is the average of the estimated coefficients in the 10000 regressions. *.95-confidence* is the .025- and .975-quantile of the coefficients estimated from the 10000 regressions. *p-value* is $1-|2s-1|$ where s is the fraction of estimated positive coefficients.

decade dummies, log strength, average log degree and difference log degree as explanatory variables. Table 3.8 shows the results of these regressions. We first observe that R^2 increases to .27 from .06 in the earlier regression reported in Table 3.4. Hence, the variation in link degree explains a large portion of the variation in link betweenness. Second, we observe that the coefficient of $AVGDEGREE$ is significantly positive, thus showing that a link between two high degree nodes has a higher betweenness. Third, we observe that the coefficient of $LNSTRENGTH$ is negative, although not significantly. These results clearly support our intuition that it is the indirect relation of between strong ties and high degree actors and between high degree actors and high betweenness that explains the results in Section 3.3, and that this indirect effect dominates the effect of high clustering of strong ties on betweenness.

3.6 Concluding remarks

This chapter examines the celebrated 'strength of weak ties' hypothesis from a structural point of view: we ask if weak ties are more critical for integrating the network as compared to strong links. The first part of the chapter shows that this hypothesis is not valid in the coauthor network of economists. The second part of the chapter argues that two features of the network together help account for this finding: one, significant inequality in number of coauthors across individuals, and two, a positive relationship between the strength of a tie and the number of coauthors of the involved authors.

The arguments in the chapter together make the following general point: The classical view has been that society consists of different communities with strong ties within and weak ties across communities. Our work provides evidence for the existence of societies which exhibit a core-periphery structure, with the strong ties being located in the core. In such societies, strong ties are more important for bridging the network than weak ties.

These findings have potentially important implications for the study of social structure and we now discuss some interesting directions for further research. A first point worth bearing in mind is that we have only analyzed the coauthor network of economists. It would be interesting to check if coauthor networks in other subjects exhibit similar patterns. Existing work shows that degree distributions are typically unequal in coauthor networks (see e.g., Newman, 2003). This research typically assumes that links are dichotomous variables. There is however little work on the relation between degrees of authors the strength of the tie between them, and this property is critical, for the failure of hypothesis 2.

More generally, our findings raise the question of whether similar patterns also obtain in non-academic social networks. One context where this would be specially interesting to study is labor market contacts. There is some evidence on labor market contacts in Easy Asia which shows that strong ties are typically more important for job seekers as compared to weak ties (Bian and Ang, 1997). It would be very interesting to relate the network structure properties to these informativeness properties of strong ties.

A second line of enquiry concerns the formation of such networks, in other words, what are the circumstances – economic, cultural and technological – under which these two properties are likely to emerge. The economic coauthors networks is a specific context. Many factors play a role in the decision to coauthor or not, such as competition for priority, or complementarities of research skills, factors that do not play a role in other social settings. Moreover, the institution of academic research is such that there is a clear hierarchy in which professors advise PhD students. Many PhD students have only one or a few papers with their advising professor, in particular those who do not continue their career in academics. We would like to develop a simple theory of how such factors may help lead to the observed coauthor network.[14]

A third line of enquiry concerns the implications of the network patterns. In this chapter the focus has been on the structural aspects of the network structure, and it remains an open question whether strong ties are indeed more important for information dissemination. In the context of scientific collaboration, a combined analysis of the coauthor network and citations would be one way to move forward on this interesting question.

[14] For a brief survey of models of strong and weak links, see Goyal (2005b).

Chapter 4

A theoretical model of research collaboration

4.1 Introduction

In Chapter 2 we studied the evolution of social distance among economists over the period 1970-2000. Our main findings were as follows. While the number of economists has more than doubled, the distance between them, which was already small, has declined significantly. The key to understanding the short average distances is the observation that economics is spanned by a collection of interlinked stars. A star is an economist who writes with many other economists, most of whom have few coauthors and generally do not write with each other.

These empirical findings are fascinating and we would like to develop a theory to account for them. There is already a large literature on the small world phenomenon in physics and mathematics. This work takes as a given that the world is small; our empirical work, however, shows that average distances and size of giant component in our network change greatly over time. We therefore need a theoretical approach which can explain the stable architectural features of the network (the interlinked stars) as well as the changes in the network (such as growing giant component).

In this chapter we therefore develop a simple incentives based model with the following features. Research papers contain ideas and involve routine work; the quality of a paper depends on the quality of the ideas contained in it. Individuals have ideas and can do routine work; however, some people are better at generating high quality ideas than others. Institutions reward individuals on their research output; this reward specifies a threshold level of output quality that is considered for evaluation and also specifies a certain credit to single authored work and coauthored work. There are costs to writing papers which increase in the number of papers written in a research area. Similarly there are costs to meeting and working with others which are increasing in the number of coauthors and which are also sensitive to the (network) distance between the authors.

Analysis of this model tells us that stars – which embody unequal distribution of links and links between well connected and poorly connected players – arise naturally in an

[0] This chapter is based on Section 4 of Goyal, Van der Leij and Moraga-González (2004).

academic environment with productivity differentials and the possibility of collaboration. We show that equilibrium networks contain interlinked stars and hence exhibit short average distances. We also show that a decline in costs of communication and an increase in credit to coauthored papers both lead to an increase in the number of collaborators and therefore an equilibrium network with a higher degree, something which helps explain the growth in the size of the giant component.

We now place this model in the current literature. In the first place, this chapter is related to the recent literature on network formation, see Bala and Goyal (2000), Jackson and Wolinsky (1996) and Kranton and Minehart (2001) for early work and Goyal (2005a) and Jackson (2005) for surveys of recent developments. The distinctive aspect of this literature is the use of individual incentives to derive predictions on network architectures. This chapter contributes to this literature by developing a simple model of coauthor network formation to explain the patterns we observe in Chapter 2.[1]

Second, this chapter may be seen as contributing to the literature on economics research. Recent work on this subject includes Ellison (2002a, 2000b), Laband and Tollison (2000), among others. Our findings on the relative role of increased coauthoring and distant coauthoring, respectively are related to themes discussed by other authors. In particular, the increase in coauthorship has been noted and the reasons for it have been explored in Hudson (1996), while the role of substantial and increasing informal intellectual collaboration is explored in Laband and Tollison (2000). A variety of arguments – such as increasing specialization and the falling costs of communication among others – have been proposed to explain increasing coauthorship among economists. Hamermesh and Oster (2002) present evidence which suggests that collaboration among distant authors has increased over the years.

Third, the analysis in this chapter also relates to complex network modeling in physics. In recent years, physicists have investigated extensively the empirical properties of large social and economic networks. For comprehensive surveys of this work see Albert and Barabási (2002) and Dorogovtsev and Mendes (2002). This work focuses on the statistical properties of large networks, and uses a variety of techniques ranging from random graph theory to mean field analysis to elaborate on different features of observed networks. The contribution to this body of work is the incentives based approach we develop. We believe that networks of scientific collaboration are an outcome of deliberate decisions by individual scientists. This means that the observed networks reflect the technology of production of knowledge and the incentives faced by individuals. We are thus interested in developing a model where technology and incentive schemes are modeled explicitly and we can study their effects on collaboration networks systematically.

This chapter is structured as follows. In Section 4.2 we develop the theoretical model. In Section 4.3 we analyze this model and we provide equilibrium results. In Section 4.4 we conclude.

[1]For a related model of coauthors, see Jackson and Wolinsky (1996). Their interest is in complementarities in collaboration and their equilibrium networks are characterized by complete components of different sizes.

4.2 Model

In this section we develop a simple model of network formation to explain the observed empirical patterns, specifically, the existence of interlinked stars and the growth in the giant component. Our model has three main aspects: a technology of knowledge production, productivity differences across individuals, and academic reward schemes.

We suppose that there are n players and that a player can be either of High type or Low type. There are n_h High-type players, and n_l Low-type players, and $n = n_h + n_l$. We shall assume that $1 < n_h << n_l$ and that n_l is sufficiently large. We shall denote the set of players by N. Players make decisions on their research strategy: whether to write alone or with others, and if with others, how many coauthorships to form and with which types of players; they also decide how many papers to write and how much effort to put in each paper that they write.

Let $g_{ij}^x \in \{0, 1\}$ model i's decision on whether to participate in a project x with author j, where a value of 1 signifies participation while a value of 0 signifies non-participation. Let e_{ii}^x denote the effort that player i spends on a single-authored paper x, and let e_{ij}^x, refer to the time that he spends on a joint paper x with coauthor j. We assume that for a paper to be written the total effort put in by its authors must be at least 1. A research strategy of a player is then given by a row vector, $s_i = \{(g_{ij}^x, e_{ij}^x)_{x\in\{1,..,m\},j\in N}\}$, where m is the number of projects that a player participates in either individually or with any other single coauthor. A player j is a coauthor of player i if $g_{ij}^x = g_{ji}^x = 1$ for some paper x. Let $\eta_i(\mathbf{s})$ be the number of coauthors of player i in research strategy $\mathbf{s}$.

A paper consists of ideas and routine/technical work.[2] The quality of a paper depends only on the quality of the ideas it contains and the ideas of the paper in turn depend on the type of the authors of the paper. A High-type author has high quality ideas, while a Low-type author has low quality ideas; the high and low quality types of ideas are denoted by t_h and t_l, respectively, where $t_h > t_l > 1$. It is natural to assume that a type i author will write single-authored papers of quality t_i only, $i = h, l$; we assume that if two authors i and j jointly work on a paper the quality of the paper is given by $t_i \cdot t_j$. Thus quality of a paper can be $q \in \{t_h^2, t_h t_l, t_h, t_l^2, t_l\} = Q$.[3]

We assume that the marginal costs of writing papers increase with the number of papers, reflecting increasing marginal opportunity costs of time.[4] Maintaining a coauthor relationship involves communication and coordination across different projects and possibly different partners and these costs are likely to increase as the number of coauthors increases. This leads us to assume that the marginal cost are increasing in the number

[2] This is similar to the formulation used in Ellison (2002b).

[3] In economics, quality of original ideas appears to be the crucial variable and physical capital and infrastructure seems to play a relatively minor role in the production of knowledge. This is quite different from the situation in subjects such as medicine and physics, where experiments require very substantial infrastructure and the provider of these resources has a very critical role. Our formulation is therefore better suited for the study of collaboration in economics.

[4] Time constraints are particularly relevant when the papers are written in parallel. This is likely to be the case when the considered publication period is very short. When papers are assumed to be written sequentially, the marginal cost might initially decrease due to a 'learning by doing' effect. However, if the production is large, the learning effect is likely to be small, in which case increasing opportunity costs of time are the most relevant factor determing the marginal cost of writing papers.

of coauthors, $\eta_i(\mathbf{s})$. Given these considerations, we are able to write down the costs of a research strategy s_i for a player i faced with a research strategy profile $\mathbf{s_{-i}}$, as

$$\sum_{j \in N} c \left[\sum_{x \in \{1,..,m\}} e^x_{ij} \right]^2 + f \frac{\eta_i(\mathbf{s})^2}{2} \tag{4.1}$$

with $f > 0$. This first part of the cost specification captures the idea that a collaboration relation between two individuals i and j is a research project and that the costs of coming up with interesting ideas and papers increase as more papers are written within the project. This leads us to suppose that writing m papers with m coauthors is less costly than writing m papers with a single coauthor. This assumption pushes individuals toward diversification of collaborators. On the other hand, our assumption that costs of linking with others are convex in the number of links pushes toward fewer collaborators. The optimal number of collaborators trades off these two pressures.

We shall suppose that a person is rewarded on the basis of quality weighted index of papers he publishes, there is discounting of joint work and that there is a minimum quality requirement such that only papers *above* this quality are accepted for publication. We shall suppose that this threshold is given by $\bar{q}$ where $\bar{q} \in [1, t_h^2]$. One interpretation of this threshold is in terms of different journals: a higher ranked journal can be more selective in the papers it publishes and so it will have a higher threshold as compared to a lower ranked journal. We suppose that a single-author paper of quality q gets a reward q, while a 2-author paper of quality q yields a reward rq to each author, where $r \in [0, 1]$ reflects the discounting for joint work in the market.[5]

For a strategy profile $\mathbf{s}$, let $I^x_{ij}(\mathbf{e})$ be an indicator function, which takes on value 1 if $g^x_{ij} = g^x_{ji} = 1$, $e^x_{ij} + e^x_{ji} \geq 1$, and $q^x_{ij} \geq \bar{q}$, and it takes a value of 0, otherwise. Given these considerations, for a strategy s_i and faced with a strategy profile $\mathbf{s_{-i}}$, the payoffs to a player are as follows:

$$\Pi_i(s_i, \mathbf{s_{-i}}) = \sum_{j \neq i} \sum_{x \in \{1,..,m\}} I^x_{ij} r q^x_{ij} + \sum_{x \in \{1,..,m\}} I^x_{ii} q^x_{ii} - \sum_{j \in N} c \left(\sum_{x \in \{1,..,m\}} e^x_{ij} \right)^2 - f \frac{\eta(\mathbf{s})^2}{2}. \tag{4.2}$$

We study the architecture of networks that are strategically stable. Our notion of strategic stability is a refinement of Nash equilibrium. A strategy profile $s^* = \{s^*_1, s^*_2, ..., s^*_n\}$ is said to be a Nash equilibrium if $\Pi_i(s^*_i, \mathbf{s^*_{-i}}) \geq \Pi_i(s_i, \mathbf{s^*_{-i}})$, for all $s_i \in S_i$, and for all $i \in N$. In our model a coauthoring decision requires that both players wish to participate in the paper. It is then easy to see that an autarchic situation in which no one does any joint work is always a Nash equilibrium. To avoid these types of coordination problems we supplement the idea of Nash equilibrium with the requirement of pairwise stability. We define pairwise stable equilibrium as follows:

Definition 4.1. *A strategy profile* $\mathbf{s}^*$ *is a pairwise-stable equilibrium if the following conditions hold:*

[5] We are assuming here that different types involved in a collaboration get the same reward; our results do not change qualitatively if we assume that Low types get a lower payoff than High types.

1. $\mathbf{s}^*$ *constitutes a Nash equilibrium.*

2. *For any pair of players, $i, j \in N$ there is no strategy pair (s_i, s_j) such that* $\Pi_i(s_i, s_j, \mathbf{s}^*_{\mathbf{-i-j}}) > \Pi_i(s_i^*, s_j^*, \mathbf{s}^*_{\mathbf{-i-j}})$ *and* $\Pi_j(s_i, s_j, \mathbf{s}^*_{\mathbf{-i-j}}) > \Pi_j(s_j^*, s_j^*, \mathbf{s}^*_{\mathbf{-i-j}})$.

We shall use the short form – pws-equilibrium – to refer to pairwise-stable equilibrium. This notion of equilibrium is taken from Goyal and Joshi (2003); it generalizes the original formulation of pairwise stability due to Jackson and Wolinsky (1996) by allowing pairs of players to form and delete links simultaneously. We shall say that a network is *symmetric* if all equal-type players have the same number of links with each of the two types of players. This will allow us to talk of the number of collaborations between a typical i and j type of players and use η_{ij} to refer to this number.

4.3 Results

We first characterize equilibrium networks under the assumption that, in a joint project, each author contributes one half of the time needed for routine work and gets credit r for the joint paper. This may be interpreted as a model with no transfers. We note that the optimal choice of number of papers is independent across pairwise collaboration ties. This is due to the cost specification which is additive across projects with different coauthors and own projects. Our first result derives the optimal number of papers that High type and Low type authors will write on their own and with others.[6]

Proposition 4.1. *Suppose $\bar{q} < t_l$. A High type player optimally chooses $m_h^* = t_h/2c$ single author papers, $m_{hh}^* = 2rt_h^2/c$ papers in a HH collaboration, and $m_{hl}^* = 2rt_ht_l/c$ papers in HL collaboration. A Low type player optimally chooses $m_l^* = t_l/2c$ single author papers, $m_{lh}^* = 2rt_ht_l/c$ papers in a LH collaboration, and $m_{ll}^* = 2rt_l^2/c$ papers in LL collaboration.*

Proof. For a High type the optimization problem with respect to single author papers is

$$\max_{m_h} \; t_h m_h - c m_h^2 \tag{4.3}$$

Straightforward calculations yield $m_h^* = t_h/2c$. Similarly, for a High type the optimal number of papers in an HH collaboration is the solution to the following optimization problem:

$$\max_{m_{hh}} \; rt_h^2 m_{hh} - c\left[\frac{m_{hh}}{2}\right]^2 \tag{4.4}$$

This optimization problem yields us the solution that $m_{hh}^* = 2rt_h^2/c$. Similarly, the optimal number if papers for a H type in a HL collaboration are given by $m_{hl}^* = 2rt_ht_l/c$. Given that the publication threshold is below t_l, L types will also write papers on their own. The computations for these players are similar and omitted. $\square$

This proposition tells us that H-types will write more single authored paper than L-types. Moreover, the optimal number of papers in a HH relationship is greater than the

[6] In what follows we treat the number of papers and the number of coauthors as continuous variables.

number of papers in a LL coauthor relation. These results follow directly from the initial productivity differences across players. We also note that the number of optimal papers varies negatively with the costs of writing papers, while they vary positively with the individual credit given in coauthored papers.

Let π_i refer to the payoff that a i type player gets from working alone, and π_{ij} refer to the reward that a type i player gets from working with a type j player. Then the above proposition allows us to write down the payoffs for different type players.

$$\pi_h^* = \frac{t_h^2}{4c};\ \pi_{hh}^* = \frac{r^2 t_h^4}{c};\ \pi_{hl}^* = \frac{r^2 t_h^2 t_l^2}{c}; \tag{4.5}$$

$$\pi_l^* = \frac{t_l^2}{4c};\ \pi_{lh}^* = \frac{r^2 t_l^2 t_h^2}{c};\ \pi_{ll}^* = \frac{r^2 t_l^4}{c}. \tag{4.6}$$

In what follows, our interest is primarily in the nature of coauthor networks that arise and we shall omit mention of single author papers throughout the discussion. The following result characterizes equilibrium networks.

Proposition 4.2. *Suppose that $n_h - 1 \geq r^2 t_h^4/cf$, $\bar{q} = t_l$ and n_h and n_l are even numbers. A symmetric equilibrium network exists and it has the following properties.*

(i) If $f > 2r^2 t_h^4/c$ then it is empty.

(ii) If $2r^2 t_l^4/c < f < 2r^2 t_h^4/c$, then $\eta_{hh}^* = \frac{r^2 t_h^4}{cf}$, $\eta_{lh}^* = 0$ and $\eta_{ll}^* = 0$.

(iii) If $f < 2r^2 t_l^4/c$, then $\eta_{hh}^* = \frac{r^2 t_h^4}{cf}$, $\eta_{hl}^* = 0$ and $\eta_{ll}^* = \frac{r^2 t_l^4}{cf}$.

Proof. We first characterize the incentives to collaborate. Part (i) follows directly from noting that $\pi_{hh}^* < f/2$ implies that there is no incentive for two H-types to collaborate. Since this is the highest possible return from coauthorship no links can arise in equilibrium. We now prove part (ii). First, we note that since $\pi_{hh}^* > \pi_{hl}^*$ an H-type will not link up with an L-type if there is an H-type available. The assumptions $n_h - 1 \geq r^2 t_h^4/cf$ and n_h is an even number guarantee that this will be the case (the critical number of high types is derived below). Second, we note that an L type would only be willing to collaborate with L-types if $f/2 < \pi_{ll}^*$.

We now turn to optimal choice of partners. If $f/2 < \pi_{hh}^*$ then the optimal number of links for an H type, η_{hh}, solves:

$$\max_{\eta_{hh}} \quad \eta_{hh}\pi_{hh}^* - f\frac{\eta_{hh}^2}{2} \tag{4.7}$$

The solution is given by $\eta_{hh}^* = \frac{r^2 t_h^4}{cf}$. Thus if $n_h - 1 > \frac{r^2 t_h^4}{cf}$, then there are enough H-types around and an H-type will not collaborate with an L-type. The computations for L-type players in case (iii) are similar and omitted.

