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Social network structure and the trade-off between social utility and economic performance☆

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ABSTRACT

We put forward a computational multi-agent model capturing the impact of social network structure on individuals' social trust, willingness to cooperate, social utility and economic performance. Social network structure is modeled as four distinct social capital dimensions: degree, centrality, bridging and bonding social capital. Model setup draws from socio-economic theory and empirical findings based on our novel survey dataset. Results include aggregate-level comparative statics and individual-level correlations. We find, *inter alia*, that societies that either are better connected, exhibit a lower frequency of local cliques, or have a smaller share of family-based cliques, record relatively better aggregate economic performance. As long as family ties are sufficiently valuable, there is a trade-off between *aggregate* social utility and economic performance, and *small world* networks are then socially optimal. We also find that in dense networks and trustful societies, there is a trade-off between *individual* social utility and economic performance; otherwise both outcomes are positively correlated in the cross section.

1. Introduction

This paper contributes to the voluminous literature on the relationships between social network structure and social trust, willingness to cooperate, social utility and economic performance. In an influential book, Putnam et al. (1993) argued that the marked difference in economic performance between Northern and Southern Italy has its roots around 1000 AD, when in Northern Italy there were many city-states and Southern Italy was conquered by the Normans. Governance in the North was horizontal and trust-enhancing, whereas in the South it was hierarchical and feudal. This resulted in big differences in levels of generalized trust which persist to the present day. According to Putnam et al. (1993), more generalized trust has then led to a relatively better economic and political situation in the North. This argument is in congruence with the earlier seminal work of Banfield (1958) who linked the distrust prevalent in Southern Italy to strong family ties. He argued that Southern Italians are often so dedicated to their family members that they distrust all strangers and refuse to cooperate with them at any initiative transcending interest of their family, a phenomenon which he called "amoral familism". As a consequence, however, they petrify their initial miserable position.

Links between social network structure, generalized trust and economic performance were also studied by Fukuyama (1995). According to this author, business success and wealth requires "spontaneous sociability" – a result of trust and shared values. However, in societies with relatively limited economic performance, business begins in families and often stays there as individuals find themselves unable to build trustful relations with non-kin, limiting economic enterprise and elevating transaction costs. In high-trust societies, in contrast, individuals more often form ties with non-kin. In consequence, social structure in high-trust societies is more complex than in low-trust societies. Distrustful societies also do not identify with intermediate institutions between the family and the state, creating a "sociological vacuum" (Nowak, 1980), which further reduces economic performance by slowing down the flow of information, preventing implementation of innovative ideas, and limiting people's cooperativeness and thrift (Zak and Knack, 2001; Florida, 2004; Algan and Cahuc, 2010).

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Relating to this theory, Woolcock (1998) emphasized that social network structure is a determinant of trust, rather than the other way round: “trust and norms of reciprocity, fairness, and cooperation are ‘benefits’ that are nurtured in and by particular combinations of social relationships; they are undeniably important for facilitating and reinforcing efficient institutional performance, but they do not exist independently of social relationships” (Woolcock, 1998, p. 185). Both social networks and trust are however crucial for economic performance, as – according to this author – every economic exchange is embedded in social context. This “embeddedness” can take a form of social ties, cultural practices or political contexts. Furthermore, there is a second complementary form of social capital: “autonomous” social ties. At the micro level, “embeddedness” (also called “integration” by Woolcock) resembles the better known concept of bonding social capital (Putnam, 2000) and represents social ties primarily among kin, whereas “autonomy” (or “linkage”) resembles bridging social capital and represents social ties with relatively dissimilar others. According to Woolcock (1998), both too little and too much of either embeddedness or autonomy can impede economic performance. From a juxtaposition of integration (high vs. low) and linkage (high vs. low), four typical forms of social relationships at the micro level are identified: amoral individualism (low integration, low linkage), amoral familism (high integration, low linkage), anomie (low integration, high linkage), and social opportunity (high integration, high linkage). Woolcock argues that it is essential to look at both forms of social capital simultaneously because they are interrelated. Furthermore, social network structures relate to economic performance both at the societal level and at the community level: Norbutas and Corten (2018) have shown that bridging social capital (linkage) is associated with better, and bonding (integration) with worse economic performance of Dutch municipalities. In sum, the established literature has identified a number of relevant mechanisms, originating at the individual level, which can plausibly affect the economic performance and well-being of entire societies. Stemming from observation of specific real-world societies (e.g., Italy), they deliver hypotheses which can be verified much more broadly. These theories are qualitative, however, and thus may face the risk of missing some important trade-offs, such as, e.g., a trade-off between aggregate social utility and economic performance.

Against this backdrop, the objective of this paper is to devise a unifying, *quantitative* framework for studying these socio-economic mechanisms in detail. Our hypothesis is that the forces described by Putnam et al. (1993), Fukuyama (1995) and Woolcock (1998) and others are universal and can be quantified in a single model. We verify this hypothesis positively by constructing a novel computational multi-agent model based on Watts and Strogatz (1998) network structure. In our model we define *social utility* of an individual as all non-economic resources drawn from her social contacts, and the individual's *economic performance* as her expected payoff from economic interactions with other individuals. (Empirical operationalizations may take a broader perspective, though. All theoretical definitions of concepts used in this paper, coupled with their empirical counterparts, are listed in Appendix A.) We have chosen to use Watts–Strogatz structure because of the conceptual convenience of controlling the transition from locally clustered networks, via *small world* networks, to highly heterogeneous networks, with a single parameter (see Section 3.1).

Our model allows us to build *artificial societies* with varying social network structures, in order to see how they affect outcome variables such as trust, cooperation, social utility and economic performance. The details of the model setup are rooted in the associated socio-economic literature, reviewed above and in Section 2, and in our empirical findings for the Polish society (Growiec et al., 2017), based on a unique, detailed survey dataset on a representative sample of the Polish population ($n = 1000$). Implications of the model, however, reach beyond the specificities of this particular society and should be tested at the cross-country level. While this may be partially hindered by the lack of internationally comparable data on the detailed social capital measures, we make a first step in this direction by presenting some preliminary evidence from European Social Survey (ESS) data as well as confronting model outcomes with implications from qualitative theory.

