The Effect of Social Networks, Organizational Coordination Structures, and Knowledge Heterogeneity on Knowledge Transfer and Aggregation

Muge Ozman
Université Paris-Saclay, Univ Evry, IMT-BS, LITEM
91025, Evry-Courcouronnes, France.
Email: muge.ozman@imt-bs.eu

Andrew Parker
Durham University Business School
Mill Hill Lane, Durham, DH1 3LB, UK
Email: andrew.parker@durham.ac.uk

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Abstract

Previous research has established the benefits of knowledge for firm competitive advantage. Knowledge does not, however, seamlessly transfer around an organization. Research suggests that the organizations coordination structures, the heterogeneity of knowledge within an organization, and social network structure are three critical factors that can enable and constrain the transfer and aggregation of knowledge that are held by individuals and units. These three factors, however, have rarely been examined together. We use an agent based model to simulate different configurations of the three factors. We find that in decentralized coordination structures, when there is a relatively high degree of knowledge homogeneity across units, there is an advantage for actors to have a social network structure that crosses unit boundaries. This is not the case in a centralized coordination structure where there is an advantage for actors to have social network structures that remain within unit boundaries. The exception is when actors have cross-unit brokerage ties that are embedded in social networks that have a small world structure, regardless of knowledge heterogeneity. At the unit level, we find that for both centralized and decentralized reporting structures, variability of knowledge aggregation across units is higher when there is greater knowledge homogeneity between units. Overall, our results are robust to various changes in the initial parameters.

Key words: social networks, coordination structures, knowledge heterogeneity, knowledge transfer, knowledge aggregation, cross-unit brokerage

1. Introduction

Previous research has established the importance of knowledge for firm competitive advantage (Argote et al. 2003; Eisenhardt and Martin 2000; Grant 1996). However, it is not just having knowledge within a firm that is important for comparative advantage, but that it transfers across the organization (Grant 1996). Knowledge transfer is dependent on an individual's ability to absorb the knowledge that they receive (Cohen and Levinthal 1990), and that this knowledge can be combined or aggregated with existing knowledge, i.e., that there is additivity of old and new knowledge (Grant 1996). Organizations that are able to facilitate knowledge transfer and aggregation are more likely to see more innovation and higher performance (Argote et al. 2000; Carlile 2004; Grant 1996; Maurer et al. 2011) and hence gain comparative advantage. This begs the question of what are the optimum organizational conditions for knowledge transfer and aggregation?

The answer to this question is not entirely satisfactory. Research on knowledge transfer and aggregation has tended to focus on the role social networks play in facilitating this process. Research has examined how individual position in a network can provide advantage (Burt 1992; Cross and Parker 2004; Krackhardt and Hanson 1993; Tushman and Scanlan 1981). There is, however, considerable debate regarding the extent to which different micro-network structures are beneficial to the transfer of knowledge. For example, there is extensive research to indicate that dense networks of social relationships, i.e., closed networks, are advantageous as they provide a trusted environment in which knowledge can more easily transfer (Coleman 1988; Cowan et al., 2004; Reagans and McEvily 2003; Szulanski 1996, 2002). An alternative explanation is that there are benefits of having open networks—where individuals are in network brokerage positions, i.e., where individuals are connected to others that are not themselves connected—for the transfer of diverse knowledge (Burt 1992, 2004). The inconclusiveness of the social network literature regarding the optimum network structure for knowledge transfer suggests there is something unaccounted for.

We argue that while the explanatory mechanisms for knowledge transfer and aggregation within the social network literature have been studied within organizations, they have generally not taken the organization itself into account (Kleinbaum and Tushman 2007; Kleinbaum and Stuart 2014;

Maoret et al. 2020; McEvily et al. 2014; Soda and Zaheer 2012, are exceptions). It has been suggested that the literature on social networks and the formal design of organizations are like 'ships passing in the night' (McEvily et al. 20142; Soda and Zaheer 2012). The focus on social networks has tended to focus on their informal nature and has neglected the fact that many network ties occur because people are connected together through the formal reporting structures and work-based interdependencies of an organization (Soda and Zaheer 2012). There is evidence to suggest that the coordination structure that links various parts of the organization both facilitates and constrains the transfer of knowledge (Marengo 1992; Soda and Zaheer 2012). Coordination structures incorporate the interdependencies of work that occurs in different teams and units. The linking of units through formal reporting structures that incorporate communication channels and meetings helps to create a network of relationships between people which in turn facilitates the likelihood knowledge will transfer between individuals (Soda and Zaheer 2012). However, coordination structures can also constrain knowledge transfer because they focus interactions between people around reporting structures and work interdependencies and away from more random interactions with colleagues in units that are not interdependent. Research on organizational coordinating structures is inconclusive as to which structure is optimum for enabling social networks and ultimately knowledge transfer. For example, Chang and Harrington (2003) found that centralized coordination structures can positively affect the transfer of knowledge. However, centralized structures have also been shown to play a part in reinforcing past behavior and limiting knowledge transfer (Fiol and Lyles 1985), suggesting that decentralized structures are better enablers of social networks and consequently knowledge transfer.

Given the inconsistencies in both the organizational design and the social networks literature regarding knowledge transfer and that they rarely take each other into account, in this paper we seek to address the issue of how social networks and organizational design jointly influence knowledge transfer and aggregation within organizations. In order to better understand the joint role of social networks and organizational design in facilitating knowledge transfer and aggregation we draw from the overarching framework of the knowledge-based theory of the firm (Grant 1996). We focus on two critical aspects of this framework: the boundaries of the firm and organizational structure as it relates to coordination within the firm. Organizations make decisions regarding which knowledge domains are within the boundaries of the firm. One of the choices that organizations face is whether competitive advantage can be gained through providing a broad range of goods and services necessitating a more heterogeneous knowledge base or whether to focus on a narrow range of goods and services with a more homogeneous knowledge base (Breschi et al. 2003). In general, the more homogeneous the knowledge within an organization the easier it is for the knowledge to transfer (Hansen 1999, 2002; Szulanski 1996). However, the more heterogeneous the knowledge within an organization the greater the opportunity that knowledge transfer can lead to radical innovation (Taylor and Greve 2006). Second, we focus on the coordination structure of a firm, specifically whether the coordination structure is centralized or decentralized. This affects how different units and departments relate to each other and it is this coordination structure that is the skeleton that the social network structure develops around (Krackhardt and Hanson 1993; Soda and Zaheer 2012).

Taking into account knowledge heterogeneity across units and coordination structures, allows for a range of different organizational designs in which different social network structures can facilitate and constrain knowledge transfer and aggregation. For example, the extremes of the knowledge heterogeneity and coordination structure spectrums give us four types of organizations 1) centralized coordination where knowledge is relatively homogenous across units such as organizations whose strategy is based upon efficient production of a narrow range of products or services; 2) centralized coordination where knowledge across units is relatively heterogeneous such as organizations whose comparative advantage is based on efficient production of a range of diverse products; 3) decentralized coordination where knowledge across units is homogenous such as organizations whose R&D and production are focused on a small number of interrelated technologies; and 4) decentralized coordination where knowledge across units is heterogeneous such as R&D focused organizations that have followed a strategy of technological diversification.

To better understand how combinations of organizational coordination structures, social network structures, and knowledge heterogeneity affects knowledge transfer and aggregation, we developed an agent-based model.[1] We use an agent-based model as it is impractical to collect the necessary primary data needed to examine the interrelationship of these three factors (Garcia 2005; Harrison et al. 2007; Macy and Willer 2002; Phelps et al. 2012). Agent-based models enable an understanding of how aggregate patterns *form* through the self-organization of micro-behaviors into emergent aggregate structures (Tesfatsion 2003). Agent based models have been used to model the dynamics of knowledge and innovation networks in a rich array of literature (Ahrweiler et al. 2016; Cassi and Zirulia 2008; Cowan and Jonard 2004; Morone and Taylor 2012).

2. Knowledge Heterogeneity, Coordination Structures, and Social Networks

2.1. Knowledge Heterogeneity Across Units and Knowledge Transfer

The knowledge-based theory of the firm (Grant 1996) suggests that organizations are better at coordinating knowledge than markets, organizations can gain comparative advantage from specialist knowledge, and that "the fundamental task of organization is to coordinate the efforts of many specialists (p. 113)." Organizations coordinate these efforts by bringing people with similar specialist skills together into organizational units (Pavitt 1998). These units can also be thought of as knowledge foci (Feld 1981, 1982), i.e., social, psychological, or physical entities around which individuals organize joint activities. While we will focus on units, the foci could also be teams, project groups (O'Leary et al. 2011), departments, innovation communities (Fleming and Waguespack 2007), or communities of practice (Cohendet and Llerena 2003). The boundaries of units are established and maintained by the organization (Marengo 1992; Thompson 1967) and are strengthened by the tendency of individuals not to seek knowledge outside their unit (Lomi et al. 2014; Tortoriello et al. 2012). The more heterogeneous the knowledge between units, the lower the amount of knowledge that transfers from one unit to another (Hansen 2002). The extent to which knowledge in one unit is similar to knowledge in another unit depends upon the design of an organization. The more firms divide work

[1] An additional aspect of knowledge that has relevance for knowledge transfer is whether knowledge is explicit, i.e., it contains facts and symbols which are easier to transfer; or whether it is tacit i.e., it is know-how such as being able to solve a particular problem and is more difficult to transfer, (Kogut and Zander 1992; Nonaka and Takeuchi 1995). We treat tacit versus explicit knowledge as a potential extension to our theorization and expand upon this in the discussion section.

into specialized units that are less related to each other such as with a technology diversification strategy (Granstrand 1998; Granstrand et al. 1997; Pavitt 1998; Brusoni et al. 2001) then the greater the heterogeneity of knowledge between units. However, when firms focus on a number of closely related technologies there will be greater knowledge homogeneity between units. The advantage of having homogeneity of knowledge across units is that knowledge more easily transfers between them (Hansen 2002). Knowledge homogeneity between business units has been shown to be beneficial for organizations innovation activities (Breschi et al. 2003; Tanriverdi and Venkatraman 2005; Marengo 1992). The trade-off is that the knowledge that transfers is likely to be less diverse, i.e., it is a limiting factor for knowledge aggregation (Granstrand et al. 1997; Parker et al. 2019; Paruchuri and Awate 2017) and is better suited for incremental rather than radical innovation (Taylor and Greve 2006).