The existence of symmetric equilibrium follows directly from the fact that an optimal number of papers and coauthors exist, n_h and n_l are even and large enough to make optimal linking feasible. □

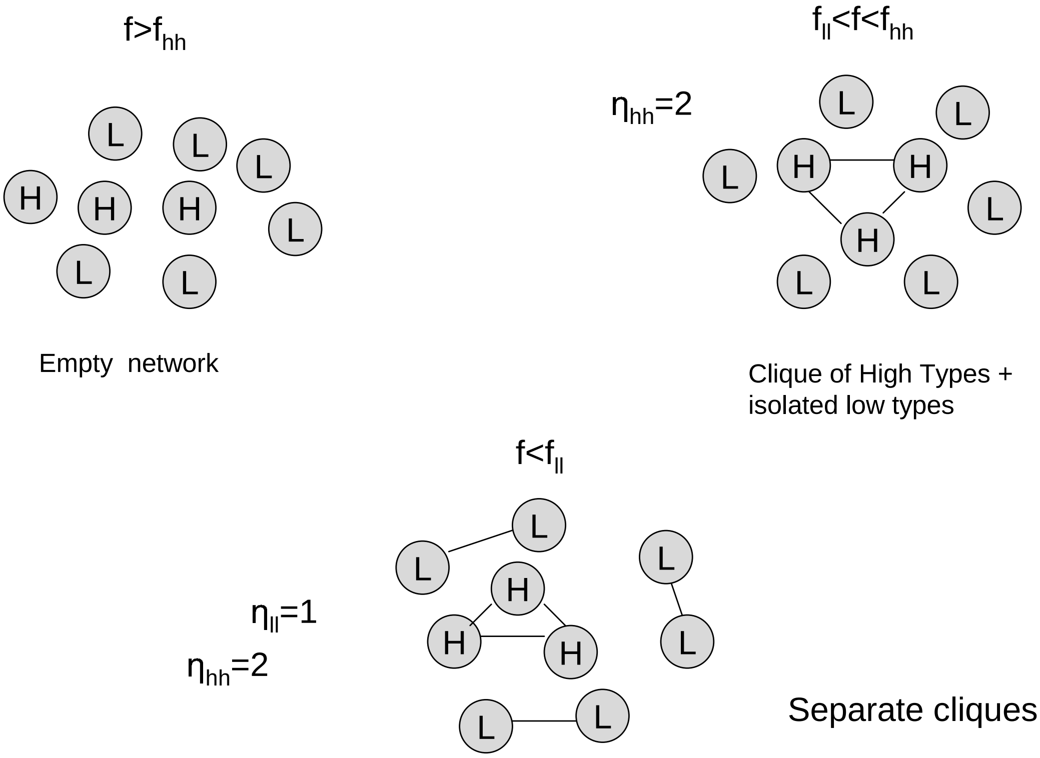


Figure 4.1: Symmetric equilibrium networks for $n_H = 3$ and $n_L = 6$.

Proposition 4.2 tells us that if two persons involved in a collaboration equally share the effort required to write a paper, then only links between same type players will form in a symmetric equilibrium. Moreover, H-types will have more coauthors than L-types. Figure 4.1 presents the equilibrium networks; in this figure $f_{hh} = 2r^2t_h^4/c$ and $f_{ll} = 2r^2t_l^4/c$.

We now comment on the role of the two institutional reward variables: the threshold level for publication, $\bar{q}$, and the credit for joint work r. The threshold $\bar{q}$ is critical in defining the level and types of coauthorship. This leads us to ask: does an increase in $\bar{q}$ always raise the proportion of coauthored papers? The answer to this depends on the relative value of t_h and t_l. If $t_h < t_l^2$ then the proportion of coauthored papers is increasing in $\bar{q}$. If $t_h > t_l^2$ then there is a non-monotonicity: as $\bar{q}$ crosses t_l the proportion increases and as it increases beyond t_l^2 it falls before rising again to a value of 1 as $\bar{q}$ crosses t_h. We also note that the number of joint papers as well as the number of coauthors is increasing in r, the level of individual credit for coauthored work.

Proposition 4.2 implies that there are no connections between Low and High type players. Moreover, in equilibrium, links only exist between players with the same number of links. This seems to be at variance with one of the crucial aspects of empirically observed networks: the existence of a large number of stars (which arise when highly connected players connect with very poorly connected players, see Table 2.6). This difference between observed patterns and equilibrium predictions leads us to explore two aspects of the model more closely: the number of H-types available and the possibility of transfers between High and Low types.

One reason for the 'same-type collaboration only' result is that there are enough players of each type. What happens if an H-type wants to collaborate with 10 H-types but there are only 5 H-types around? In this case, High type players may be induced to collaborate with L-type players. This observation leads us to the following result.

Proposition 4.3. *Suppose that $n_h - 1 < r^2 t_h^4/cf$ and the threshold for publication is $\bar{q} = t_l$. Then a symmetric equilibrium has the following features.*

(i) If $f > 2r^2 t_h^4/c$ then it is empty.

(ii) If $2r^2 t_l^4/c < f < 2r^2 t_h^4/c$, every H-type has $n_h - 1$ H-type coauthors, and also has $\eta_{hl} = \max\{0, \frac{r^2 t_h^2 t_l^2}{cf} - n_h + 1\}$ L-type coauthors. L-types do not work with each other.

(iii) If $f < 2r^2 t_l^4/c$ an H-type has exactly the same coauthor pattern as in (2), while each L-type has $\eta_{lh} \in (1, n_h)$ H-type coauthors and $\max\{0, \frac{r^2 t_l^4}{cf} - \eta_{lh}\}$ L-type coauthors.

Proof. Part (i) follows as in Proposition 4.2. We now prove part (ii). Since $n_h - 1 < r^2 t_h^4/cf = n_{hh}^*$, it follows that there are not enough High-type players around so that a High-type may find it worthwhile to form collaborations with Low-types. Since $\pi_{lh}^* > \pi_{ll}^*$ a Low-type always prefers to collaborate with a High-type rather than with another Low-type. Thus, the payoff to a High-type may be written as

$$\left(t_h m_h - c m_h^2\right) + (n_h - 1)\pi_{hh}^* + \eta_{hl}\pi_{hl}^* - f\frac{(n_h - 1 + \eta_{hl})^2}{2}. \tag{4.8}$$

It is now easy to see that the optimal number of HL collaborations is given by $\eta_{hl} = r^2 t_h^2 t_l^2/cf - n_h + 1$. We now consider the incentives of L types. First note that since $f > 2r^2 t_l^4/c$ there will be no LL coauthor papers. It then follows that an L-type player will have $\eta_{lh} \in \{1, n_h\}$ H-type coauthors in a symmetric equilibrium. This completes the proof of part (ii). The proof of part (iii) is similar and omitted. □

A scarcity of H-types implies that there is a wide range of parameters for which HL collaborations arise in equilibrium. Moreover, since $n_h << n_l$, in part (2) equilibrium networks will have an interlinked stars structure: all H types will coauthor with each other while each of them will coauthor with a number of L-types, who do not coauthor with each other. Figure 4.2 presents equilibrium networks when the number of H types is small; in this figure f_{hh} and f_{ll} are defined as before, while $f_{hl} = r^2 t_h^2 t_l^2/(n_h - 1)c$

We now examine the scope of 'a sharing of scarce resources' motivation for collaboration between an H-type and an L-type. We start by examining a case in which L-types offer 'time' for routine work and in return get High quality ideas from H-types. An important issue here is how the exchange of ideas and time takes place. We first discuss the case where an L-type only shares in the routine work and does not share the costs of maintaining links f.

To keep matters simple we shall suppose that an H-type makes a take-it-or-leave-it offer $\alpha \in (1/2, 1]$ to an L-type, where α measures the amount of time the Low-type must contribute per paper the two parties write together.[7] What will be the optimal level for α

[7] We assume that the α-contract is enforceable.

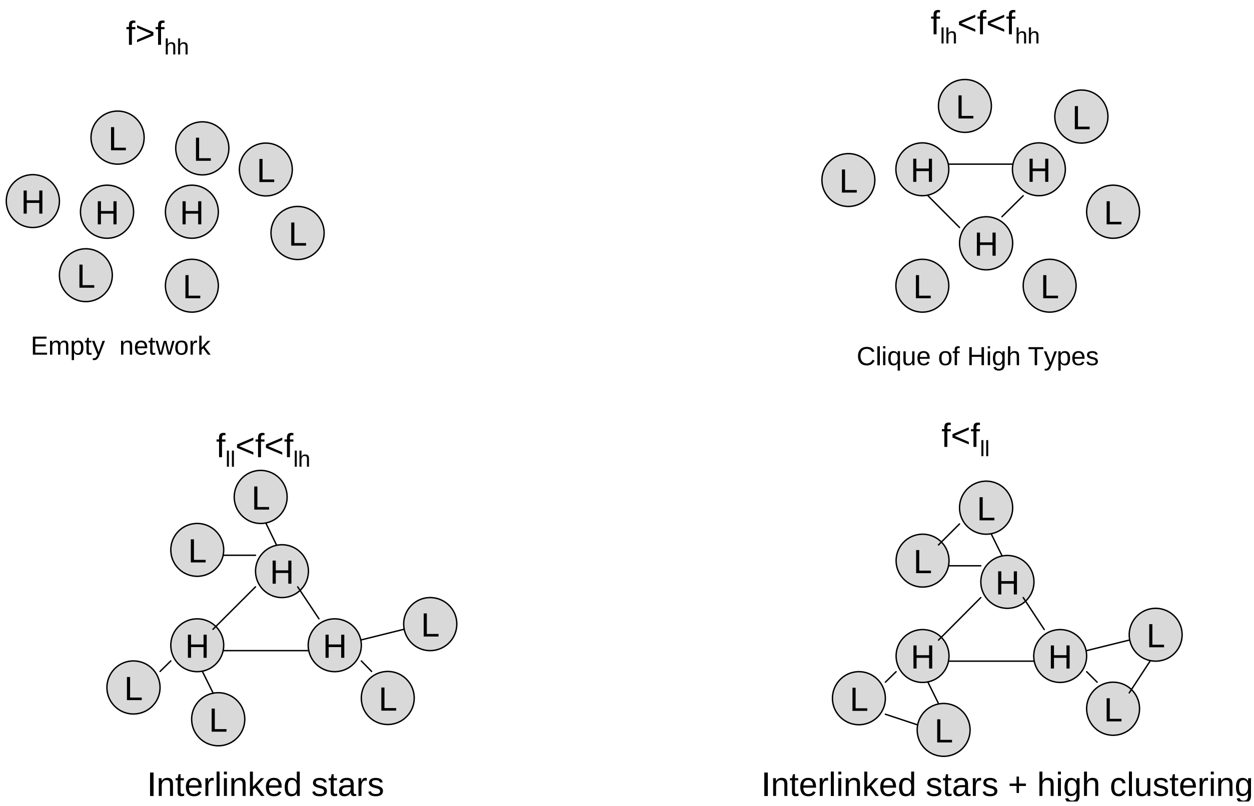


Figure 4.2: Symmetric equilibrium networks with size constraints. $n_H = 3$, $n_L = 6$ and $\eta_{HH} > n_H - 1$.

and how many coauthorships between H and L types will arise in this case? The following proposition provides a complete answer to this question.

Proposition 4.4. *Assume that* $n_h - 1 \geq r^2 t_h^4/cf$ *and* $\bar{q} = t_l$. *Suppose that an H-type makes a take-it-or-leave-it offer of* $\alpha \in (1/2, 1]$ *to an L-type with regard to sharing routine work in a joint paper. Then in equilibrium there will be no HL coauthorships and therefore networks will have the same structure as in Proposition 4.2.*

Proof. Given an $\alpha \in (1/2, 1]$, an L-type faces a trade-off: work with other L-types and share routine work equally or work with an H-type and put in a fraction of time $\alpha > 1/2$ per paper in exchange for high quality ideas. From 4.6 we know that if an L-type works with another L-type then he receives a payoff given by $\pi_{ll} = r^2 t_l^4/c$. If a Low-type works with an H-type instead, then he receives a payoff given by

$$rt_h t_l m_{lh} - c(\alpha m_{lh})^2,$$

where α denotes the fraction of time an L-type must put in to be able to work with an H-type. From the first order conditions it follows that $m_{lh} = rt_h t_l/2c\alpha^2$, which yields a payoff given by $\pi_{lh}(\alpha) = r^2 t_h^2 t_l^2/4c\alpha^2$ to the Low-type. We can compare π_{ll}^* and π_{lh} and we find that $\pi_{lh} > \pi_{ll}$ if and only if $t_h^2 > 4\alpha^2 t_l^2$. This gives us the set of α that an L-type will accept.

Consider now the decision of an H-type. An H-type faces a trade-off: work with High-types and share writing costs or work with Low-types and exchange quality of ideas for working time. From (4.5) we know that the payoff from an HH link to an H-type player are $\pi_{hh}^* = r^2 t_h^4/c$. Consider now the payoffs to an H-type from a HL link, where the L-type puts in α share of the routine work, while the H-type puts in $(1-\alpha)$ fraction of the routine work.

$$rt_h t_l m_{hl} - c((1-\alpha)m_{hl})^2$$

From the first order condition, it follows that $m_{hl} = rt_h t_l/2c(1 - 2\alpha + \alpha^2)$. Since $\alpha \geq 1/2$ it follows that $m_{hl} \geq m_{lh}$. We assume that for a given α, the number of papers written in a HL relation is $\min\{m_{hl}, m_{lh}\}$. Thus the payoff to an H-type from a link with an L-type is

$$\bar{\pi}_{hl}(\alpha) = \frac{r^2 t_h^2 t_l^2}{2c\alpha^2} \frac{\alpha(\alpha+2) - 1}{2\alpha^2}$$

We now note that $\bar{\pi}_{hl}(\alpha) \geq \pi_{hh}^*$ if and only if $t_h^2 < (\alpha(\alpha+2) - 1)/4\alpha^4)t_l^2$. This gives us the set of parameters for which an H-type would be willing to coauthor with an L-type for a given α.

Putting together the restrictions for the H and L types we get that for a fixed $\alpha \in (1/2, 1]$, an HL pair will coauthor only if

$$4\alpha^2 t_l^2 < t_h^2 < (\alpha(\alpha+2) - 1)/4\alpha^4)t_l^2$$

It is easy to verify that $4\alpha^2 > (\alpha(\alpha+2) - 1)/4\alpha^4)$ for all $\alpha \in (1/2, 1]$. Thus there is no sharing of routine work between H and L types that can make a HL relation mutually incentive-compatible. $\square$

The above proposition says that if transfers are restricted to the sharing of routine work then there will be no HL coauthor relation in equilibrium. The intuition here is as follows: when two H-types collaborate the surplus generated (at the optimal level of projects m^*_{hh}) is much higher as compared to the surplus generated when an H-type and an L-type collaborate. To induce an H-type to collaborate with an L-type the share for the H-type must therefore be much higher. This however reduces the share of the L-type and leads to lower number of projects undertaken which in turn renders an HL collaboration less attractive than a fair HH collaboration for a H-type player.

This argument leads us to ask: are there other richer transfer schemes which would allow mutually profitable HL collaboration? An obvious candidate is an arrangement by which an L type does all the routine work and also bears the costs of maintaining the relation. In that extreme case, an H type incurs no costs in writing papers with an L-type, while a L-type has to compare the relative returns of entering into such an unequal relation as compared to working on equal terms with another L-type. Suppose the L-type contributes all the time needed for the routine work. Then the payoffs to an L-type from such an HL relation are: $\pi_{lh} = r^2 t_h^2 t_l^2/4c$. On the other hand, the payoffs to an L-type from an LL relation are $\pi^*_{ll} = r^2 t_l^4/c$. Now it is easy to see that if $t_l > 2t_h$, then an L-type would prefer to link with an H type rather than link with another L type. Moreover, since the H-type bears no costs, clearly he is happy to enter into such a collaboration. This collaboration relation corresponds to a simple trade: an H-type player offers ideas in return for which the L-type collaborator offers time and resources for routine work. This collaboration relation leads to a network in which every H-type has η^*_{hh} HH-collaborations and possibly a very large number of HL-collaborations. Moreover, each of the L-type partner has relatively very few HL-collaborations and a few LL-collaborations (assuming $\bar{q} < t_l^2$.) This is consistent with an interlinked stars architecture as depicted in Figure 4.2.

We conclude this section by noting that in the equilibrium networks discussed so far there is no a priori reason to expect high clustering levels. In the context of part (iii) of Proposition 4.3, we know that an equilibrium network will have the property that L types will coauthor with each other. The equilibrium characterization however does not say whether these L-types will be linked to the same H-type or to different H-types. In the former case we will get reasonable levels of clustering and an inverse relation between degree and clustering, while in the latter case aggregate clustering levels will be close to 0 and the H-types will have the highest levels of clustering. The former is consistent with the empirical patterns while the latter is clearly not. A simple way to rule out the latter type of equilibrium is to suppose that the costs of coauthoring between i and j are slightly less if they have a common coauthor. This captures the idea that we usually start collaborating with individuals whom we already know and we are more likely to know someone with whom we share a common acquaintance. A slight difference in cost is sufficient to induce two L-types who share a common H-type coauthor to form a link and de-link from other more distant L-types.

4.4 Concluding remarks

We propose a simple model of production of knowledge in economics with the feature that a paper consists of novel ideas and routine work. The quality of the paper depends on the quality of ideas. We embed this basic technology in a setting where individuals are differentiated by the quality of ideas they have. Every individual chooses how many papers to write, and also with whom to write them. We find that an unequal distribution of collaborations and interlinked stars arise naturally in this environment. Falling costs of communication and higher individual credit for coauthored work both lead to greater coauthoring and this is consistent with a growth in the giant component.

This chapter provides an explanation for the emerging smallness of this academic world. We argue that there are good incentive based reasons to expect such architectures to arise in academic environments.

Part II

Job contact networks

Chapter 5

Occupational segregation in the labor market: a social network analysis

5.1 Introduction

Occupational segregation between various social groups is a persistent and pervasive phenomenon in the labor market. Richard Posner recently pointed out that "a glance of the composition of different occupations shows that in many of them, particularly racial, ethnic, and religious groups, along with one or the other sex and even groups defined by sexual orientation (heterosexual vs. homosexual), are disproportionately present or absent".[1] There are countless empirical studies that investigated the measurement and extent of occupational segregation, both in sociology and in economics,[2] documenting its enduring relevance. Most studies analyzing possible causes of occupational segregation agree that pure taste discrimination or theories based on market factors cannot explain alone occupational disparities. While a few alternative candidate theories have been considered,[3] Arrow (1998) particularly indicated the concepts of direct social interaction and networks as most promising avenues for research in this context.

[0]This chapter is based on Buhai and Van der Leij (2006).

[1]The quote is from an entry in "The Becker-Posner Blog", see http://www.becker-posner-blog.com. Posner also gives an example of gender occupational segregation: "a much higher percentage of biologists than of physicists are women, and at least one branch of biology, primatology, appears to be dominated by female scientists. It seems unlikely that all sex-related differences in occupational choice are due to discrimination..."

[2]Among the numerous studies documenting gender or racial occupational segregation, we mention a few that also have detailed literature review sections: Albelda (1986), Jacobs and Lim (1992), Blau, Simpson and Anderson (1998), Rich (1999)

[3]Theories advanced for explaining segregation in general and inequality among various social groups include a. pure discrimination theories, eg. Becker (1957), Arrow (1972); b. various statistical discrimination theories, eg. Phelps (1972) , Arrow (1973), Lazear and Rosen (1990), Coate and Loury (1993); c. theories based on intrinsic differences in ability or in attachment to the labor market, such as the human capital model by eg. Polachek (1981) ; d. theories based on group membership/ identity, adopted mainly from the residential segregation literature, eg. the review by Durlauf (2006) e. theories based on personal identity" developed by Akerlof and Kranton (2000)

In this chapter we apply social network theory to dynamically model occupational segregation in the labor market. Significant progress has been achieved in modeling labor market phenomena by means of social network analysis. Recent articles have investigated the effect of social networks on employment, wage inequality, labor market transitions, social welfare etc.[4] To our knowledge this is however the first application of social network analysis to modeling occupational segregation.

