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SIMULATING KNOWLEDGE DIFFUSION IN FOUR STRUCTURALLY DISTINCT NETWORKS – AN AGENT-BASED SIMULATION MODEL

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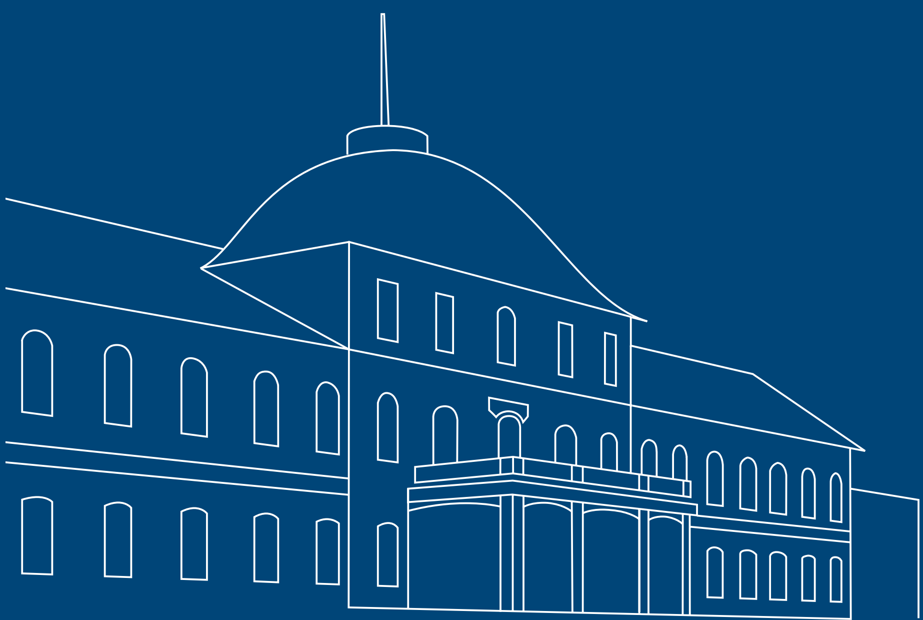

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Simulating knowledge diffusion in four structurally distinct networks – An agent-based simulation model

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Abstract: In our work we adopt a structural perspective and apply an agent-based simulation approach to analyse knowledge diffusion processes in four structurally distinct networks. The aim of this paper is to gain an in-depth understanding of how network characteristics, such as path length, cliquishness and the distribution and asymmetry of degree centrality affect the knowledge distribution properties of the system. Our results show – in line with the results of Cowan and Jonard (2007) – that an asymmetric or skewed degree distribution actually can have a negative impact on a network's knowledge diffusion performance in case of a barter trade knowledge diffusion process. Their key argument is that stars rapidly acquire so much knowledge that they interrupt the trading process at an early stage, which finally disconnects the network. However, our findings reveal that stars cannot be the sole explanation for negative effects on the diffusion properties of a network. In contrast, interestingly and quite surprisingly, our simulation results led to the conclusion that in particular very small, inadequately embedded agents can be a bottleneck for the efficient diffusion of knowledge throughout the networks.

Key words: innovation networks, knowledge diffusion, agent-based simulation, scale free networks

1. Introduction

There is a rich body of literature which clearly indicates that firm positioning in innovation networks (Powell et al. 1996), network dynamics (Powell et al. 2005) and the structural configuration of the entire system (Schilling and Phelps 2007) affect both the knowledge transfer processes among actors involved in the knowledge transfer process as well as innovation outcomes at the firm level. Nonetheless, we still have a rather incomplete understanding of how the network topology and its structural evolution affect the generation and diffusion of knowledge. One of the crucial questions for policy makers and managers in this context therefore is: how is the knowledge distributed across actors in the system and how can knowledge transfer be organized in efficiently?

In this paper we apply a structural perspective on networks. When it comes to the relation between network structure and knowledge diffusion processes, we still face more questions than answers. Previous research indicates the formation and solidification of typical patterns such as core-periphery structures (Borgatti and Everett 1999), fat-tailed degree distributions (Barabási and Albert 1999) and small-world properties (Watts and Strogatz 1998). At the same time there is an ongoing debate in the literature about what an 'optimal' collaborative network structure should look like in order to foster fast and efficient diffusion of knowledge, thereby spurring collective innovation (Morone et al. 2007). While small-world properties – short path length and high cliquishness – are typically assumed to foster knowledge diffusion processes, there are also other large-scale network topologies (Mueller et al. 2014), which have significant effects on the diffusion properties of the entire system.

The aim of this paper is twofold. On the one hand, we conduct several simulation experiments to gain an in-depth understanding of how network characteristics, such as path length, cliquishness and the distribution of degree centrality, affect the knowledge distribution properties of the system. On the other hand, we study the interplay between these network characteristics to gain an in-depth understanding how mutually interdependent processes affect the diffusion of knowledge among the actors involved. To do so, we implement a barter trade knowledge diffusion process in our agent-based simulation model. With this model we analyse how the structural properties of four structurally different network topologies affect the overall knowledge diffusion properties within these networks. The rationale behind this approach is straightforward. The overall topology of a network is the result of individual cooperation decisions at the micro-level. We account for this fact by explicitly considering the structural network patterns, which can be traced back to very simple cooperation rules. By using this approach, we focus on the diffusion processes of the system over time to identify the network structures and properties that ensure efficient knowledge diffusion on both the actor as well as on the aggregate level.

This paper is organized as follows: Section 2 will give a brief overview of the literature on knowledge exchange processes in networks and network formation algorithms by placing a particular emphasis on barter trade processes. In Section 3, we conduct our simulation-based analysis of knowledge diffusion processes in networks. In doing so, we explore how characteristics such as path-length, cliquishness and degree distribution affect the performance of our networks. Additionally, we conduct a policy experiment to analyse the effect of different policy measures. The results are finally discussed in Section 4 together with some remarks on limitations and fruitful avenues for further research.

2. Knowledge exchange and network formation mechanisms

Modern economic growth is without doubt largely based on innovations and thus on the generation, acquisition and application of knowledge. Consequently, the term *knowledge-based economy* became popular among economists as well as among politicians. Knowledge-based economies are "directly based on the production, distribution and use of knowledge" (OECD 1996, p. 7). This triggered a growing interest in the role of knowledge generation and diffusion for economic growth. The conceptualization of knowledge as an ubiquitous public good that can be acquired for free is being replaced by a concept according to which a firm needs to be embedded in a network to absorb and make use of knowledge. This holds in particular for situations in which knowledge is exchanged informally.