With our model we study how social networks may give rise to the accumulation of *social capital*, defined as the aggregate of resources accessible to individuals through their social networks (Bourdieu, 1986), and how in turn social capital may enable the creation of trust and cooperation. We then trace how these individual-level outcomes aggregate up to the society level, ultimately shaping the society's social utility and economic performance. In doing so, we forge links between “traditional” social capital theory and the emerging literature on computational multi-agent models (Prell, 2012).

Even under Bourdieu's definition, however, social capital remains an ambiguous, complex concept. In this paper, we handle this complexity by considering four dimensions of individuals' social capital: (i) degree, (ii) centrality, (iii) bridging and (iv) bonding social capital. To capture all four network characteristics as distinct variables, a minimal model has to explicitly acknowledge individuals' heterogeneity not only in terms of their position in the social network, but also in terms of at least two additional individual traits. We consider the following two traits:

- *family location* f_i, with the presumption that social ties between individuals who are close to each other in terms of f_i represent (relatively strong and exclusive but economically less valuable) kinship ties whose aggregation represents the individual's stock of bonding social capital;
- *agent type* v_i, with the presumption that social ties between individuals who are distant in terms of v_i – i.e., who have different individual characteristics – represent (relatively weak but economically profitable) bridging ties whose aggregation represents the individual's stock of bridging social capital.

The contribution of this study to the literature is to demonstrate that our computational agent-based model, whose properties have been analyzed following a systematic simulation design, is a useful tool for simulating social capital stocks, as well as their *immediate outcomes*: social trust and cooperation, and *ultimate outcomes*: social utility and economic performance, at the aggregate and individual level in the economy. Assuming that different countries or communities may feature different topologies of social networks and exhibit different social norms (e.g., how much value is attached to social ties with family members), we investigate the mechanisms which translate these differences into varying levels of social capital, trust and cooperation in the economy. We then identify the circumstances under which a trade-off is observed between aggregate social utility and economic performance; in particular we specify the conditions under which *small world*-type social networks (observed in most real-life societies) can be socially optimal. Our key findings are as follows:

(i) societies that either are globally better connected, exhibit a lower frequency of local cliques, or have a smaller share of family-based cliques, record relatively better economic performance;
(ii) social utility presents a $\cap$-shaped relationship with network density and a positive relationship with the frequency of family-based local cliques;
(iii) if contacts with family are highly valued in the society, then *there is a trade-off between aggregate social utility and aggregate*

economic performance. In such a case, *small world* networks are socially optimal; otherwise they are outperformed by highly diversified, inclusive networks.

Identification of a multi-layered social capital-based mechanism behind this trade-off, leading *small world* networks to provide the optimal balance between social utility and economic performance, is the most important take-away message from this paper. We have, however, exploited the richness of the model specification to obtain additional empirically relevant results. Namely, we have addressed the micro–macro linkages, implicit in the model, by answering the question, how the aggregate variables affect individual-level trade-offs such as, e.g., the trade-off between *individual* social utility and economic performance. We find that:

- in dense networks, social ties are individually less valuable;
- social trust is a functional substitute to social networks: in trustful societies, social ties are individually less valuable, and vice versa;
- in dense networks and trustful societies, *there is a trade-off between individuals' social utility and economic performance*, and otherwise both outcomes are positively correlated in the cross section;
- in dense networks, there is a relatively clearer trade-off between bonding social capital and other forms of social capital at the individual level (i.e., degree, centrality and bridging social capital);
- in dense networks, bridging social capital is relatively more conducive to cooperation and economic performance at the individual level.

Hence, our computational multi-agent model provides a rich array of additional empirically testable predictions. The remainder of the article is structured as follows. Section 2 presents the background literature. Section 3 describes the model setup. Section 4 outlines the simulation design allowing for a systematic analysis of model properties. Section 5 discusses the impact of social network structure on aggregate-level variables. Section 6 discusses the results regarding individual-level correlations. Section 7 concludes.

2. Background literature

The purpose of the current section is to motivate the key assumptions underlying our model setup with an extensive literature review.

2.1. Social capital theory

The current paper adopts the following definition of social capital due to Bourdieu (1986): "social capital is 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 – or in other words, to membership in a group – which provides each of its members with the backing of the collectivity-owned capital, a 'credential' which entitles them to credit, in the various senses of the word." (p. 128). The principal reason for accepting this purely network-based definition, widely shared in sociology (e.g., Lin, 2001; Kadushin, 2002; Li et al., 2005; Burt, 2005), is that it enables us to precisely delineate people's objective behavior (maintaining social contacts with others) from social norms (trust, cooperation) which we treat as social capital outcomes rather than its dimensions. Another advantage of using a purely network-based definition of social capital is that multifaceted measures of social capital are relatively more likely to suffer from incoherence, insufficient differentiation from other concepts (e.g., community, social support, trust), and low resonance of some of those concepts (Bjørnskov and Sønderskov, 2013). Disentangling the roles of social networks and social norms in shaping social capital and concentrating on the former only allows to reduce the incoherence and improve resonance of the social capital concept.

It is also important to note that this definition links the social networks people maintain to the resources that may be accessed through them (Bourdieu, 1986; Lin, 2001), because access to network resources is vital for the identification of linkages between social capital and individuals' economic performance or social utility.

While Bourdieu's definition of social capital provides a useful theoretical frame for our study, it does not precisely specify the structure of this concept, which in fact could be affected by a range of network features. Our choice of the four social capital dimensions – (i) degree, (ii) centrality, (iii) bridging and (iv) bonding social capital – is motivated as follows.

