

A Simulation Model Perspective on Social Capital

Andreas Koch(✉)

University of Salzburg, Salzburg, Austria
andreas.koch@sbg.ac.at

Abstract. This paper proposes an agent-based simulation model approach as one theoretical and methodological approach which helps derive knowledge that refers to the mechanisms and functions of social networks as a means of social capital production and dissemination. The approach is embedded in an empirical case study of two Austrian regions where a social project on enhancing well-being has been conducted. The data obtained from the simulation models are thus semi-empirical and semi-simulated. The primary aim of the paper is to investigate the selection processes of agents of different types and the linkage processes between them.

Keywords: Quantification of social capital · Mechanisms of social capital creation · Social network simulation

1 Introduction

The idea to conceptualise social relations also, if not primarily, in economic terms has, among others, been elaborated by Pierre Bourdieu and rests upon the empirical observation that economic principles such as competition, access to scarce resources and positions have been permeated into the social domain. For example, the valuation of scientific work has been expanded from the work's findings to scientific capital like reputation and prestige of scientists. Meanwhile, this successive inclusion of economic parameters into social relations is profound and comprehensive which justifies a Bourdieuian approach to extend the properties of economic capital towards the social relationships in general [26].

However, the idea of capitalising social relations is challenging, because it requires the ascription of numbers to them, which (shall) represent social values that are exchanged within and between communities, and which enable the mapping of differences discriminatorily, e.g., as rankings, ratings, and distinct positions. One difficulty of quantifying social-relational values such as trust, solidarity, or reciprocity, however, is given with their normative grounding which prohibits a direct translation of their qualities into quantities. Furthermore, it is questionable whether an approach that associates social actions with capitalistic characteristics is wishful since we often are reluctant to consider our social behaviour as prevailing rational or profit-oriented. Therefore, efforts to operationalise social capital are difficult to achieve by making a too strong analogy with economic capital. As [4, p. 241] claims: "The social world is accumulated history". The challenge is to adequately translate the definition of capital

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as "accumulated time" and, derived from this, "accumulated labour" into the realm of social interactions (see also [2], p. 211).

A core issue that frames the argumentation of this paper is the interrelationship between all sorts of capital. While economic markets rely strongly on the characteristics that are associated with social capital (trust and reciprocity), social capital, in turn, does so on economic capital's properties (efficiency and effectivity, benefit, or profit). However, these interrelations can be thought of as asymmetric, i.e., for every sort of capital there remains a nucleus which cannot be dissolved and represented by the others sorts. A complete translation and transformation of, for example, social capital's currencies (trust, solidarity, and reciprocity) are not feasible. The places where all these different currencies will be exchanged and valued are, in Bourdieu's terminology, the "social fields", which have multiple organisational functions without determining the structure of the superior "social spaces". In fact, the differentiation of the social fields will be regulated and organised by the social spaces [16].

This paper connects to this idea. The creation, growth and decline, and change of social capital depend on social networks. The availability of positions that are intrinsically tied to the distribution of resources which are capitalised through trust, reciprocity, solidarity (and many more) results from social network mechanisms. Network mechanisms' dynamics are, in turn, partially determined by temporal dynamics (from processes to evolution) and spatial dynamics (from local to global). The amalgamation of social networks, distribution of resources, temporal and spatial dynamics take place in social spaces which are composed of different and multiple communities on the one hand and different and multiple geographical places on the other. In other words, social spaces with their concrete geographical places influence the creation and distribution of social resources. Referring to Bourdieu on this line of arguments is still helpful: "[B]ourdieu's entire sociological work is steeped in the idea of a radical bondage of any social praxis to its social place […]" [26, p. 10; translation A.K.].

The paper does not intend to deal with social spaces in a comprehensive manner but will focus on their meaning as a co-determinant in the production of social capital. With this focus, we attempt to approach social capital in a way that helps bypass an immediate capitalisation of social relations' currencies by emphasising a social-spatial dummy variable – the number of face-to-face meeting opportunities – that can be used to account for a quantitative representation of social capital *as a precondition*.