The following section will give a brief overview of the literature on knowledge exchange processes in networks (2.1) and on different network formation algorithms (2.2). This is followed by the presentation of the knowledge barter trade diffusion model, which is used for the simulation experiments (2.3).

2.1 Informal knowledge exchange within networks

In this paper we focus on informal knowledge exchange networks. In real life, informal networks are rather the rule than the exception. Nonetheless the broad majority of network studies are based on data from formalized cooperation agreements. The rationale behind this is straightforward: econometric network studies are dependent on reliable raw data sources (e.g. patent data) that allow replicating the cooperation behavior of a well-specified population of actors. Irrespective of how good these raw data sources are, the informal dimension of cooperation is hardly reflected in this kind of data. Therefore, a lot of research still has to be done to further investigate informal knowledge exchange.

Informal network structures can be found within industries but they also span between regional borders. They are even present between competing firms for barter trading knowledge (von Hippel 1987; Hicks 1995; Schrader 1991). This shows that ties in innovation networks not only reflect formal contracts but also informal relationships (Hanson and Krackhardt 1993; Pyka 1997). Moreover, informal ties are also important for formal contractual relationships because informal personal relations facilitate the transfer of information through more formal channels (von Hippel 1987). In 1991 Freeman (1991 p. 500) finds: “Although rarely measured systematically, informal networks appeared to be the most important.” Dahl and Pedersen (2004) find for the case of a cluster of wireless communication firms in Northern Denmark that especially informal contacts considerably accelerate knowledge diffusion. A particular type of informal network is observed by von Hippel (1987) as informal knowledge exchange among scientists and engineers working for different and even competing firms. “Informal know-how trading is the extensive exchange of proprietary know-how in informal networks of engineers in rival (and non-rival) firms” (von Hippel 1987, p. 291). On the side of the giver, this deliberate transfer of information creates the expectation that he receives something back in return. Hence, informal knowledge exchange has the character of a barter exchange (Cowan and Jonard 2004).

With our analysis, we follow Cowan and Jonard (2004) in modeling knowledge exchange between actors as a barter process and knowledge as an individual vector of different knowledge categories, which mirrors the concept of informal knowledge exchange. Actors in a network are linked to a small fixed number of other actors with whom they repeatedly exchange knowledge if trading is mutually beneficial for both actors. By this process of mutual giving and taking knowledge diffuses throughout the network until a steady state is achieved and the knowledge level of all actors stays constant. The interesting question is now: which network structure is most supportive for the diffusion performance on an individual but also on the aggregated level and why do certain structures perform better than others?

We argue that the picture of diffusion processes we have thus far is not complete. A lot of research focused on small-world network properties and concluded that they speed up innovation or knowledge diffusion. Small-world networks are characterized by short average path-lengths with, at the same time, a high level of clustering. However, in this paper we are able to show that these characteristics alone do not fully explain the knowledge diffusion performance of a network. By studying knowledge diffusion in four structurally different networks, we show that there has to be more to fully explain knowledge diffusion performance.

2.2 Algorithms for the creation of networks

In this section, we introduce the four structurally distinct networks analysed in our work. These are the Erdös-Rényi or random network, the Barabási-Albert network, the Watts-Strogatz network and the Evolutionary network.

The first models of complex network structures used Erdös' and Rényi's (1959) algorithm to transform a regular graph into a random graph. The attachment logic is quite simple; each node attracts ties with the same probability. This algorithm is not linked to considerations on the strategic behavior of agents and functions therefore it is used as a baseline model against which the other network topologies are compared.

Another network that is analysed in our work is the Barabási-Albert network. In 1991, Barabási and Albert (1999) discovered a network characteristic in real-world networks (e.g. in scientific citation networks) that is not reflected in random graphs, namely that the probability *P (k)* that a node in the network is linked with *k* other nodes decreases according to a power law described by the following expression: $P(k) \sim k^{-\gamma}$. The implication is that in large-scale networks a kind of self-organizing process leads to the emergence of a scale free structure. The explanation for this phenomenon is that real-world networks are typically characterized by growth and preferential attachment. The random graph model, in contrast, is described by the following rule: At the starting point we have *n* nodes and each pair is linked by the probability *p*. This leads to a Poisson distribution of the probability that a node has *k* ties.

In 1998, Watts and Strogatz (1998) stress that biological, technical and social networks are typically neither fully regular nor fully random but exhibit a somewhat in between structure. They introduce an algorithm that transforms a regular network into this in between network structure by rewiring ties. The resulting networks have a high tendency for clustering, like a regular network, and at the same time small average paths lengths, like in a random graph. The long-range connections generated by this process decrease the distance between the nodes, leading to a small-world phenomenon. In these small-world structures, signal diffusion was found to be increased and as well as the speed of infectious diseases. The exact rewiring procedure works as follows: The starting point is a ring lattice with n nodes and k links. In a second step, each link is rewired randomly with the probability p by altering the parameter p between $p = 0$ and $p = 1$, i.e. the network can be transformed from regularity to disorder. Consequently, the average number of connections remains stable but the algorithm creates variety in the individual connectedness. Watts and Strogatz (1998) point out that in their approach the dynamics of diffusion is an explicit function of structure, which is different from approaches that focus on specific topologies only such as stars or random graphs. According to Barabási and Albert (1999), in random and small-world networks, nodes with large connectivity (high k) are virtually nonexistent since this probability decreases exponentially with k. However, in real-world networks, the existence of highly connected nodes is very common leading to a power law tail. That is, in random network models the probability that two nodes are linked to each other is random and uniformly distributed, while Barabási and Albert (1999) found that in most real networks there is a preferential attachment mechanism in place.