Firstly, the inclusion of *degree* (the number of social ties a given individual maintains) as a dimension of social capital is based on the assumption that more network resources should be available to individuals who maintain more social ties, at least on average. Secondly, in line with the "structural holes" argument due to Burt (1992), relatively more resources should also be available to the individuals who are central to the network or form a bridge between otherwise separated sub-networks (cliques) because they are crucial for the flow of information and all other resources in the network. By exploiting structural holes, individuals may gain a unique position in their network and use it for their benefit. This motivates the inclusion of *centrality* as our second social capital dimension. (For a formal discussion of the similarities and differences between centrality and forming a network bridge, as well as the role of redundancy, see Borgatti (2006), Valente and Fujimoto (2010).) Thirdly, the associated literature points out that the access to network resources is also largely affected by the distinction between *bridging social capital* (social ties with dissimilar others) and *bonding social capital* (social ties with similar others), as proposed by Gittell and Vidal (1998) and Putnam (2000). While bridging ties can be formed among arbitrary strangers, bonding ties are limited within relatively impermeable confines (Putnam, 2000). Thus many of the bonding ties are in fact kinship ties (Kääriäinen and Lehtonen, 2006; Alesina and Giuliano, 2010), and hence both concepts are sometimes identified with one another, in line with the presumption that "kin ties are a conservative measure of strong ties" (Tian and Lin, 2016, p. 123). Importantly, bridging and bonding social ties are related to different resources, serving different purposes, and thus they should be viewed as conceptually distinct dimensions of social capital and not just opposite sides of the same spectrum. Ties with similar others are formed to satisfy the safety drive (the need for affiliation, emotional support, etc.) whereas ties with dissimilar others – the effectiveness drive (towards personal development, professional success, etc. (Bowlby, 1969; Greenberg, 1991; Kadushin, 2002)). Hence, in terms of our model, we expect bridging social capital to be more closely linked to individuals' economic performance, and bonding social capital – to their social utility.

2.2. Social capital, trust and willingness to cooperate

Social trust and willingness to cooperate are the key channels through which social capital may influence the economic performance and social utility of individuals and societies. According to Granovetter (2005), social networks affect economic outcomes because they affect the flow and quality of information, they are an effective source of reward and punishment, and they are therefore a context in which trust can emerge. This, in turn, has far-reaching consequences because trust is "essential for stable relations, vital for the maintenance of cooperation, fundamental for any exchange and necessary for even the most routine of everyday interactions" (Misztal, 1996, p. 12). At the same time, social networks are also the usual context in which people learn to cooperate with one another (Field, 2010), which then also affects their willingness to cooperate with strangers. We emphasize that social trust and cooperation, although sometimes treated jointly (e.g., Butler et al., 2016), are related but not equivalent concepts. The distinction between them is going to be important for our theoretical model.

As the formation process of trust and cooperation happens in a social network, characteristics of this network can have an impact on the outcomes. Dense networks – typically formed among similar individuals due to the homophily principle (Lazarsfeld and Merton, 1954; Lin, 2001) – are relatively less conducive to social trust because dense networks facilitate reputation formation and social control which are functional substitutes of social trust (Coleman, 1988; Dasgupta, 1988). Conversely, sparse networks – relatively more likely to include social ties with dissimilar others and feature more "structural holes" and network bridges – convey relatively less information about the reputation of other people in the network and are less efficient in imposing social control, and hence members of such networks need more social trust to behave cooperatively. However, social ties within such a network are more likely to provide non-redundant, potentially useful information, thus increasing the expected payoff of prospective cooperation (Granovetter, 2005). The value of social ties – regardless of whether evaluated in terms of emotional, economic, informational or status benefits – positively affects their strength, further promoting cooperation (Melamed and Simpson, 2016). It has also been found that the extent and structure of individuals' social networks affects the magnitude of transaction costs they face, the possibility of implementing innovative (but risky) ideas in cooperation with others, and hence the individuals' overall cooperativeness and thrift (Inglehart and Baker, 2000; Florida, 2004; Klapwijk and van Lange, 2009).

In line with these findings, in our model we view social trust a key determinant of the probability of engaging in economic interaction with others. Once there is an interaction, however, it also matters if the agents choose to cooperate or not. We model this decision as a "prisoner's dilemma" game: both agents are better off when both cooperate than when both defect, but each of them is also individually tempted to defect. The model is calibrated so that an interaction where both agents defect is better than no interaction at all, but it is better not to interact at all than to interact, cooperate, and be cheated.

The simulation results obtained in this paper imply an empirically testable hypothesis that societies which form diverse, inclusive networks should be more trustful and more willing to cooperate, and thus exhibit better economic performance, than societies which are permeated by visible and invisible barriers, fragmenting the networks into locally dense cliques of individuals who think alike and have similar sets of information and other resources. Unfortunately, sufficiently detailed and internationally comparable data on social network structure which could directly validate or falsify this hypothesis is yet to be collected. There is however plentiful macro-level empirical evidence justifying the robustness of links between social trust, cooperation and economic performance (see e.g., Knack and Keefer, 1997; Zak and Knack, 2001; Algan and Cahuc, 2010).

2.3. Social capital, earnings and subjective well-being

The ultimate outcome variables of the current study are social utility and economic performance. The linkages between social capital and these two outcomes, as well as self-reported well-being, measured as e.g. self-reported life satisfaction or happiness, have been studied at the level of individuals, communities, regions and whole countries. (We review also the studies on subjective well-being because social utility as such has been relatively rarely discussed in the social capital literature whereas, arguably, subjective well-being is an amalgamation of both economic performance and social utility, see Appendix A). The identified correlations and causal links may vary depending on the considered empirical operationalization of the social capital concept but are typically positive; a broad overview of these results can be found in Durlauf and Fafchamps (2005), amongst other sources.

At the macro level it has been found that bridging social capital, as opposed to bonding social capital, tends to go together with civil liberties, support for equality and democracy, and low corruption (Putnam et al., 1993; Putnam, 2000). On the other hand, "bonding social capital (as distinct from bridging social capital) has negative effects for society as a whole, but may have positive effects for the members belonging to this closed social group or network" (Beugelsdijk and Smulders, 2003). Beugelsdijk and Smulders (2003) proceed to show empirically that bridging social capital accelerates whereas bonding social capital retards economic growth across European regions. At the micro level it has been found that social ties between dissimilar people ("weak ties") are typically more helpful than ties between similar people ("strong ties") for finding a job, being promoted, and earning higher wages (Granovetter, 1973; Podolny and Baron, 1997; Mouw, 2003; Słomczyński and Tomescu-Dubrow, 2005; Franzen and Hangartner, 2006; Growiec and Growiec, 2010; Zhang et al., 2011). Strengthening this message, negative wage effects of social ties with similar others have been identified by Franzen and Hangartner (2006), Kim (2009) and Sabatini (2009).