In doing so, this paper proposes an agent-based simulation model approach as one theoretical and methodological approach which helps derive knowledge that refers to the mechanisms and functions of social networks as a means of social capital production and dissemination. The approach is embedded in an empirical case study of two Austrian regions where a social project on enhancing well-being has been conducted. The data obtained from the simulation models are thus semi-empirical and semi-simulated. The primary aim of the paper is to investigate the selection processes of agents of different types and the linkage processes between them. In the context of selection, it is assumed that the number of face-to-face meeting opportunities plays a central role.

The agents represent people in different positions, in teams of up to approx. eight members, collaborating together in order to implement projects that are dedicated to enhancing local wellbeing. Characteristics of within-team collaboration (density,

intensity, etc.) and between-team collaboration (new network connections) are used to compute network structure parameters (closeness and betweenness centrality) which serve as a quantitative proxy for social interactions and thus social capital.

2 Social Capital as a Source and Resource of/in Social Networks

The enabling meaning of versatile social interactions in collective human relations is commonly understood as a *conditio sine qua non* for human beings to live a decent life [9, 15]. To establish personal identity and autonomy, or the possibility to live one's life according to one's own capabilities and aspirations, requires a continuous exchange with other members of the communities and societies one is embedded into. While the nature of social interactions is seen as an unquestioned fact [22, 24], their valuation in operational terms is much harder to achieve because it inevitably relates to norms, expectations, and attitudes: "Each social relation stipulates norms and expectations about my behavior and the behavior of others" [30, p. 40]. According to Sack [29, p. 28], social relations are interrelated with (subjective) meaning and nature (space), and all three forces interdependently influence the relationship between self and place.

One generally accepted approach to quantify the value of social interactions is given by the theory of social capital. A huge body of theoretical reflections as well as empirical studies are available that considers the idea of transferring the concept of economic capital into the social realm as a suitable methodology in order to cope with social relations (see, for example, [10, 14]). The intention of this contribution is not, principally, to criticise this epistemological transfer, but to highlight some problematic implications of this approach that can be – at least partly – surmounted by a computational and generative simulation approach.

Social capital as a resource for knitting social ties between persons (we do not consider here non-human nodes as part of social networks, though these are important, see [19]) is theoretically addressed to different functions on different scales. Coleman [5, p. 302], for example, advocates a functional and meso-scaled approach: "Social capital is defined by its function. It is not a single entity, but a variety of different entities having two characteristics in common: They all consist of some aspect of a social structure, and they facilitate certain actions of individuals who are within the structure". Bourdieu [4, p. 248], in contrast, prefers a structural and micro-scaled definition of social capital as "the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition". By referring to different forms of social capital – bonding and bridging social capital – Putnam [28, p. 18ff; 27], in turn, directs his attention primarily to the societal benefits and challenges and thus the macro-scale perspective.

A common tendency can be seen in attempts that conceptualise social capital in the most comprehensive way possible; as basic ingredients of social networks. Such all-encompassing definitions, however, provide no concise understanding of the subject matter. Dill [7, p. 85], for example, offers such a broad definition and claims for his own approach that a definition should be a clear and simple one: "Social capital is the

sum of intangible merits and goods within a community" (translation A.K.). His definition, for example, is anything but clear and simple. What can be accepted as "intangible merits" in communities and by whom? Who or what defines communities, and why are we dealing now with communities instead of networks? Are they identical? Who is producing and who is consuming intangible goods, based on which distribution rules? How does one sum up intangible goods? This definition is different from the accumulation and the "unit of calculation" concepts of social capital, because it provides no clues about distributional rules (it is a simple sum), the nature of intangible goods, and the nature of communities which is much harder to specify than talking about social networks [19]. Hence, such attempts are less suitable when attempting to grasp the very nature of social capital in qualitative as well as quantitative ways.

Bourdieu's approach, with its tighter and thus more appropriate relationship between the different sorts of capital, rests on the idea that the creation, consolidation, and transformation of social relations take time to evolve. "The social world is accumulated history, and if it is not to be reduced to a discontinuous series of instantaneous mechanical equilibria between agents who are treated as interchangeable particles, one must reintroduce into it the notion of capital and with it, accumulation and all its effects" [4, p. 241]. Availability and utilisation of social relations, of interacting with other individuals, are not realised in an environment that provides instantaneous linkages without any reference or framing, because social networks cannot emerge out of nothing. Social spaces with their material, relational and symbolic dimensions are one of the core presumptions to serve as a reference or frame. Capital, understood as 'accumulated labour', takes time to be recognised as trust, solidarity, or empathy. This perspective nurtures the idea of utilising a computational simulation approach in order to incorporate time and dynamics explicitly.