A university is illustrative of an organization that can have knowledge in units or departments that is more or less heterogeneous. A university can focus on a set of closely related knowledge domains such as the social sciences where there is some overlap in the knowledge between departments such as economics, psychology, sociology, or anthropology. In this case the departments will have greater knowledge homogeneity, and this will have implications for the upper limit of knowledge aggregation of employees and units. In addition, it may ultimately limit the creation of innovative research and teaching initiatives. In contrast, in a university that includes colleges of medicine, humanities, social sciences, physical sciences and environmental sciences there will be, on average, much higher knowledge heterogeneity between the departments, but knowledge will be less likely to transfer across the departments in the university. However, where it does transfer it can create greater knowledge aggregation for people and units. Overall, where there is greater average knowledge heterogeneity between units or departments it suggests that an organization is more diversified, for example it may have adopted a technological or knowledge diversification strategy; where there is greater knowledge homogeneity across departments it suggests the organization is a specialist that focuses on a number of closely aligned knowledge and technology domains.

2.2. Coordination Structures and Knowledge Transfer

The way in which organizations enable and constrain knowledge transfer is linked to the systems that coordinate tasks across an organization and ensure some level of organizational control (Thompson 1967). Organizational activities are divided into smaller tasks that are allocated to roles. Each role sits within a department or unit and for the efficient functioning of an organization there needs to be coordination across the roles and tasks (Lawrence and Lorsch 1967). Coordination is important for knowledge transfer as it links different teams, departments, and units to each other in network-like structures (Soda and Zaheer 2012). As stated by Marengo (1992, p. 315): "accumulation of knowledge.... requires agents to build new representations of the environment and develop new skills and routines which were not known to them before" and "the relations between different parts of the organization, as defined by its structure, play a fundamental role in driving and shaping the collective learning process". In addition, information processing theory suggests that there is formal communication up and down the hierarchy, which helps to bring about coordination of activities and reduce uncertainty (Galbraith 1973; Tushman and Nadler 1978). This coordination facilitates the transfer of knowledge between certain units, but also limits knowledge transfer between others. However, it is not the coordination structure itself that is the primary mechanism by which knowledge transfers, rather the structure acts as a mechanism by which individuals are connected together, i.e., it facilitates the social network ties that individuals have.[2] This aligns with the recent conceptualization and research of multilevel networks where networks of individuals are embedded in networks of units, teams, or organizations (Brennecke et al. 2021; Wang et al. 2013; Zappa & Lomi 2015; Zappa & Robins 2016)

On one end of the coordination structure spectrum is an organization with centralized coordination, where a small number of units are central to the organization and the formal reporting structure radiates out from them. The units not in the centre have few if any links to each other. An example of a centralized coordination structure is a multinational company where organizational units, such as subsidiaries, have a strong relationship with units that are part of headquarters and limited

[2] Knowledge can transfer through the coordination structure such as via an email from one person to all people lower in the coordination structure. In this paper, however, we limit ourselves to modelling knowledge transfer through dyadic social network ties in an organization.

interaction with other subsidiary units (Kostova et al. 2016). This scenario typifies organizations with a higher degree of bureaucracy where there tends to be greater oversight (Lawrence and Lorsch 1967). In this scenario there are limited formal processes to facilitate knowledge transfer between people across the white spaces in an organizational chart. At the other end of the spectrum there are organizations with no central units and all of the units can potentially have links with each other. This structure represents a decentralized organization with lower oversight. Decentralized organizations are representative of the trend in organizations towards being "post-bureaucratic, flat, decentralized, lean structures intended to ease the flow of resources and integrate actors across units" (McEvily et al. 2014, p. 302). In this scenario there are fewer structural limitations to the transfer of knowledge between people across the organization, but there are also fewer systematic coordinating processes to bring people together for knowledge transfer.

Research on organizational learning offers some suggestions as to how different coordination structures influence knowledge transfer. For example, Chang and Harrington (2003) used simulation models to understand the relationship between the centralization within organizations and knowledge transfer, especially under conditions of intense competition. They found that centralization results in higher knowledge transfer when competition is more intense. In contrast, there is support for the role that centralized structures play in reinforcing past behavior and limiting learning, while decentralized structures promote learning as a result of reduced cognitive overload (Fiol and Lyles 1985). More recent research suggests it is beneficial to have a decentralized structure with semi-isolated groups that have a moderate amount of linking between the groups in order to allow for independent development of innovative ideas that are then able to diffuse between groups (Fang et al. 2010).

2.3. Cross-Unit Brokers, Social Networks, and Knowledge Transfer

While coordination structures take into account how units are related to each other, social networks are the relationships between individuals (Borgatti et al. 2009). These relationships may or may not have developed as a result of coordination structures facilitating interaction between individuals based upon hierarchical reporting systems or work interdependence between units. The focus of research on social networks has generally been on the advantages that accrue to individuals with regard to benefiting from knowledge transfer as a result of occupying certain positions in the social network structure (Brass et al. 2004). There is, however, considerable debate over which network position is the most advantageous with regard to benefiting from knowledge transfer. For example, Reagans and McEvily (2003) show the benefits to individuals of having network range—i.e., having ties that cross boundaries to disparate parts of an organization. The benefit of reaching across boundaries for knowledge is that it increases the diversity of the available knowledge (Hargadon 2002). However, seeking knowledge beyond one's own organizational unit is more complex due to the accessibility and transferability of the knowledge (Lomi et al. 2014; Parker et al. 2018; Tushman 1977). When individuals have ties to units with related knowledge there is more likely to be knowledge transfer, whereas if the knowledge is too diverse it does not easily transfer (Hansen 2002).

A related stream of literature on individual network advantage suggests that individuals with closed networks, where people in an individual's network also have ties to each other, facilitates knowledge transfer due to their being a high level of trust (Coleman 1988; Reagans and McEvily 2003; Szulanski 1996, 2002). In contrast, Burt (1992, 2004) shows the benefits of having open networks—where individuals are connected to others that are not themselves connected—for the transfer of knowledge. In general, individuals in structural brokerage positions benefit from access to knowledge that is more diverse which aids knowledge aggregation (Burt 1992, 2004; Halevy et al. 2019; Stovel and Shaw 2012). Although, other research highlights that open networks are not always beneficial for enabling knowledge transfer (Fleming et al. 2007b; Obstfeld 2005). We specifically examine individuals who are in structural brokerage positions that span boundaries. Being in a structural brokerage position that spans a boundary should increase the diversity of the available knowledge an individual receives compared to those who are not in structural brokerage positions, but knowledge diversity also potentially limits the transfer of knowledge across the boundary to the broker (Hansen 2002; Parker et al. 2019; Tortoriello et al. 2012).

While research at the individual level has tended to focus on how position within a social network can give individual advantage; research that examines the network as a whole suggests that higher overall connectivity of the network results in innovation (Ebadi and Utterback 1984). Network connectivity, however, is not always a useful depiction of the structure of networks within organizations as measures of connectivity are inversely related to the size of an organization. While small organizations can be highly connected this tends to be impractical for large organizations. A more useful approximation of social network structure within organizations is the research on small world networks (Watts 1999; Watts and Strogatz 1998). On one end of the small world spectrum is a social network structure where all ties are within the same cluster, and no ties are between clusters. This depicts localized search for knowledge (March and Simon 1958). At the other end of the spectrum is a random network structure, here ties could be between any two individuals. Small world networks, which are towards the end of the spectrum where all ties are within clusters, consist of many ties within a cluster and a few ties between the clusters (Watts 1999; Watts and Strogatz 1998). Small world networks have been shown to be advantageous for creativity (Uzzi and Spiro 2005), knowledge diffusion and distribution (Cassi and Zirulia 2008; Cowan and Jonard 2004) and innovation (Fleming et al. 2007a; Schilling and Phelps 2007).

2.4. Combining Coordination Structures, Knowledge Heterogeneity, and Social Networks

Based upon different combinations of coordination structures and knowledge heterogeneity we can examine how knowledge transfers through different social network structures and the extent to which knowledge aggregation occurs. A useful way of examining social network structures is to use the spectrum of structures used in the small-world research detailed above. At one end of the spectrum, we can think of social network ties as being only within units, with no ties between units. Here knowledge transfer is highly constrained by the internal boundaries of the organization and knowledge transfer is localized within the unit. At the other end of the spectrum is a random social network structure, here ties could theoretically be between any two individuals regardless of the unit they are in. However, coordination structures, notably a centralized structure will constrain these social relationships to only be with individuals in units that are themselves connected by the coordination structure.