We construct a very simple three-stage model of occupational segregation between two homogeneous, exogenously defined, social groups acting in a 2-job labor market. In the first stage each individual chooses one of the two specialized educations to become a worker. In the second stage individuals randomly form friendship ties with other individuals, with a tendency to form more ties with individuals from the same social group, what we call inbreeding bias. In the third stage workers use their friendship contacts to search for jobs.

We show that with a positive inbreeding bias a complete polarization in terms of occupations across the two groups can arise as a stable equilibrium outcome. We extend our model by allowing for 'good' and 'bad' jobs, to analyze wage and unemployment inequality between the two social groups. We show that with large differences in job attraction a natural outcome of the model is that one group specializes in the good job, while the other group mixes over the jobs. Further, the group that specializes in the good job has a lower unemployment rate and a higher payoff. Thus our model is able to explain typical empirical patterns of gender, race or ethnical inequality.

In the remainder of this chapter we review some empirical evidence on the existence of inbreeding bias and occupational segregation in Section 5.2, we describe our model of occupational segregation in Section 5.3, and we discuss the results on segregation in Section 5.4. We then derive results when jobs are not equally attractive in Section 5.5, and we summarize and conclude the chapter in Section 5.6.

5.2 Evidence on job contact networks and inbreeding bias

There is a well established set of stylized facts that show the importance of the informal job networks in searching and finding jobs. First, it is known that on average 50-60 percent of the workers obtain jobs through their personal contacts. Evidence in this sense comes both from sociology and economics, starting back in the 1960's and covering multiple countries, e.g. Rees (1966), Granovetter (1995), Holzer (1987), Staiger (1990), Montgomery (1991), Topa (2001). A second empirical fact is that on average 40-50 percent of the employers use social networks of their current employees (i.e. they hire recommended applicants) to fill their job openings: e.g. Holzer (1987). Third, the employee-employer matches obtained by making use of job contact networks appear to be of high quality: there is evidence that those who found jobs through personal contacts were less likely to quit, e.g. Datcher (1983), Devine and Kiefer (1991), and also had longer tenure on these jobs, e.g. Simon

[4] See for instance Montgomery (1991), Arrow and Borzekowski (2003), Calvó-Armengol and Jackson (2004, 2006), Bramoullé and Saint-Paul (2006), Fontaine (2004), Lavezzi & Meccheri (2004).

and Warner (1992).[5] For a more detailed overview of studies on job information networks Ioannides and Datcher Loury (2004) is a very good reference. Job contact networks are thus documented to be very relevant in the labor dynamics process of matching employees to employers.

There is also extensive empirical evidence on the existence of inbreeding biases within social groups, i.e. individuals are more likely to maintain ties to others within the same group, e.g. Doeringer and Piore (1971), Marsden (1987), Staiger (1990). Staiger (1990) documents for instance the existence of large inbreeding biases within gender groups:[6] over all occupations in a U.S. sample, about 87 percent of the jobs obtained through contacts by men were based on information received from other men and 70 percent of the jobs obtained informally by women were based on information from other women. His results are very similar when looking at each occupation or industry separately. Evidence from other fields such as social psychology indicates that in fact membership in exogenously-defined (where the individual could not choose its group) group comes with strong intragroup solidarity, even when the groups are arbitrary categorized, as documented for instance in the "Robbers Cave" study by Sherif (1961).[7]

Using these stylized facts, we build a simple theoretical model based on social networks, able to explain stable occupational segregation equilibria without a need for other ingredients often used in this context. Our model should of course be seen as complementary to such existing theories in explaining the empirically observed occupational segregation patterns. While our study has common elements with theories concerned with group membership used on a large scale in sociology for explaining general segregation patterns (neighborhood segregation, school segregation, workplace segregation, etc.), it differs from these theories by explicitly modeling the dynamic network interaction.[8]

[5] There is however recent empirical evidence that jobs obtained through networks of personal contacts are not always better than those obtained through formal means. Using US and European data Bentolila, Michelacci and Suarez (2004) find that the use of social contacts, although helping in finding a job faster, can generate mismatches between a worker's occupational choice and his comparative productive advantage, leading to individual wage discounts of 5 to 7 percent. Pellizarri (2004) using European data finds that wage penalties and wage premiums of jobs obtained through contacts relative to jobs obtained formally are equally frequent across countries and industries.

[6] Intuitively the inbreeding bias by gender is likely to be smaller than inbreeding biases by social groups differentiated along race or ethnicity, given the possible close-knit relationships between men and women.

[7] A different literature stream looks at penalties associated with acting differently than according to the "behavioral prescriptions" of different social groups. Such studies investigating the (often negative) peer-pressure effect in one's social group are for instance the recent ones on "acting white" by Austen-Smith and Fryer (2005) and Fryer (2006). This theory can be seen as an alternative to the intragroup inbreeding bias hypothesis we use in here. For this chapter what matters is that a member of a certain social group is more likely to link ties with members of the same group and that this likelihood is not endogenously determined.

[8] The precursor of many such studies is the work by Schelling (1971) on emergence of segregated communities starting from a mild preference of individuals to be in an ethnic majority in their communities. In fact Schelling's model starts from similar assumptions as the ones we use here: two social groups, a stated mild preference in terms of neighbors (this is somewhat analogous to our inbreeding bias). The whole context and the dynamic modeling are however very much different.

5.3 A model of occupational segregation

Consider the following model. A continuum of $2N$ workers is equally divided into two social groups, reds (R) and greens (G). They can work in two occupations, A or B. Both occupations require a thorough specialized education (training), hence a worker cannot work in an occupation if she is not qualified to do so by having followed one of the educational tracks corresponding to each of the two occupations. Therefore workers have to choose their education before they enter the labor market, in other words they have to make a decision regarding one of their two available career choices.

We consider the following timing:

1. Workers choose one education in order to specialize either in occupation A or in occupation B;

2. Workers randomly establish "friendship" relationships, thus forming a network of contacts;

3. Workers participate in the labor market and if they have a job they earn a wage w_A or w_B, respectively.

The choice of education in the first stage involves strategic behavior and we therefore look for a Nash equilibrium in this stage. The expected payoff of a worker's educational choice given the choices of other workers is determined by the network formation process in the second stage and by the employment process in the third stage. We now make these two other stages more specific.

In the second stage the workers form a network of contacts. We assume this network to be random with an inbreeding bias (also known in the literature as assortative mixing). That is, we assume that the probability for two workers to create a tie is p when the two workers are from different social groups; however when two workers are from the same social group, the probability of creating a tie is λp with $\lambda > 1$. We will refer to two workers that created a tie as "friends".[9]

The third stage we envision is that of a dynamic labor process a la Calvó-Armengol and Jackson (2004) or Bramoullé and Saint-Paul (2006), in which employed workers randomly lose their jobs while unemployed workers search for jobs. Unemployed workers receive job information either directly, or indirectly from their friends. The details of such a process are unimportant for our purposes. However, what is important is that we assume that unemployed workers have a higher propensity to receive job information when they have more friends with the *same* job background, that is, with the same choice of education. By this we implicitly assume that everybody has the same chance on the formal labor market, or in other words, that direct job search intensity is exogenously given for everybody. Since the details of the labor market process are not relevant, we ignore the precise dynamics and we simply assume that the probability that one is employed increases in the number

[9] We do not consider in our model the complication that individuals of one social group might have a higher probability of making contacts than members of the other group. There is evidence that men have a better access to contact networks than women, see for instance the introductory discussion in Petersen, Saporta and Seidel (2000) and the references therein.

of friends with the same education. Denote η_i^A as the number of friends of individual i that are A-educated, and denote η_i^B similarly for the number of friends of i that are B-educated. Further denote the probability that i becomes employed as s_i. Then $s_i = s(\eta_i^A)$ if i is A-educated and $s_i = s(\eta_i^B)$ if i is B-educated. We assume that $s(0) = s_0 > 0$ and $s'(x) > 0$ for all $x > 0$.

The eventual payoff of the workers depends on the employment status in each period and on the wage they receive. We assume that the wage rate decreases in the number of workers that choose a particular type of education. The assumption of a decreasing wage when the total number of employed workers increases can be explained with a simple classical model of a 2-goods economy with Cobb-Douglas utility functions, and a linear production function with labor as single input. Intuitively, when more workers are educated as A, more workers are employed as A. Thus the economy produces more A-products, which have to find their way to the consumer market. As the market price drops whenever production output increases, it follows that, in a competitive product and labor market, wages drop as well. Thus wages of A (B)-jobs are negatively related with the number of workers that choose an A (B)-education.

The assumption is formalized as follows.

Assumption 5.1. *Let n_A be the total number of workers that are educated as A and let n_B be defined analogously. Define $\phi_A = n_A/2N$ and $\phi_B = n_B/2N$ as the proportion of workers A or respectively B-educated. Then the wage of an A-job, $w_A(\phi_A)$, (and a B-job, $w_B(\phi_B)$) is decreasing in ϕ_A (or ϕ_B), and $\forall x: \ w_A(x) = w_B(x)$. Further, w_A and w_B are continuous and*

$$\lim_{\phi_A \downarrow 0} w_A(\phi_A) = \lim_{\phi_B \downarrow 0} w_B(\phi_B) = \infty.$$

Note that we initially assume that wages for A and B jobs are equal if there are as many A-educated workers as B-educated workers. In Section 5.5 we relax this assumption.

We can now define the payoff of a worker. First, define μ_R and μ_G as the fraction of workers in R (G) that choose education A. Next, denote $S(x, y)$ as the expected employment probability of i, when a fraction x of i's own social group has the same education as i and a fraction y of the other social group has the same education as i. That is,

$$S(x, y) = \sum_{k=0}^{\infty} s(k) f(k|x, y),$$

where $f(k|x, y)$ is the probability that a worker i has k friends of the same education, given that a fraction x of i's social group and a fraction y of the other social group choose the same education as i.

Then the payoff function of a worker i who is from group R and A-educated is

$$\Pi_i^R(A; \mu_R, \mu_G) = w_A\left(\frac{\mu_R + \mu_G}{2}\right) S(\mu_R, \mu_G). \tag{5.1}$$

Similarly,

$$\Pi_i^R(B; \mu_R, \mu_G) = w_B\left(1 - \frac{\mu_R + \mu_G}{2}\right) S(1 - \mu_R, 1 - \mu_G). \tag{5.2}$$

$$\Pi_i^G(A;\mu_R,\mu_G) = w_A\left(\frac{\mu_R+\mu_G}{2}\right)S(\mu_G,\mu_R). \tag{5.3}$$

$$\Pi_i^G(B;\mu_R,\mu_G) = w_B\left(1-\frac{\mu_R+\mu_G}{2}\right)S(1-\mu_G,1-\mu_R). \tag{5.4}$$

We note that if there is an inbreeding bias in the social network ($\lambda > 1$) and $s'(\eta) > 0$ for $\eta > 0$, then for all $x > y$

$$S(x,y) > S(y,x),$$

since a worker is more likely to form a friendship relation with a worker from its own group, than with a worker from the other group.

5.3.1 Equilibrium

We would like to characterize the Nash equilibria in the model above. We are, in particular, interested in those equilibria in which there is segregation. We define segregation as follows:

Definition 5.1. *Let μ_X, $X \in \{R,G\}$ be the fraction of workers in social group X that choose education A. There is* complete segregation *if $\mu_R = 0$ and $\mu_G = 1$, or, vice versa, $\mu_R = 1$ and $\mu_G = 0$. There is* partial segregation *if for $X \in \{R,G\}$ and $Y \in \{R,G\}$, $Y \neq X$: $\mu_X = 0$ but $\mu_Y < 1$, or, vice versa, $\mu_X = 1$ but $\mu_Y > 0$.*

In a Nash equilibrium each worker chooses the education that gives the highest payoff given the education choices of all other workers. Since workers of the same group are homogenous, a Nash equilibrium implies that if *some* worker in a group chooses education A (B), then no other worker in the same group should prefer education B (A). With this idea in mind we reformulate the equilibrium concept in a way that turns out to be useful.

Definition 5.2. *Let μ_X, $X \in \{R,G\}$ be the fraction of workers in social group X that choose education A. A pair (μ_R,μ_G) is an* equilibrium *if and only if, for $X \in \{R,G\}$, the following hold*

$$\Pi_i^X(A;\mu_R,\mu_G) \leq \Pi_i^X(B;\mu_R,\mu_G) \text{ if } \mu_X = 0 \tag{5.5}$$
$$\Pi_i^X(A;\mu_R,\mu_G) = \Pi_i^X(B;\mu_R,\mu_G) \text{ if } 0 < \mu_X < 1 \tag{5.6}$$
$$\Pi_i^X(A;\mu_R,\mu_G) \geq \Pi_i^X(B;\mu_R,\mu_G) \text{ if } \mu_X = 1 \tag{5.7}$$

In our initial analysis we often find multiple equilibria. However, some of these equilibria are not dynamically stable. We therefore use a simple stability concept based on a standard myopic adjustment process of strategies. That is, we think of the equilibrium as the outcome of an adjustment process in which more and more workers revise their education choice if it is profitable to do so given the choice of the other workers. To be concrete, we consider stationary points of a dynamic system in which

$$\frac{d\mu_X}{dt} = k\left(\Pi_i^X(A;\mu_R(t),\mu_G(t)) - \Pi_i^X(B;\mu_R(t),\mu_G(t))\right).$$

The stability properties of stationary points in such dynamic systems are well-known, see e.g. Chiang (1984, p.641-645). We base our definition on these properties, taking into account that the process might converge to a segregation equilibrium, thus to the boundaries of the solution space.

Definition 5.3. *Let (μ_R^*, μ_G^*) be an equilibrium and define*

$$G = \begin{bmatrix} \frac{\partial(\Pi_i^R(A;\mu_R^*,\mu_G^*)-\Pi_i^R(B;\mu_R^*,\mu_G^*))}{\partial\mu_R} & \frac{\partial(\Pi_i^R(A;\mu_R^*,\mu_G^*)-\Pi_i^R(B;\mu_R^*,\mu_G^*))}{\partial\mu_G} \\ \\ \frac{\partial(\Pi_i^G(A;\mu_R^*,\mu_G^*)-\Pi_i^G(B;\mu_R^*,\mu_G^*))}{\partial\mu_R} & \frac{\partial(\Pi_i^G(A;\mu_R^*,\mu_G^*)-\Pi_i^G(B;\mu_R^*,\mu_G^*))}{\partial\mu_G}. \end{bmatrix} \tag{5.8}$$

The equilibrium is stable under the following conditions for $X, Y \in \{R, G\}$, $X \neq Y$;

(i) if $\mu_X^* = 0$, then $\Pi_i^X(A;\mu_R^*,\mu_G^*) < \Pi_i^X(B;\mu_R^*,\mu_G^*)$;

(ii) if $\mu_X^* = 1$, then $\Pi_i^X(A;\mu_R^*,\mu_G^*) > \Pi_i^X(B;\mu_R^*,\mu_G^*)$;

(iii) if $\mu_X^* = 0$ or 1, and $\mu_Y^* \in (0,1)$, then

$$\frac{\partial(\Pi_i^Y(A;\mu_R^*,\mu_G^*) - \Pi_i^Y(B;\mu_R^*,\mu_G^*))}{\partial\mu_Y} < 0;$$

(iv) if $\mu_R^* \in (0,1)$ and $\mu_G^* \in (0,1)$, then

$$\textit{trace}(G) < 0 \textit{ and } \textit{det}(G) > 0.$$

The equilibrium is weakly stable *if the above conditions only hold with weak inequality signs.*

Conditions (i), (ii) and (iii) are applied to segregation equilibria, while condition (iv) is applied to non-segregation equilibria. If an equilibrium is stable, then the dynamic system converges back to the equilibrium after any small perturbation. This is not necessarily true for a weakly stable equilibrium.

5.4 Occupational segregation

We next characterize equilibria for three cases. In the benchmark case network effects are nonexistent. In the second case network effects are important, but there is no inbreeding bias in the social network, that is, $\lambda = 1$. In the third case, we consider the full model including network effects and an inbreeding bias.

5.4.1 A market without network effects

We first consider a labor market in which the probability to get a job does not depend on a worker's social network. That is $s(\eta) = s_0$. We obtain a standard result

Proposition 5.1. *Suppose $s(\eta) = s_0 \in (0,1]$. (μ_R^*, μ_G^*) is a weakly stable equilibrium if and only if*

$$w_A\left(\frac{\mu_R^* + \mu_G^*}{2}\right) = w_B\left(1 - \frac{\mu_R^* + \mu_G^*}{2}\right). \tag{5.9}$$

Proof. If $s(\eta) = s_0$, then equation (5.9) is equivalent to

$$\Pi_i^X(A; \mu_R^*, \mu_G^*) = \Pi_i^X(B; \mu_R^*, \mu_G^*)$$

for $X \in \{R, G\}$. Clearly, if (5.9) holds then (μ_R^*, μ_G^*) is an equilibrium.

Further, since $w_A(x)$ and $w_B(x)$ are decreasing in x, it is easy to see that

$$\frac{\partial(\Pi_i^X(A;\cdot) - \Pi_i^X(B;\cdot))}{\partial \mu_X} = \frac{\partial(\Pi_i^X(A;\cdot) - \Pi_i^X(B;\cdot))}{\partial \mu_Y} = \frac{s_0}{2}(w_A'(\cdot) + w_B'(\cdot)) < 0$$

for $X, Y \in \{R, G\}$, $X \neq Y$. This implies that for G defined as (5.8) we have trace$(G) < 0$ and $\det(G) = 0$. Hence, all conditions for *weak* stability are satisfied.

Moreover any (μ_R', μ_G') for which $w_A > w_B$ cannot be equilibria since then

$$\Pi_i^X(A; \mu_R', \mu_G') > \Pi_i^X(B; \mu_R', \mu_G').$$

This would only be consistent with an equilibrium if all workers chose A as education, that is $\mu_R = \mu_G = 1$. However, in Assumption 5.1 we have assumed that $w_B \to \infty$ if $(\mu_R + \mu_G)/2 \to 1$. Hence, if $(\mu_R + \mu_G)/2 = 1$, then $w_A < w_B$, and we have a contradiction.

Similarly in an equilibrium it is not possible that $w_A(\cdot) < w_B(\cdot)$. □

This proposition simply restates the classical view that the price of labor, wage, is equal to the value of the marginal product of labor. Since workers are homogenous with respect to their productivity, everyone earns the same wage and occupational segregation or social inequality does not arise.[10] Note that Proposition 5.1 does not give a unique equilibrium, but a (convex) set of equilibria (μ_R^*, μ_G^*) for which $w_A(\cdot) = w_B(\cdot)$. This is also the reason why each equilibrium is only *weakly* stable. After a small perturbation to an equilibrium, a best response dynamic process as the one described above converges back to the set for which $w_A = w_B$. However, the process does not converge to the 'starting' equilibrium that was originally perturbed. Thus the equilibria cannot be strongly stable.

5.4.2 A labor market with network effects, but without inbreeding in the social network

We further assume that having a social network is important to get a job. However, if we do not introduce an inbreeding bias in the network of friendship relations, the result of Proposition 5.1 hardly changes. That is, all workers receive the same payoff.

Proposition 5.2. *Suppose $s'(\eta) > 0$, but $\lambda = 1$. Then (μ_R^*, μ_G^*) is a weakly stable equilibrium if and only if*

$$w_A\left(\frac{\mu_R^* + \mu_G^*}{2}\right) S(\mu_R^*, \mu_G^*) = w_B\left(1 - \frac{\mu_R^* + \mu_G^*}{2}\right) S(1 - \mu_R^*, 1 - \mu_G^*). \tag{5.10}$$

[10] Since all workers are indifferent between education A or B, a segregation equilibrium does exist. However, this equilibrium would be excluded if workers in the same social group are slightly heterogeneous with respect to their education preferences or their productivity.

We omit the proof as it is similar to that of Proposition 5.1.

If we compare Propositions 5.1 and 5.2, we notice that the network effects allow for a difference in the probability to become employed. This also implies that in the equilibrium there might be a wage difference between A and B-workers. Thus, while the wage of A-workers might be lower than that of B-workers, this is compensated by a higher probability of getting a job for A-educated workers.