The actor-centred and utilitarian perspective of Bourdieu's approach – in the sense that the holder of a position in the network is the addressee and beneficiary of resources and not the individual person [16, p. 48] – not only presupposes an affiliation to one or many social networks, but also assumes knowledge about the structure and function(s) therewithin. Networks vary significantly in size and complexity; they can be concrete and manageable as, for instance, families and cliques, as well as abstract and opaque, as is the case for associations, organisations, labour markets, or electoral rolls. Furthermore it is remarkable that the unit of value, the currency, is implicitly given by solidarity, reciprocity, and trust, expressed explicitly as network connections, however (there are, obviously, more currency units than these three, but we focus here on these because they are in the core focus of our studies). "The volume of the social capital possessed by a given agent thus depends on the size of the network of connections he can effectively mobilize and on the volume of the capital (economic, cultural or symbolic) possessed in his own right by each of those to whom he is connected" (ibid.). This quantitative relation – the more connections one has the higher his/her social capital is – sounds odd, because it makes no qualitative difference in terms of network structure (intensity of relations), or the nature and value of relations (positions and roles of agents, weights of directions). "Resources" within the social capital context are understood as the availability of network relationships, which are, however, not specified – neither quantitatively nor qualitatively.

Capital can be assigned to three functions: (i) a means of exchange, (ii) a means of value hedge and preservation, and (iii) a unit of calculation. Accumulation may play a major role in all of these functions, but is not restricted to them. The worth of capital also stretches to the functions of distribution and circulation within a commodity and service economy. In addition, economic capital accumulation implies accumulation of both surplus and debt. The execution of all these functions requires not only a general usability of capital but also a (statistical) scale of measurement that enables comparisons and evaluations across a diverse field of objectives, and of spatial and temporal scales. All this is not given – or not sufficiently so – with social capital. It is possible to weigh and to qualify the direction of network relations as well as to explore network-related measures such as centralities, cliques, and positions; but still no adequate measures are available which account for the latent variables associated with social capital in an explicit and direct way. This statement does not negate approaches to social capital like, for example, "a network theory of social capital" [23] or empirical studies about "solidarity and mutual support" [3]. The approach that will be presented here belongs to the same category of approaches. They all, however, do not provide an immediate translation. In other words, it makes no sense to say "we must double solidarity or trust by doubling X".

One approach to investigate the creation and variation of social capital as mechanisms in social networks in order to derive quantitative measure is given with simulation modelling which will be presented in the next chapters.

3 The Empirical Case Studies to Investigate Social Capital

As a conclusion of Sect. 2, it would be a scientifically fruitful endeavour to develop indexes of social capital – based on trust, solidarity, network relations, etc. – to investigate social networks comparatively [19]. One way to follow this endeavour is to use a computational agent-based modelling approach since this approach allows for the qualification of network mechanisms, network structures, and network functions in quantitative measures [the generative methodology is delineated in 8]. In addition to the theoretical argumentation, it is also methodologically reasonable to apply a computational approach, because the development of network-analytical techniques and methods has been rapidly increased [2, 6, 25].

The following model approach can be characterised as semi-empirical as the initialisation of the simulation runs has been realised with data we collected as part of a project that has been conducted in four Austrian regions between 2011 and 2017. Semi-standardised questionnaires have been used as a first step to gain knowledge about the team networks, their sizes and compositions involved in the overall social project. Based on the results of the questionnaires, we selected actors for interviews who represented particular topological node properties. The models presented here refer to two of the four regions, one in Styria and the other in Upper Austria. The empirical networks of the Styrian region comprise of 79 team leaders with 396 team members and 441 connections, while the ones of the Upper Austrian region comprise of 59 team leaders and 418 team members with 655 connections. A detailed description of the

project background together with the model approach that has been used in another context is given in [11, 12, 20].

4 The Agent-Based Model Design

In order to explore social network mechanisms as an indicator to derive knowledge about processes of social capital creation and variation, an agent-based simulation model has been developed whose origin grounds on ideas about team assembly mechanisms [13]. The NetLogo library includes this original model which has been implemented by [1]. The team assembly mechanisms' approach has been modified by the author in several ways to study different topics of social networks, among which the relationship between social and spatial topologies is one of them [18, 20, 21]. This approach provides a well justified methodological starting point as its central idea is to investigate processes of network growth due to new ties between existing and/or new actors of the network.