Based upon various combinations of coordination structures, knowledge heterogeneity, and social network structure we develop an agent-based model to examine knowledge transfer and aggregation. The agent-based model allows us to understand how the different scenarios influence the aggregation of knowledge within people and by unit. In addition, we examine the relevance of cross-unit brokers for knowledge transfer and aggregation. Finally, we model the extent to which knowledge aggregation is evenly or unevenly distributed across organizational units under different scenarios. We detail the agent-based model in the following section.

3. Model

We have highlighted above how knowledge transfer between individuals may vary depending on different configurations of social networks of individuals, the coordination structures that connects units within organizations, and the extent to which knowledge across units is heterogeneous. To test which configurations result in knowledge transfer leading to greater or less knowledge aggregation by individuals and units we specify a formal model of knowledge barter (Cowan and Jonard 2004; Ozman, 2010). In the model there are P agents and *N* units. Each agent *i* is assigned to one unit, representing the agent's area of specialization. Each agent is also characterized by a vector V_i of size N showing their aggregation of knowledge for each of the N units, where v_{im} shows the total knowledge aggregation of agent *i* in unit *m.* The knowledge that an agent holds is highest for the unit that they are assigned to in the initial setting. This knowledge vector is continuously updated as the agents seek knowledge from others within and outside their unit through their social network.

3.1. Social Network

We construct a parameter for the social network *I* between the P agents $I = \{a_i | i \in [0, P]\}$. We model the social network *I*, according to a model developed by Watts and Strogatz (1998) in their study of small worlds. The model contrasts networks that have a tendency toward triadic structures or clusters of ties versus social networks that have no localized features such as clusters of ties and is hence based upon a random structure of connections between individuals (Cowan et al. 2004; Cowan and Jonard 2004; Robins et al. 2005). This model permits changing the social network structure from a clustered network structure to a random network structure with the help of a single parameter. Examples of social networks in a decentralized reporting structure are given in the top section of Figure 1. At one extreme is a perfectly clustered social network structure (1a) and at the other is a random network structure, shown as (1c) in Figure 1. In between these two extremes is a small world network structure (1b). A perfectly clustered network structure represents a case in which agents only benefit from the transfer of knowledge from others in their own unit. At the other extreme, is a random social network structure where an agent can potentially receive knowledge from any other person in the organization that he or she is linked to, and there are no localized social network structures. The spectrum of social network structures also gives us the opportunity to understand knowledge transfer to agents who have specific positions in the social network, for example agents who are in cross-unit brokerage positions. It is important to note that the extent to which knowledge transfers through the social network structure is constrained by coordination structures of the firm, with knowledge only able to transfer through social networks when there is also a connection at the unit level, and the extent of knowledge heterogeneity between units, which we detail below.

<Insert Figure 1 about here>

3.2 Unit Network Structure

We model the coordination structure between organizational units (S) as a unit network structure such that $S = \{s_m | m \in [0, K]\}$ and $\Gamma(m) = \{n \in I \setminus \{m\} | d(m, n) = 1\}$, where d($m$, n) is the shortest path between units m and n in the unit network S. In a decentralized organization with unit network S the units are all connected with each other illustrating a disaggregated coordination structure, as shown in Figure 1d. In the decentralized organization, social network ties can occur between actors in any units. We then consider centralization of the organizational units in the unit network S that is representative of a centralized coordination structure (Figure 1e). In the centralized organizational structure, social network ties can only occur between actors in units that have a unit network tie. As can be seen in Figure 1f, having a centralized coordination structure compared to a decentralized one does not have an effect on knowledge transfer in the perfectly clustered network. However, it should be noted that in Figure 1g and 1h there can only be social network ties between clusters if there is also a unit network link between two units. Therefore, in our model, a centralized coordination structure does impose constraints on the social network structure.

We model knowledge heterogeneity between units based upon the extent to which knowledge between each pair of units is heterogeneous. We use a fixed parameter (ρ_{mn}), representing the weight of the knowledge heterogeneity between two units *n* and *m*. For high knowledge heterogeneity (diversified organizations) there are low weights between each pair of units. In contrast, for high knowledge homogeneity between each pair of units we have high weights between units. We model knowledge heterogeneity for two kinds of organizational coordination structures, decentralized and centralized, which are illustrated in Figure 1d and 1e, respectively.

In sum, the unit network *S* accounts for the coordination structure, i.e., whether the organization is centralized or decentralized. In addition, the weight of the ties in unit network *S* accounts for the knowledge heterogeneity between each pair of units.

3.3. Knowledge Transfer Between Agents

When two agents *i* and *j* are connected in the social network *I*, knowledge transfers from one to the other when they interact. Two agents can only interact if they are connected in the social network. These interactions follow a random order. In other words, agents are not selecting other agents based on calculations to maximize learning, but random encounters lead to knowledge transfer.

Formally the set of alters (i.e., people i can interact with) of agent i is given by $\Gamma(i) = \{j \in I \setminus \{i\} | d(i,j) = 1\}$, where $d(i, j)$ is the shortest path between *i* and *j* in social network *I*. In line with previous literature on learning (Gilsing et al. 2008; Mowery et al. 1998; Nooteboom 1998; Nooteboom et al. 2007; Schoenmakers and Duysters 2006; Wuyts et al. 2005) it is assumed that knowledge transfer is curvilinear based upon the knowledge distance—or what is sometimes termed cognitive distance—between agents. In other words, agents tend to benefit less from knowledge transfer from others that are either too similar or too different. According to this framework, there is an optimal knowledge distance between agents in which they tend to contribute the most to each other's knowledge. In previous literature, curvilinear knowledge transfer has been empirically observed. For example, firms in chemicals, automotive and pharmaceutical industries had an inverse U-shaped relationship between the knowledge distance with regard to knowledge transfer and innovation patents (Gilsing et al. 2008). Likewise, there is an inverse U-shaped relationship between technological overlap of patents and firms forming an alliance (Mowery et al. 1998).

Knowledge transfers to agent *i* (in unit *m*) from agent *j* (in unit *n*), if and only if $v_{im} < v_{jn}$, in line with the models of knowledge barter (Cowan and Jonard 2004). That is to say, knowledge transfer depends on the relative knowledge aggregations of *i* and *j*, and the knowledge homogeneity between the units that they are members of. In other words, knowledge transfer depends first on *i* having a lower aggregation of knowledge than *j*, and second on the knowledge homogeneity of the units with higher knowledge homogeneity leading to more knowledge transfer.

The knowledge transfer function that measures the extent to which knowledge transfers to agent *i* from *j* is given by the following equation. As each agent is assigned to one unit, agent *i* belongs to unit *m*, and agent *j* belongs to unit *n*.

$$k_{ij}^{t+1} = k_{ij}^{t}\left(1 + \rho_{mn} r_{ij}^{t}\left(1 - r_{ij}^{t}\right)\right)\ for\ r_{ij} < 1 \text{ and } \rho_{mn} = \begin{cases} 0\ if\ d(m,n) = 0 \\ \rho_{mn}\ if\ d(m,n) = 1 \end{cases}$$

where k_{ij} is the amount of knowledge transfer by *i* from *j*, ρ_{mn} is the knowledge homogeneity between unit *m* and *n*, r_{ij} is the relative knowledge distance between agents *i* and *j*, measured by the cosine of the angle between two knowledge vectors, v_i and v_j. High cosine values indicate that two agents are closer to each other with regard to their knowledge distance compared to low cosine values. In addition, high cosine values indicate lower relative knowledge distance between the agents' knowledge aggregations, compared to low cosine values. Overall, midrange cosine values result in greater knowledge transfer. In Figure 2, we plot the knowledge transfer function for four values of knowledge homogeneity (ρ) across units. In the lowest line, the knowledge homogeneity across units is 0.1 (high knowledge heterogeneity), and knowledge transfer is lowest for each value of the relative knowledge distance between agents. Knowledge transfer is highest for knowledge homogeneity across units of 0.9 (low knowledge heterogeneity).

<Insert Figure 2 about here>

3.4. Knowledge Transfer for Cross-Unit Brokers

In our simulations we also examine actors who benefit from being in structural positions of brokerage across boundaries as this has been shown to give individuals access to more diverse knowledge (Stovel and Shaw 2012). The role of actors that span boundaries is critical to the transfer of knowledge in organizations (Reagans and McEvily 2003; Parker et al. 2019; Tortoriello et al. 2012), as it is these actors that are conduits of knowledge between units, and consequently increase the transfer of more diverse knowledge within an organization and hence help to increase aggregate knowledge. Likewise, individuals that have network ties to others who are not themselves connected (i.e., brokers) have been shown to be advantageous for knowledge transfer (Burt 1992, 2004). We combine the two criteria of being a broker and having cross-unit ties to examine whether cross-unit brokers have different knowledge aggregation across the parameters in our model. To measure cross-unit brokerage we use the gatekeeper construct developed by Gould and Fernandez (1989), whereby gatekeepers connect people in their own unit with someone in a different unit. This measure explicitly takes into account brokerage across boundaries. An agent is considered a gatekeeper in the social network if there exist at least two actors, each having ties with the focal agent and not with each other, and one of them being in the same unit as the agent, and the other being in a unit different from the agent. The gatekeeper construct is consistent with our focus on knowledge transfer across boundaries. Other definitions of brokerage such as Burt's (1992) notion of structural holes do not explicitly consider boundaries.