In 2014, Mueller, Buchmann and Kudic (2014) suggested an algorithm by directly deriving network formation theory from considerations of actor behavior. This algorithm is based on the assumption that actors are faced with a situation of information scarcity and accordingly adapt their behavior in selection cooperation partners for knowledge exchange. Hence, partner selections strategies are aimed at compensating the information deficit problem. It is suggested that the trade-off between the need for reliable information and the cost of the search process is reflected in a two-stage selection process in which firms randomly or based on the transitive closure principle pre-select a group of firms from which they make their final choice. The transitive closure mechanism works as follows (Holland and Leinhardt 1971; Davis 1970): When firms operate in an uncertain environment they may use existing connections in order to gain information about potential partners. For instance, if actor i cooperates with actor j and j also cooperates with a third actor k, then i may get information about the trustworthiness, reliability and value of the knowledge base of k from j. Whereas, it is much more difficult and costly to collect information about other firms that are more than two steps away or not connected at all. Consequently, the probability that i connects to k is higher than the probability to connect to more distant actors. Thus, network cohesion fosters knowledge sharing.

Subsequently, the principle of (structural) homophily between firms and preferential attachment is applied as strategies for the final selection of a knowledge exchange partner.

Homophily refers to a preference for similarity between potential cooperation partners (McPherson et al. 2001). Two actors are assumed to be similar if they possess a similar structural position in a network, which reflects a similar status level. Consequently, highly attractive central actors prefer to connect to other central actors rather than to peripheral actors. Different from previous approaches, the model focuses directly on the actors and their strategic behavior and less on connecting probabilities as such. The applied algorithm leads to networks structures that are characterized by both small-world characteristics and a power-law degree distribution.

In the literature we already find contributions to the discussion on how network structure affects network performance in terms of knowledge diffusion. In the work of Cowan and Jonard (2007), knowledge diffusion performance is investigated in small-world and random networks. Cowan and Jonard (2004, 2007) show that in a small-world state structure, we have fast knowledge diffusion but high knowledge inequality. They show that there actually exists a positive relationship between small-world properties (local clustering and about 10% long distance links) and diffusion performance. However, the authors also state that path-length and cliquishness cannot be the sole explanation for network performance differences between different networks. They found that the asymmetry of the degree distribution is a decisive factor and, to be more concrete, that networks with a relatively asymmetric degree distribution perform worst. In their work, Cowan and Jonard (2007) identify trading stars, i.e. nodes with a relatively high number of direct linkages, while the direct partners have nearly no linkages among one another. According to the authors, these star nodes can significantly slow down knowledge diffusion processes. This is because stars can rapidly absorb the knowledge they are lacking (mainly due to their high level of connectedness) and hence stop trading relatively early. Thereby, they block many paths between actors that no longer function as channels of knowledge diffusion, which can even lead to a disconnected network (Cowan and Jonard 2007). The authors use the existence of these stars as an explanation for why networks with highly asymmetric degree distribution perform worst (because there they have many stars). In contrast to Cowan and Jonard’s (2007) findings about the positive effect of small-world structures on network performance, Morone, Morone and Taylor (2007) find that random networks perform best in terms of knowledge diffusion, even compared with small-world networks. Morone and Taylor (2004) developed a model in which knowledge exchange is based on face-to-face interactions. Thereby it could be shown how small-world structures emerged. With regard to knowledge diffusion, the results could be an equal or rather unequal state depending on initial conditions. Knowledge exchange is modelled as a complex learning process. Drawing on their earlier model, Morone, Morone and Taylor (2007) found that three factors determine the speed of knowledge diffusion in closed networks, namely the learning strategies, the networks architecture and the geographical distribution of actors as well as the initial knowledge level. Moreover, by analysing the influence of network size on knowledge diffusion they find that size is positively correlated with diffusion speed independent of a particular knowledge structure. In view of numerous factors that potentially influence diffusion processes, Morone, Morone and Taylor (2007) aim at making an attempt towards a clear taxonomy of all the factors that affect knowledge flows in social networks.

2.3 The barter trade process

In the literature there exists a great variety of diffusion models focusing on different aspects of knowledge exchange within networks. For our simulation model we use a barter trade diffusion model introduced by Cowan and Jonard (2004). We adapt the barter trade process of Cowan and Jonard (2004) as this process represents an informal knowledge exchange between actors in a network. This barter trade knowledge diffusion process is modelled as follows:

In the model we start with a set of agents $I = \{1, \dots, N\}$. Any pair of agents $i, j \in I$ with $i \neq j$ can be either directly connected (indicated by the binary variable $\chi(i,j) = 1$) or directly unconnected (indicated by the binary variable $\chi(i,j) = 0$). An agent's neighborhood N_i is defined as the set $N_i = j \in I$ with $\chi(i,j) = 1$, i.e. the set of all other agents in the network to which agent i is directly connected. The network $G_{(n,p)} = \chi(i,j);\ i,j \in I$ therefore is "the list of all pairwise relationships between agents" (Cowan and Jonard 2004, p. 1560). The distance $d(i,j)$ between two agents i and j is defined as the length of the shortest path connecting these agents, with a path in $G_{(n,p)}$ between i and j characterized as the set of pairwise relationships $\{(i, i_1), \dots, (i_k, j)\}$ for which $\chi(i, i_1) = \cdots = \chi(i_k, j) = 1$.

Every agent $i \in I$ is endowed with a knowledge vector $v_i = (v_{i,c})$ with $i = 1, \dots, l; c = 1, \dots, K$. Knowledge is exchanged between agents in a barter exchange process. Agents follow simple behavioral rules in a sense that they trade knowledge if trading is mutually beneficial. An exchange therefore takes places if two agents are directly connected via a link and if both agents can receive unknown knowledge from the respective other agent, independent of the amount of knowledge they actually receive. This assumption allows us to incorporate the realistic idea that agents can only assess whether or not the potential partner has some relevant knowledge to share and not to a priori assess how much can be gained exactly from the knowledge exchange. This is in line with the particularity of knowledge that its exact value can only be assessed after its consumption (if at all).