There also exists a wide range of studies confirming the importance of maintaining frequent social interactions, both with similar and dissimilar others, for individuals' life satisfaction and happiness (e.g., Winkelmann, 2009; Alesina and Giuliano, 2010; Kroll, 2011; Leung et al., 2011; Growiec and Growiec, 2014). Complementary to these results, some authors have also studied the possible benefits of certain locations in the social network. Possessing "structural holes" (missing links among acquaintances) in one's network, i.e., being a critical connector (Valente and Fujimoto, 2010), has been found to be positively related to individuals' creativity, social trust, economic performance and happiness (Burt, 2005). Centrality, in turn, has been found to have positive effects for individuals' economic performance (Granovetter, 2005; Kadushin, 2012) and happiness (Christakis and Fowler, 2009). However, context may matter in this regard: for example, Barnes et al. (2016) show that in ethnically diverse, highly competitive environments, where there is distrust across social divides, being a network bridge may actually have detrimental effects for economic performance.

3. Model description

3.1. Network structure

We consider a population of N agents who are connected. The connections between agents $i, j \in \{1, 2, \ldots, N\}$ are interpreted as *social ties*, defined following Bourdieu (1986). Let $x_{i,j}$ denote if there is a connection between agents ($x_{i,j} = 1$) or not ($x_{i,j} = 0$). We assume that social ties are symmetric, i.e., $x_{i,j} = x_{j,i}$, as in e.g. Norbutas and Corten (2018). For the sake of completeness of the definition we take $x_{i,i} = 0$.

We model the graph of connections between agents using Watts and Strogatz (1998) algorithm. It has three parameters: N denoting the number of agents in the model, r denoting the graph radius (so that $2r$ is the average node degree in the social graph, i.e., the average number of social ties per agent), and p denoting the edge rewiring probability.

According to the algorithm, agents are located one after the other on a circle (so that agent 1 is adjacent to agents 2 and N). Initially each agent i is connected to agents $\{j : 0 < \min\{|i-j|, n-|i-j|\} \le r\}$, i.e., to her $2r$ closest neighbors along the circle. Next, with probability p each existing link is replaced by a random link. Hence, the resulting graph is always between a lattice ($p = 0$) and a random network ($p = 1$). For moderate values of p we obtain networks that exhibit at the same time relatively high clustering and a low diameter.

The principal reasons for generating the social network structure with Watts and Strogatz (1998) algorithm are that this model of undirected graphs (i) has a relatively low number of easily interpretable parameters, (ii) is able to incorporate family similarity (via our f_i parameter) in the network topology, and (iii) allows to analyze different levels of clustering of the network as well as to model long ties. Compared to alternative models which are also used in literature to generate social network structures, e.g. Erdös and Rényi (1959), Albert and Barabási (2002) or the Spatial Preferential Attachment model (SPA, see Aiello et al., 2009), we find Watts–Strogatz approach most suitable given our criteria. Most notably, it lets us analyze the transition from locally clustered networks, via *small world* networks, to highly heterogeneous networks, by controlling a single parameter p, interpreted as the (inverted) probability of occurrence of local cliques. Moreover, Watts–Strogatz model has also been very thoroughly analyzed in the literature and most of the researchers in social simulation know its properties. Hence, we can build our work based on a widely accepted reference. On the other hand, extensions of Watts–Strogatz model present in the literature, most prominently Kleinberg (2000a,b), make it more realistic at the expense of changing the assumptions that we directly use in our model, while the improvements they provide do not have a direct influence on our results.

In what follows, by D_i we denote the degree of agent i in the graph and by C_i her eigenvector centrality, cf. Bonacich (1972). Furthermore, by $L_{i,j}$ we denote the length of the shortest path between agents i and j in the graph. We impose $L_{i,j} = N$ if such a path does not exist.

3.2. Bonding and bridging social capital

We assume that every agent $i \in \{1, 2, \ldots, N\}$ has two independent traits: family location f_i and agent type v_i.

Family location of agent i is denoted as $f_i \in [0, 1]$ and interpreted such that for any two agents i and j, the smaller the difference between f_i and f_j, the closer are the family ties between them. To treat every value of f_i in the same way, we assume that the values are positioned on a circle; therefore we assume that values 0 and 1 are identical. Accordingly, we define family similarity s_f between agents i and j as

$$s_f(i, j) = 1 - \min\{|f_i - f_j|, 1 - |f_i - f_j|\}.$$

Observe that $s_f(i, j) \in [0, 0.5]$. Using the notion of family similarity we define *bonding social capital* of agent i as:

$$Bo_i = \begin{cases} \sum_{j=1}^{N} x_{i,j} s_f(i, j)/D_i & \text{if} \quad D_i > 0 \\ 0 & \text{if} \quad D_i = 0 \end{cases}.$$

Hence, bonding social capital of agent i represents the average level of family similarity across all agent i's social ties (remember that $x_{i,j} = 1$ if there is a link between agents i and j and 0 otherwise). This definition agrees with the view that bonding social capital refers to forming social ties within relatively impermeable confines (Putnam, 2000) which may be narrowed down to kinship ties (Kääriäinen and Lehtonen, 2006; Alesina and Giuliano, 2010), in line with the presumption that “kin ties are a conservative measure of strong ties” (Tian and Lin, 2016, p. 123).

Agent type is denoted as $v_i \in \mathbb{R}$ and interpreted as a unidimensional representation of the agent's individual characteristics such as age, interests, skills, place of residence etc. Values of v_i are assumed to be normally distributed in the population, $v_i \sim \mathcal{N}(0, 1)$. Hence, agents can be more or less *typical* in terms of their type v_i: values close to 0 are considered typical whereas extreme values that are very positive or very negative are non-typical. For any two agents i and j, the smaller the difference between v_i and v_j, the more similar are their characteristics.