3.5. Simulations

We run two sets of simulations, one for a decentralized coordination structure and another for a centralized coordination structure. In each set there are 20 runs[3]. In a single simulation run all the parameter space of social networks and knowledge homogeneity across units is included and all agents have the *same* initial knowledge aggregation. Each of the different runs in each set, have a different initial knowledge distribution (i.e., agents' initial knowledge aggregation), although within a run it is

[3] The number of runs in a simulation model is decided based on the tradeoff between the variation in observed results over different runs, and the computing time. The higher is the variation, the higher should be the number of runs to overcome the effects of patterns caused by different random seeds. Given that the observed variability in results was very low, and the computing times was very long, 20 simulation runs was decided on heuristically.

always the same initial knowledge aggregation for each agent. This is necessary to offset the effects of accidental results caused by random seeds. In further extensions of the model, we try different statistical distributions of initial knowledge aggregation, so as to evaluate the sensitivity of the results obtained to different parameter settings. The parameters used in the base model and extensions are presented in Table 1. Knowledge transfer happens in the model through interactions between agents, and they complete a loop of 50 periods with randomly ordered interactions. In one period all agents that are connected in the social network interact at least once. This is repeated for all combinations of social networks and knowledge heterogeneity across units. For a specific level of knowledge heterogeneity across units, social network structures are gradually changed, via the rewiring parameter τ of Watts and Strogatz algorithm, from a clustered network structure to a random network structure. The range of knowledge heterogeneity across units $\rho \in [0.1, 0.9]$ are the link weights of S. Therefore, in one simulation run, there are on the average, (50 loops) x (100 social networks) x (9 unit networks) = 45,000 loops of interactions.

<Insert Table 1 about here>

We model the centralized coordination structure as a core-periphery network (Borgatti and Everett 2000). In a centralized coordination structure, the social network interactions only occur if there is also a unit network tie between a pair of units. The level of connectivity in the unit network, i.e., its density, is measured by the actual number of ties divided by the total number of ties. In the baseline model the core group density is 0.8, the peripheral members' density is 0.2, and the density between the core and the periphery is also 0.2. In the extensions of the model, simulations with different density parameter values are presented, as given in Table 1.

One of the model's strengths is that nonlinear dynamics and cumulative mechanisms play a role because the order of interactions between agents is not fixed a priori but happens following a random order. This ensures that knowledge aggregation does not depend on the order of interactions. Additional details regarding the technical aspects and parameter values are given in Table 1.

4. Results

4.1. Baseline Model

Figures 3a and 3b present average knowledge aggregation for all actors after knowledge transfer has occurred during the 20 simulation runs for the base model parameters (see Table 1).[4] The average knowledge aggregation is a function of the structure of the social network (τ) and knowledge homogeneity across units (ρ). Decentralized and centralized coordination structures show differences in their average knowledge aggregation. In the decentralized case (Figure 3a), when there is a clustered social network structure (low τ) with ties tending to be within units there is only limited difference with regard to average knowledge aggregation by actors, depending upon the amount of knowledge homogeneity across units (ρ). However, as social network structures become less clustered (high τ), i.e., there are more ties outside of units, the role of knowledge homogeneity across units (ρ) becomes prominent with higher knowledge aggregation when there is knowledge homogeneity across units (high ρ) and lower knowledge aggregations when there is knowledge heterogeneity (low ρ). Overall, a decentralized coordination structure can facilitate knowledge transfer under certain conditions. Notably, there is an advantage to having a social network that crosses unit boundaries (high τ) when there is a relatively high degree of knowledge homogeneity across units (high ρ).

<Insert Figure 3a and 3b about here>

In contrast, in a centralized coordination structure (Figure 3b), the highest average knowledge aggregation by actors is for clustered social network structures (low τ) where knowledge transfer between actors occurs within units. Knowledge aggregation decreases as social network structures become less clustered and there are more ties across units. The effect of different levels of knowledge homogeneity across units (ρ)is relatively small for clustered social network structures (low τ), but as the social network structure gets less clustered and the number of ties across units increases there is some divergence with knowledge homogeneity (high ρ) across units resulting in higher knowledge aggregation than for knowledge heterogeneity (low ρ). Overall, centralized coordination structures

[4] We examine average knowledge aggregation rather than the net amount of knowledge in the organization because each actor could recombine different pieces of knowledge in different ways to solve problems and innovate.

constrain the transfer of knowledge through social network structures to such an extent that there is no advantage in having social network structures that cross unit boundaries, regardless of the levels of knowledge heterogeneity across units.

When comparing the different combinations of social network structure (τ), knowledge heterogeneity (ρ), and coordination structure the simulations reveal that the highest knowledge aggregation occurs in the decentralized coordination structure, with high knowledge homogeneity across units (high ρ), and where there is a random social network structure, i.e., with many ties occurring between units (high τ). The lowest knowledge aggregation occurs in the centralized coordination structure, with high knowledge heterogeneity across units (low ρ), and where there is a random social network structure with ties occurring between units (high τ). In this scenario, the social network ties between units are constrained by the centralized coordination structure.

Figures 4a and 4b show average knowledge aggregation of cross-unit brokers in the case of the decentralized and centralized coordination structure, respectively. In the decentralized case (Figure 4a), there is an increase in the knowledge aggregation curve from the clustered social network structure (low τ) to the region that represents the small world network structure (τ = 0.1), with slightly higher average knowledge aggregations for cross-unit brokers in conditions of knowledge homogeneity between units (high ρ). Once the social network structure is less clustered (high τ), however, there is considerable divergence in knowledge aggregation of cross-unit brokers depending on knowledge heterogeneity between units (ρ). Where there is knowledge homogeneity between units (high ρ) the cross-unit brokers have higher knowledge aggregation, whereas for high knowledge heterogeneity between units (low ρ) there is lower knowledge aggregation for cross-unit brokers.

In centralized coordination structures (Figure 4b), there is also a difference in knowledge aggregation for cross-unit brokers depending on the configuration of the social network structure (τ) and knowledge homogeneity across units (ρ). In this case some of the highest knowledge aggregation for actors occurs in the region of the small world network structure ($\tau = 0.1$). Once the social network structure (τ) becomes more random there is a notable decrease in knowledge aggregation for the cross-unit brokers. Knowledge homogeneity across units (ρ) also makes a difference with knowledge aggregation being higher when there is high knowledge homogeneity across units (high ρ) for all social network structures (τ).

Overall, when comparing decentralized and centralized coordination structures, we find that the benefits of being a cross-unit broker differ depending on different combinations of knowledge homogeneity across units (ρ), and social network structure (τ). Cross-unit brokers play a particularly prominent role with regard to knowledge aggregation in centralized coordination structures when there is a small world social network structure ($\tau = 0.1$) and in decentralized coordination structures with high knowledge homogeneity between units (high ρ) and random social network structures (high τ) where ties are more likely to cross unit boundaries.

<Insert Figure 4a and 4b about here>

To date, we have examined average knowledge aggregation by all actors and the special case of cross-unit brokers. An additional issue of interest is the extent to which knowledge aggregation differs across units. To understand this effect, we calculated the Shannon entropy index[5] (Shannon 1948) regarding the average knowledge aggregation for units, calculated by summing knowledge aggregation by actors in the units. In Figure 5a, we can see that when there is a random social network structure (high τ) there is more variation, (i.e., a higher Shannon entropy index) in knowledge aggregation by units in both decentralized and centralized coordination structures. In conditions of high knowledge homogeneity across units (high ρ), there is greater variation, especially for the more random social network structure (high τ). In a decentralized coordination structure, we see greater variation in knowledge aggregation for units with high knowledge homogeneity across units (high ρ), when the social network structure (τ) is above 0.3, whereas this tends to only occur in centralized coordination structures when the social network structure is random (τ = 0.6-1.0). Overall, when social networks have a random network structure (high τ) and when there is high knowledge homogeneity between units (high ρ), some units have more advantage than others in terms of their knowledge

[5] Shannon entropy index is calculated as: $H = -\sum_{i=1}^{s}(p_i)(ln\, p_i)$, where p_i denotes the proportion of unit i in total knowledge aggregation, and $ln\, p_i$ is the natural logarithm of this proportion.

aggregation. This is of particular interest for the decentralized structure as this is when knowledge aggregation is at its highest (see Figure 3a).

We repeated the same procedure with respect to the variability of different knowledge pools, regardless of units, which is illustrated in Figure 5b. It is observed that the variability between different knowledge pools is significantly less responsive to changes in the social network structure, as compared to the variability between units. This is seen by comparing the values of Shannon's index in Figures 5a and 5b. In other words, different combinations of social networks and the coordination structure can make some units better off than others in terms of the average knowledge aggregation, but it has little effect on overall variability in pools of knowledge. However, there is some effect, albeit minimal, in the centralized coordination structure with high levels of knowledge homogeneity (high ρ). As social network randomness increases (high τ), knowledge aggregation in some knowledge pools grow faster than others.

<Insert Figure 5a and 5b about here>

4.2. Extensions of the Baseline Model

We ran further simulations, in order to gain additional insights over a larger parameter space and to test the sensitivity of our results to changes in initial parameters. Overall, we find that the patterns observed in the baseline model are robust to changes in initial parameters.

One of the factors that could be important in knowledge aggregation is the configuration of initial knowledge aggregation in units. In general, departments, groups, and teams can have members of various levels or aggregations of knowledge. Figure 6 illustrates a comparison of two cases; one in which cognitive distance between agents is very low in units (highly similar agents), and the other in which this distance is high (highly different agents). In both cases, agents are specialized in the unit specific knowledge, yet the level of this specialization, and their knowledge in other knowledge pools determine their cognitive distance. The results show that increased similarity of agents within units (i.e., knowledge homogeneity in the unit) tends to augment the positive effect of social network randomness on knowledge aggregation, in both centralized and decentralized coordination structures.