In a more formal description, two conditions have to be fulfilled. Let $j \in N_i$ and assume there is a number of knowledge categories $n(i,j) = \#\{c: v_{i,c} > v_{j,c}\}$ in which agent i's knowledge strictly dominates agent j's knowledge. As we already know, agent j will only be interested in a trade with agent i if $n(i,j) > 0$ and *vice versa*. Hence, the barter exchange takes place and agents i and j exchange knowledge if and only if first, $j \in N_i$, and if second, $min\{n(i,j), n(j,i)\} > 0$. This is also called a "double coincidence of wants" (Cowan and Jonard 2004, p. 1562). If the 'double coincidence of wants' condition holds true, the agents exchange knowledge in as many categories of their knowledge vector as mutually beneficial. If the number of categories in which the agents strictly dominate each other is not equal among the trading agents (i.e. $n(i,j) \neq n(j,i)$), the number of categories in which the agents exchange knowledge will be equal to $min\{n(i,j), n(j,i)\}$, while the decision in which categories the agents eventually exchange knowledge is randomly chosen with a uniform probability. Besides the particularity of knowledge named above, the model also incorporates the fact that the internalization of knowledge is difficult and the assimilation of knowledge is only partly possible due to the different absorptive capacities of the agents. This means that only a constant share of α with $0 < \alpha < 1$ can be actually assimilated by the receiver. Therefore, each period in time the knowledge stock of an agent can either increase to a before the exchange unknown amount (if an exchange takes place) or stay constant (if no exchange takes place).

Agents in the model mutually learn from each other and by doing so knowledge diffuses through the network and the mean knowledge stock of all agents within the network $\bar{v} = \sum_{i \in I} v_i / I$ increases over time. As knowledge is considered to be non-rival in consumption, the knowledge stock in the economy can only increase or stay constant, but an agent will never lose knowledge by sharing it with other agents. Assume, for instance, that $n(i,j) = n(j,i) = 1$ and that in category c_1 agent j's knowledge strictly dominates agent i's knowledge and that in category c_2 agent i's knowledge strictly dominates agent j's knowledge. In this situation agent i will receive knowledge from agent j in category c_1 (with his knowledge in category c_2 being unaffected) and agent j will receive knowledge from agent i in category c_2 (with his knowledge in category c_1 being unaffected). Therefore, after the trade the knowledge of agent i changes according to $v_{i,c1}(t+1) = v_{i,c1}(t) +$

$\alpha(v_{j,c1}(t) - v_{i,c1}(t))$ and the knowledge of agent j changes according to $v_{j,c2}(t+1) = v_{j,c2}(t) + \alpha(v_{i,c2}(t) - v_{j,c2}(t))$. As agents exchange their knowledge as long as this trade is mutually advantageous, the barter trade process takes place until all trading possibilities are exhausted, i.e. "there are no further double coincidences of wants: $\forall i \in I, \forall j \in N_i: min\{n(i,j), n(j,i)\} = 0$" (Cowan and Jonard 2004, p. 1562).

3. Numerical model analysis

In this section we present the findings of our simulation analyzes where we explore how different network topologies affect the diffusion of knowledge. First, we address the relationship between network characteristics such as path-length and cliquishness and the network performance in terms of the average knowledge level of all actors. We then investigate how the asymmetry of the distribution of degrees affects network performance. In doing do, we first explain the model setup and the parameters used in the analysis. Then, we stepwise analyze the simulations' outcomes to investigate the role of network structure for knowledge diffusion. Finally, we run policy experiments for each of the four networks to gain an in-depth understanding how policy interventions may affect our initially reported findings.

3.1 Path length, cliquishness and network performance

Before the first run, the model is initialized with a standard setting of parameters as follows: We assume a model population of $I = 100$ agents connected by 200 links for all networks. The agents and links within the network are placed according to the algorithm described before which leads to the following four networks: (i) Random - Erdös / Renyi (n,M), (ii) Watts-Strogatz, (iii) Barabási-Albert and (iv) Evolutionary network algorithm. More precisely, we assume for the Watts-Strogatz algorithm a probability $p = 0.15$ and for the Evolutionary network algorithm a preselection group of 5 and 100 time steps for the initiation of the network. Figure 1 illustrates the network patterns produced by these formation algorithms.

Throughout each model run, every agent is equipped with a knowledge vector v_i with 10 different knowledge categories drawn from a uniform distribution, i.e. $v_{i,c}(0) \sim U[0,10]$. For the agents' absorptive capacities we assume a value of $\alpha_i = 10\%$. Finally we assume the knowledge levels of agents to be similar if the difference is not higher than 1%.

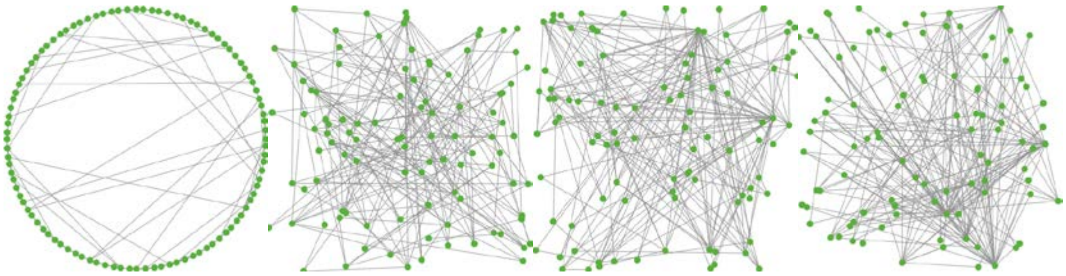

Figure 1: Visualization of networks topologies created in NetLogo. From left to right: The Watts-Strogatz network, the random/ Erdös-Renyi network, the Barabási-Albert network and the Evolutionary Network Algorithm.

In theory, it is often argued that average path-length and average cliquishness are the main forces influencing network performance. Figure 2 shows the average overall knowledge stock of all agents over time, i.e. the mean knowledge of agents within the network $\overline{v_t} = \sum_{i \in I} v_{i,t} / I$ of our four different networks obtained by 500 simulation runs for all network algorithms. Over time, the average knowledge stocks increase, however, there are significant differences between the four network topologies. In more detail, Watts-Strogatz networks perform best followed by random networks, networks created via the Barabási-Albert algorithm and the Evolutionary network algorithm.

Following the idea that path length and cliquishness are the main factors influencing the diffusion of knowledge, we show both the average path length as well as the average cliquishness of the four groups of networks in Table 1. As pointed out by Cowan and Jonard (2004, p. 1564), a low path length as well as a high cliquishness favor network performance which is why small-world networks, showing both short path lengths and a high cliquishness are identified as networks fostering the diffusion of knowledge. This is what Cowan and Jonard call an 'interior maximum' (Cowan and Jonard 2004, p. 1569).