While there might be wage differences between A and B-workers, segregation by occupation is not a likely outcome if there is no inbreeding bias in the social network. Although there exists a weakly stable equilibrium with segregation, this equilibrium would be ruled out if we would introduce a small amount of heterogeneity in the worker's education preferences or in their productivity.

Perhaps it is slightly surprising that the network effects do not directly result in segregation. One has to remember that if there is no inbreeding bias in the social network these network effects, as well as the wages, are group-independent. Thus the value of an A-education or B-education only depends on the total number of other workers that choose education A or B, not on the number of workers choosing A or B in each group. It should then be clear that there is no reason to expect segregation as the group identity does not matter in making an education choice.

5.4.3 A labor market with network effects and a social network with inbreeding

We now consider the unrestricted version of our labor market model. Our first observation is that the equilibrium changes drastically, even with a small amount of inbreeding bias.

Proposition 5.3. *Suppose $s'(\eta) > 0$ and $\lambda > 1$. A weakly stable equilibrium (μ_R^*, μ_G^*), in which $0 < \mu_R^* < 1$ and $0 < \mu_G^* < 1$, does not exist.*

Proof. Suppose (μ_R^*, μ_G^*) is a stable equilibrium, and $\mu_R^* \in (0,1)$ and $\mu_G^* \in (0,1)$. By condition (5.6)

$$\Pi_i^R(A; \mu_R^*, \mu_G^*) = \Pi_i^R(B; \mu_R^*, \mu_G^*) \text{ and } \Pi_i^G(A; \mu_R^*, \mu_G^*) = \Pi_i^G(B; \mu_R^*, \mu_G^*) \tag{5.11}$$

Substituting (5.1)-(5.4) into (5.11) and rewriting these equations become

$$\frac{w_A(\frac{\mu_R^*+\mu_G^*}{2})}{w_B(1-\frac{\mu_R^*+\mu_G^*}{2})} = \frac{S(1-\mu_R^*, 1-\mu_G^*)}{S(\mu_R^*, \mu_G^*)} = \frac{S(1-\mu_G^*, 1-\mu_R^*)}{S(\mu_G^*, \mu_R^*)}. \tag{5.12}$$

Since $\lambda > 1$, $x > y$ implies $S(x,y) > S(y,x)$. But this means that if $\mu_R^* > \mu_G^*$, then

$$\frac{S(1-\mu_R^*, 1-\mu_G^*)}{S(\mu_R^*, \mu_G^*)} < \frac{S(1-\mu_G^*, 1-\mu_R^*)}{S(\mu_G^*, \mu_R^*)},$$

which contradicts (5.12). The same reasoning holds for $\mu_R^* < \mu_G^*$. Hence, it must be that $\mu_R^* = \mu_G^*$.

However (μ_R^*, μ_G^*) with $\mu_R^* = \mu_G^*$ cannot be a weakly stable equilibrium. To see this, suppose that (μ^*, μ^*) with $\mu^* \in (0,1)$ is a weakly stable equilibrium. Hence $\Pi_i^X(A; \mu^*, \mu^*) =$

$\Pi_i^X(B;\mu^*,\mu^*)$ for $X \in \{R,G\}$ and $\mathrm{trace}(G) \leq 0$ and $\det(G) \geq 0$, where G is defined in (5.8). Now for $X \in \{R,G\}$

$$\begin{aligned}\frac{\partial(\Pi_i^X(A;\cdot)-\Pi_i^X(B;\cdot))}{\partial\mu_X} &= \frac{1}{2}w_A'(\mu^*)S(\mu^*,\mu^*)+w_A(\mu^*)S_1(\mu^*,\mu^*)\\ &+\frac{1}{2}w_B'(\mu^*)S(1-\mu^*,1-\mu^*)+w_B(1-\mu^*)S_1(1-\mu^*,1-\mu^*),\end{aligned}$$

where $S_j(\mu,\mu) = \frac{\partial S(x_1,x_2)}{\partial x_i j}\Big|_{x_1=\mu,x_2=\mu}$ for $j=1,2$. The cross effect is

$$\begin{aligned}\frac{\partial(\Pi_i^X(A;\cdot)-\Pi_i^X(B;\cdot))}{\partial\mu_Y} &= \frac{1}{2}w_A'(\mu^*)S(\mu^*,\mu^*)+w_A(\mu^*)S_2(\mu^*,\mu^*)\\ &+\frac{1}{2}w_B'(\mu^*)S(1-\mu^*,1-\mu^*)+w_B(1-\mu^*)S_2(1-\mu^*,1-\mu^*),\end{aligned}$$

for $Y \in \{R,G\}$, $Y \neq X$.

Since $\lambda > 1$, it must be that $S_1(\mu,\mu) > S_2(\mu,\mu)$ for all $\mu \in (0,1)$. Therefore,

$$\frac{\partial(\Pi_i^X(A;\cdot)-\Pi_i^X(B;\cdot))}{\partial\mu_X} > \frac{\partial(\Pi_i^X(A;\cdot)-\Pi_i^X(B;\cdot))}{\partial\mu_Y}$$

for $X,Y \in \{R,G\}$, $X \neq Y$.

Because $\mathrm{trace}(G) \leq 0$, it must be that

$$\frac{\partial(\Pi_i^X(A;\cdot)-\Pi_i^X(B;\cdot))}{\partial\mu_Y} < \frac{\partial(\Pi_i^X(A;\cdot)-\Pi_i^X(B;\cdot))}{\partial\mu_X} \leq 0.$$

But then it is easy to see that $\det(G) < 0$. This contradicts weak stability. □

This proposition shows that even with a small inbreeding bias, segregation by occupation is a natural outcome. At least one social group specializes fully in one type of occupation. The intuition is that an inbreeding bias in the social network creates a group-dependent network effect. Thus if in group R slightly more workers choose A than in group G, then the value of an A-education is higher in group R than in group G, while the value of a B-education is lower in group R. Positive feedback then ensures that the initially small differences in education choices between the two groups widen and widen until at least one group segregates into one type of education.

While we have shown that in a labor market model with network effects and inbreeding bias segregation is a natural outcome, the question remains what the segregation equilibria look like and whether there can be sustained wage differences between groups. Depending on the functional form of $w_A(\cdot)$ and $w_B(\cdot)$ and $s(\cdot)$, there could be many equilibria. However, *complete* segregation is the most prominent outcome.

Proposition 5.4. *Suppose $s'(\eta) > 0$ and $\lambda > 1$. Then*

(i) $(\mu_R,\mu_G) = (1,0)$ and $(\mu_R,\mu_G) = (0,1)$ are stable equilibria.

(ii) if for all $x \in [0,1]$

$$\frac{w_A(x/2)}{w_B(1-x/2)} > \frac{S(1-x,1)}{S(x,0)}, \tag{5.13}$$

and

$$\frac{w_A((1+x)/2)}{w_B((1-x)/2)} < \frac{S(1-x,0)}{S(x,1)}, \tag{5.14}$$

then $(\mu_R, \mu_G) = (1,0)$ and $(\mu_R, \mu_G) = (0,1)$ are the only two stable equilibria.

Proof. (i) We have

$$\Pi_i^R(A;1,0) = w_A(1/2)S(1,0) > w_B(1/2)S(0,1) = \Pi_i^R(B;1,0)$$

and

$$\Pi_i^G(A;1,0) = w_A(1/2)S(0,1) < w_B(1/2)S(1,0) = \Pi_i^G(B;1,0)$$

for $(\mu_R, \mu_G) = (1,0)$. This is clearly a stable equilibrium. The same is true for $(\mu_R, \mu_G) = (0,1)$.

(ii) We only have to show that there are no other stable equilibria. From Proposition 5.3 we already know that (μ_R, μ_G) with $0 < \mu_R < 1$ and $0 < \mu_G < 1$ cannot be a stable equilibrium. So consider $\mu_R = 0$. If $\mu_G < 1$, then (μ_R, μ_G) can be an equilibrium only if $\Pi^G(A;0,\mu_G) \leq \Pi^G(B;0,\mu_G)$. However, this is excluded by condition (5.13). Similarly, if $\mu_R = 1$, then $\mu_G > 0$ is excluded as an equilibrium by condition (5.14). □

Part (i) shows that complete segregation is always an equilibrium outcome. That is, one social group specializes in one occupation, and the other group in the other occupation. Part (ii) establishes sufficient conditions for uniqueness of a fully segregated equilibrium. To understand these conditions, note that if all workers would choose A as education, $(\mu_R, \mu_G) = (1,1)$, then everyone has an incentive to choose education B, as the wage of B-jobs is infinitely higher. The conditions (5.13) and (5.14) then say that if all green workers would choose A, then the red workers *always* have an incentive to choose education B, either because the wage of B-jobs is in equilibrium higher than that of A-jobs, or the prospects of finding a B-job are much higher due to the social network effects.

5.5 Social inequality

The discussion above ignores differences in wages and unemployment. In fact, since we have assumed that A and B jobs are equally attractive, it is easily seen that under complete segregation there is no wage and unemployment inequality. However, not only is this in sharp contrast to observed gender and race gaps in wages and unemployment, it is also not obvious how our result of complete segregation can be sustained when there are large wage-induced incentives. That is: why would someone stick to the education choice of her social group when the wage benefits of choosing the other education are very large? This motivates us to extend our framework in order to look at the robustness of our results under wage and employment inequality. We do this by making the following assumption on the wage function

Assumption 5.2. *For every $x \in (0,1)$, $w_A(x) > w_B(x)$.*

Thus if there are as many A-educated workers as B-educated workers, then the A-educated workers earn a higher wage. The implicit assumption behind Assumption 5.2 is that the marginal utility consumers derive from product A is larger than the marginal utility from product B. This is a natural assumption as there is no reason to expect that different products are equally liked.

We derive results on wage and unemployment inequality under Assumption 5.2. Our first observation is that the proof of Proposition 5.3 does not depend on the fact that $w_A(x) = w_B(x)$ for every x. Hence, this proposition also holds under Assumption 5.2.

Proposition 5.5. *Suppose $s'(\eta) > 0$, $\lambda > 1$ and Assumption 5.2 holds. A weakly stable equilibrium (μ_R^*, μ_G^*), in which $0 < \mu_R^* < 1$ and $0 < \mu_G^* < 1$, does not exist.*

We next characterize the segregation equilibria. We consider two cases; either the difference between A and B-jobs is relatively small compared to the social network effect, or the difference is relatively large. We first consider the case in which the job difference is relatively small. In this case, *complete* segregation is the most prominent outcome.

Proposition 5.6. *Suppose $s'(\eta) > 0$, $\lambda > 1$, Assumption 5.2 holds and*

$$\frac{w_A(1/2)}{w_B(1/2)} < \frac{S(1,0)}{S(0,1)}. \tag{5.15}$$

Then $(\mu_R, \mu_G) = (1,0)$ and $(\mu_R, \mu_G) = (0,1)$ are stable equilibria. In these equilibria,

$$w_A(\cdot) > w_B(\cdot),$$

and, if $\mu_X = 1$ and $\mu_Y = 0$ for $X, Y \in \{R, G\}$, $X \neq Y$, then

$$\Pi_i^X(A;\cdot) > \Pi_i^Y(B;\cdot) > \Pi_i^Y(A;\cdot) > \Pi_i^X(B;\cdot). \tag{5.16}$$

Proof. If (5.15) holds, then

$$\Pi_i^R(A;1,0) > \Pi_i^R(B;1,0) \text{ and } \Pi_i^G(A;1,0) < \Pi_i^G(B;1,0)$$

for $(\mu_R, \mu_G) = (1,0)$. This is clearly a stable equilibrium. Further, as $(\mu_R + \mu_G)/2 = 1 - (\mu_R + \mu_G)/2 = 1/2$, it holds that $w_A > w_B$. Finally

$$S(1,0)w_A(1/2) > S(1,0)w_B(1/2) > S(0,1)w_A(1/2) > S(0,1)w_B(1/2),$$

and this is equivalent to (5.16).

The same is true for $(\mu_R, \mu_G) = (0,1)$. □

This proposition states that if the difference in wages is not too large, complete segregation is always an equilibrium outcome. Thus one social group specializes in one occupation, and the other group in the other occupation. Since the social groups are of equal size, the employment probabilities in the two social groups are the same. However, since the wage of A is higher in the equilibrium, the social group that specializes in occupation A obtains a higher payoff than the other group. Hence, social inequality is a natural outcome of this model.

Interestingly, if some workers make mistakes in their education choice, then the workers that are the worst off are from the same social group as the workers that are the best off. Thus, if $\mu_R = 1$ and $\mu_G = 0$, then the red workers that choose A receive the highest wage and have the best employment probabilities. However, if some of the red workers choose B by mistake, then these red B-worker are the most disadvantaged, as they earn the lowest wage and have the lowest employment chances.

We turn next to the case in which wage differentials are large. We have the following proposition.

Proposition 5.7. *Suppose $s'(\eta) > 0$, $\lambda > 1$, Assumption 5.2 holds and*

$$\frac{w_A(1/2)}{w_B(1/2)} > \frac{S(1,0)}{S(0,1)}. \tag{5.17}$$

(i) There is no equilibrium with complete segregation.

(ii) There are at least two stable equilibria with partial segregation, in which either $\mu_R = 1$ or $\mu_G = 1$. If $\mu_X = 1$ for $X \in \{R, G\}$, then for $Y \in \{R, G\}$, $Y \neq X$

$$\Pi_i^X(A;\cdot) > \Pi_i^Y(B;\cdot) = \Pi_i^Y(A;\cdot) > \Pi_i^X(B;\cdot). \tag{5.18}$$

Proof. (i) If (5.17) is true, then for $(\mu_R, \mu_G) = (1, 0)$

$$\Pi_i^G(A;1,0) > \Pi_i^G(B;1,0). \tag{5.19}$$

Thus G-workers would like to deviate by choosing education A, and therefore $(\mu_R, \mu_G) = (1, 0)$ cannot be an equilibrium. The same holds for $(\mu_R, \mu_G) = (0, 1)$.

(ii) As $\Pi_i^X(\cdot)$ is continuous in μ_G, it follows from equation (5.19) and Assumption 5.1 that there must be a μ^*, such that

$$\Pi_i^G(A;1,\mu^*) = \Pi_i^G(B;1,\mu^*),$$

and

$$\frac{\partial(\Pi_i^G(A;1,\mu^*) - \Pi_i^G(B;1,\mu^*))}{\partial \mu_G} < 0.$$

Moreover, $S(1,\mu^*) > S(\mu^*,1)$ and $S(1-\mu^*,0) > S(0,1-\mu^*)$, so we have

$$S(1,\mu^*)w_A(\cdot) > S(\mu^*,1)w_A(\cdot) = S(1-\mu^*,0)w_B(\cdot) > S(0,1-\mu^*)w_B(\cdot),$$

and this is equivalent to (5.18) for $X = R$ and $Y = G$. As

$$\Pi_i^R(A;1,\mu^*) > \Pi_i^R(B;1,\mu^*),$$

it is also clear that $(\mu_R, \mu_G) = (1, \mu^*)$ is a stable equilibrium. The same is true for $(\mu_R, \mu_G) = (\mu^*, 1)$. □

The proposition makes clear that complete segregation cannot be sustained if the wage differential is too large. Starting from complete segregation, a large wage differential gives incentives to the group specialized in B-jobs to switch to A-jobs. Interestingly, the unsustainable complete segregation equilibrium is then replaced by a partial equilibrium in which one group specializes in job A, while the other group has both A and B-workers. As in the previous case of small wage differentials, the workers of the group specializing in A-jobs receive the highest payoffs, hence we have again a social inequality outcome. However in this case the wages of A-workers in the equilibrium are not necessarily higher than that of B-workers. It is the higher employment rate of the group specializing in A that makes the difference. The employment rate of the group specializing in A-jobs is given by $S(1,x)$ where x is the fraction of A workers in the group that does not specialize. On the other hand the employment rate of the group that does not specialize is $xS(x,1)+(1-x)S(x,0)$. Thus the group that specializes in the A-job has a lower unemployment rate than the other group.

5.6 Summary and conclusions

We have investigated in this chapter a simple social network framework where jobs are obtained through a network of contacts formed stochastically. We have shown that even with a very small amount of inbreeding bias within each social group, dynamically stable occupational segregation equilibria will arise. If the wage differential across the occupations is not too large, complete segregation will always be sustainable. If the wage differential is large, complete segregation cannot be sustained, but a partial segregation equilibrium in which one of the group fully specializes in one type of educations while the other group mixes, is sustainable. Furthermore, this model is able to explain sustained wage and unemployment differences between the social groups.

While our oversimplified model is able to describe patterns of occupational segregation and inequality, we neither claim nor think that our explanation should be seen in isolation as the ideal candidate to explain occupational segregation and inequality. Other factors are very likely (and documented) to be relevant. What is important is to consider our model as complementary to other frameworks and as possibly accounting for part of the persistent occupational segregation observed in practice. To this end it is of course important to empirically document in future research how relevant are the mechanisms described in this chapter. Another avenue for future research is to extend the framework to other very relevant issues, such as the position of minority vs. majority groups, by looking at the interaction in this context of social groups of different sizes.

Part III

Transport networks

Chapter 6

Competing transport networks

6.1 Introduction

In many countries privatization and deregulation of transport industries raises a lot of opposition. One of the greatest fears is that a privatized transport firm would change its network structure, that is, the location of their stations and the connections between cities, such that some cities would be deprived of a good connection to other cities. Indeed the events after the deregulation of the U.S. airline industry in 1978 have shown that this is not unlikely. Since 1978 almost all airline carriers have transformed their U.S. networks into hub-and-spoke networks. As a result, most airline passengers can not reach their destination directly. Moreover, the hub-and-spoke network structure has raised concerns on market dominance at hub airports.[1]

Although the emergence of hub-and-spoke networks has been analyzed extensively, the airline literature typically ignores the presence of competing transport modes. This approach is reasonable in the case of the U.S. airline industry, as the distance between cities in the U.S. is large and the railway industry in the U.S. does not offer a feasible alternative to airline travel. However, in Europe and Japan the situation is different due to the availability of a network of high-speed train connections. Furthermore, competition from other transport modes is even more important in other transport industries. For example, railway transport has always faced fierce competition from transport by car, since the speed of a train and a car is comparable. In urban areas, underground transport faces competition from bus and tram services. One should note that these competing transport networks differ in speed and accessibility. Typically the faster transport mode is less accessible than the slower transport mode. With the current wave of deregulation in other transport industries than the airline industry, it is necessary to understand network design

[0]This chapter is based on Van der Leij (2003).

[1]A hub-and-spoke network is a network in which one airport, the hub, has direct connections to all other airports, while all other airports, the spoke airports, are only connected to the hub airport. Hendricks, Piccione and Tan (1995) show that under economies of density either the empty network, the hub-and-spoke network or the point-to-point network is optimal. Hendricks, Piccione and Tan (1997) show that a hub-and-spoke network may prevent entry into a hub-to-spoke market. Borenstein (1989) shows that route and airport dominance enable carriers to raise prices.

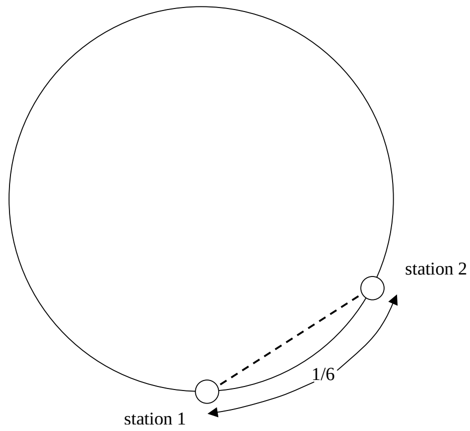


Figure 6.1: A fast transport network in the circular city where the distance between the stations is 1/6 of the circle.

decisions in case a transport network operator faces competition from other transport services.

In this chapter we therefore introduce a model to analyze these issues. The model is simple but reasonable, and it provides interesting results and intuition for the role of competing transport networks in network design. Individuals live and work at random locations on a circular city and they need to travel between their home and work. Each combination of home location and work place, therefore, constitutes a trip, having an origin and a destination. An individual can make a trip by a slow transport mode *around* the circle, either clockwise or counterclockwise. Alternatively he or she can use the fast transport system to *cross* the circle. It is crucial that slow mode transport is necessary to access the fast transport network. Hence, a trip by fast mode consists of three complementary journeys; a trip by slow mode from home to the departure station, a trip by fast mode from station to station, and finally a trip by slow mode from the terminating station to the work place. In this model we first derive demand for the fast transport connection. For that purpose we derive the size of the market area for the fast connection, which we define as the set of trips for which a fast transport connection is preferred. This definition differs from the usual interpretation of a market area as being a region around a station.