To analyse the issue of social capital metrics by incorporating empirical data, we modified the original model in a couple of ways concerning, for example, the initialisation of the model, the size and network structure of initial teams, the merging procedure, and the qualification of network ties. Since there is a comprehensive description in [18, 20, 21], we only briefly delineate the basic model design characteristics here. Figure 1 illustrates the selection process of agents as a flow diagram.

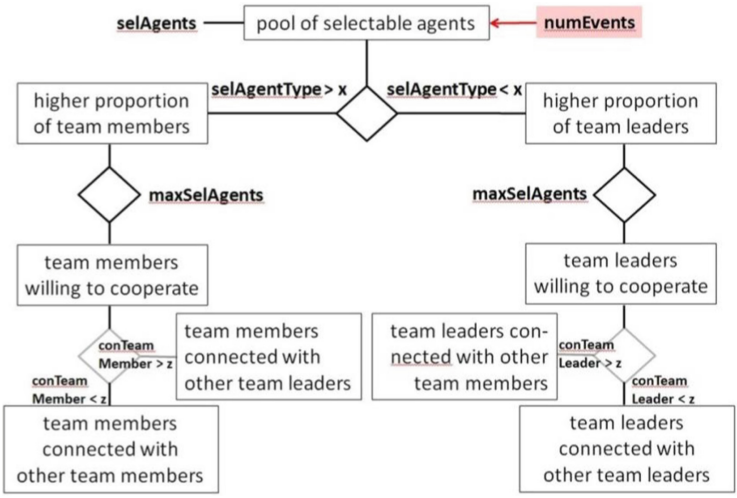

Fig. 1. The selection of agents within the simulation process. Source: [18]

As stated in Sect. 1, the central 'medium' to select agents as potential collaborators across the initial project-related networks is given with the number of opportunities to meet face-to-face during the project period (and thereafter). 'Meeting opportunities'

can, for example, take the form of formal stakeholder meetings, announced workshops or informal meetings. The model-theoretical number of meetings varies from 1 to 160, representing the range of having at least one meeting to a situation of a weekly meeting rhythm (the project period comprises of 160 weeks, with 80 weeks of project implementation and another 80 weeks of post-project evaluation). Based on the empirical situation, however, there are three formal meetings (jury meetings with project presentations) to be included in any case. Virtual meetings had taken place for sure, but we have no valid information about these.

After the pool of selectable agents has been created, the model distinguishes the likelihood of selecting actors according to their function – team leaders and team members. The last step in the selection procedure takes the four principal types of ties into account by explicitly considering the initiator of a new cooperation. All steps represented in Fig. 1 will be repeated with reference to the simulated number of meetings. In order to simulate the modelled topology of the network empirically more realistic, we introduced a varying probability of dissolving ties between agents from time to time. The variation correlates inversely with the assigned intensity. The social network simulation models have been created with NetLogo 6.0 [30]; the Styrian case study model is available at OpenABM (https://www.openabm.org/model/5583/vers-ion/1).

5 Some Selected Model Results

Before discussing some relevant results of the simulation model presented here, we briefly summarise the outcomes of the statistical analysis conducted by the predecessor model [18, 20, 21]. Table 1 illustrates that the variable 'number of meetings' is statistically the most relevant in both regions in terms of explaining the statistical bivariate correlations of the number of connections among and between team leaders and team members against the independent variables described above. The correlations of the other independent variables with the dependent variables differ, however. The number of selectable agents and the composition of the pool with team leaders and team members are relevant explanatory measurements to explain the number of connections among team leaders, while the actual realisation of ties between team members is the second most important measurement to explain the number of connections among team members. Connections between all involved agents, again, depend on the size of the pool of agents. Furthermore, it is worth noting that the final modelled networks do not differ significantly between the two regions when comparing the types of connections (among team leaders, among team members, and between team leaders and team members).

In addition to the bivariate correlation analysis, multiple regression analyses of the two regions highlight the isolated influence of the independent variables in explaining the variation of the quantitative dimension of the connection types (see Tables 2 and 3). Isolated influence refers to as the exclusion of multicollinearity, i.e., interdependencies between the independent variables. This has been achieved by applying the 'stepwise selection' function.