Looking in more detail at the diffusion performance of the networks and the respective path length and cliquishness we see an increasing network performance for increasing path length of the networks. These results are inversely to our expectations derived by theory. In fact, the network with the lowest average path length is the network that performs worst in our analysis, namely the Evolutionary network. This leads to the idea that, in our context, not the average path length might be the decisive factor influencing network performance but the average cliquishness. Regarding the results of our simulation, however, this seems to only hold true for the Watts-Strogatz networks which show high cliquishness. The networks with the second best performance, the Random networks, have the lowest average cliquishness.

Moreover, even though the average path length of the Barabási-Albert and the Evolutionary networks are quite similar, the average cliquishness of the Evolutionary network is two times the average cliquishness of the Barabási-Albert networks and still the Barabási-Albert networks outperform the Evolutionary networks. So, the networks with the second highest average cliquishness are networks that perform worst.

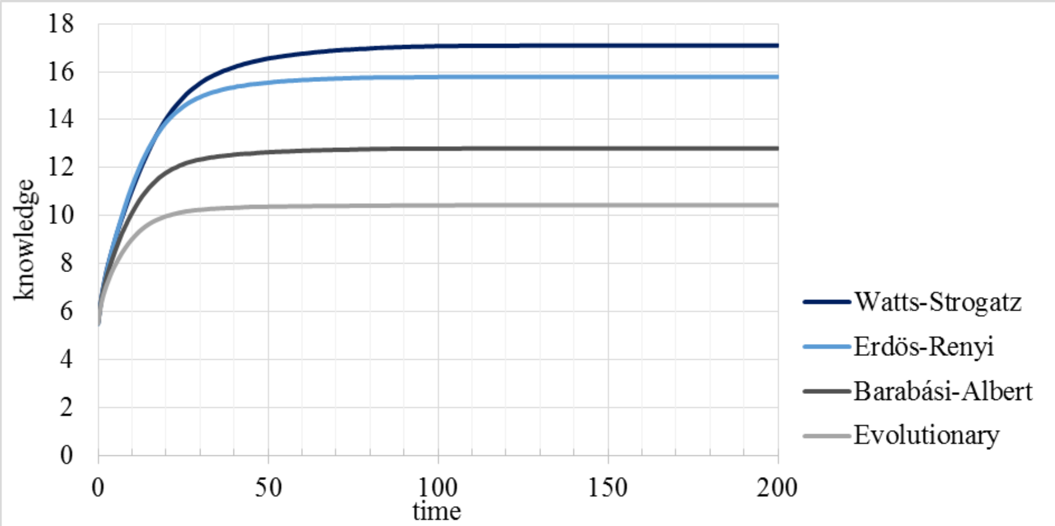

Figure 2: Average knowledge levels of agents in the respective networks over time over 500 simulation runs.

	Watts-Strogatz	Erdös-Renyi	Barabási-Albert	Evolutionary
Path length	4,49	3,45	2,99	2,74
Cliquishness	0,32	0,03	0,13	0,27

Table 1: Average path length and cliquishness of all four network topologies over 500 simulation runs.

These counter-intuitive results lead to the question whether a network's path length and its cliquishness are fully able to explain the performance differences between the observed networks. Following the idea of Cowan and Jonard (2007), another network characteristic that could explain the differences in network performance is the distribution of links among agents. The authors found that, in a barter economy, the existence of 'stars' with a high degree centrality has a negative effect on network performance. According to the authors, this is the case as stars have so many partners that they acquire a high knowledge level in a very short time. This rapidly leads to a lack of double coincidences of wants which stops the knowledge trading process within the network which may even disconnect the whole network (Cowan and Jonard 2007, p. 108):

"If the stars are traders, because they have many partners, they will rapidly acquire all the knowledge they need, and so stop trading. This blocks many paths between agents, and in the most extreme case, can disconnect the network." (Cowan and Jonard 2007, p. 108)

To test this hypothesis we conduct in the following section several simulation experiments to show to what extend the degree distribution of a network has an effect on the diffusion processes and if the explanation by Cowan and Jonard (2007) fully explains the obtained differences in the simulation results.

3.2 Degree distribution and network performance

In Figure 3, it can be seen that the networks analysed in this paper significantly differ concerning the distribution of degrees. The worst performing networks, namely the Barabási-Albert and the Evolutionary network, are networks that have a highly skewed degree distribution following a power law approximately, with a large number of small nodes (having only few links) and some big nodes (i.e. stars having a high number of links). Watts-Strogatz and random networks in contrast, have more symmetric degree distributions with only small deviations from the average degree of the network.

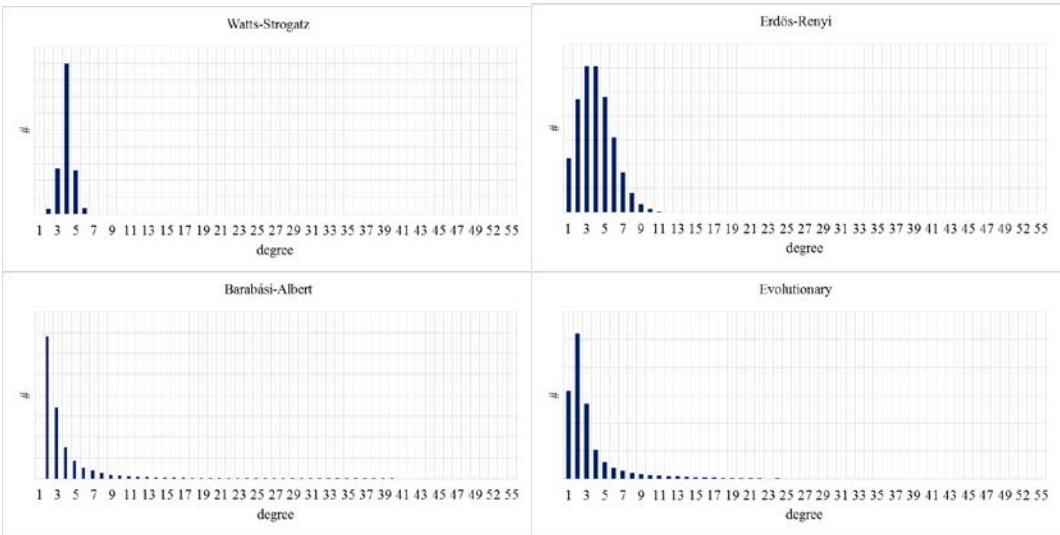

Figure 3: Average agents' degree distribution in the respective networks.