Next, we derive the main result of the chapter. We consider location and pricing decision in case the fast transport connection is operated by a profit-maximizing firm. Contrary to intuition, we show that the stations of the fast connection are not located on opposite sides of the circle but somewhat closer. Hence, the monopolist typically clusters the stations. This tendency of clustering becomes stronger if competition from the slow transport mode is stronger. In an extreme case, when there is little difference between the velocity of a fast transport mode and a slow transport mode, the distance between the two stations is only one sixth of the circle (Figure 6.1). On the other hand, in the absence of competition the stations are located symmetrically on the circle. The intuition behind these results is that competition is more severe for trips whose origin and destination is between the two stations, than for trips whose origin and destination is in the hinterland of the two stations. In case the stations are located on opposite sides of the circle, there is no hinterland and competition creeps in from both sides of the circle. Hence, the firm has an incentive to cluster the stations such that it obtains an area where competition is absent.

We also consider the socially optimal locations of the two stations. Again, the stations are not located on opposite sides of the circle. However the distance between the socially optimal locations is larger than the distance between the monopolist's optimal locations, since a social planner is also concerned about the benefit from a trip.

Literature that considers location decisions of transport networks is sparse. The model in this chapter is indeed the first model that introduces competition between transport networks to analyze the impact on location decisions. There is some related literature. Braid (1989) uses the linear city model to find the optimal locations of bridges across a river, where individuals live on one side of the river and work on the other side. Also, Crampton (2000) uses the linear city model to compute optimal urban-rail station spacing. However, in these two papers it is assumed that transportation across a bridge or by train occurs instantaneously without any costs, while in this chapter individuals still face transportation costs and a fare that are increasing in distance when they use a fast transportation connection. This difference is crucial in the analysis of the design of the transport network. There is also some literature that consider the market areas that competing transport firms serve, when the transportation costs between transport modes differ (Hyson and Hyson, 1950). However, in this literature the network structure is given, while in this chapter decisions on the network design are the primary focus of the analysis.

The structure of the chapter is as follows. In Section 6.2, we lay out the model and we derive the demand function for the fast transport connection. In Section 6.3, we assume that the fast transport network is operated by a profit-maximizing firm, and we derive the optimal fare and station locations for the firm. Next, in Section 6.4, we assume that a social planner chooses the location of the two stations and the optimal fare. Finally, in Section 6.5 we conclude.

6.2 The model

In this section we describe the transportation model. Infinitesimal individuals are uniformly distributed with density 1 on a circle $\mathcal{C}$ of unit circumference. All individuals travel to one random destination that is also uniformly distributed on the circle. This destination is independent of the location of the individuals. Together, the set of individual's locations and the set of destinations form the set of trips $\mathcal{T} = \mathcal{C} \times \mathcal{C}$.

To make a trip, an individual can choose between two transport modes, a 'slow' transport mode or a 'fast' transport mode. We assume that the *slow mode* is offered competitively at price 0, and that all individuals can access the slow mode network directly from their location. Furthermore, we assume that the time costs are linear in distance, and that every trip yields a value u to the individual. Hence an individual on a trip $(x, y) \in \mathcal{T}$ obtains a utility of

$$U_S(x, y) = u - g\,|y - x|\,,$$

if he chooses the slow mode. Here $g > 0$ is the time cost of traveling by slow mode, and the distance $|y - x|$ is the shortest arc length between x and y. Note that the longest distance a traveler could make is a trip where the destination is opposite to the starting point. Hence, the utility of a trip is bounded from below by $U_S(x, \frac{1}{2}) = u - g/2$. We assume that u is high enough to persuade all individuals to travel, that is, $u \geq g/2$.

On the other hand, an individual might choose the *fast mode* for her trip. We assume that the fast mode network consists of only one (two-way) connection between two stations, located at z_1 and z_2 on the circle. Hence, only individuals on a trip (z_1, z_2) (or (z_2, z_1) in the opposite direction) can access their destination directly through the fast mode network. All other individuals have to travel by slow mode first to and then from the stations to complete a trip. We therefore assume that the utility of a trip $(x, y) \in \mathcal{T}$ to an individual x traveling to y by fast mode is

$$U_F(x, y; d, p) = u - fd - p - g\,|z_i - x| - g\,|y - z_j|\,,$$

where $i, j \in \{1, 2\}$, $i \neq j$ are chosen such that $|z_i - x| + |y - z_j|$ is minimal. Here $d \equiv |z_2 - z_1|$ is the distance between the two stations, f is the time cost of traveling on the fast mode connection, $0 < f < g$, and $p \geq 0$ is the fare (price) of the fast connection.

In Figure 6.2 we illustrate the transportation costs of the two travel mode options for a trip from x to y, where the upper and lower half of the figure only differ in the destination y. The solid arrow in the two pictures illustrates a trip from x to y by slow mode. The transportation cost of such a trip is $g\,|y - x|$. On the other hand, the three dotted arrows illustrate a trip from x to y by fast mode, which consists of three different journeys with a total cost of $g\,|z_1 - x| + fd + p + g\,|y - z_2|$. Note that for the trip (x, y) in the bottom picture an individual incurs a cost for a journey from z_2 to y both for the fast mode option as for the slow mode option.

6.2.1 Demand

We derive the demand for fast mode transport when prices and station locations are given. The procedure is similar to that in spatial models. However, derivation of the market area is more complicated, because the utility an individual obtains depends both on the location of the individual as on its destination. Hence, for each home location there is a different region of workplaces for which the fast mode is preferred. Moreover, it turns out that the market area is not lying symmetrically around a station. We therefore introduce the following notation. We define a location x to be *between the stations* if x lies on the shortest arc length between z_1 and z_2, such that $|z_2 - x| + |x - z_1| = d$. On the other hand, a location x is *behind the stations* if x lies on the longest arc length between z_1 and z_2, such that $|z_2 - x| + |x - z_1| = 1 - d$. Note that if z_1 and z_2 are on opposite sides of the circle x is both between and behind the stations.

We assume that an individual on a trip $(x, y) \in \mathcal{T}$ prefers the fast mode if and only if

$$U_F(x, y; d, p) \geq U_S(x, y).$$

or equivalently

$$|y - x| - |z_i - x| - |y - z_j| \geq \frac{fd + p}{g}. \tag{6.1}$$

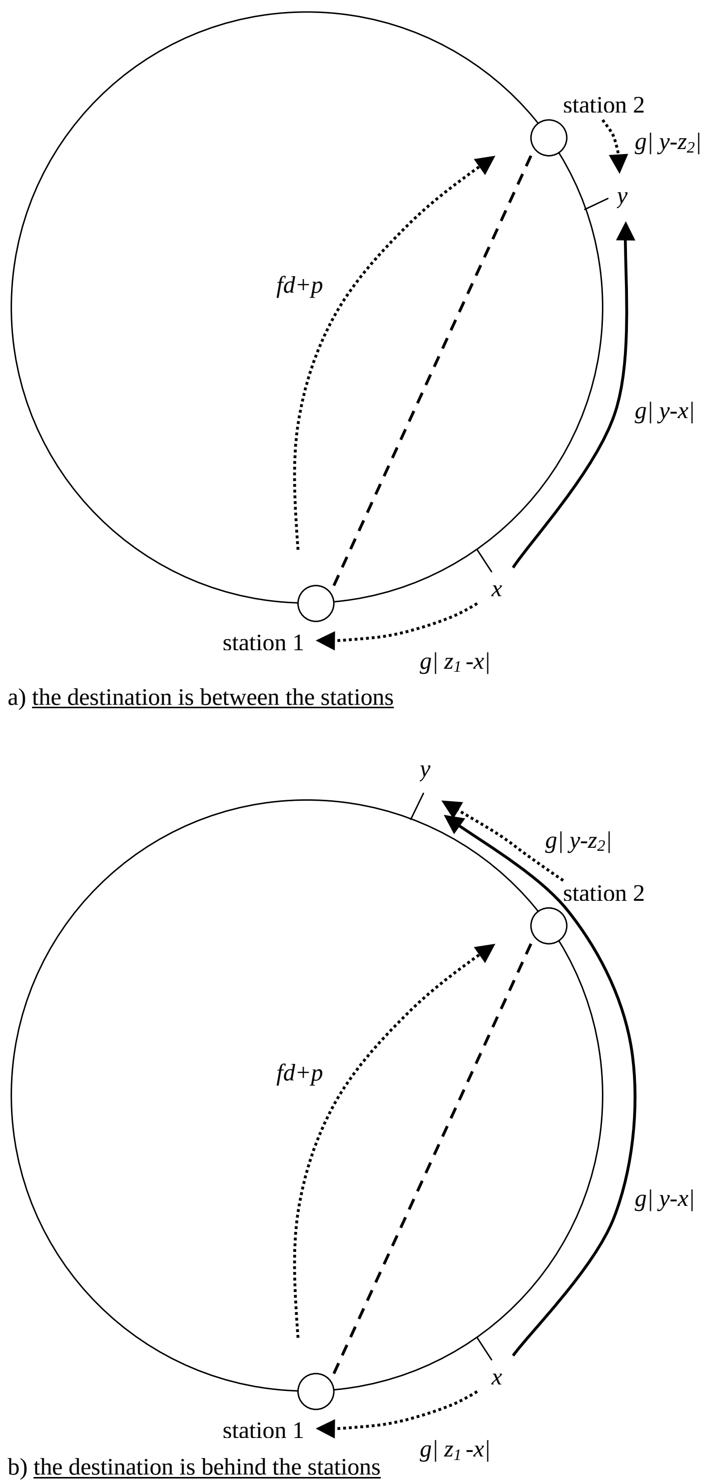


Figure 6.2: Transportation costs in two competing transport networks.

for i, j such that $|z_i - x| + |y - z_j|$ is minimal. It follows that an individual will only choose the fast transport mode if the fast transport connection offers a 'shortcut' to transportation by slow mode, that is, traveling from home to station i and then from station j to the workplace involves a shorter distance than traveling directly from home to work. Note that it immediately follows that the distance of the trip $|y - x|$ can not be too small. Hence, there are always trips where travel by slow mode is preferred.

Let us now consider the market area for the fast mode, which is the set of trips $\mathcal{T}_F \subset \mathcal{T}$ where the fast mode connection is preferred to the slow mode network. This area can be split into four parts. *First* we consider the trips $(x, y) \in \mathcal{T}_F$, where both x and y are located between the stations (Figure 6.2a). Because the stations are chosen such that $|z_i - x| + |y - z_j|$ is minimal, it must hold that $|z_i - x| + |y - x| + |y - z_j| = d$. Substituting into (6.1) and rewriting, it becomes clear that the fast mode is preferred as long as

$$|z_i - x| + |y - z_j| \leq \frac{1}{2g}(gd - fd - p). \tag{6.2}$$

It immediately follows that both $|z_i - x| \leq (gd - fd - p)/2g$ and $|y - z_j| \leq (gd - fd - p)/2g$.

In the *second* case, suppose that x is between the stations but the destination y is behind the stations (Figure 6.2b). Since the distance $|y - x|$ is the length of the shortest path between x and y, it holds that

$$|y - x| = \min\{\ |y - z_i| + |z_i - x|\,,\ \ |y - z_j| + |z_j - x|\ \}.$$

Substituting into (6.1) the decision criterium becomes

$$\begin{aligned} |y - z_i| - |y - z_j| \ &\geq\ \frac{fd + p}{g} \ \text{ and} && (6.3)\\ |x - z_j| - |x - z_i| \ &\geq\ \frac{fd + p}{g}. && (6.4) \end{aligned}$$

Because x is between the stations, and y is behind, (6.3) and (6.4) can be rewritten as

$$|y - z_j| \leq \frac{1}{2} - d + \frac{1}{2g}(gd - fd - p),$$

and

$$|x - z_i| \leq \frac{1}{2g}(gd - fd - p). \tag{6.5}$$

Given some starting point between the stations, x, cases 1 and 2 define a range of destinations for which the fast mode is preferred. This range is drawn in Figure 6.3a. The size of the range is

$$1/2 - d + 2\hat{x} - |z_i - x|\,,$$

where

$$\hat{x} \equiv \hat{x}(p, d) \equiv \frac{1}{2g}(gd - fd - p). \tag{6.6}$$

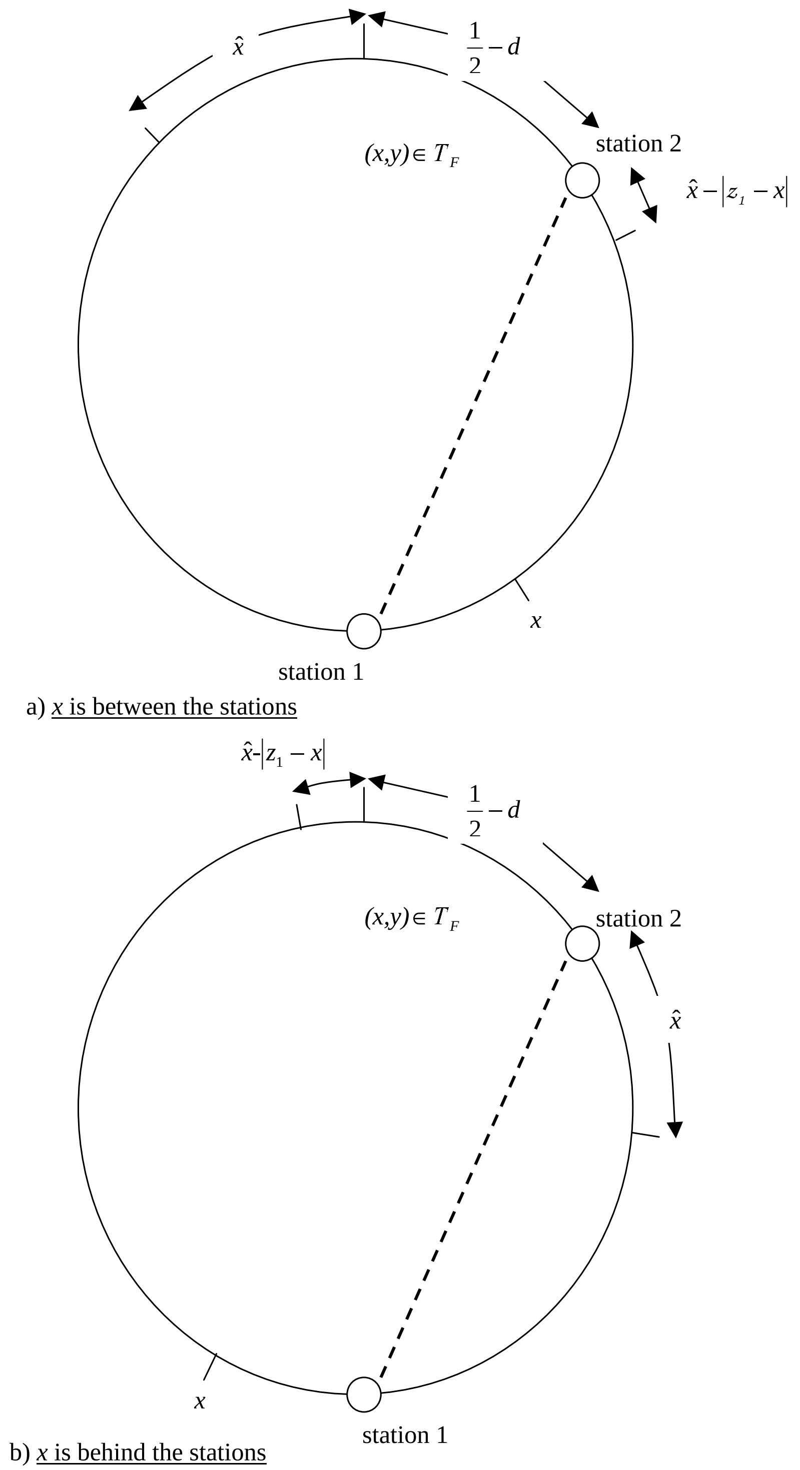


Figure 6.3: Range of destination for which the fast mode is preferred, given some starting point, x.

Consider now the *third* case, where x is behind but y is between the stations. This case is equivalent to the second case, except that starting and destination points are switched. Hence, in this case, $(x, y) \in \mathcal{T}_F$ if and only if

$$|x - z_i| \leq \frac{1}{2} - d + \hat{x}, \tag{6.7}$$

and

$$|y - z_j| \leq \hat{x}. \tag{6.8}$$

The *fourth* and last case considers a trip (x, y) where both x and y are behind the stations. In this case

$$|y - x| = \min\{\ 1 - d - |y - z_j| - |z_i - x|\,,\ \ d + |y - z_j| + |z_i - x|\ \}. \tag{6.9}$$

Substituting (6.9) into (6.1) and rewriting, the condition for $(x, y) \in \mathcal{T}_F$ becomes

$$|z_i - x| + |y - z_j| \leq \frac{1}{2} - d + \hat{x}, \tag{6.10}$$

and

$$\hat{x} \geq 0. \tag{6.11}$$

Cases 3 and 4 also constitute a range of destinations for which the fast mode is preferred whenever the starting point x is behind the stations. This range is shown in Figure 6.3b. Again, the size of this range is $1/2 - d + 2\hat{x} - |z_i - x|$.

Now that we have found the market area, we can derive the demand function. The following proposition states the demand function.

Proposition 6.1. *Consider the transportation model of Section 6.2. If the distance between the stations is d, and the fare of a fast mode connection is p with $p \leq gd - fd$, then demand is given by*

$$D(p, d) = 6\hat{x}^2 + 6\hat{x}(1/2 - d) + (1/2 - d)^2,$$

where

$$\hat{x} \equiv \hat{x}(p, d) \equiv \frac{1}{2g}(gd - fd - p).$$

If $p > gd - fd$, then $D(p, d) = 0$.

Proof. Consider a trip $(x, y) \in \mathcal{T}_F$, and suppose that $p \leq gd - fd$, such that $\hat{x} \geq 0$. From (6.2) and (6.5) it follows that if x is between the stations then $|z_i - x| \leq \hat{x}$. On the other hand, if x is behind the stations, equations (6.7) and (6.10) imply that $|z_i - x| \leq 1/2 - d + \hat{x}$. Moreover, for a trip originating at x the size of the range of destinations y, such that $(x, y) \in \mathcal{T}_F$, is

$$1/2 - d + 2\hat{x}(p; d) - |z_i - x|\,,$$

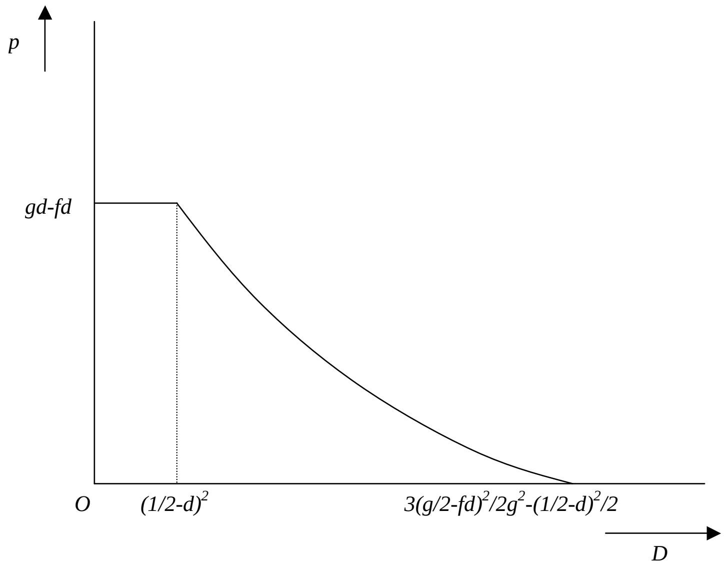


Figure 6.4: Demand function in the transport model.

where $\hat{x} \equiv \hat{x}(p; d)$ is given in (6.6). Hence, because there are two stations, demand is given by

$$\begin{aligned} D(p, d) &= 2\int_0^{\hat{x}} 1/2 - d + 2\hat{x} - x \; dx \\ &\quad +2\int_0^{\hat{x}+1/2-d} 1/2 - d + 2\hat{x} - x \; dx \\ &= 6\hat{x}^2 + 6\hat{x}(1/2 - d) + (1/2 - d)^2. \end{aligned}$$

Furthermore, if $p > gd - fd$, then $\hat{x} < 0$, and one of the conditions (6.2), (6.5), (6.8) or (6.11) is violated. Hence, if $p > gd - fd$, then the set $\mathcal{T}_F$ is empty. □

Figure 6.4 shows a typical demand function. The demand function is a quadratic function in p and d, and for all feasible prices $0 \leq p \leq gd - fd$ the demand function is downward sloping and convex in p. Hence, the demand function has a familiar shape, except that there is an upperbound for p. If $p = gd - fd$, then

$$D(gd - fd, d) = (1/2 - d)^2,$$

while demand collapses to zero if p becomes larger than $gd - fd$.