We assume that social ties between dissimilar others (i.e., agents of very different types) are relatively advantageous in terms of transmitting information and other network resources (Burt, 2005; Granovetter, 2005). Hence, although we do not impose any valuation of types, we implicitly assume that less typical agents (far from 0) offer potentially more unique values to their connections so they would tend to be more central in the network. At the same time the assumption about normality of distribution of v_i implies that less typical agents (high $|v_i|$) are more rare in the community than typical ones (v_i close to 0). We define type distance d_v between agents i and j as:

$$d_v(i, j) = 1 - \exp(-|v_i - v_j|),$$

so that $d_v \in [0, 1)$. Consequently, based on the concept of type similarity we define *bridging social capital* of agent i as

$$Br_i = \begin{cases} \sum_{j=1}^{N} x_{i,j} d_v(i, j)/D_i & \text{if} \quad D_i > 0 \\ 0 & \text{if} \quad D_i = 0 \end{cases}.$$

Hence, bridging social capital of agent i represents the average level of type distance (trait heterogeneity) across all agent i's social ties. This definition agrees with the idea that bridging social capital refers to forming social ties across social cleavages and requires people to transcend their simple social identity (Putnam, 2000; Leonard, 2008).

3.3. Relationships among the four dimensions of social capital

An important challenge to our modeling approach is to assign values of f_i and v_i to agents in a way that would both reflect the underlying micro-level theory (see the overview in Section 2) and empirical observations (Growiec et al. (2017), see Appendix B), and allow us to test the emergent aggregate implications of the model for different setups of the social network structure. In particular, following the associated socio-economic theory and empirical findings we would like our model to satisfy the following postulates:

- there should be a strong positive correlation between agent centrality and degree;
- the framework should allow us to simulate the entire spectrum of societies ranging from strongly family-oriented ones (where almost all social ties are between family members) to societies where social ties are uncorrelated with family location;
- bonding social capital should be negatively correlated with agent centrality and degree;
- bridging social capital should be strongly positively correlated with agent centrality and degree;
- bridging social capital should be essentially uncorrelated (or, if anything, slightly negatively correlated) with bonding social capital.

The choice of Watts and Strogatz (1998) algorithm for generating the social network directly ensures property (P1) and allows us to have property (P2) as long as there is a relationship between f_i and the agent index i. Therefore we take the following approach to calculating f_i. First we define $\tilde{f}_i = i/N + z_i$, where z_i has a uniform distribution over the interval $[-\lambda, \lambda]$, where $\lambda \in [0, 0.5]$. Next we compute each agent's family location as $f_i = \tilde{f}_i - \lfloor \tilde{f}_i \rfloor$. In this way f_i is uniformly distributed over the interval [0, 1] while λ governs the strength of relationship between each agent's family location f_i and her location in the social network. For $\lambda = 0$ we have a strong association between f_i and the agent's position in the graph. For $\lambda = 0.5$ there is no association between them. An additional insight follows from considering the parameter λ jointly with the *edge rewiring* probability p, which also governs the probability of occurrence of local cliques in the network. Namely, for low values of p, the network is fragmented into a number of local cliques (such that there are many links within each cluster but very few links between the clusters). In such a situation, the parameter λ governs the share of local cliques that are family based: for $\lambda = 0$, they are predominantly family based, whereas for $\lambda = 0.5$ they are not family based at all. In sum, the consequences of setting low and high values of λ and p are the following:

- low λ, low p: highly clustered social ties primarily among family members;
- high λ, low p: highly clustered social ties with arbitrary agents;
- high p (λ not important): random social ties with arbitrary agents.

Observe that the above assumptions also lead to property (P3). Agents who have higher centrality C_i have more *rewired* links, and thus tend to have, on average, a lower fraction of social ties within family. Those different types of communities are described for example by Woolcock (1998), Halpern (2005), Rothstein (2011).

In order to ensure property (P4) – a positive correlation between bridging social capital and agent's centrality and degree – we assume that people who have a more unique type (v_i further away from 0) are also more central to the network (a higher C_i). This assumption is in line with claims made in numerous sociological studies (e.g., Burt, 1992, 2005, 2010; Granovetter, 2005; Kadushin, 2002, 2012) and reflects the finding that social ties between dissimilar others tend to be relatively advantageous in terms of transmitting information and other network resources.

Formally, we assign v_i to agents according to the following procedure:

1. For each agent i, we calculate her rank q_i with respect to her eigenvector centrality. We assume that the agent with lowest C_i has $q_i = 1$ whereas the agent with highest C_j has $q_j = N$. In the case a few agents have the same eigenvector centrality coefficient, they are ranked randomly.
2. We generate N independent draws from a normal distribution, $u_i \sim \mathcal{N}(0, \sigma^2)$, where $\sigma^2 \in (0, 1)$, and sort them in order of increasing absolute value; by $\tilde{u}_i$ we denote this sorted sequence (i.e. $|\tilde{u}_i| \leq |\tilde{u}_{i+1}|$).
3. We set $v_i = \tilde{u}_{q_i} + w_i$, where $w_i \sim \mathcal{N}(0, 1 - \sigma^2)$.

Observe that under this procedure, unconditionally $v_i \sim \mathcal{N}(0, 1)$. Agent types v_i are however correlated with their centrality C_i. Agents with a low C_i will tend to have their v_i close to 0 and the ones with high C_i will tend to have v_i far from 0. The parameter σ^2 captures the strength of association between v_i and C_i: if $\sigma^2 = 1$ then the correlation is perfect, and if $\sigma^2 = 0$ then there is no relationship. Therefore, varying σ^2 allows us to compare different assumptions about the relationship between uniqueness of the agent (value of v_i) and her centrality C_i. The strength of this relationship mirrors the likelihood that, in a given society, new social ties would be created based on expected economic benefits from the interaction. Given that, by definition, agents who are non-typical in terms of their type v_i tend to have more bridging social capital, the proposed procedure of generation of v_i ensures that bridging social capital will be positively correlated with C_i in the population, thus ensuring that the property (P4) holds.