In figure 4 we analyse how the variance in the degree distribution relates to the resulting network performance. Figure 4 reports the findings of this simulation run, measured after 200 time steps. It can be seen that the higher the variance of the degree distribution of a network, the lower the performance of the respective network. The Watts-Strogatz networks, which outperform the other networks, are characterized by the lowest variance of nodes' degrees. This relationship between low variance and high network performance also holds true for the other networks, e.g. the worst performing networks, Evolutionary networks, are at the same time networks with the highest variance of their degree distribution.

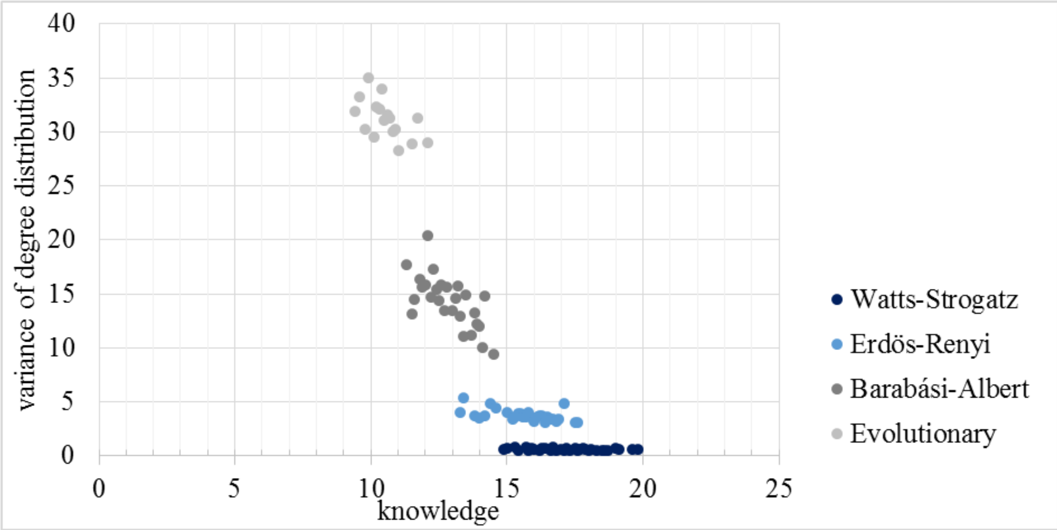

Figure 4: Relationship between the variance of degree distribution of the respective networks and the mean average knowledge levels after 200 time steps.

However, in contrast to the results of Cowan and Jonard (2007), our results indicate that the weak performance of networks with a highly skewed degree distribution cannot (exclusively) be explained by Cowan and Jonas "star argument", according to which the stop of the barter trade process (initialized by stars) eventually disconnects the network. We argue that this is only a part of the story. Our results indicate that the diffusion of knowledge within scale-free networks does stop because of the existence of relatively *small, inadequately embedded* nodes.

Figure 5 illustrates the cumulative number of agents that stopped trading over time. Not surprisingly, in the worst performing networks (i.e. lowest level of knowledge diffusion), i.e. the Evolutionary networks, agents stop trading earlier than in the better performing networks (i.e. higher level of knowledge diffusion). Comparing Evolutionary and Watts-Strogatz networks after 40 time steps shows that in Evolutionary networks almost 90% of the agents already stopped trading whereas in Watts-Strogatz networks 65% of all agents are still trading. Moreover, in Evolutionary networks almost all agents stopped trading after 70 time periods whereas in Watts-Strogatz networks this only happens after 100 time periods.

To test whether stars block paths between agents because they rapidly acquire all the knowledge they need, and so stop trading, we measure the average point in time at which the biggest node of a network stops trading. As can be seen in Table 2, our results show, in all four networks the stars stop trading not before 70 to 85 percent of the other agents have already stopped trading. As we can see in table 2 for the Barabási networks the biggest nodes stop trading after 39 steps and for Evolutionary networks stars stop trading after 36 steps. In

Evolutionary networks, stars stop trading in a situation in which only 15% of the remaining non-stars still trade. In Barabási-Albert networks, stars stop trading in a situation in which only 25% of the remaining non-stars still trade. In random networks, stars also stop trading in a situation in which only 25% of the remaining non-stars still trade. In Watts-Strogatz networks, stars stop trading in a situation in which only 30% of the remaining non-stars still trade.

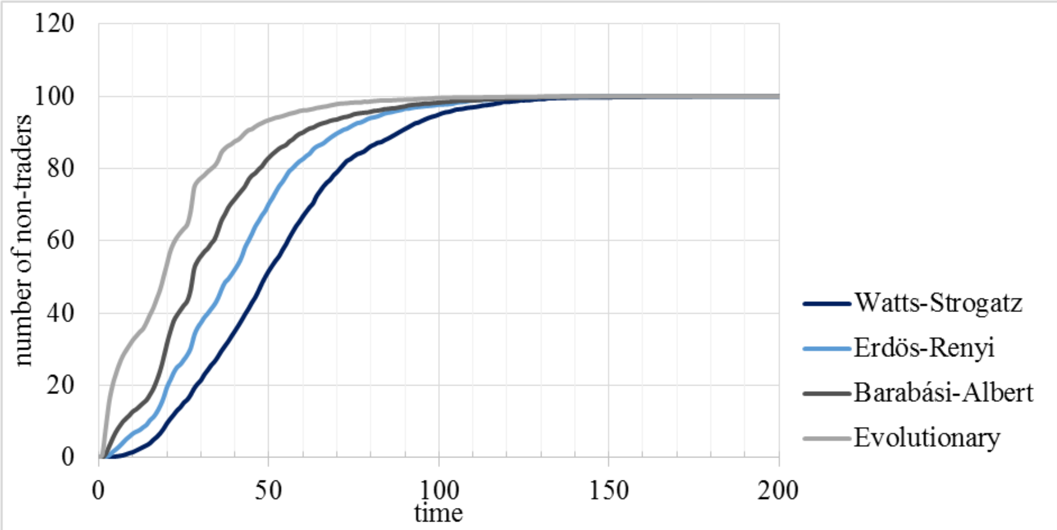

Figure 5: Average cumulative number of non-traders in the respective network topologies over time over 500 simulation runs.