6.3 Profit maximizing location and pricing

In this section we consider the optimal price and location in case the fast mode network is operated by a monopolist. To focus on the demand side we assume that a firm operating the connection incurs no costs.

We derive the optimal price and location for the monopolist operator. The monopolist maximizes profits

$$\pi(p,d) = \begin{cases} pD(p,d) & \text{if } 0 \le p \le gd - fd \\ 0 & \text{otherwise.} \end{cases}$$

Since the fast mode's comparative advantage is greater the larger is d, one would expect that the optimal location of the two stations for the monopolist would be such that the stations are located on the opposite site of the circle, such that $d = 1/2$. However, the following proposition shows that this is not true.

Proposition 6.2. *Consider the distance d^M between the two stations and price p^M that maximize monopoly profits. The optimal price is*

$$p^M = \frac{g-f}{6}$$

and the optimal distance is $d^M = 1/6$ for $f < g \le 3f$, and

$$d^M = \frac{g^2 - f^2 - 2gf}{2g^2 - 6f^2}$$

for $g \ge 3f$.

Proof. For the moment, allow $d = 0$ in the feasible set $\mathcal{F}$, such that

$$\mathcal{F} = \{(p,d) \in \mathbb{R}^2 \mid 0 \le d \le 1/2;\ 0 \le p \le gd - fd\ \}.$$

Then the monopolist solves the optimization problem

$$\begin{array}{ll} \max_{p\ge 0, d\ge 0} & pD(p,d) \\ \text{s.t.} & p \le (g-f)d \\ \text{and} & d \le 1/2. \end{array} \tag{6.12}$$

Note that the feasible set $\mathcal{F}$ is closed and bounded with linear restrictions, and that the profit function $pD(p,d)$ is continuously differentiable at p and d. Hence, for any value of f and g, $0 < f < g$, a maximum exists and the optimal solution satisfies the Kuhn-Tucker first order conditions.

It is easy to check that $d > 0$ and $p > 0$. Hence the first order conditions are given by

$$p\frac{\partial D(p;d)}{\partial p} + D(p;d) - \lambda = 0, \tag{6.13}$$

$$p\frac{\partial D(p;d)}{\partial d} + \lambda(g-f) - \mu = 0, \tag{6.14}$$

$$p \le (g-f)d \text{ and } \lambda(gd - fd - p) = 0, \tag{6.15}$$

$$d \le 1/2 \text{ and } \mu(1/2 - d) = 0, \tag{6.16}$$

for some $\lambda \ge 0$ and $\mu \ge 0$. Remember that $\hat{x} \equiv \hat{x}(p;d) \equiv \frac{1}{2g}(gd - fd - p)$. Conditions (6.13) and (6.14) can be rewritten as

$$\lambda = 18\hat{x}^2 + \frac{1}{g}(18g - 6f)\hat{x}(1/2 - d) + \frac{1}{g}(4g - 3f)(1/2 - d)^2 - 3\frac{g-f}{2g}(2\hat{x} + 1/2 - d), \tag{6.17}$$

and

$$\mu = \lambda(g - f) + \frac{p}{g}\{\ (g - 3f)(1/2 - d) - 6f\hat{x}\ \}. \tag{6.18}$$

Now suppose that both $\lambda = 0$ and $\mu = 0$. Then by (6.18)

$$\hat{x} = \frac{g - 3f}{6f}(1/2 - d). \tag{6.19}$$

It is immediately clear that if $g < 3f$ condition (6.15) is violated. Substituting (6.19) into (6.17) and solving, one obtains

$$d = \frac{g^2 - f^2 - 2gf}{2g^2 - 6f^2} \text{ or } d = 1/2.$$

After some manipulations it follows from (6.19) that if $d = \frac{g^2-f^2-2gf}{2g^2-6f^2}$, then $p = (g-f)/6$, and if $d = 1/2$, then $p = (g - f)/2$. These are two solution candidates in case $g \geq 3f$, $\lambda = 0$ and $\mu = 0$.

Now suppose that $\lambda > 0$, but $\mu = 0$. Then $p = gd - fd$ by condition (6.15) and $\hat{x} = 0$. By equations (6.17) and (6.18)

$$\lambda = (1/2 - d)^2 - 3d\frac{g - f}{g}(1/2 - d) = 2d(1/2 - d) - 3d\frac{g - f}{g}(1/2 - d).$$

Solving for d, one gets $d = 1/2$ or $d = 1/6$. If $d = 1/2$, then $\lambda = 0$, a contradiction, and if $d = 1/6$ then $p = (g - f)/6$. Note that for $d = 1/6$, $\lambda > 0$ if and only if $g < 3f$.

Now suppose that $\mu > 0$, but $\lambda = 0$. Then $d = 1/2$ and by (6.18)

$$\mu = -6\frac{f}{g}p\hat{x}(p, 1/2) \leq 0.$$

This is a contradiction.

Finally, suppose that $\mu > 0$ and $\lambda > 0$. Then $d = 1/2$ and $p = (g - f)/2$. However, substituting these values into (6.17) one gets $\lambda = 0$, again a contradiction.

Summarizing, if $g < 3f$, then the only solution candidate is $d = 1/6$ and $p = (g-f)/6$. If $g \leq 3f$ there are two candidates, $d = 1/2$ and $d = \frac{g^2-f^2-2gf}{2g^2-6f^2}$. However, for $d = 1/2$ and $p = (g - f)/2$, profits are zero, while for $d = \frac{g^2-f^2-2gf}{2g^2-6f^2}$ and $p = (g - f)/6$ profits are strictly positive. Hence, $d = 1/2$ and $p = (g - f)/2$ can not be a maximum.

For each value of g we now have a single remaining candidate that satisfies the first order conditions. Since a solution exists, this candidate must be the maximum. That is, if $g < 3f$, then $d^M = 1/6$ and $p^M = (g - f)/6$. If $g \leq 3f$, then $d^M = \frac{g^2-f^2-2gf}{2g^2-6f^2}$, and $p^M = (g - f)/6$. Note that if $g = 3f$, then $d^M = 1/6$. □

The proof follows from standard constrained optimization. Note that d^M is continuous in g, even at $g = 3f$, and that $d^M \to 1/2$ whenever $g \to \infty$.

Why do the stations not lie on opposite sides of the circle? The answer is hidden in the nature of competition in this transport model. Competition between the two transport modes is more severe for trips starting and ending *between* the two stations. In this case the length of the trip $|y - x|$ is typically smaller than the distance between the two stations (Figure 6.2a). For these trips, the slow mode becomes an attractive alternative if the price of the fast mode increases or if the start or destination of the trip is located further away from the stations.

However, the fast mode network virtually does not face any competition for trips between the station's *hinterlands*, which are the locations behind the two stations. The reason is simple. Suppose that for a trip to station 2, (x, z_2) the fast mode is optimal. If the destination of a trip (x, y) is further away from x than station 2 (Figure 6.2b), an additional travel distance has to be covered. However, this additional travel distance is in both cases made by slow mode transport and therefore the additional travel costs does not depend on the choice of transport mode. Hence, if fast mode transport has a comparative advantage for a trip to station 2, it also has a comparative advantage for all trips to the hinterland of station 2. Clearly the size of the hinterland weighs heavily on the monopolist's demand. This can also be seen from Figure 6.3. Demand from the hinterland is bounded, however, as it becomes attractive to use the slow mode network in the *opposite direction* when the destination is located far away in the hinterland.

It now becomes clear why demand is not maximal when the stations are located on opposite sides of the circle. In this case the stations lack a big hinterland, as the fast mode network faces competition from the slow mode network from both sides of the circle. Only if the stations are located closer, the fast mode network is able to create and serve a hinterland, where competition from the slow mode network is less severe. Following this reasoning, one might think that it is optimal to minimize the distance between the stations. However, if the distance becomes smaller, the reservation price for a trip from station to station, $gd - fd$, decreases. At some point, a smaller distance between the two stations has to be combined with lower prices, which has a negative impact on profits, and as a result the optimal distance is bounded from below.

Note that the above result depends on the competitiveness of the transport modes. As g increases or if f decreases the slow mode becomes less competitive, and therefore there is less reason for the fast network operator to take competition from slow mode transport into account. Therefore, if $g \to \infty$ or if $f \to 0$, then the distance between the stations goes to a half.

6.4 Social welfare

Since the optimal station locations from a monopolist's view are quite surprising, one wonders if results differ when the firm is operated by a social planner. Therefore, we turn to the question what price a social planner would set, and what station locations he would choose. We assume that a social planner maximizes the social welfare function

$$W(p; d) = \pi(p; d) + CS(p; d),$$

where $CS(p; d)$ is aggregate consumer surplus.

Consumer surplus has a simple structure. Consider first CS^S, the consumer surplus in case all travelers choose the slow mode, that is if $p > gd - fd$. Then

$$CS^S = 2\int_0^{1/2} u - gx\ dx = u - \frac{1}{4}g.$$

If $p < gd - fd$, such that some travelers choose the fast mode, the consumer surplus must be higher than CS^S. This additional surplus that travelers obtain from using the fast mode network is given by the usual consumer surplus triangle under the demand function $D(p; d)$. Hence

$$CS(p, d) = CS^S + \int_p^{gd-fd} D(s; d)\ ds$$

and one can apply the usual social welfare analysis in a partial equilibrium model. At the social optimum price equals marginal cost, that is $p^S = 0$, and social welfare is given by

$$\begin{aligned} W(0; d) &= 0 + CS^S + \int_0^{gd-fd} 6\{\hat{x}(p, d)\}^2 + 6\hat{x}(p, d)(1/2 - d) + (1/2 - d)^2\ dp \\ &= CS^S + 2g\int_0^{(gd-fd)/2g} 6x^2 + 6x(1/2 - d) + (1/2 - d)^2\ dx \\ &= u - g/4 + 2gx_0\left(2x_0^2 + 3x_0(1/2 - d) + (1/2 - d)^2\right), \end{aligned}$$

where $x_0 = (gd - fd)/2g$.

We now turn to the socially optimal distance between the stations, d^S. The first order derivative of the welfare function is given by

$$\frac{\partial W(0; d)}{\partial d} = -6fx_0^2 + (2g - 6f)x_0(1/2 - d) + (g - f)(1/2 - d)^2.$$

Note that if $d = 0$, then $\partial W/\partial d = (g - f)/4 > 0$, and if $d = 1/2$, then $\partial W/\partial d = -6fx_0^2 < 0$. Since the welfare function is a cubic function in d, the optimal distance d^S must be between 0 and 1/2. Solving $\partial W/\partial d = 0$ after some manipulations, it turns out that the only optimal solution is

$$d^S = \frac{g}{g + 3f + \sqrt{g^2 + 3f^2}}.$$

It is easy to check that $d^S > 1/6$ for $g > f$. Furthermore

$$d^S > \frac{g}{2g + 4f} = \frac{g^2 - 2gf}{2g^2 - 8f^2} > \frac{g^2 - f^2 - 2gf}{2g^2 - 6f^2} = d^M.$$

for $g \geq 3f$. Hence, we have the following proposition

Proposition 6.3. *For all $g > f$, the distance between the two stations that maximizes social welfare, d_S, and the distance between the stations that maximizes firm's profits, d_M, are such that*

$$d^M < d^S < 1/2.$$

So a social planner would not locate the stations on opposite sides of the circle either. This is in line with the monopolist's decision. However, from the point of view of the social planner, the monopolist separates the stations too little. The reason is as follows. A social planner is not only concerned about the level of demand for the fast connection, but also about the utility individuals obtain. This utility depends on the reduction in transport costs due to availability of a fast transport connection. The individual that benefits the most from the fast mode connection is an individual making a trip from station to station, (z_i, z_j), in which case the cost reduction is

$$U_F(z_1, z_2; d, 0) - U_S(z_1, z_2) = gd - fd.$$

Hence, the greater the distance between the stations, the higher the maximum cost reduction, and this effect pushes the socially optimal distance, d^S, away from the monopolist's optimal distance, d^M.

That the socially optimal distance between the stations is still smaller than a half is not directly obvious given that the maximum cost reduction is increasing in d. The reason of this result lies in the fact that *more individuals obtain the maximum cost reduction* if d is smaller. In fact all individuals making a trip from the hinterland of station i to the hinterland of station j obtain the maximal cost reduction of $gd - fd$, as long as the stations are between the origin and destination of the trip. That is, if (x, y) is such that $|y - x| = |z_i - x| + d + |y - z_j|$ then

$$U_F(x, y; d, 0) - U_S(x, y) = gd - fd.$$

The reason is already explained in the monopoly case. If the fast mode has a comparative advantage on a trip from station to station, it also has the same comparative advantage on a trip from the hinterland of a station to the hinterland of the other station since traveling behind a station is always made by slow mode. Hence the cost of traveling behind a station adds up to the transportation costs whatever transport mode is chosen. If $d = 1/2$ then the stations lack a big hinterland. In fact, if $d = 1/2$, then the maximum cost reduction in only obtained for a trip from station to station, and consequently the cost reduction effect becomes second order. Hence, social welfare is not optimal if $d = 1/2$.

6.5 Conclusion

In this chapter we have shown that a simple transportation model with competing transport modes can give interesting insights into the optimal network design of a transport network. Competition from a slower but more accessible transport network incites a monopolist transport operator not to locate the stations on opposite sides of the circle, as the size of the hinterland increases if the stations are located closer to each other. This incentive to diminish the distance between stations is also present for a social planner; however, it is stronger for a monopolist than for a social planner. On the other hand, if the difference in speed between the slow and the fast mode is very large, competition is not an issue and the fast mode operator locates its stations near opposite sides of the circle.

Of course, the model we have presented uses strong assumptions and future research should try to generalize and extend this restricted model to analyze a broader range of issues in transport economics. To our opinion, the most interesting extension would be to solve the transportation model for n stations and endogenize the number of stations and connections. Such an extension could be used to analyze the impact of new technologies on the density and the structure of transportation networks. To see the relevance of such issues, consider the history of railway industries. In the beginning of the 20th century railway transport was by far the most efficient transport method for longer distances. However, in course of the 20th century it has lost its comparative advantage to airplane and car. This has resulted in a reduction of stations and connections in the railway network. Nowadays, the railway industry is coming back with the introduction of high-speed trains, reviving the competition between airline and railroad travel. It is not clear what the implications on airline networks are. A model of competing transport networks with an endogenous number of stations could shed more light on this issue.

Chapter 7

Conclusion

Wherever we are, networks are all around us. The roads that we travel form a network; the websites that we visit form an enormous information network, the WorldWideWeb. But, above all, we are part of a network ourselves, the network of social contacts and relations.

These networks are there for a reason. Without roads we would not be able to travel and it would not be possible to trade. Without the WorldWideWeb it would require much more time and effort to search for information. And without social contacts we would have to do everything ourselves, as no one would be able to help us. Given the importance of networks on economic life, it is not surprising that networks have a big influence on economic decision-making. However, it is not clear in what way. It is also the question if society should embrace network effects.

The field of network economics tries to clarify the role of networks in economics. It aims at the following three questions:

1. What structural properties do networks have?

2. How does the network structure influence economic decision-making?

3. What role do economic incentives play in the formation of the network structure?

This thesis contributes to this research area by analyzing several issues. These issues are related to three types of networks: a network of collaborating economists, a network of job contacts, and a transport network. Each type of networks covers a part of this thesis.

In *Part 1* we investigate networks of collaborating economists. We are, in particular, interested in collaborations that lead to a coauthored publication. Data on these coauthor relations are obtained from the bibliography EconLit.

In Chapter 2 we analyze the structure of this network and the changes in the network structure. Physicists discovered that many large networks have the same three properties: short network distances, a high clustering coefficient and a large inequality in the distribution of links. The first property refers to the fact that each node in the network can be reached by a short chain of nodes, even if the whole network contains thousands of nodes. The second property refers to the fact that in many networks “a friend of my friend is also my friend". The third property refers to the fact that in many networks a few nodes have numerous connections.

In Chapter 2 we discover that the coauthor network of economists has these three properties as well. For example, there are a few economists with many connections. These are the stars in the network. We also discover that these stars are crucial for connecting different parts of the network. However, in contrast to the physics literature on complex networks we show that these network properties are not constant. On the contrary, we observe a major change in the network structure. In the 1970s only 15 percent of the economists was directly or indirectly connected and 13 nodes separated two arbitrary economists. However, in the 1990s about 40 percent of the economists were connected in one giant island, and the average network distance in this giant component diminished to around 9. Hence, we conclude that economics is an emerging small world.

In Chapter 3 we incorporate the strength of network ties in our empirical analysis. We test an important sociological theory, Granovetter's 'strength of weak ties' theory, with our data on coauthor relations. The theory states that weak ties are often very important for the cohesion of the network, as weak ties often form bridges between different subgroups in the network.

The results in Chapter 3, however, show that the theory is rejected for the coauthor network of economists. Importantly, we provide a structural explanation for this surprising result. Our explanation consists of two parts. First, there are a few stars in the network that have many links. Second, we discover that the ties between these stars are usually strong. Since the stars are crucial for the cohesion of the network, the strong ties between the stars are crucial for the cohesion as well. The results in this chapter increase our understanding of the network structure and the role of the strength of ties.

In Chapter 4 we give a theoretical explanation for the network structure that we observe in Chapters 2 and 3. Our model is based on the usual economic assumption of rational behavior. Players form a link if the benefits of forming a link are higher than the costs. The benefits depend on the number of links, the quality of the two players, and the rewards for collaborative research. The costs depend on the effort that is put into these collaborations.

We analyze this model in Chapter 4. Our analysis shows, as expected, that the amount of collaboration increases when the rewards are higher or the communication costs are lower. But, surprisingly, our analysis also shows that the formation of stars is not straightforward. Of course, low quality researchers would prefer to work with high quality researchers. One might suspect that this enhances the formation of stars. However, high quality researchers do not have an incentive to collaborate with low quality researchers, unless the low quality researchers take up all the costs. This creates a disincentive for low quality researchers because they prefer to share the effort. High-low collaboration is only feasible with additional assumptions, such as a restriction on the number of high quality players.

To conclude, Chapter 4 shows that the formation of stars does not directly follow from economic incentives, whereas the physics literature, for example Barabási and Albert (1999), tends to assume this directly.

In *Part 2* we consider the role of networks on the job search process. It is generally accepted that social networks are crucial when looking for a job. We also observe a large wage and employment gap between men and women and between different races, and there is a large occupational segregation on the labor market as well. Therefore, it is understandable that many social scientists blame networks for occupational segregation and inequality on the labor market. However, it is not clear either if this is true, or how this network mechanism would work.

In Chapter 5 we therefore analyze the role of networks on the labor market. We propose a three-stage model with two groups of individuals and two occupations. In the first stage, individuals choose a specialization. Then, in the second stage, they form a social network. Finally, in the third stage, individuals search for a job, and when they become employed they earn a wage. The analysis in Chapter 5 shows that occupational segregation is an equilibrium in this model under two conditions. First, job contacts should increase the probability of finding a job. Second, individuals should tend to form more social links within their own ethnic or gender group. Under these two conditions individuals prefer to choose the same specialization as the majority in their group. In this way, individuals are able to build more useful job contacts and have a higher chance to find a job. However, one group will tend to specialize in one occupation as a consequence.