<Insert Figure 6a and 6b about here>

Another potential issue is the level of connectivity (i.e., density) of the unit network in the centralized versus decentralized coordination structure. In general, a core-periphery unit network structure is composed of tightly connected units in the core, and weakly connected units in the periphery, which are also weakly connected to the core. Therefore, the overall connectedness between units in a core-periphery centralized structure is lower compared to a fully connected decentralized structure. This implies that knowledge aggregation is likely to be higher, as there are more between unit ties in the coordination structure which allows for more social network ties between units and hence greater opportunity for knowledge transfer in the decentralized coordination structure and may result in biases when comparing to centralized coordination structures. To isolate the effect of coordination structure, we experimented with different simulations by reducing the network density of the decentralized unit network. Figure 7 shows the ratio of knowledge aggregation in a decentralized coordination structures with unit network density of 0.20[6], to that of centralized coordination structures.

<Insert Figure 7 about here>

Overall, we find that lower unit network connectivity in decentralized coordination structures yields similar patterns, except the absolute values of average knowledge aggregation are reduced. We find that when the unit network density of centralized and decentralized coordination structures is the same, the overall knowledge aggregation in a decentralized coordination structure outweighs that of the centralized coordination structure, for most ranges of the parameter space, i.e., the ratio is above one on the y-axis. This is particularly notable when there is higher knowledge homogeneity between units (high ρ) and when the social network structure is more random (high τ), i.e., when there are more ties between units. This aligns with our baseline model (Figures 3a and 3b).

We also examined how our results change with respect to the time horizon. Figures 8a and 8b show knowledge aggregation for all actors and also for actors who are cross-unit brokers in decentralized and centralized structures respectively, over the short run (10 loops of interactions),

[6] The density is based on a core-periphery unit network structure with six core, and 14 peripheral units (see section 4.2.4 for extensions of these parameters). This gives a total of approximately 39 ties in the centralized structure. For a decentralized structure, this converts to a network density of 0.20.

medium run (50 loops of interactions), and long run (100 loops of interactions). The results of the short run are confirmed in the long run, with random social network structures (high τ) resulting in higher knowledge aggregation in the decentralized coordination structure, when there is high knowledge homogeneity between units (high ρ) (Figure 8a). In contrast, a random social network structure (high τ) has the effect of reducing knowledge aggregation in centralized coordination structures (Figure 8b). In the figures on the right, we see that cross-unit brokers continue to have a key role in centralized coordination structures, especially when the social network is in the region of a small world network structure ($\tau = 0.1$) (Figure 8b).

<Insert Figure 8a and 8b about here>

To characterize organizations with centralized coordination structures we use a unit network based upon a core-periphery structure. A core periphery structure consists of two groups in the unit network, where core members are strongly connected among themselves, and peripheral members are weakly connected among themselves and to the core members (Borgatti and Everett 2000). Based on this definition, different unit networks can be created, depending on the number of members of the core group, and relative network density between the periphery and the core. Figures 9a and 9b show knowledge aggregation in different configurations of core-periphery unit network structures. As seen in the results, the overall patterns are quite robust to changes in the parameters of the unit networks.

<Insert Figure 9a and 9b about here>

Overall, these results suggest that for a given scenario, there could be a critical level of knowledge homogeneity across units (ρ) and social network structure (τ) for which the two effects cancel each other out. One of these settings is illustrated in Figure 10, which reveals that for mid-levels of knowledge heterogeneity across units (e.g., ρ = 0.45-0.49) and a social network structure τ = 0.4 to 1.0, there is little difference with regard to knowledge aggregation.

<Insert Figure 10 about here>

5. Discussion

One of the issues of interest in agent-based simulation models is to explain the internal dynamics of the model that drive the results. In this model, some of the variables tend to increase knowledge aggregation, and some of the variables reduce knowledge aggregation. Understanding the balance between these two forces, with respect to different variables, is important for model interpretation. In the model, knowledge transfer depends on the distance between agents in cognitive space. This cognitive distance is not only a function of agents' unit-specific knowledge, but also includes their knowledge in other knowledge pools. The initial knowledge configurations in units, knowledge homogeneity in the organization, the structure of social networks, as well as the coordination structure enable or constrain the extent to which productive encounters occur between agents. Here, productive encounters refer to encounters that occur in spaces that enable matching between pairs of actors near their optimal cognitive distance, so as to maximize knowledge aggregation opportunities. In other words, knowledge aggregation depends on how different variable spaces enable or restrict these productive encounters.

As social networks become more random (higher τ), agents form pairs that cross unit boundaries. In the majority of the cases, this results in pairs of agents who are highly different from each other, compared to within unit encounters, in which agents have unit specific knowledge in common. This is why, in the majority of the cases, knowledge aggregation tends to fall when encounters happen increasingly outside an agent's own unit. Within-unit encounters have the advantage of keeping agents around the optimal cognitive distance: their common unit specific knowledge brings them closer, while their distinct knowledge in other knowledge pools enables knowledge transfer based on knowledge diversity.

In some cases, however, increased encounters outside units (i.e., as social networks get more random) results in the negative effect of network randomness being less pronounced, or randomness can even increase knowledge aggregation. One of these cases is when there is very high unit homogeneity in the beginning of the simulation. This is illustrated in the extensions of the model, in Figure 5. The more similar are the agents inside units in the beginning, the greater is the effect of social network ties that cross unit boundaries on knowledge aggregation. In other words, being too similar to each other in units pushes pairs away from their optimal cognitive distance, and hence it is the encounters that cross unit boundaries that enable the transfer of diverse knowledge leading to greater knowledge aggregation. This suggests that the extent to which social network ties cross units and facilitate productive encounters, depends on initial knowledge configurations in units. The implication is that when units in an organization are composed of highly similar agents, it is always better to maintain ties that cross boundaries for knowledge aggregation.

Another factor that plays a key role is knowledge homogeneity in the organization. Homogeneity always increases knowledge aggregation, as imposed by the initial learning function. When knowledge homogeneity is high enough, it can offset the possible negative effect of social network ties outside an agent's own unit. Indeed, in the extensions of the model we showed that there tends to be a level of knowledge homogeneity for which the effect of social network structure on knowledge aggregation is minimal.

Another driver of the results is the organizational coordination structure, which is a factor that can restrict or enable the productive encounters between agents. We find that in organizations with centralized coordination structures, there is always a downward trend in knowledge aggregation as social network randomness increases, regardless of knowledge homogeneity. In decentralized coordination structures, on the other hand, the effect of knowledge homogeneity can be significant: when it is high enough, it even tends to offset the negative effect on unproductive encounters due to network randomness. When knowledge homogeneity is low, localized search within units gives the highest level of knowledge aggregation as it increases the likelihood of productive encounters, where agents are close to optimal cognitive distance. In sum, centralized coordination structure restricts productive encounters between different units more than decentralized coordination structure does.

Our findings suggests that in organizations with decentralized coordination structures it is important for units to be focused on relatively similar areas of knowledge. This aligns with the research on knowledge-relatedness (Breschi et al. 2003, p. 70) that has shown the benefits of local learning and learning spillovers in cases where firms "follow a coherent pattern of technological diversification, which clusters around groups of technologies that share a common or complementary knowledge base, rely upon common scientific principles or have similar heuristics of search". While the highest level of knowledge aggregation occurs in decentralized coordination structures, with high knowledge homogeneity between units, and where networks are predominantly across units, we also find this scenario to have the highest level of unit and knowledge variability, with regard to knowledge aggregation (Figure 5). This suggests that choosing to have a decentralized coordination structure and encouraging many inter-unit social network ties when there is knowledge homogeneity across units is a high-risk option where some units will benefit, but others will see lower knowledge aggregation. The advantages of this option may well depend on the strategy of an organization. In cases of new product development where only a few ideas are successful then a high-risk and high-reward strategy may be beneficial. Whereas, in a consulting organization where all units are expected to deliver high quality knowledge-based solutions to their clients, this high-risk strategy may have less appeal.

There are various extensions that could be usefully applied to the model. First, it is possible to differentiate how the tacit versus explicit nature of knowledge (Nonaka & Takeuchi 1995) influences knowledge transfer and aggregation. One potential avenue for doing this would be to examine repeat ties which are important for the transfer of tacit knowledge. Second, we have only examined knowledge flow within a single firm. Obviously, knowledge does flow from outside the firm. This could be accounted for by adapting the unit network structure to take into account whether a unit was inside or outside the firm. Third, there is no differentiation between social network ties. In firms the strength of ties between two actors differs with some being stronger than others based upon factors such as trust, reciprocity, repeat interactions over time, etc. Tie strength could be another potential extension of our model.

6. Conclusion

Overall, our paper heeds the call to better understand the interplay between organization design and social network structure (McEvily et al. 2014). Our focus has been on social network structures, unit network coordination structures and the homogeneity of knowledge between units. We have shown that the aggregation of knowledge that transfers through social networks differs based upon coordination structures and knowledge homogeneity. In doing so we also show that the configuration of units in terms of the cognitive proximity between actors is important. Our findings add to theories of knowledge transfer (Brusoni et al. 2021; Cowan and Jonard 2004; Hansen 2002; Morone and Taylor 2012; Tortoriello et al. 2012) by indicating under what combinations of coordination structure and social network structure the highest levels of knowledge aggregation is most likely to occur. Our study brings into question research on knowledge transfer that only examines social network structure in a single organization as this does not account for the range of possible research designs that can influence the relationship between social networks and knowledge aggregation. Our findings also add to theories of brokerage across boundaries within organizations (Burt 1992, 2004; Burt et al. 2013; Gould and Fernandez 1989; Halevy et al. 2019; Stovel and Shaw 2012). Brokerage by individuals within organizations has generally been theorized and empirically tested within a single organization. Variations in the context as well as variations in the social network structure itself have generally not been considered when theorizing about brokerage (Stovel and Shaw 2012). Overall, our findings suggest that findings in previous research may have been the result of the context in which the research was conducted.