	Watts-Strogatz	Erdös-Renyi	Barabási-Albert	Evolutionary
Star stops trading	57,60	51,84	38,88	35,86

Table 2: Average point in time the star stops trading depending on the network topology over 500 simulation runs.

Additionally, if we transfer the data from Table 2 to Figure 2 we see that big nodes stop trading after the increase in knowledge levels has reached its turning point and almost no knowledge is traded within the network anymore. Combined with the result of figure 5, this data clearly indicates that the low network performance cannot be exclusively explained by stars that stop trading early and disrupt the knowledge flow.

To stress this idea we show in Figure 6 (left-hand side) the relationship between the number of degrees of a node and the time these nodes stop trading. These explorations provide that we have to differentiate between three groups of actors. First, very small, inadequately embedded agents with a degree smaller than 5 stop trading at the very beginning of the process. Second, it can be seen that in all four networks, agents with a degree between 5 and 15 trades longest. This means that agents with a medium degree seem to be very important for network performance. Third, and this confirms our hypothesis, agents with more than 20 ties stop trading after time step 30 to 45, whether or not these agents just have 20 ties or these agents are stars with more than 50 ties.

Finally, figure 6 (right-hand side) shows the relationship between the agents' degree in the different networks and the mean knowledge level these agents reached after 200 periods. The figure shows that stars do not have a considerably higher knowledge level than agents from 15 ties on. Only inadequately imbedded small agents with less than 15 ties have significantly lower knowledge endowment than the other agents. This result shows that stars trade over longer time periods compared to most other agents. In addition, stars have no significantly higher mean knowledge endowment than non-stars and therefore stop trading with other agents. This implies that the actual explanation for the worse performance of networks with a relatively asymmetric degree distribution is that these networks have a high number of very small agents and these very small agents have too little knowledge to continue trading. This, in turn, leads to a disruption of the knowledge flow. In other words, it seems not to be the case that the high knowledge level of stars causes the lack in double coincidences of wants but rather that the very small knowledge level of the small agents does.

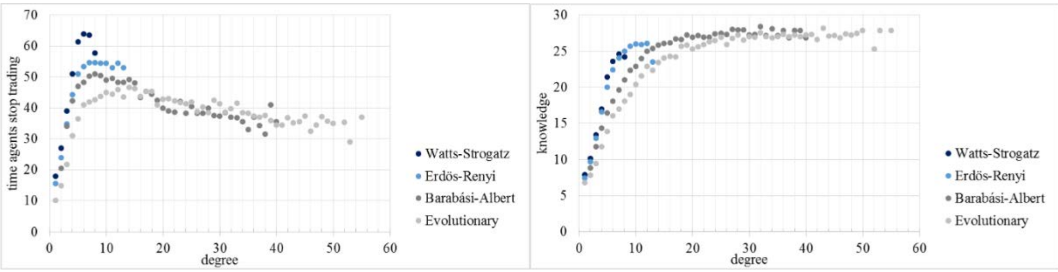

Figure 6: Relationship between the time the agents in the network stop trading and their degree (l.h.s.) and the relationship between the mean knowledge levels and the degree (r.h.s.).

Interestingly, these results also occur for networks with higher density. Figure 7 shows that even for networks with 100 nodes and 600 links the results explained above hold true although in this case small nodes still have a relatively high number of connections (see Figure 7). From this we conclude that variance in the degree distribution itself is the limiting factor and not the absolute number of links of small nodes. To put it more simple, what 'small' or 'inadequately embedded' means depends on the embeddedness of the other actors in the network.

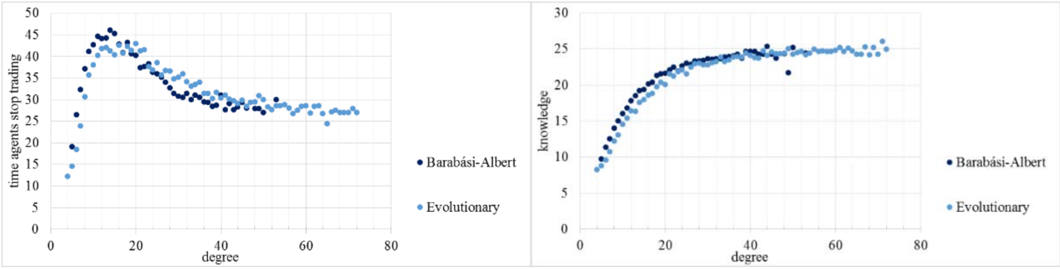

Figure 7: Relationship between the time the agents in the network stop trading and their degree in a network with 100 nodes and 600 links (l.h.s.) and the relationship between the mean average knowledge stock and the degree in a network with 100 nodes and 600 links (r.h.s.).

The results we present in this section demonstrate that neither path length nor cliquishness are sufficient to explain the knowledge diffusion performance of networks. We need to account for other factors such as the degree distribution to fully understand the relevant processes within networks. In contrast to the findings of Cowan and Jonard (2007), however, our results show that the dissimilarities between nodes, especially for scale free structures, can create gaps of knowledge levels. These gaps create a situation where small nodes, as the majority of nodes, do not gain knowledge fast enough to keep up to the other nodes in the network. Hence, the small agents fall behind and stop trading, disrupting and disconnecting the network and the knowledge flow.

3.3 Policy experiment

To further investigate the relationship between degree distribution and network performance, we implement a policy experiment in the simulation where we analyse the effect of four different network modifications. Scenario 1, '*no intervention*' shows the network performance of all four network topologies in a situation where we have no intervention at all, i.e. the number of links in the network does not change. This scenario is used as a reference scenario for the actual policy intervention. Scenario 2, '*nonstars*' shows the network performance of all four network topologies in a situation where we distributed 20 new links to the 10 agents with the smallest degree. Scenario 3, '*random*' shows the network performance of all four networks in a situation where we distributed 20 new links to 10 randomly chosen agents, independent of their degree. Scenario 4, '*stars*' shows the network performance of all four networks in a situation where we distributed 20 new links to the 10 agents with the highest degree. The results of the policy experiment in terms of its impact on the networks' knowledge level can be seen in figure 8.