Table 1. Bivariate correlation (Pearson) between the independent variables which determine the structure of the networks in the study regions of Steirische Eisenstrasse (Styria, S) and the Mühlviertler Alm (Upper Austria, UA). All variables do have a metrical or interval scale. *statistically significant for the 95% confidence interval; n = 3,888. Source: own data 1 = number of connections among team leaders, 1a for S, 1b for UA; 2 = number of connections among team members, 2a for S, 2b for UA; 3 = number of connections among all actors, 3a for S, 3b for UA

Dependent variable	Independent variables					
	Num of meetings	Sel. of agents	Sel. of agent types	Max. num of agents selected	Ties of team leaders	Ties of team members
1a	0.785*	0.234*	0.235*	0.169*	0.065*	0.002
1b	0.779*	0.238*	0.236*	0.168*	0.068*	−0.005
2a	0.633*	0.185*	−0.188*	0.130*	−0.001	0.194*
2b	0.623*	0.176*	−0.181*	0.124*	0.003	0.194*
3a	0.756*	0.267*	−0.084*	0.194*	−0.004	−0.001
3b	0.735*	0.259*	−0.097*	0.189*	−0.001	−0.005

All multiple regression models start with the number of events, but differ then according to the type of connections. While connections among team leaders and connections of all agents are then dependent on the number of selectable agents, it is the realised connections between team members that affect the connections among team members second most. This pattern can be detected in both regions though there are some (empirical) differences at the beginning of the simulation runs.

One conclusion drawn from the results presented in Tables 1, 2 and 3 is that although the 'number of events' parameter is most significant for all network compositions, the other independent variables also contribute to explain the variation of the size and composition of the networks though to a lesser extent and in different ways. Thus, measuring social capital implies a multi-dimensional consideration of determinants even though the number of meeting opportunities appears to be highly relevant.

A further conclusion is that team leaders, on average, benefit more from an increase of workshops and meetings than team members do. This is partially due to an implicit bias, occurring because there are fewer team leaders than team members, which leads more quickly to a higher number of linkages. In fact, considering the results of the cluster analyses (achieved through the Ward method, which yields more or less evenly distributed clusters), it can be concluded that team members also benefit significantly from an increase of events.

The relativity of benefit refers to the situation that there are five times more team members than team leaders in the Styrian region and even seven times more in the Upper Austrian region. According to the results for the Styrian region, team members increased their connectivity by a factor of 2.6 and team leaders by a factor of 1.5. Therefore, we can conclude that team leaders, on average, benefit more but team members also benefit from an increase in the number of events (for more cluster analysis details, see [20].

Table 2. Multiple regression analysis of the dependent variable 'number of meeting opportunities' and the independent variables (Upper Austria); Source: own data

Models	R	R^2
Connections among team leaders		
Number of meeting opportunities	0.779	0.606
+ number of selectable agents	0.814	0.662
+ number of team leaders or team members	0.847	0.718
+ maximum number of selectable agents	0.864	0.746
+ realised ties of team leaders	0.867	0.751
Connections among team members		
Number of meeting opportunities	0.623	0.388
+ realised ties of team members	0.653	0.426
+ number of team leaders or team members	0.677	0.459
+ number of selectable agents	0.700	0.489
+ maximum number of selectable agents	0.711	0.505
Connections of all agents		
Number of meeting opportunities	0.735	0.540
+ number of selectable agents	0.779	0.607
+ maximum number of selectable agents	0.802	0.643
+ number of team leaders or team members	0.808	0.652

Table 3. Multiple regression analysis of the dependent variable 'number of meeting opportunities' and the independent variables (Styria); Source: own data.