We also show that there are stable equilibria that exhibit wage gaps. Individuals that are specialized in a low wage occupation are not prepared to choose a better paying occupation because they are not able to get good job contacts in the other occupation. In other words, individuals are prepared to sacrifice wage if they are more likely to find a job through their social network.

The analysis of Chapter 5 offers an alternative to discrimination theories. It also differs from other labor network research, because we do not assume a priori that one group has a better network than the other group. On the contrary, we show that wage gaps between groups can persist, even if there is no discrimination and if everyone is endowed with the same social, human and financial assets. This also implies that policies to counter discrimination cannot offer a complete solution to the problem of labor market inequality.

In *Part 3* we analyze a different type of network, transport networks. These are the roads, railways and airline routes that we travel. We focus on the network strategies of public transport operators. Railway and airline firms need to decide what routes to operate and what fare to set.

Current research on public transport does not take into account the role of alternative transport modes. For example, research on network strategies of airlines does not take into account the role of high speed trains. However, it is important to take this into account, as different transport networks compete with each other as well as complement each other.

In Chapter 6 we therefore focus on the effect of competition between transport modes on transport routes and fares. We analyze a simple abstract transport model. In this model we assume that individuals live and work in a circular city. Individuals can choose between two transport modes, slow transport or fast transport. The fast transport operator is only allowed to offer one connection, and it has to choose the location of the departing and terminating station on the circle.

The analysis of Chapter 6 indicates that, in this model, the fast transport operator tends to cluster the stations, much more than what the society desires. That is, the operator does not offer a trip from one side of the circle to the opposite side. Instead, the fast transport operator only offers a very short trip by fast transport mode. The reason for this behavior is that the operator creates a higher demand for its services by setting the stations very close to each other. Our analysis also shows that the incentive to cluster the stations increases when the speed difference between fast and slow transport diminishes.

Hence, Chapter 6 shows how important it is in the analysis of one transport mode to take into account the influence of other competing transport modes. This is, however, neglected in the current transport literature.

To summarize, this thesis focuses on economic problems surrounding networks. We show what role networks play in economics, the labor market and the transport market. With this analysis the thesis contributes to the research in the area of network economics.

Bibliography

[1] Akerlof, G. A and R. E. Kranton (2000), Economics and identity, *Quarterly Journal of Economics*, 115(3), 715–733.

[2] Albert, R. and A-L. Barabási (2002), Statistical mechanics of complex networks, *Review of Modern Physics*, 74, 47–97.

[3] Albelda, R.P. (1986), Occupational segregation by race and gender: 1958–1981, *Industrial and Labor Relations Review*, 39(3), pp. 404-411

[4] Albert, R., H. Jeong, and A.-L. Barabási (1999), The diameter of the world-wide web, *Nature*, 401, 130–131.

[5] Albert, R., H. Jeong, and A.-L. Barabási (2000), Error and attack tolerance of complex networks, *Nature*, 406, 378–382.

[6] Arrow, K.J (1972), Models of job discrimination, in A.H. Pascal (ed.), *Racial Discrimination in Economic Life*, Lexington, MA.

[7] Arrow, K.J. (1973), The theory of discrimination, in. O. Ashenfelter, A. Rees (eds.), *Discrimination in Labor Markets*, Princeton, NJ: Princeton University Press.

[8] Arrow, K.J. (1998), What has economics to say about racial discrimination?, *Journal of Economic Perspectives*, 12(2), pp. 91-100.

[9] Arrow, K.J. and R. Borzekowski (2004), Limited network connections and the distribution of wages, Finance and Economics Discussion Series 2004-41, Federal Reserve Board, Washington, D.C..

[10] Aumann, R. and R. Myerson (1988), Endogenous formation of links between players and coalitions: An application of the Shapley value, in *The Shapley Value*, A. Roth (ed.). Cambridge: Cambridge University Press, 175–191.

[11] Austen-Smith, D. and R.G. Fryer (2005), An economic analysis of 'acting white', *Quarterly Journal of Economics*, 120(2), 551-583.

[12] Aveneri, S. and A. de Shalit (1992), *Communitarianism and Individualism.* Oxford: Oxford University Press.

[13] Bala V. and S. Goyal (1998), Learning from neighbours, *Review of Economic Studies* 65, 595-621.

[14] Bala, V. and S. Goyal (2000), A non-cooperative model of network formation, *Econometrica*, 68(5), 1181-1231.

[15] Ballester, C., A. Calvó-Armengol, and Y. Zenou (2006), Who is who in networks. Wanted: the key-player, *Econometrica*, 75(4), 1403-1418.

[16] Barabási A.-L. and R. Albert (1999), Emergence of scaling in random network, *Science*, 286, 509–512.

[17] Barrat, A., M. Barthélemy, and A. Vespignani (2004a), Modeling the evolution of weighted networks, *Physical Review E*, 70, 066149.

[18] Barrat, A., M. Barthélemy, R. Pastor-Satorras, and A. Vespignani (2004b), The architecture of complex weighted networks, *Proceedings of the National Academy of Sciences of the U.S.A.*, 101(11), 3747–3752.

[19] Becker, G. (1957), *The Economics of Discrimination*, Chicago: University of Chicago Press

[20] Bentolila, S., C. Michelacci and J. Suárez (2004), Social contacts and educational choice, CEMFI Working Paper 0406, Madrid.

[21] Bian, Y. and S. Ang (1997), Guanxi networks and job mobility in China and Singapore, *Social Forces*, 75(3), 981–1005.

[22] Billand, P. and C. Bravard (2004), Non-cooperative networks in oligopolies, *International Journal of Industrial Organization*, 22, 593–609.

[23] Blau, F.D., P. Simpson and D. Anderson (1998), Continuing progress? Trends in occupational segregation in the United States over the 1970s and 1980s, *Feminist Economics* , 4(3), 29–71.

[24] Bollobás, B. and O. Riordan (2004), The diameter of a scale-free random graph, *Combinatorica*, 4, 5–34.

[25] Boorman, S.A. (1975), A combinatorial optimization model for transmission of job information through contact networks, *Bell Journal of Economics*, 6(1), 216–249.

[26] Borenstein, S. (1989) , Hubs and high fares: dominance and market power in the u.s. airline industry, *RAND Journal of Economics* 20(3), 344–365.

[27] Borenstein, S. (1992), The evolution of U.S. airline competition, *Journal of Economic Perspectives*, 6(2), 45–73.

[28] Borgatti, S.P. and S.L. Feld (1994), How to test the strength of weak ties theory, *Connections*. 17, 45–46.

[29] Braid, R. M. (1989) , The optimal locations of multiple bridges, connecting facilities, or product varieties, *Journal of Regional Science* **29**(1), 63–70.

[30] Bramoullé, Y. and R. Kranton (2006), Public goods in networks, *Journal of Economic Theory*, forthcoming.

[31] Bramoullé, Y. and G. Saint-Paul (2006), Social networks and labor market transitions, *mimeo*, Université Laval and Université Toulouse.

[32] Buhai, I.S. and M.J. van der Leij (2006), A social network analysis of occupational segregation, Tinbergen Institute Discussion Paper 2006-016/1, Tinbergen Institute Amsterdam/Rotterdam.

[33] Burt, R.S. (1994), *Structural Holes: The social structure of competition.* Cambridge, MA: Harvard University Press.

[34] Calvó-Armengol, A. and M.O. Jackson (2004), The effects of social networks on employment and inequality, *American Economic Review*, 94(3), 426-454.

[35] Calvó-Armengol, A. and M.O. Jackson (2006), Networks in labor markets: Wage and employment dynamics and inequality, *Journal of Economic Theory*, forthcoming.

[36] Calvó-Armengol, A. and Y. Zenou (2004), Social networks and crime decisions: The role of social structure in facilitating delinquent behavior, *International Economic Review*, 45(3), 939–958.

[37] Card, D. and A. Krueger (1992), School quality and black-white relative earnings: A direct assessment, *Quarterly Journal of Economics*, 107, 151–200.

[38] Castells, M. (1996), *The Rise of the Network Society.* Volume I of *The Information Age: Economy, Society and Culture*. Oxford: Blackwell.

[39] Cairncross, F. (2001), *The Death of Distance: How the Communications Revolution Is Changing Our Lives.* 2nd edition. Boston: Harvard Business School Press.

[40] Caves, D.W., L.R. Christensen, and M.W. Thretheway (1984), Economies of density versus economies of scale: Why trunk and local service airlines costs differ, *RAND Journal of Economics*, 15(4), 471–489.

[41] Chiang A.C. (1984), *Fundamental Methods of Mathematical Economics.* 3rd edition. New York: McGraw-Hill.

[42] Coate, S. and G.C. Loury (1993), Will affirmative-action policies eliminate negative stereotypes?, *American Economic Review*, 83(5), 1220-1240

[43] Coleman, J.S. (1966), *Medical Innovation: A Diffusion Study.* 2nd edition. New York: Bobbs-Merrill.

[44] Coleman, J.S. (1988), Social capital in the creation of human capital, *American Journal of Sociology*, 94(Supplement), S95–S120.

[45] Crampton, G. R. (2000) , Urban economic structure and the optimal rail system, *Urban Studies*, 37(3), 623–632.

[46] Datcher, L. (1983), The impact of informal networks on quit behavior, *Review of Economics and Statistics*, 65(3), 491-495.

[47] de Solla Price, D.J. (1963) , *Little Science, Big Science*. New York: Columbia University Press.

[48] Devine, T.J. and N.M. Kiefer (1991), *Empirical Labor Economics: The Search Approach*, New York: Oxford University Press.

[49] Dodds, P.S., R. Muhamad, and D.J. Watts (2003), An experimental study of search in global social networks, *Science*, 301, 827–829.

[50] Doeringer P.B. and M.J. Piore (1971), *Internal Labor Markets and Manpower Analysis*, Lexington: Heath Lexington Books.

[51] Dorogovtsev, S.N. and J.F.F. Mendes (2002), Evolution of networks, *Advances in Physics*, 51, 1079-1187.

[52] Durlauf, S.N. (2006), Groups, social influences and inequality: A memberships theory perspective on poverty traps, in *Poverty Traps*, S. Bowles, S. Durlauf, and K. Hoff (eds.). Princeton: Princeton University Press, forthcoming.

[53] Dutta, B. and M.O. Jackson (eds.) (2003), *Networks and Groups: Models of Strategic Formation*, Studies in Economic Design. Berlin: Springer-Verlag.

[54] Eisenhauer, J. (1997), Multi-authored papers in economics, *Journal of Economic Perspectives*, 11, 191-192.

[55] Ellison, G. (2002a), The slowdown of the economics publishing process, *Journal of Political Economy*, 110(5), 947–993.

[56] Ellison, G. (2002b), Evolving standards for academic publishing: A q-r theory, *Journal of Political Economy*, 110(5), 994-1034.

[57] Ellison, G. and D. Fudenberg (1993), Rules of thumb for social learning, *Journal of Political Economy*, 101(4), 612-643.

[58] Eshel, I., L. Samuelson, and A. Shaked (1998), Altruists, egoists, and hooligans in a local interaction model, *American Economic Review*, 88, 157-179.

[59] Fafchamps, M., M.J. van der Leij, and S. Goyal (2006), Matching and network effects, Department of Economics Discussion Paper 611, University of Essex.

[60] Fontaine, F. (2004), Do workers really benefit from their social networks?, IZA Discussion Paper 1282, Bonn.

[61] Freeman, L.C. (1977), A set of measures of centrality based on betweenness, *Sociometry*, 40(1), 35–41.

[62] Friedkin, N. (1980), A test of the structural features of Granovetter's strength of weak ties theory., *Social Networks*, 2, 411–422.

[63] Fryer, R.G. (2006), "Acting white", *Education Next* , 6(1), 52–59

[64] Galeotti, A. (2005a), Consumer networks and search equilibria, *mimeo*, California Institute of Technology.

[65] Galeotti, A. (2005b), *On Social and Economic Networks*, Tinbergen Institute Research Series 352. Ph.D. thesis, Erasmus University Rotterdam.

[66] Galeotti, A., S. Goyal, M.O. Jackson, F. Vega-Redondo, and L. Yariv (2006), Network Games, *mimeo*, University of Essex and California Institute of Technology.

[67] Girvan, M. and M.E.J. Newman (2002), Community structure in social and biological networks, *Proceedings of the National Academy of Sciences of the U.S.A.*, 99(12), 7821–7826.

[68] Glaeser, E., B. Sacerdote and J. Scheinkman (1996), Crime and social interactions, *Quarterly Journal of Economics*, 111(2), 507-548.

[69] Goyal, S. (2005a), Learning in networks, in *Group Formation in Economics: Networks, Clubs and Coalitions*, G. Demange and M. Wooders (eds.). Cambridge: Cambridge University Press.

[70] Goyal, S. (2005b), Strong and weak links, *Journal of European Economic Association*, 3(2-3), 608-616.

[71] Goyal, S. and S. Joshi (2003), Networks of collaboration in oligopoly, *Games and Economic Behavior*, 43, 57-85.

[72] Goyal, S., M.J. van der Leij, and J.L. Moraga-González (2004), Economics: an emerging small world?, Tinbergen Institute Discussion Paper 04-001/1, Tinbergen Institute Amsterdam/Rotterdam.

[73] Goyal, S., M.J. van der Leij, and J.L. Moraga-González (2006), Economics: an emerging small world, *Journal of Political Economy*, 114(2), 403–412.

[74] Goyal, S. and F. Vega-Redondo (2004), Structural holes in social networks, *mimeo*, University of Essex.

[75] Granovetter, M. (1973), The strength of weak ties, *American Journal of Sociology*, 78(6), 1360–1380.

[76] Granovetter, M. (1983), The strength of weak ties: A network theory revisited, *Sociological Theory*, 1, 201–233.

[77] Granovetter, M. (1985), Economic action and social structure: The problem of embeddedness, *American Journal of Sociology*, 91(3), 481–510.

[78] Granovetter, M. (1995), *Getting a Job: A Study of Contacts and Careers*, 2nd edition, Chicago: University of Chicago Press.

[79] Gregg, P. and J. Wadsworth (1996), How effective are state employment agencies? Jobcentre use and job matching in Britain, *Oxford Bulletin of Economics and Statistics*, 58, 43–67.

[80] Grossman, J. (2002), The evolution of the mathematical research collaboration graph, *Congressus Numerantium*, 158, 201–212.

[81] Hamermesh, D. and Oster, S. (2002), Tools or toys: The impact of high technology on scholarly productivity, *Economic Inquiry*, 40, 539–555.

[82] Hägerstrand, T. (1969), *Innovation diffusion as a spatial process.* University of Chicago Press. Chicago.

[83] Hendricks, K., M. Piccione, and G. Tan (1995), The economics of hubs: The case of monopoly, *Review of Economic Studies*, 62(1), 83–99.

[84] Hendricks, K., M. Piccione, and G. Tan (1997), Entry and exit in hub-spoke networks, *RAND Journal of Economics*, 28(2), 291–303.

[85] Hendricks, K., M. Piccione, and G. Tan (1999), Equilibria in networks, *Econometrica*, 67(6), 1407–1434.

[86] Holzer, H.J. (1987), Informal job search and black youth unemployment, *American Economic Review*, 77(3), 446-452.

[87] Holzer, H.J. (1988), Search methods used by unemployed youth, *Journal of Labor Economics*, 6, 1–21.

[88] Hudson, J. (1996), Trends in multi-authored papers in economics, *Journal of Economic Perspectives*, 10(3), 153-158.

[89] Hyson, C. and Hyson, W. (1950) , The economic law of market areas, *Quarterly Journal of Economics* **64**(2), 319–327.

[90] Ioannides, Y.M. and L. Datcher Loury (2004), Job information networks, neighborhood effects, and inequality, *Journal of Economic Literature*, 42(4), 1056–1093.

[91] Jackson, M.O. (2005), A survey of network formation models: Stability and efficiency, in *Group Formation in Economics: Networks, Clubs and Coalitions*, G. Demange and M. Wooders (eds.). Cambridge: Cambridge University Press.

[92] Jackson, M.O. and B. Rogers (2005), Search in the Formation of Large Networks: How Random are Socially Generated Networks? *mimeo*, California Institute of Technology.

[93] Jackson, M.O. and A. Wolinsky (1996), A strategic model of economic and social networks, *Journal of Economic Theory*, 71, 44–74.

[94] Jacobs, J.A. and S.T. Lim (1992), Trends in Occupational and Industrial Sex Segregation in 56 Countries, 1960-1980, *Work and Occupations*, 19(4), 450–486.

[95] Kochen, M. (ed.) (1989), *The Small World: A Volume of Recent Research Advances Commemorating Ithiel de Sola Pool, Stanley Milgram, Theodore Newcomb*, Norwood, NJ: Ablex.

[96] Kranton, R.E. and D.F. Minehart (2001), A theory of buyer-seller networks, *American Economic Review,* 91(3), 485-508.

[97] Laband, D. and Tollison, R. (2000), Intellectual collaboration, *Journal of Political Economy*, 108(3), 632-662.

[98] Lavezzi, A.M. and N. Meccheri (2005), Job Contact Networks, Inequality and Aggregate Output, in *Innovation, Unemployment and Policy in the Theories of Growth and Distribution*, N. Salvadori and R. Balducci (eds.), Cheltenham: Edgar Elgar.

[99] Lazear, E.P. and S. Rosen (1990), Male-female wage differentials in job ladders, *Journal of Labor Economics*, 8(1), S106-S123

[100] Marsden, P.V. (1987), Core discussion networks of americans, *American Sociological Review*, 52(1), 122-131.

[101] McDowell, J.M. and M. Melvin (1983), The determinants of co-authorship: An analysis of the economics literature, *Review of Economics and Statistics*, 65(1), 155–160.

[102] McLuhan, M. (1994), *Understanding Media: The extensions of man.* Cambridge: MIT Press.

[103] Milgram, S. (1967), The small world problem, *Psychology Today*, 2, 60-67.

[104] Montgomery, J.D. (1991), Social networks and labor-market outcomes: Toward an economic analysis, *American Economic Review*, 81(5), 1408-1418.

[105] Montgomery, J.D. (1998), Toward a role-theoretic conception of embeddedness, *American Journal of Sociology* ,104(1), 95–125.

[106] Moody, J. (2004), The structure of a social science collaboration network: Disciplinary cohesion from 1963 to 1999, *American Sociological Review*, 69, 213–238.

[107] Morris, S. (2000), Contagion, *Review of Economic Studies*, 67(1), 57-78.

[108] Munshi, K. (2003), Networks in the modern economy: Mexican migrants in the U.S. labor market. *Quarterly Journal of Economics*, 118(2), 549–599.

[109] Newman, M.E.J. (2001), The structure of scientific collaboration networks, *Proceedings of the National Academy of Sciences*, 98, 404-409.

[110] Newman, M.E.J. (2003), The structure and function of complex networks, *SIAM Review*, 45(2), 167–256.

[111] Newman, M.E.J. (2004), Analysis of weighted networks, *Physical Review E*, 70, 056131.

[112] Niérat, P. (1997), Market area of rail-truck terminals: Pertinence of the spatial theory, *Transportation Research A*, 31(2), 109–127.

[113] Pellizzari, M. (2004), Do friends and relatives really help in getting a good job?, CEP Discussion Paper 623, London School of Economics.

[114] Peterson, T., I. Saporta and M.-D.L. Seidel (2000), Offering a job: meritocracy and social networks, *American Journal of Sociology*, 106, 763-816.

[115] Phelps, E.S. (1972), The statistical theory of racism and sexism, *American Economic Review*, 62(4), 659-661.

[116] Polacheck, S. (1981), Occupational self-selection: A human capital approach to sex differences in occupational structure, *Review of Economics and Statistics*, 63(1), 60–69.

[117] Rees, A. (1966), Information networks in labor markets, *American Economic Review*, 56(1-2), 559-566.

[118] Rich, J. (1999), Gender segregation in the academic staff of universities in Great Britain, 1980/81-1993/94, *Economica*, 66(264), 509–531.

[119] Rogers, E.M. (1995), *Diffusion of Innovations.* 4th edition. New York: Free Press.