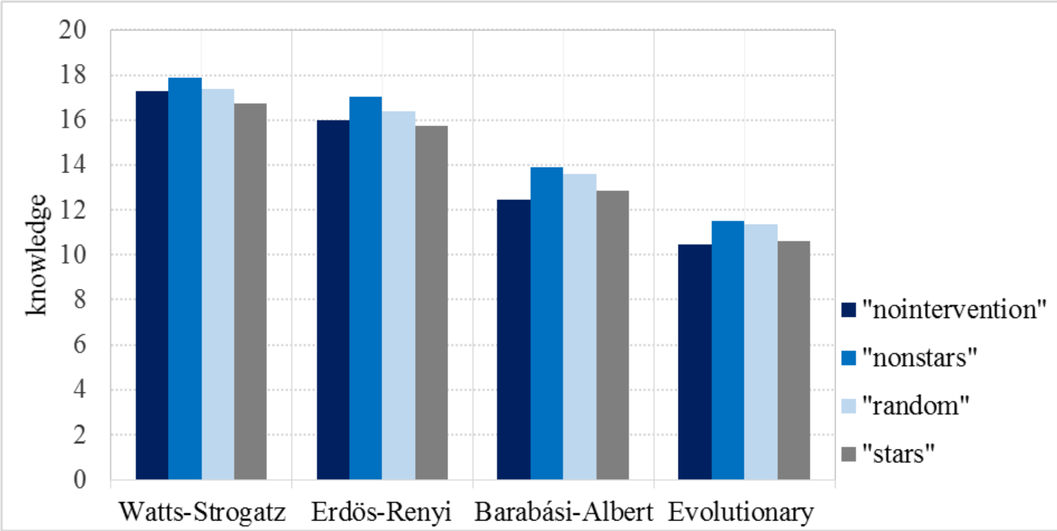

Figure 8: Average knowledge levels in the respective networks with policy interventions over 500 simulation runs.

For random networks and Watts-Strogatz networks, it can be seen that the increase of the size of big nodes actually seems to have a negative impact on network performance as explained by the results of Cowan and Jonard (2007). In these networks, the lowest average knowledge level can be observed when stars get more links, and the highest average knowledge level can be observed when the smallest get more links. However, it has to be kept in mind that, as the degree distribution in these networks is relatively symmetric compared to the other networks, the 'stars' intervention considerably increases the variance of the degree distribution. This is not the case in the networks that already have a highly skewed degree distribution with a high variance. One important implication is that the worse performance in the 'stars' intervention is not due to the negative effect of stars but due to the increase in the asymmetry of the degree distribution due to an increase in links. This is in line with the fact that in the two highly skewed networks, the Barabási-Albert and the Evolutionary network, the intervention 'stars' has no negative but a positive effect on network performance (as it does not increase the already relatively asymmetric degree distribution but only increase the networks density).

On the other hand, the positive effect of the 'nonstars' intervention can be observed in all four networks. This means that all four networks benefit from very small agents that get more links. As already mentioned before, this is in line with our theory that actually small agents with too little knowledge stop trading and so disrupt the network. This leads to the conclusion that policy makers must be aware of the complex relationship between degree distribution and network performance. In more detail, our results support the idea that policy measures should focus on small nodes instead of big nodes. This has to be done to guarantee an efficient knowledge flow throughout the network. Therefore, for instance in the case of research funding, always ‘picking-the-winner’ without knowing the exact underlying network structure can be harmful.

4. Discussion and conclusions

Economic actors – or more technically spoken “agents” - in today’s economies become more and more connected and interlinked. Most scholars in the field of interdisciplinary innovation research would agree that „networks contribute significantly to the innovative capabilities of firms by exposing them to novel sources of ideas, enabling fast access to resources, and enhancing the transfer of knowledge“ (Powell and Grodal 2005, p. 79). However, we still face the question which network topologies are most effective and efficient in enabling the diffusion of knowledge. In this context, it has been frequently argued that small-world networks – characterized by short path lengths and high cliquishness – show superior knowledge diffusion properties.

One seminal study in this context is conducted by Cowan and Jonard (2007). They found that not only a network’s path length and its cliquishness are important, but also the network’s degree distribution seems to be decisive for the diffusion of knowledge through the network. Inspired by these interesting insights, we wanted to gain an in-depth understanding of how the degree distribution affects knowledge diffusion process. To be more concrete, we used an agent-based simulation model to analyse if and how the degree distribution affects the diffusion of knowledge that is exchanged in a barter trade exchange process in four structurally distinct network topologies.

Our analysis showed that, in line with the findings of Cowan and Jonard (2007), a highly asymmetric degree distribution actually has a negative impact on the overall network performance. However, different to Cowan and Jonard (2007), we found that this negative effect cannot be explained (solely) by the existence of stars that rapidly acquire knowledge and so interrupt the trading process. Our results show that neither do stars acquire more knowledge than most of the other agents, nor do they stop trading earlier. Our findings indicate that stars trade longer than 70% of the nodes and only stop trading after most of the knowledge already has diffused throughout the network. A group of agents that actually has a very low level of knowledge and stops trading long before most of the knowledge already diffused throughout the network is the group of very small, inadequately embedded agents. Notably, our results support the idea that it’s actually the dissimilarity in degree distribution itself. This effect also holds for dense networks and hence, for networks in which small nodes still have a high number of links.

Finally we conducted several policy experiments. The results indicate that in all four networks the group which benefited most from an increase in its links is the group of very small agents. Our results clearly show that in networks with a skewed degree distribution not the stars hinder knowledge diffusion but very small agents do. Summing up, our analyses lead us to the conclusion that first, a highly skewed degree distribution negatively influences the diffusion of knowledge that is exchanged in a barter trade process. Second, very small agents are the bottleneck for the efficient diffusion of knowledge throughout the networks.

Our work lead us to the following two policy recommendations. First, without knowing the exact underlying network structure, it is almost impossible to increase knowledge diffusion performance by policy intervention that affects network structures. Our policy experiment shows that for some network structures some policy measures can even be harmful. The second policy recommendation is that, if the practical relevance of our results could be confirmed by further research, policy makers should take care of the dissimilarity of agents' links in informal networks. This would implicate that especially the very small agents have to be sufficiently integrated into the network. To confirm our results as well as to get as deeper understanding of the explanation of our results, further research, especially on network structure's that evolve over time, has to be done.

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