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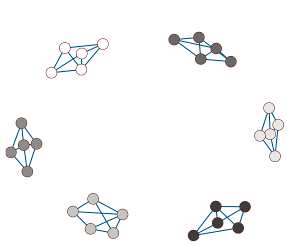
Table 1. Simulation parameters

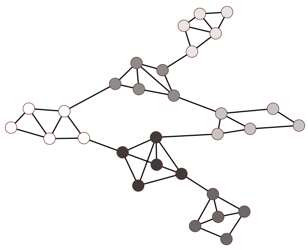
Simulation parameters	**Base model**	**Extensions of the model**
Density of the unit network (decentralized coordination structure)	1	0.20
Initial knowledge distribution in own unit	Uniform [0.02, 0.5]	Uniform distribution U [0.15, 0.2]
Initial knowledge distribution in other unit	U [0,0.02)	U [0,0.02]
Knowledge homogeneity between units (p)	0.1-0.9	0.1-0.9
Population	100	100
Number of units	20	20
Density of the core and periphery in the unit network	Core = 0.8, periphery = 0.2	Core = 0.6, periphery = 0.3
Number of core units	6	4
Watts and Strogatz rewiring parameter (τ)	0-1	0-1
Number of loops of random interactions for each social network	50	10-100
Total number of simulation runs with different initial random seeds	20	20

Note: The simulations are conducted through the code written in C++ environment.

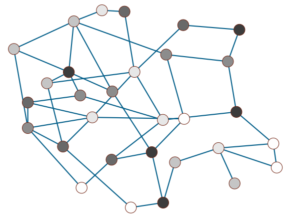
Figure 1. Example Social Network Structure and Coordination Structure of Units



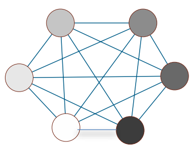
1a. Clustered social network structure in a decentralized unit network structure



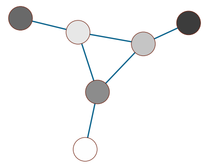
1b. Small world social network structure in a decentralized unit network structure



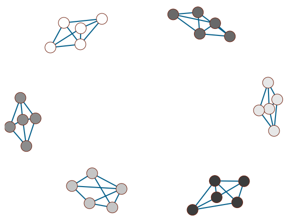
1c. Random social network structure in a decentralized unit network structure



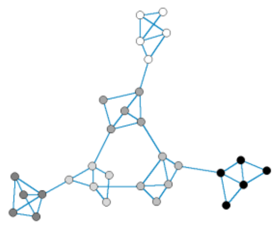
1d. Unit network decentralized structure



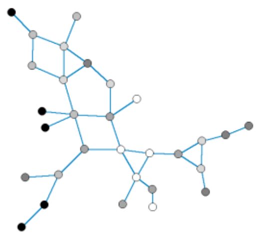
1e. Unit network centralized structure



1f. Clustered social network structure in a centralized unit network structure



1g. Small world social network in a centralized unit network structure



1h. Random social network in a centralized unit network structure

Note: Node colors in social network structures show which units agents belong to.

Figure 2. Knowledge Transfer Function for Different Levels of Knowledge Heterogeneity (ρ) Across Units

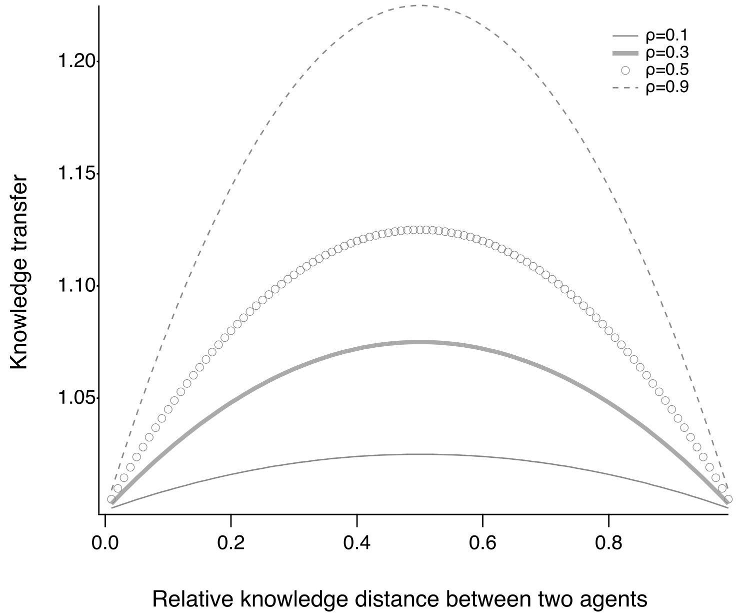


Figure 3a. Average Knowledge Aggregation in Decentralized Coordination Structures for Different Levels of (ρ) and (τ)

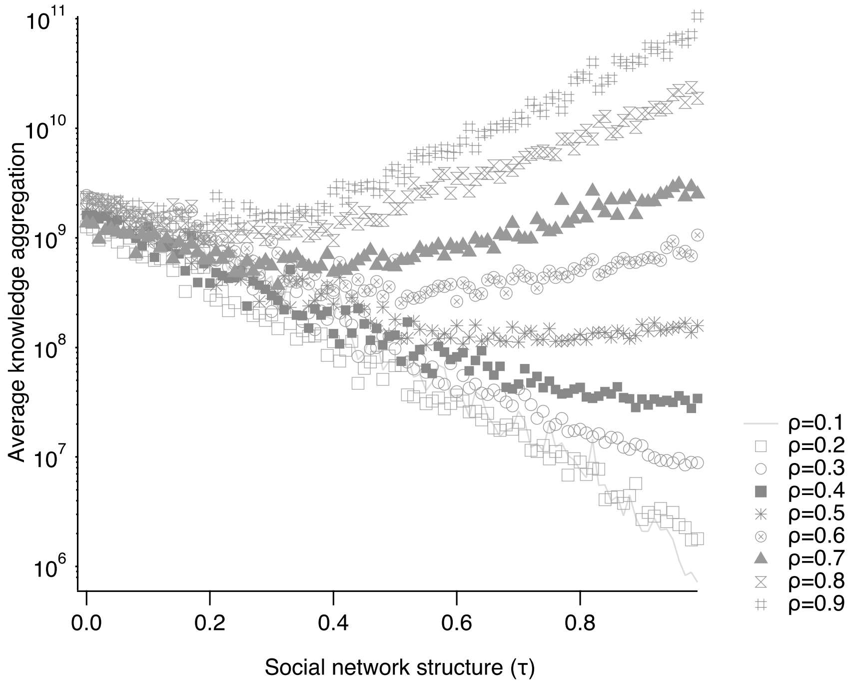


Figure 3b. Average Knowledge Aggregation in Centralized Coordination Structures for Different Levels of (ρ) and (τ)

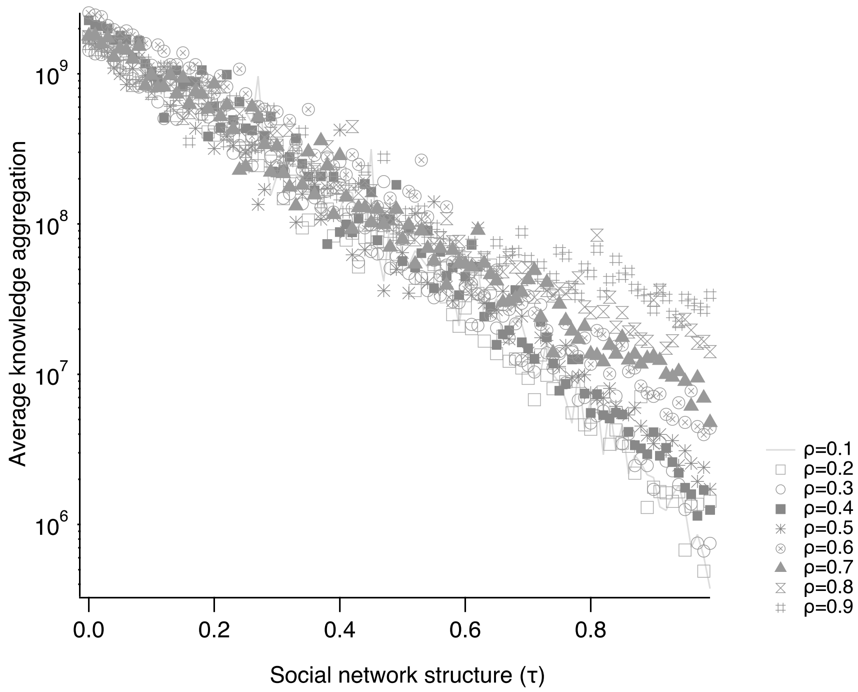


Figure 4a. Average Knowledge Aggregation for Cross-Unit Brokers in Decentralized Coordination Structures for Different Levels of (ρ) and (τ)