Models	R	R^2
Connections among team leaders		
Number of meeting opportunities	0.785	0.617
+ number of selectable agents	0.820	0.672
+ number of team leaders or team members	0.852	0.726
+ maximum number of selectable agents	0.869	0.755
+ realised ties of team leaders	0.872	0.759
Connections among team members		
Number of meeting opportunities	0.633	0.401
+ realised ties of team members	0.662	0.438
+ number of team leaders or team members	0.689	0.474
+ number of selectable agents	0.713	0.508
+ maximum number of selectable agents	0.725	0.525
Connections of all agents		
Number of meeting opportunities	0.756	0.572
+ number of selectable agents	0.802	0.643
+ maximum number of selectable agents	0.825	0.681
+ number of team leaders or team members	0.829	0.687

Descriptive Statistics of Centrality Measures in the Styrian Study Region

In order to investigate the course of the network creation, two common centrality measures have been used namely the closeness centrality and the betweenness centrality. Both centrality measures characterise an agent's position or role in the entire network. Commonly, closeness centrality (more precisely, actor closeness centrality) "[…] was developed to reflect how near a node is to the other nodes in a social network […]. Closeness and distance refer to how quickly an actor can interact with others, for example, by communicating directly or through very few intermediaries" [17, p. 65]. One index of (actor) closeness centrality is given with "[…] the inverse of the sum of the geodesic distances [topological shortest distances, A.K.] between actor i and the $g - 1$ other actors" (ibid.). In NetLogo closeness centrality is defined slightly different "[…] as the inverse of the average of an [agent's] distances to all other [agents]" [30, n. p.]. Distances are also defined as the shortest paths. Betweenness centrality (again, in the sense of an actor betweenness centrality) in contrast refers to the mediator function of an agent (for example, mediating communication flows). This measure calculates "[…] the extent to which other actors lie on the geodesic path (shortest distance) between pairs of actors in the network. Betweenness centrality is an important indicator of control over information exchange or resource flows within a network" [17, p. 67]. The calculation of betweenness centrality in NetLogo refers to this approach: To calculate the betweenness centrality of an agent "[…] you take every other possible pairs of [agents] and, for each pair, you calculate the proportion of shortest paths between members of the pair that passes through the current [agent]. The betweenness centrality of an [agent] is the sum of these" [30, n.p.]. For the establishment of agents that possess a high closeness *and* betweenness centrality, it is remarkable that the range of involved team leaders (between 9% and 76%) and team members (between 3% and 58%) is very large. An attempt to explain this follows below. "High" closeness and betweenness centrality is defined as equal to, or larger than, two standard deviations from a standardised mean value.

Descriptive Statistics of Centrality Measures in the Upper Austrian Study Region

The networking processes in the Upper Austrian study region shows some similarities with the Styrian region, but also some distinct differences. The correlation pattern of variables is similar as a low number of events is given. What is different is the actual linkage process. While in the Styrian network (henceforth referred to as S-network) only 1% of all cases have at least 10% new relations with team leaders being created, it is 11% of all cases in the Upper Austrian-network (henceforth referred to as UA-network). With respect to all new relations, however, it is 2% in the UA-network but 4% in the S-network. Notwithstanding, the simulated UA-networks produce a higher number of highly centralised agents: there is a maximum of eight agents with high betweenness and closeness centrality compared with only four in the S-network.

As the number of meeting opportunities increases to 32, a high probability of selectable agents in general and of selectable team leaders, in particular, is less important for the emergence of cooperative team leaders. For the actual creation of ties, it remains crucial to have a high likelihood of repeated linkages. Furthermore, with 13% of all cases, there are many more cases given that create agents with a significantly high betweenness and closeness centrality (with at least six agents). With the lower

number of events (4) there are only 4% of all cases available that help establish outstanding network agents. Thus, the UA-network not only supports the creation of a higher number of highly centralised agents (up to eight) than the S-network (up to four), but also promotes more chances for the emergence of these agents (13% compared with 4%).

A biweekly frequency of events, in turn, has more similarities with the low frequency of only four meetings in the course of 160 simulation steps. The number of cases with half of all team leaders involved in the simulated network decreases to 10%, and team leader involvement again depends more on the passive selection by team members. Knitting ties also requires a high linkage probability again. More meeting events, however, enable up to 95% of team leaders and 34% of team members to share new relations with other members of the network – a share that has not been reached with less frequent meeting opportunities.

Centrality Measures as a Means to Understand the Dissemination of Social Capital

The analysis of simulation results, as has been conducted so far, aimed to detect some patterns of correlations between relevant node- and edge-based parameters of the two social networks. The number of meeting events as a precondition (or framing condition) for the transformation of more or less fragmented, small, and project-related networks towards a large(r) connected collaborative network served as a reference point and guideline throughout the analysis.