Finally, property (P5) follows from the fact that family location f_i and agent type v_i are modeled as independent agent characteristics. Hence, there is no direct link between bonding and bridging social capital. Slight negative correlation will be observed, however, because of the bilateral links between both variables and centrality, one of which is negative and the other – positive.

3.4. Social utility

We assume that the overall well-being of the agents has two components: social utility and economic performance.

Social utility SU_i of an agent is interpreted as all non-economic resources drawn from her social contacts. Following the literature (Alesina and Giuliano, 2010; Roberts and Dunbar, 2011; Curry and Dunbar, 2013a,b) we assume that if agent i has a social tie with agent j, her social utility from this contact is increased if they have strong family ties (there is high family similarity $s_f(i, j)$) as well as if agent j has many valuable contacts (j has a high centrality coefficient C_j in terms of our model). This reflects the two diverse purposes social ties may serve (Kadushin, 2002): the need for affiliation and emotional closeness (addressed by strong kinship ties) and the need for personal development and success (addressed by the informational advantages of social ties with agents who are central to the network). We assume that the relationship between these two sources of social utility follows a Cobb–Douglas utility function. Because for different graphs, the shape of the distribution of eigenvector centrality C_i is not constant, we introduce Q_i corresponding to the rank of C_i divided by the total number of agents. If two or more agents have the same C_i, we average their ranks. Formally, let F_{emp} be empirical cumulative distribution function of C_i. Then $Q_i \in [0, 1]$ is defined as:

$$Q_i = \frac{\lim_{x \to C_i^-} F_{\text{emp}}(x) + \lim_{x \to C_i^+} F_{\text{emp}}(x)}{2}.$$

Under this definition Q_i is defined over the interval [0, 1] and its mean is always equal to 0.5, independent of graph structure. Observe that $Q_i N = q_i$, where q_i is used to generate v_i.

We are now in a position to define *social utility* of agent i as:

$$SU_i = \begin{cases} \sum_{j=1}^{N} x_{i,j} s_f(i,j)^{\rho} Q_j^{1-\rho} / D_i & \text{if} \quad D_i > 0 \\ 0 & \text{if} \quad D_i = 0 \end{cases},$$

where $\rho \in [0, 1]$ captures the prevailing social norm on family importance. In societies with a high ρ, family is perceived as relatively important for social utility when compared to social ties outside of family. The opposite is true for societies with a low ρ.

3.5. Social trust, willingness to cooperate and economic performance

Economic performance EU_i of an agent i is defined as total value generated by the agent thanks to her engagement in joint private enterprises with other agents. The success of these enterprises is assumed to depend on mutual trust and willingness to cooperate between the agents as well as on the volume of non-redundant information available to the group. As a simplification, we model the enterprises as interactions between two agents only, who play a "prisoner's dilemma" game in the social network. Agents are matched in pairs and engage in economic interaction. The matching is random but the probability of a match depends on the degree of mutual trust between the two agents, implying that agents who are generally more trustful are also relatively more likely to engage in economic interaction. (As a simplifying assumption, we ignore the process of reputation building. The agents in our model do not track the history of their interactions with other agents. This assumption becomes innocuous for sufficiently large populations where the probability of meeting the same opponent again becomes negligible.) Once agents i and j are matched then they act in two steps: first they announce if they want to cooperate or defect and next they actually play the game, which allows them to randomly deviate from their original declaration.

Following the findings from the empirical literature (Dasgupta, 1988; Gambetta, 1988; Gellner, 1988; Yamagishi et al., 1998; Burt, 2005, 2010; Alesina and Giuliano, 2010; Ermisch and Gambetta, 2010) we assume that mutual trust between two agents is negatively related to their distance in the social network ($L_{i,j}$) as well as to the stocks of bonding social capital each of them holds (Bo_i, Bo_j). We model the links between these sources of mutual trust with a Cobb–Douglas function and assume symmetry between the two agents. Hence, we formally assume that the probability $P_{i,j}$ that agents i and j are randomly matched follows:

$$P_{i,j} = \frac{\sqrt{(1-Bo_i)(1-Bo_j)}}{L_{i,j}}.$$

This formulation allows us to posit a model-based definition of *social trust* of agent i, being the average level of mutual trust she holds towards everyone else in the population:

$$Tr_i = \sum_{i \neq j} \frac{P_{i,j}}{N-1}.$$

Hence, social trust is expected to be negatively related to agents' bonding social capital and (indirectly) positively related to their degree and centrality.

If agents i and j are matched, they engage in economic interaction, modeled as a "prisoner's dilemma" game. The outcome of the interaction depends on their decisions to cooperate or defect. We assume that if i and j cooperate then they both get a high positive outcome ("reward"), if they both defect then they get a low positive outcome ("punishment"), and if agent i cooperates while agent j defects, then agent i gets a negative outcome whereas agent j gets a very high "temptation" outcome. We assume that this game is symmetric for both agents. It is implicit that under such parametrization, economic interaction is socially desirable even if both agents defect: the sum of "punishment" outcomes is positive. From an agent's perspective, however, it is still better not to interact at all and get a zero payoff than to cooperate, be cheated and get a negative payoff. This underscores the role that social trust plays in our setup: it is the confidence that one will not be cheated if engaged in an economic interaction.

We also assume that the expected payoff from an economic interaction increases with the type difference between the agents, $d_v(i,j)$, reflecting the fact that social ties between dissimilar others tend to be relatively more beneficial for the flow of information and other network resources (Granovetter, 2005).

Given all these assumptions, and normalizing the "reward" outcome to unity, we obtain the following payoff matrix of our "prisoner's dilemma" game (payoffs are given for agent i):

$$G_{i,j} = d_v(i,j)\begin{bmatrix} 1 & g_{cn} \\ g_{nc} & g_{nn} \end{bmatrix},$$

where the values are ordered according to $g_{nc} > 1 > g_{nn} > 0 > g_{cn}$.