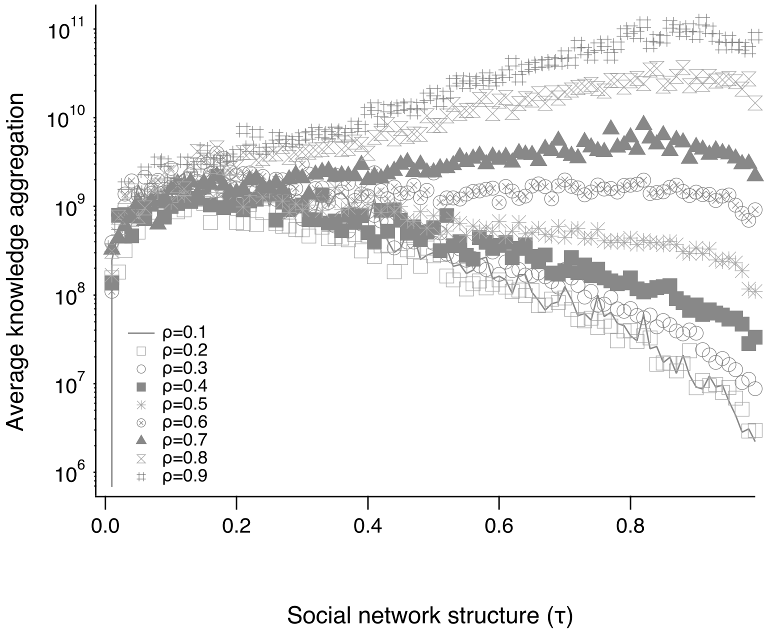


Figure 4b. Average Knowledge Aggregation for Cross-Unit Brokers in Centralized Coordination Structures for Different Levels of (ρ) and (τ)

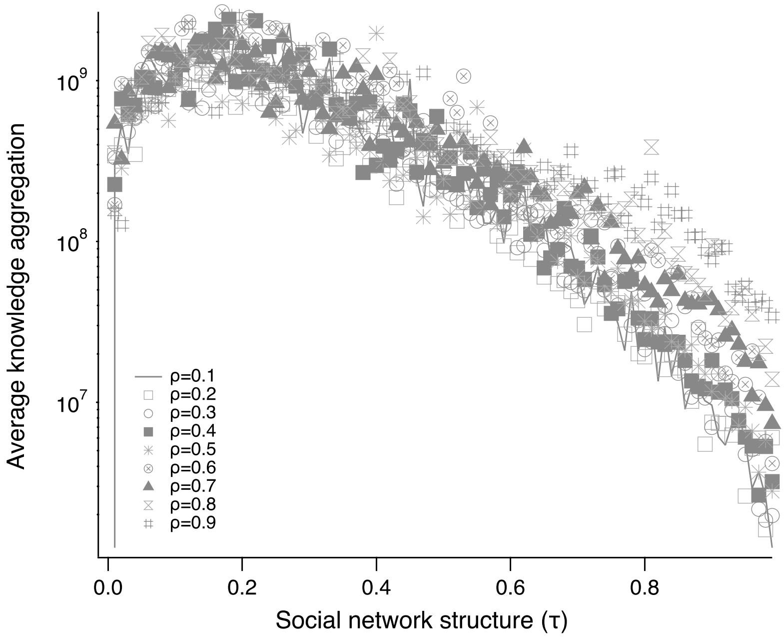


Figure 5a. Variability of Knowledge Aggregation by Unit

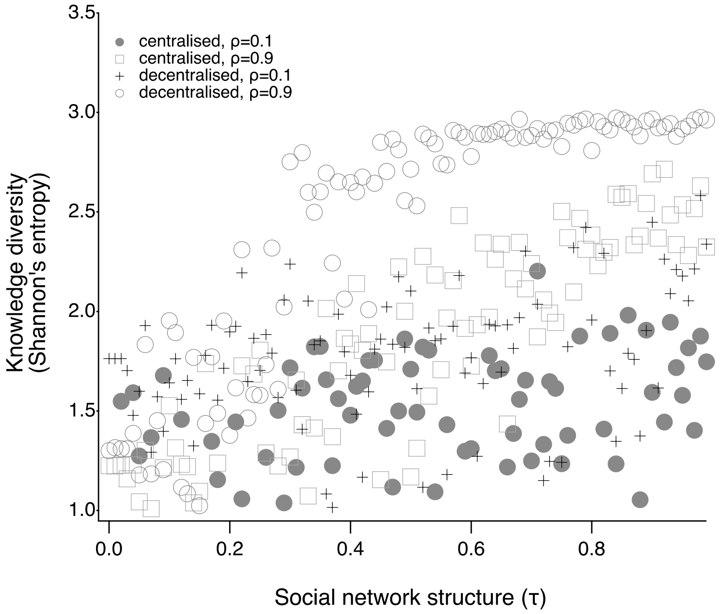


Figure 5b. Variability of Knowledge Aggregation by Knowledge Pools

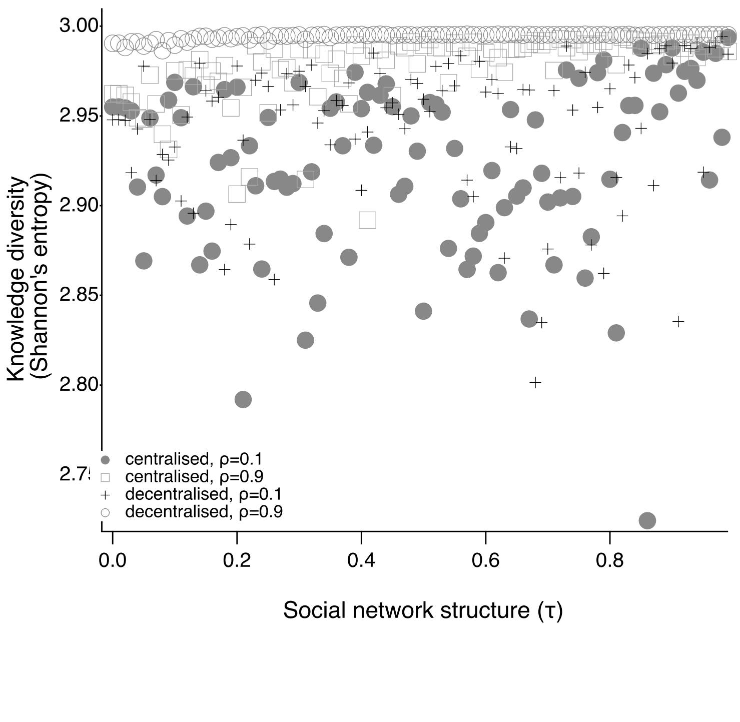


Figure 6a. Initial Knowledge Composition of Units in Decentralized Coordination Structures for Different Levels of (ρ) and (τ)

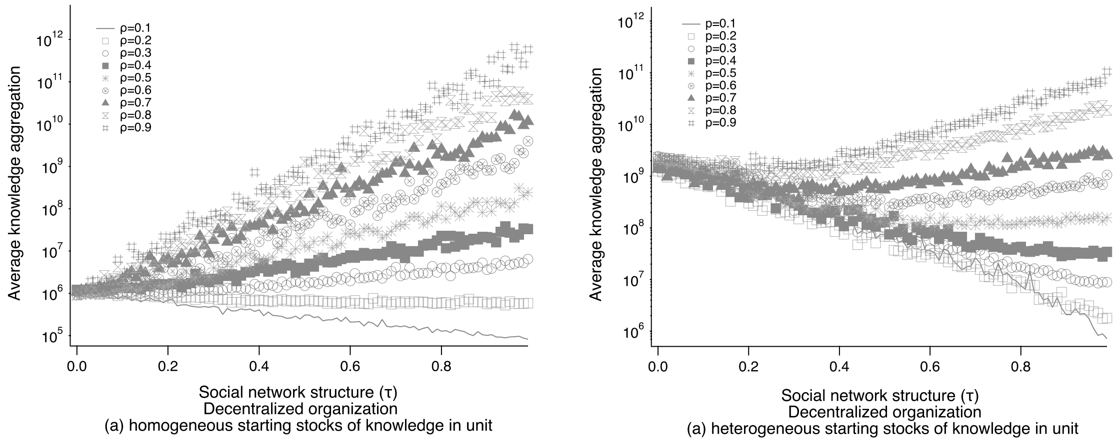


Figure 6b. Initial Knowledge Composition of Units in Centralized Coordination Structures for Different Levels of (ρ) and (τ)

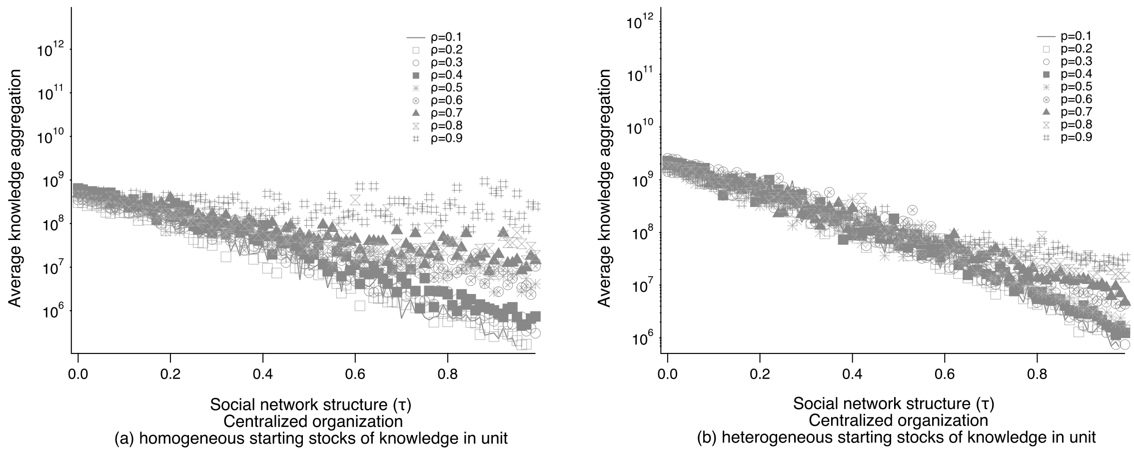


Figure 7. Comparison of Average Knowledge Aggregation in Decentralized (Unit Density of 0.2) and Centralized Coordination Structures