A measure of a computationally derived sustainable network structure which promotes a proper generation and distribution of social capital should incorporate the following two criteria [31]:

- A good mix of ties of different strengths. Neither a network with a high proportion of strong (intense) ties, which would potentially imply lock-in effects of elite agents nor with a high proportion of weak ties, which would potentially imply fragmentation effects of non-committed agents, seem appropriate to maintain stable social networks.
- A good mix of agents with high betweenness and/or closeness centralities as well as low(er) betweenness and/or closeness centralities. This assumption refers to the thesis that a balanced structure of a network in terms of centralisation and decentralisation is beneficial for task allocation and communication.

The results of the semi-empirical network analyses can help us to approach to these two topics of suitable social network structures. In addition to the results presented above, we now briefly review the correlative significance – the strength of relationships between centralised agents and network characteristics – of the two networks. Besides the ‘ordinary’ agents (henceforth referred to as o-agents) in the networks whose relevance in transmitting and controlling communication processes is below the fixed threshold, we distinguish agents with a high betweenness *and* closeness centrality (bc-agents), those with a high closeness centrality (c-agents), and those with a high betweenness centrality (b-agents). Table 4 lists mean values and standard deviations of these agents and of relevant influential variables.

The values of Table 4 reveal that the initial network structures differ between the two regions since all simulation runs are designed in the same way in terms of

Table 4. Descriptive statistics of the central agents and of independent variables explaining their centralities for the Styrian network (left) and the Upper Austrian network (right). n = 243

Variables	Styrian network		Upper Austrian network	
	Mean	Standard deviation	Mean	Standard deviation
bc-agents	1.41	0.682	5.01	1.126
b-agents	1.44	0.895	1.34	0.687
c-agents	2.88	1.536	4.49	1.826
o-agents	469.27	0.999	466.16	2.034
New team leaders	2.49	3.078	10.35	6.928
New team members	2.24	2.747	8.37	10.847
New ties among team leaders	26.91	3.210	19.72	7.788
New ties among team members	1.21	1.659	11.14	11.591
New ties in total	107.67	8.292	166.81	5.370

parameter values and temporal structure. The simulation runs used here excluded extreme values of meeting opportunities because they are empirically unrealistic: the range covers values from four events up to 80 events. On average, considerably more team leaders and team members with new connections are involved in the Upper Austrian networks, but these new connections are – for both agent types – relatively more often created with other team members (by comparing the means and standard deviations of 'new team leaders' and 'new team members' with 'new ties among team leaders', 'new ties among team members' and 'new ties in total'). Furthermore, the variation of the network structures is significantly higher in the Upper Austrian case than in the Styrian (considering the larger standard deviations). Also, there is a higher chance for agents to achieve a high betweenness *and* closeness centrality (bc-agents) or a high closeness centrality (c-agents) in the Upper Austrian networks. This will be briefly discussed here by including Pearson's correlation coefficients.

A closer look at the correlations between the three centrality types reveals a different structural pattern in the empirical networks of the two study regions (see Tables 5 and 6). Correlations here refer to the bivariate strength of the relationship between the three agent types of particular centrality and the influencing variables of new (cooperative) agents and new ties.

Table 5. Correlation coefficients between the highly centralised agents and the outcome of node and edge characteristics of the Styrian network. **correlations are significant at the 99% level.

	Cooperative team leaders	Cooperative team members	New ties among team leaders	New ties among team members	New ties in total
bc-agents	0.637**	0.580**	0.593**	0.567**	0.477**
b-agents	0.386**	0.420**	0.348**	0.369**	0.317**
c-agents	−0.667**	−0.695**	−0.473**	−0.612**	−0.321**

Table 6. Correlation coefficients between the highly centralised agents and the outcome of node and edge characteristics of the Upper Austrian network. **correlations are significant at the 99% level.

	Cooperative team leaders	Cooperative team members	New ties among team leaders	New ties among team members	New ties in total
bc-agents	0.474**	0.077	0.458**	0.168**	0.188**
b-agents	0.073	0.274**	0.126	0.237**	0.340**
c-agents	0.223**	−0.156*	0.099	−0.107	0.075

The fact that correlation values and correlation directions of the newly established nodes and links in both networks differ in a noticeable way must be caused by different initial conditions of the network structures. Not only do correlations of bc-agents, b-agents, and c-agents differ in terms of their strengths and statistical significance, but also in terms of the direction of correlations. While in the UA-network c-agents have both no significant correlation with new ties and a highly significant but weak positive correlation with cooperative team leaders and a significant but weak negative correlation with cooperative team members, the S-network represents a homogenous pattern with highly significant and strong positive correlations in all respects.