Instead of allowing the agents to pick their optimal strategy in a dynamic game, which would (amongst other problems) involve the calculation of the probability of being matched to the same agent repeatedly in the future, we simplify the analysis by assuming that agents' choices are random. Following the associated literature (Granovetter, 2005; Field, 2010) we assume that the probability that agent i will choose to cooperate with agent j is negatively related to their distance in the social network ($L_{i,j}$) and positively related to the decision maker's bridging social capital (Br_i),

$$W_{i,j} = \frac{Br_i}{L_{i,j}}.$$

Additionally, for each agent i we also define her overall *willingness to cooperate* as the average probability of cooperation with anyone else in the population,

$$Co_i = \sum_{i \neq j} \frac{W_{i,j}}{N-1}.$$

Hence, willingness to cooperate is expected to be positively related to agents' bridging social capital and (indirectly) positively related to their degree and centrality.

We assume that in the first stage of the game, agents make their claims to cooperate or defect independently. There are two possibilities. First, one or both of them may refuse to cooperate. In such a case, both agents will play the individually rational "defect" strategy. This happens with the probability $1 - W_{i,j}W_{j,i}$. Second, both of them may agree to cooperate. This happens with probability $W_{i,j}W_{j,i}$. In such a case, however, the agents enter the second stage of the game where they are allowed to independently keep their promise, with probability ε, or otherwise break it. In summary, we obtain the following matrix of probabilities of decisions of agents i and j:

$$D_{i,j} = \begin{bmatrix} \varepsilon^2 W_{i,j}W_{j,i} & \varepsilon(1-\varepsilon)W_{i,j}W_{j,i} \\ \varepsilon(1-\varepsilon)W_{i,j}W_{j,i} & 1-\varepsilon(2-\varepsilon)W_{i,j}W_{j,i} \end{bmatrix},$$

which incorporates the fact that the "defect–defect" outcome may happen either when at least one of the agents refuses to cooperate in the first stage of the game ($1 - W_{i,j}W_{j,i}$), or when both of them break their promise to cooperate in the second stage ($(1-\varepsilon)^2 W_{i,j}W_{j,i}$).

On the basis of the above discussion, *economic performance* of agent i is defined as her expected aggregate payoff from economic interactions with all other agents:

$$EU_i = \sum_{j \neq i} P_{i,j} d_v(i,j)\left(W_{i,j}W_{j,i}\left(\varepsilon^2 + \varepsilon(1-\varepsilon)(g_{cn}+g_{nc}) - \varepsilon(2-\varepsilon)g_{nn}\right) + g_{nn}\right).$$

Hence, economic performance depends directly: positively on social trust, willingness to cooperate and bridging social capital, and indirectly: negatively on bonding social capital (via social trust) and positively on bridging social capital (via willingness to cooperate) as well as degree and centrality (via both social trust and willingness to cooperate).

4. Simulation analysis of model properties

One of the key advantages of the model proposed in this paper is its ability to embrace different structures of networks representing social ties between agents. However, this feature introduces a challenge to the analysis of model properties because the model setup is too complex to allow for an analytical solution. Therefore, as recommended in the literature (see, e.g., Law and Kelton, 1991), we investigate the relationship between model parameters and outputs using simulation. This approach requires the researcher

Table 1
Parametrization of the simulation experiment.

Parameter	Values	Interpretation
N	2048	Number of agents in the model
r	$\{1, \ldots, 15\}$	$2r$ is average number of social ties per agent
p	$[0, 1]$	(inverted) probability of occurrence of local cliques
λ	$[0, 0.5]$	(inverted) share of local cliques that are family based
σ^2	$[0, 1]$	The degree to which value of information is an important factor in the creation of social ties in the network (correlation between $\lvert v_i \rvert$ and C_i)
ρ	$[0, 1]$	Relative importance of family ties for social utility
g_{nc}	$[1.25, 2]$	"temptation" payoff in the $G_{i,j}$ matrix
g_{cn}	$[-0.5, 0]$	"sucker's" payoff in the $G_{i,j}$ matrix
g_{nn}	$[0.25, 0.75]$	"punishment" payoff in the $G_{i,j}$ matrix
ε	$[0.5, 1]$	Probability that an agent keeps the promise to cooperate

Note: see Section 3 for a more detailed discussion of the parameters.

to carefully design the simulation experiment and next, using the results of the experiment, to estimate the response surface of the model, which represents the relationship between parameters of the model and its outputs. The methodology is described in detail in the simulation literature, see e.g. Kleijnen and Sargent (2000). In order to ensure that the results of estimation of input–output relationships in our model are accurate, the simulation was executed 65,536 times for the parameterization range given in Table 1. We minimized the discrepancy of the coverage of the investigated parameter space by using a Sobol sequence (Bratley and Fox, 1988) with Owen+Faure-Tezuka scrambling (Hong and Hickernell, 2003). The product of the ranges of parameters given in Table 1 defines the parameter space Ω from which uniform sampling is made.

An advantage of our modeling approach is that the computational model is able to match (at least qualitatively) the key features of our individual–level data (Growiec et al., 2017) even when no variables are specifically targeted in any calibration procedure. For example, Table 2 demonstrates that the cross-sectional correlations among the four considered social capital dimensions as generated from our model under two different parameterizations remain in the ballpark of our empirical results.