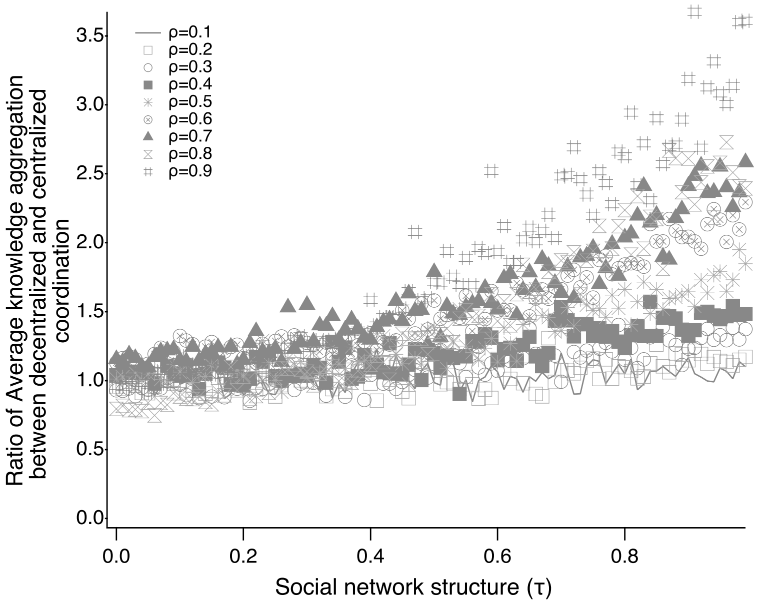


Figure 8a. Effect of Different Time Horizons in Decentralized Coordination Structures for Different Levels of (ρ) and (τ)

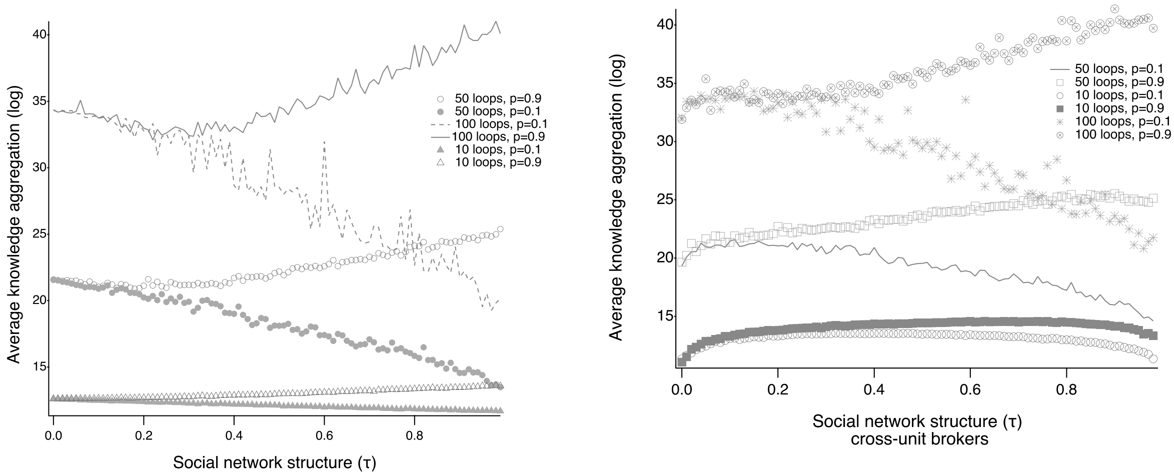


Figure 8b. Effect of Different Time Horizons in Centralized Reporting Structures for Different Levels of (ρ) and (τ)

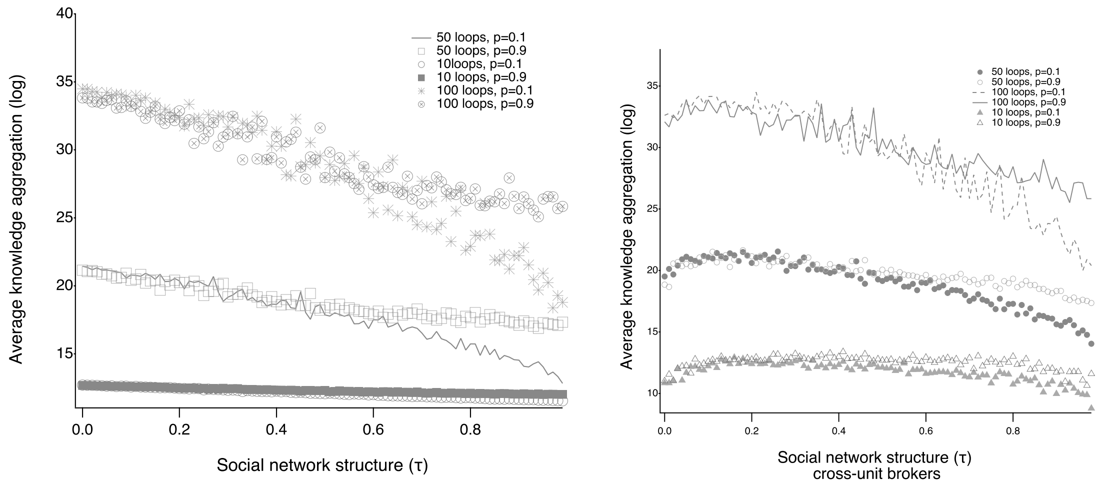


Figure 9a. Effect of Reducing the Density Gap Between Core and Periphery of Centralized Coordination Structures for Different Levels of (ρ) and (τ)

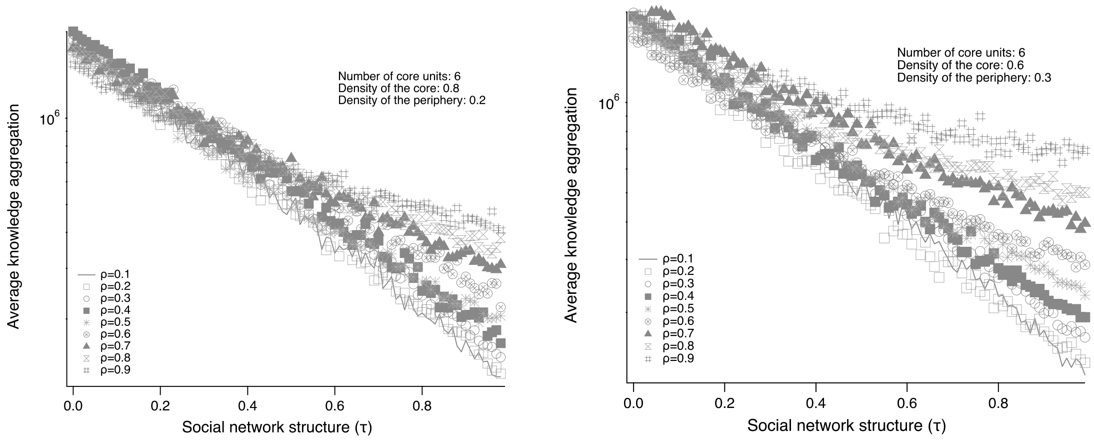


Figure 9b. Effect of Reducing the Number of Core Members of Centralized Coordination Structures for Different Levels of (ρ) and (τ)

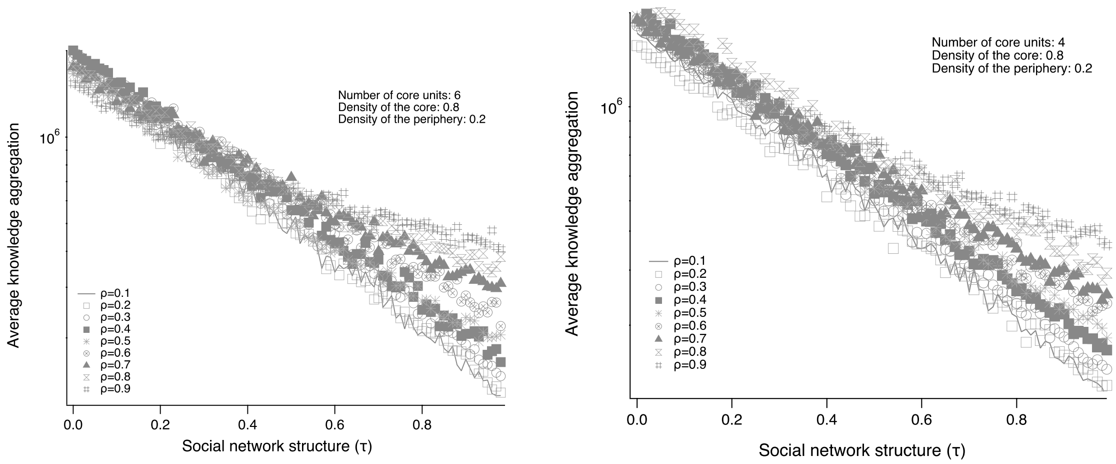


Figure 10. Parameter Range for Different Levels of (ρ) and (τ) Which Have the Same Influence on Average Knowledge Aggregation