[120] Rosenblat, T.S. and M.M. Mobius (2004), Getting closer or drifting apart? *Quarterly Journal of Economics*, 119, 971–1009.

[121] Schelling, T.C. (1971), Dynamic models of segregation, *Journal of Mathematical Sociology*, 1, 143-186.

[122] Schelling, T.C. (1978), *Micromotives and Macrobehavior*, Fels Lectures on Public Policy Analysis. New York: W.W. Norton.

[123] Sherif, M. (1961), *Intergroup Conflict and Cooperation: The Robbers Cave Experiment*, Norman: University Book Exchange.

[124] Simon, C.J. and J.T. Warner (1992), Matchmaker, matchmaker: The effect of old boy networks on job match quality, earnings, and tenure, *Journal of Labor Economics*, 10(3), 306-330.

[125] Singh, J. (2005), Collaborative networks as determinants of knowledge diffusion patterns, *Management Science*, 51(5), 756–770.

[126] Sobel, J. (2002), Can we trust social capital?, *Journal of Economic Literature*, 40, 139–154.

[127] Staiger, D. (1990), The effect of connections on the wages and mobility of young workers, *mimeo*, MIT.

[128] Taylor, C. (1989), *Sources of the Self: the Making of the Modern Identity.* Cambridge, MA: Harvard University Press.

[129] Topa, G. (2001), Social interactions, local spillovers and unemployment, *Review of Economic Studies*, 68(2), 261-295.

[130] van der Leij, M.J. (2003), Competing transport networks, Tinbergen Institute Discussion Paper 2003-009/1, Tinbergen Institute Amsterdam/Rotterdam.

[131] van der Leij, M.J. and S. Goyal (2006), Strong ties in a small world, Tinbergen Institute Discussion Paper 2006-008/1, Tinbergen Institute Amsterdam/Rotterdam.

[132] Watts, D.J. (1999), *Small Worlds: The Dynamics of Networks between Order and Randomness*, Princeton Studies in Complexity. Princeton University Press, Princeton, New Jersey.

[133] Watts, D.J. and S.H. Strogatz (1998), Collective dynamics of 'small world' networks, *Nature*, 393, 440–442.

[134] Williamson, O.E. (1975), *Markets and Hierarchies: Analysis and Antitrust Implications*, New York: Free Press.

[135] Yook, S.H., H. Jeong, A.-L. Barabási, and Y. Tu (2001), Weighted evolving networks, *Physical Review Letters*, 86(25), 5835–5838.

[136] Zachary, W. (1977), An information flow model for conflict and fission in small groups, *Journal of Anthropological Research*, 33, 452–473.

Samenvatting (Summary in Dutch)

Waar we ook kijken, netwerken zijn alom aanwezig. De wegen en kruispunten waarover we reizen vormen een netwerk; de websites die we bekijken en de hyperlinks waarop we klikken vormen een gigantisch informatienetwerk, het WorldWideWeb. Maar bovenal maken wijzelf allemaal deel uit van een netwerk, het netwerk van sociale contacten en relaties.

Deze netwerken zijn er niet voor de lol. Ze vervullen belangrijke economische functies. Zonder wegen zouden we geen auto kunnen rijden, en zou het ook onmogelijk zijn om handel te drijven. Zonder het WorldWideWeb zou het veel meer tijd en moeite kosten om informatie op te zoeken. En zonder sociale contacten zouden we alles alleen moeten doen, van het zoeken naar een baan tot het klussen in het huis. Gegeven het economische belang van netwerken spreekt het voor zich dat netwerken een grote invloed hebben op onze beslissingen. Maar op welke manier dat gebeurt en of we als maatschappij blij met de invloed van netwerken moeten zijn is niet duidelijk.

Het onderzoeksgebied van de netwerkeconomie probeert hier duidelijkheid in te verschaffen. Zij richt zich met name op de volgende vragen:

1. Welke kenmerkende eigenschappen hebben netwerken?

2. Hoe beïnvloeden netwerken economische beslissingen?

3. Wat voor rol spelen economische prikkels in de vorming van netwerken?

Het onderzoek in dit proefschrift poogt bij te dragen aan dit onderzoeksgebied door een aantal vraagstukken te analyseren. Deze vraagstukken hebben met drie verschillende soorten netwerken te maken: een netwerk van economische onderzoekers, een netwerk van arbeidscontacten en een vervoersnetwerk. Aan ieder soort netwerk is een deel van dit proefschrift gewijd.

In *Deel 1* onderzoeken we netwerken van economische onderzoekers. We richten ons met name op samenwerkingsverbanden waarbij onderzoekers samen een artikel schrijven en publiceren. Gegevens over deze onderzoeksverbanden tussen economen zijn via de bibliografie EconLit verkregen.

In Hoofdstuk 2 analyseren we de structuur van dit netwerk en de veranderingen die in de loop der jaren in deze netwerkstructuur hebben plaatsgevonden. Uit de natuurkundige literatuur is het al bekend dat grote netwerken drie kenmerkende eigenschappen hebben:

korte netwerkafstanden, een hoge clustering coëfficiënt, en een grote ongelijkheid in de verdeling van connecties. De eerste eigenschap slaat op het feit dat in veel grote netwerken ieder punt in slechts een aantal stappen te bereiken is, ook al bestaat het netwerk zelf uit duizenden punten. De tweede eigenschap betreft het feit dat in veel netwerken "de vriend van mijn vriend ook mijn vriend" is. De derde eigenschap betreft het feit dat er in veel netwerken een aantal centrale punten bestaan waar extreem veel connecties naar toe leiden.

In Hoofdstuk 2 ontdekken we dat het netwerk van economische medeauteurs ook deze algemeen geldende kenmerken heeft. Er zijn bijvoorbeeld een aantal economen die heel veel connecties hebben. Dit zijn de sterren in het netwerk. Ook ontdekken we dat deze sterren cruciaal zijn voor de samenhang van het netwerk. In tegenstelling tot de natuurkundige literatuur over complexe netwerken laten we echter zien dat deze netwerkeigenschappen niet statisch zijn. Integendeel, we nemen een grote verandering in de netwerkstructuur waar. In de jaren '70 was slechts 15 procent van de economen direct of indirect met elkaar verbonden en er waren in deze groep gemiddeld 13 tussenpersonen nodig om iemand te bereiken. Daarentegen was in de jaren '90 40 procent van de economen met elkaar in één groot eiland verbonden, en de netwerkafstand in dit grote eiland was gekrompen naar gemiddeld negen tussenpersonen. We concluderen dus dat de wereld van economen in de laatste 30 jaar opmerkelijk kleiner is geworden.

In Hoofdstuk 3 nemen we de sterkte van de netwerkverbanden mee in onze empirische analyse. Met onze data over medeauteur-relaties toetsen we een gezaghebbende sociologische netwerktheorie: Granovetter's 'strength of weak ties'-theorie. Deze theorie stelt dat zwakke schakels vaak erg belangrijk voor de samenhang van het netwerk zijn, omdat de zwakke schakels vaak bruggen tussen subgroepen in het netwerk vormen.

De resultaten in Hoofdstuk 3 laten zien dat deze theorie verworpen moet worden voor het netwerk van medeauteur-relaties. Erg belangrijk is dat we een structurele verklaring voor dit verrassende resultaat vinden. Onze verklaring bestaat ten eerste uit het feit dat er een aantal sterren in het netwerk zijn met ontzettend veel connecties. Ten tweede ontdekken we dat de verbanden tussen de sterren vaak sterk zijn. Aangezien sterren cruciaal voor de samenhang van het netwerk zijn, zijn de sterke verbanden ook vaak belangrijk voor de samenhang. Met deze resultaten levert dit hoofdstuk een grote bijdrage aan ons begrip over de structuur van netwerken waar het de sterkte van netwerkverbanden betreft.

In Hoofdstuk 4 geven we een theoretische verklaring voor de in Hoofdstuk 2 en 3 waargenomen netwerkstructuur. Ons model gaat uit van de typisch economische aanname van rationeel gedrag. Spelers gaan een samenwerkingsverband aan als het hun meer baadt dan schaadt. De baten hangen af van het aantal aangegane samenwerkingsverbanden, het onderzoeksniveau van de twee spelers, en de beloning voor samengemaakt onderzoek. De kosten hangen af van de moeite die in de samenwerkingsverbanden worden gestopt.

In Hoofdstuk 4 analyseren we dit model. Zoals verwacht blijkt uit onze analyse dat er meer samenwerking plaatsvindt als de beloning ervoor toeneemt of als de communicatiekosten afnemen. Wat echter verrassend is, is dat uit onze analyse blijkt dat de vorming van sterren niet vanzelfsprekend is. Het spreekt voor zich dat onderzoekers van een laag niveau graag met onderzoekers van een hoog niveau willen werken, en wellicht zou men daarom verwachten dat dit de vorming van sterren stimuleert. Onderzoekers van hoog niveau hebben er echter geen belang bij om met onderzoekers van laag niveau te werken, tenzij de onderzoekers van laag niveau al het werk opknappen. Dit levert een dilemma op voor de onderzoekers van laag niveau, aangezien zij liever de werkzaamheden zouden willen delen. Het gevolg is dat onder normale omstandigheden samenwerking tussen onderzoekers van hoog en laag niveau niet plaatsvindt. Alleen onder extra aannames, zoals een beperking van het aantal onderzoekers van hoog niveau, kan een samenwerking tussen onderzoekers van hoog en laag niveau ontstaan.

Hoofdstuk 4 laat dus zien dat de vorming van sterren uit economische motieven niet vanzelfsprekend is, terwijl dit in natuurkundige theorieën zoals die van Barabási en Albert (1999) wel wordt verondersteld.

In *Deel 2* kijken we naar de rol van netwerken bij het zoeken naar een nieuwe baan. Het is nu algemeen geaccepteerd dat sociale netwerken van cruciaal belang zijn bij het zoeken naar een baan. Tegelijkertijd hebben vrouwen en minderheden een grote loon- en werkgelegenheidsachterstand en bestaat er een grote segregatie op de arbeidsmarkt. Het is dan ook begrijpelijk dat veel sociale onderzoekers naar netwerken wijzen als een oorzaak van de segregatie en ongelijkheid tussen rassen en geslachten op de arbeidsmarkt. Men begrijpt echter niet goed hoe dit proces precies werkt.

In Hoofdstuk 5 analyseren we daarom de rol van netwerken op de arbeidsmarkt. We stellen een model met twee groepen en twee beroepen voor, waarin mensen drie stadia doorlopen. In het eerste stadium kiezen mensen een specialisatie. In het tweede stadium vormen mensen een netwerk, en in het derde stadium zoeken mensen een baan en, als ze die vinden, dan verdienen ze een loon. De analyse in Hoofdstuk 5 laat zien dat er in dit model twee voorwaarden nodig zijn om segregatie op de arbeidsmarkt te bewerkstelligen. Ten eerste dienen netwerkcontacten de kans op het vinden van een baan vergroten. Ten tweede dienen mensen de neiging te hebben om meer vrienden binnen de eigen etnische groep of sexe te hebben. Onder deze twee voorwaarden zullen mensen er de voorkeur aan geven om dezelfde specialisatie als de meerderheid in hun eigen groep te kiezen. Op deze wijze kunnen mensen meer nuttige contacten opbouwen en hebben ze een grotere kans op een baan. Het gevolg is wel dat één groep zich volledig specialiseert in één soort beroep.

In Hoofdstuk 5 laten we ook zien dat in dit model loonverschillen in stand worden gehouden. Mensen in een groep die gespecialiseerd is in een slechtbetaald beroep, zijn niet bereid om een ander, beter betalend beroep te kiezen, omdat ze geen goede arbeidscontacten in dat andere beroep kunnen krijgen. Met andere woorden, mensen zijn bereid om loon op te geven als ze een grotere kans op een baan hebben. Hun sociale netwerk kan hun die kans bieden.

De analyse in Hoofdstuk 5 biedt een alternatief voor discriminatietheorieën. Ook verschilt onze analyse van andere arbeidsmarktonderzoeken, omdat wij niet van te voren aannemen dat het netwerk van één groep slechter is dan die van de andere. Integendeel, wij laten zien dat persistente loonverschillen tussen groepen kunnen ontstaan, zelfs als er geen discriminatie bestaat en als iedereen met dezelfde kwaliteiten geboren wordt. Dit betekent dus ook dat het tegengaan van discriminatie nooit een volledige oplossing kan bieden voor het probleem van de achterstand van vrouwen en minderheden op de arbeidsmarkt.

In *Deel 3* kijken we naar een geheel ander soort netwerken, vervoersnetwerken. Dit zijn de wegen, spoorlijnen en vliegroutes die we allen bereizen. We richten ons op de netwerkstrategieën van openbaar vervoersbedrijven. Bedrijven als de NS en KLM dienen te beslissen op welke routes ze opereren en welke prijs ze voor hun vervoersdiensten vragen.

Het huidig onderzoek naar het openbaar vervoer houdt niet goed rekening met de rol van alternatieve vervoersnetwerken. Onderzoek naar bijvoorbeeld de netwerkstrategieën van vliegmaatschappijen houden geen rekening met de rol van hogesnelheidstreinen. Dit is echter wel belangrijk, omdat deze verschillende vervoersnetwerken zowel op elkaar aansluiten als met elkaar concurreren.

In Hoofdstuk 6 bekijken we daarom wat de gevolgen van concurrentie tussen twee transportnetwerken op de routes en prijzen van vervoersmaatschappijen zijn. We analyseren een eenvoudig abstract vervoersmodel. In dit model nemen we aan dat mensen wonen en werken op een cirkel. Mensen kunnen kiezen uit twee vervoersmogelijkheden, langzaam of snel vervoer. De aanbieder van snel vervoer heeft slechts de mogelijkheid tot één verbinding, en hij moet de locaties van het begin- en eindpunt van de verbinding op de cirkel kiezen.

De analyse in Hoofdstuk 6 wijst erop dat in dit model de snelle vervoerder de neiging heeft om de stations erg dicht bij elkaar te zetten, veel dichter dan maatschappelijk gewenst. De vervoerder biedt dus geen rit van de ene kant van de cirkel naar de andere kant aan. In plaats daarvan kunnen mensen het snelle vervoer slecht over een korte afstand gebruiken. De reden is dat de vervoerder meer mensen kan vervoeren als de vervoerder een strategie voert om de stations dicht bij elkaar te zetten. Onze analyse laat ook zien dat de prikkel om de stations dichter bij elkaar te zetten sterker wordt als het verschil tussen snel en langzaam vervoer kleiner is.

Hoofdstuk 6 laat dus zien hoe belangrijk het bij de analyse van één vervoersmogelijkheid is om met de invloed van andere concurrerende vervoersmogelijkheden rekening te houden. Dit wordt nogal eens vergeten in de literatuur tot nu toe.

Om samen te vatten, dit proefschrift richt zich op economische problemen die met netwerken te maken hebben. We laten zien wat voor rol netwerken spelen in de economische wetenschap, op de arbeidsmarkt en in het openbaar vervoer. Hiermee levert dit proefschrift een bijdrage aan het wetenschappelijk onderzoek op het gebied van de netwerkeconomie.

The Tinbergen Institute is the Institute for Economic Research, which was founded in 1987 by the Faculties of Economics and Econometrics of the Erasmus Universiteit Rotterdam, Universiteit van Amsterdam and Vrije Universiteit Amsterdam. The Institute is named after the late Professor Jan Tinbergen, Dutch Nobel Prize laureate in economics in 1969. The Tinbergen Institute is located in Amsterdam and Rotterdam. The following books recently appeared in the Tinbergen Institute Research Series:

333. C.M. VAN VEELEN, *Survival of the fair: Modelling the evolution of altruism, fairness and morality.*
334. R. PHISALAPHONG, *The impact of economic integration programs on inward foreign direct investment.*
335. A.H. NÖTEBERG, *The medium matters: The impact of electronic communication media and evidence strength on belief revision during auditor-client inquiry.*
336. M. MASTROGIACOMO, *Retirement, expectations and realizations. Essays on the Netherlands and Italy.*
337. E. KENJOH, *Balancing work and family life in Japan and four European countries: Econometric analyses on mothers' employment and timing of maternity.*
338. A.H. BRUMMANS, *Adoption and diffusion of EDI in multilateral networks of organizations.*
339. K. STAAL, *Voting, public goods and violence.*
340. R.H.J. MOSCH, *The economic effects of trust. Theory and empirical evidence.*
341. F. ESCHENBACH, *The impact of banks and asset markets on economic growth and fiscal stability.*
342. D. LI, *On extreme value approximation to tails of distribution functions.*
343. S. VAN DER HOOG, *Micro-economic disequilibrium dynamics.*
344. B. BRYS, *Tax-arbitrage in the Netherlands evaluation of the capital income tax reform of January 1, 2001.*
345. V. PRUZHANSKY, *Topics in game theory.*
346. P.D.M.L. CARDOSO, *The future of old-age pensions: Its implosion and explosion.*
347. C.J.H. BOSSINK, *To go or not to go...? International relocation willingness of dual-career couples.*
348. R.D. VAN OEST, *Essays on quantitative marketing models and Monte Carlo integration methods.*
349. H.A. ROJAS-ROMAGOSA, *Essays on trade and equity.*
350. A.J. VAN STEL, *Entrepreneurship and economic growth: Some empirical studies.*
351. R. ANGLINGKUSUMO, *Preparatory studies for inflation targeting in post crisis Indonesia.*
352. A. GALEOTTI, *On social and economic networks.*
353. Y.C. CHEUNG, *Essays on European bond markets.*
354. A. ULE, *Exclusion and cooperation in networks.*
355. I.S. SCHINDELE, *Three essays on venture capital contracting.*
356. C.M. VAN DER HEIDE, *An economic analysis of nature policy.*

357. Y. HU, *Essays on labour economics: Empirical studies on wage differentials across categories of working hours, employment contracts, gender and cohorts.*
358. S. LONGHI, *Open regional labour markets and socio-economic developments: Studies on adjustment and spatial interaction.*
359. K.J. BENIERS, *The quality of political decision making: Information and motivation.*
360. R.J.A. LAEVEN, *Essays on risk measures and stochastic dependence: With applications to insurance and finance.*
361. N. VAN HOREN, *Economic effects of financial integration for developing countries.*
362. J.J.A. KAMPHORST, *Networks and learning.*
363. E. PORRAS MUSALEM, *Inventory theory in practice: Joint replenishments and spare parts control.*
364. M. ABREU, *Spatial determinants of economic growth and technology diffusion.*
365. S.M. BAJDECHI-RAITA, *The risk of investment in human capital.*
366. A.P.C. VAN DER PLOEG, *Stochastic volatility and the pricing of financial derivatives.*
367. R. VAN DER KRUK, *Hedonic valuation of Dutch Wetlands.*
368. P. WRASAI, *Agency problems in political decision making.*
369. B.K. BIERUT, *Essays on the making and implementation of monetary policy decisions.*
370. E. REUBEN, *Fairness in the lab: The effects of norm enforcement in economic decisions.*
371. G.J.M. LINDERS, *Intangible barriers to trade: The impact of institutions, culture, and distance on patterns of trade.*
372. A. HOPFENSITZ, *The role of affect in reciprocity and risk taking: Experimental studies of economic behavior.*
373. R.A. SPARROW, *Health, education and economic crisis: Protecting the poor in Indonesia.*
374. M.J. KOETSE, *Determinants of investment behaviour: Methods and applications of meta-analysis.*
375. G. MÜLLER, *On the role of personality traits and social skills in adult economic attainment.*
376. E.H.B. FEIJEN, *The influence of powerful firms on financial markets.*
377. J.W. GROSSER, *Voting in the laboratory.*
378. M.R.E. BRONS, *Meta-analytical studies in transport economics: Methodology and applications.*
379. L.F. HOOGERHEIDE, *Essays on neural network sampling methods and instrumental variables.*
380. M. DE GRAAF-ZIJL, *Economic and social consequences of temporary employment.*
381. O.A.C. VAN HEMERT, *Dynamic investor decisions.*
382. Z. ŠAŠOVOVÁ, *Liking and disliking: The dynamic effects of social networks during a large-scale information system implementation.*
383. P. RODENBURG, *The construction of instruments for measuring unemployment.*