There are two issues that may help explain these results: first, c-agents and b-agents can be seen as residuals of centralised agents, because bc-agents already incorporate both centrality qualities. Second, the empirical S-network is less fragmented than the UA-network. As mentioned above, the S-network has 79 team leaders, of which 18% act simultaneously as team members in other project teams. The UA-network has only 59 team leaders, of which only 11% are in this double function and this by almost 50% more connections in total than compared with the S-network. New ties and the inclusion of additional cooperative agents may have the potential to decrease network fragmentation, but with the effect of a lower share of centralised agents as is the case in the S-network. In this respect, the S-network seems to be in a more balanced situation (across all value combinations of the involved variables).

This conclusion can claim some modest validity when taking distributional statistics into account. The mean value of the new cooperative team leaders in the UA-network is four times higher than it is in the S-network (Table 4). However, the standard deviation is also more than twice as high in the UA-network as it is in the S-network. A comparable situation is given with the new cooperative team members: on average, they are four times more often involved in the simulated UA-networks than in the S-networks, but, again, with a (here) four times higher standard deviation.

Finally, new connections among team leaders vary between 4% and 17% across all parameter value combinations in the UA-network while in the S-network they vary only between 5% and 7%. All these values indicate that the S-network is far less fragmented in the beginning (the empirical network) and hence depends less on the number of events than the UA-network. In other words: the number of events can be supportive for networks that are fairly fragmented, i.e. in our case they represent a network structure that is based on many unconnected small project-related networks with one centre each and a couple of team members tied to this centre.

6 Conclusion

The simulation models of the two Austrian regions were built to serve as a kind of missing link. Our empirical investigations of the emerging social networks as part of the empirical project focused primarily on an inquiry of the team leaders and their individual projects as well as the representatives of social institutions involved in the general project environment. Due to budgetary and temporal restrictions, we were not able to extend the inquiry to the team members and their network ties. This lack of data can be surmounted to a certain degree by utilising a model that simulates possible and probable linkage strategies of all participating agents based on knowledge we partly found through workshops and stakeholder meetings and through the literature. Based on these linkage strategies we obtain an idea of how mechanisms of social capital creation, variation, and dissemination may vary according to the parameters that have been investigated by social simulation techniques.

Relating the number of face-to-face meeting opportunities as one potential supportive determinant to enhance trust and solidarity in the creation and development of central positions or functions in social networks can be seen as a strategy to approach to social capital through the application of computational simulation techniques. It is, in other words, an attempt to explicitly translate Bourdieu's statement of "a radical bondage of any social praxis to its social place" and Sack's statement that "social relations, subjective meaning and space influence the relationship between self and place" into concrete situations of collaboration at local and regional levels.

With respect to the two criteria mentioned above we tried to detect some structural characteristics of the two regional social networks that help to better understand what is meant by social capital as a resource in social interactions. Referring to the "mix of ties" criterion we can conclude that both networks are equipped with a sustainable sample of ties of different intensity that would allow for both a sufficient strength to survive as a huge connected network and a sufficient flexibility to grow or shrink without losing fundamental bridging qualities.

Referring to the "mix of highly centralised agents" the network structures are less balanced, because in both cases the team leaders do play a crucial role as glue to preserve the networks as large connected graphs. One reason for this asymmetry can be explained by the initial structure of the networks which is characterised by the central team leaders surrounded by team members who are not connected with one another. The growth of the final network does not completely separate itself from this initial configuration (due to a lack of empirical data). In order to generate and disseminate social capital more equally within the whole network, it would be suggestive to strengthen the position and role of the team members.

With a small modification of Putnam's [28, p. 23] statement: "It would obviously be valuable to have distinct measures [of the evolution] of these various forms of social capital [over time]" (original quote includes the phrases within the brackets), we can conclude that a computational simulation approach can contribute to enrich the understanding of social capital from a generative, mechanism-sensitive, and quantitative point of view.

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