The results reported in the following sections capture the impact of changes in specific model parameters on two types of outcomes: (i) aggregate variables (e.g., average social utility or economic performance in the entire society), and (ii) individual-level correlations (e.g., the cross-sectional correlation between the agents' centrality and willingness to cooperate). In each case, we report the expected value of the outcome variable Y based on its marginal distribution with respect to a certain parameter θ in question – i.e., the expected value of Y conditional on θ while allowing the other parameters (collected in the vector $\omega \in \Omega$) to follow their distributions, as in $\theta \mapsto E(Y|\theta) = \int_\Omega Y(\omega) dF_\theta(\omega)$, where F_θ is conditional cumulative distribution function of all parameters. For instance, the impact of network density r on aggregate social utility in the society is reported as values of the mapping $r \mapsto E(\langle SU \rangle | r)$. Furthermore, wherever we find important interactions between parameters, we also report expected values conditioned on the confounding parameter. For example, we report the impact of p on aggregate social utility SU conditional on λ as $p \mapsto E(\langle SU \rangle | p; \lambda)$. Thus we maintain the *ceteris paribus* assumption required in comparative statics studies while refraining from specifying a unique baseline model calibration. We also note that the influence of model parameters on simulation output variables is sometimes non-linear and its sign may depend on the value of other model parameters; therefore in the text we comment only on the most significant and robust relationships.

Table 2
Overview of correlations: data vs. model.

	Degree	Centrality	Bridging	Bonding
Data: simple correlation				
Degree	1			
Centrality	0.839***	1		
Bridging	0.210***	0.210***	1	
Bonding	−0.107***	−0.104***	−0.044	1
Data: partial correlation with controls				
Degree	1			
Centrality	0.759***	1		
Bridging	0.115***	0.040	1	
Bonding	0.005	−0.045	0.007	1
Model (with $p = 0.1$, $\rho = 0.5$)				
Degree	1			
Centrality	0.863	1		
Bridging	0.165	0.246	1	
Bonding	−0.159	−0.133	−0.052	1
Model (with $p = 0.2$, $\rho = 0.75$)				
Degree	1			
Centrality	0.929	1		
Bridging	0.145	0.200	1	
Bonding	−0.142	−0.133	−0.008	1

The data come from a survey of a representative sample of the Polish population ($n = 1000$), cf. Growiec et al. (2017).
Controls: sociability (2 variables), gender, age, age squared, choice and control, widowed, size of town of residence, education, cooperation, trust, trust inside the network.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Following the standard requirements for computational research (Peng, 2011), in order to ensure reproducibility of the results all the source code used to generate the presented results is available for download at https://gist.github.com/bkamins/a41e84bebaf107b4c89d78cc54f329e7. Simulation results discussed in this paper include only selected, relatively more important relationships present in the data. The whole simulation results file contains 65,536 observations, where each single observation consists of 10 parameter combinations and 67 simulation output variables.

5. Results for aggregate variables

As we are primarily interested in assessing the impact of *social network structure* on a range of socio-economic outcomes, the key model parameters which are considered here are r – network density, p – the (inverted) probability of occurrence of local cliques, and λ – the (inverted) share of local cliques that are family based. We also comment on the role of parameter ρ which captures the importance of family ties for social utility, prevailing in a given society.

5.1. Social capital, trust and cooperation

The first set of results describes the impact of social network structure on the aggregate stocks of bridging and bonding social capital as well as average levels of social trust and willingness to cooperate in the society. The results are summarized in Table 3 and should be interpreted as follows: if we pick any parameterization of the model and change only one parameter (in rows), keeping other parameters unchanged, the table provides the direction of change of the given output variable (in columns).

While internationally comparable data on social network structure – as summarized by r, p and λ in our model – do not exist (to our knowledge), the signs of all our results are well aligned with the associated theoretical literature. First, we find that more dense net-

Table 3
Relationship between model parameters and average bonding social capital, bridging social capital, social trust and willingness to cooperate.

	Bo	*Br*	*Tr*	*Co*
Network density r	Positive	Positive	Positive	Positive
Rewire probability p	Negative	Positive	Positive	Positive
Non-family-based cliques λ	Negative	Unrelated	Positive	Unrelated

works (higher r) exhibit higher bridging and bonding social capital, higher trust and cooperativeness. This reflects the basic observation that when the individuals are more connected, all kinds of network resources become easier to obtain (Bourdieu, 1986).

Partial confirmation of this result is also provided by ESS data, covering representative samples of population in 28 countries in 6 bi-annual waves (2002–2012). Unfortunately, this dataset does not contain sufficient information to identify the four considered dimensions of social capital, and hence we can only tentatively hint if the relationships obtained from the theoretical model agree with the available cross-country evidence. Looking at country–year averages, we find that the average *frequency of social contacts* (the closest available proxy for social capital in ESS data) correlates strongly with average social trust in a society (0.4795***, $n = 152$).

Second, we observe that bridging social capital, social trust and willingness to cooperate are relatively higher in societies whose social networks are relatively more random, i.e., if there is a relatively low probability of occurrence of local cliques (high p). This aligns well with Burt's (1992; 2005; 2010) argument on the importance of "structural holes", network bridges and ties with dissimilar others for social trust and cooperation, and with Granovetter's (1973; 2005) observations on the crucial role of diverse social networks in building social trust.

Finally, we also find that aggregate bonding social capital increases with the frequency of local cliques in the network (decreases with p) as well as with the share of local cliques that are family based (decreases with λ). The frequency of family based cliques also exerts a negative influence on social trust. All of this precisely mirrors Putnam's findings for Italy (Putnam et al., 1993) and the US (Putnam, 2000).

5.2. Social utility and economic performance

The next two outcome variables which we consider are the average levels of social utility and economic performance in the society. The impacts of r, p, λ and ρ (the importance of family ties for social utility) on these aggregate outcomes are depicted in Figs. 1 and 2 . Both figures show one-way non-parametric regressions between the given model parameter and mean *EU* and *SU* respectively. This means that the effect of all other parameters on the presented results is averaged out. However, we have also analyzed all other relationships between model parameters and simulation outputs, including the possible interactions between parameters; here we report only the relationships which are of significant strength and are relevant to our study objective. The impact of social network structure on economic performance is discussed first because, despite its relatively more involved definition in the model setup, the results for this variable are more straightforward to interpret.

Fig. 1 demonstrates that average economic performance grows with r, p and λ. We find that, other things equal, societies that either are globally better connected, exhibit a lower frequency of local cliques, or have a smaller share of family-based cliques, are relatively more efficient in terms of aggregate economic performance. These broadly positive effects of dense, diverse and inclusive networks are in line with the theoretical arguments put forward by, among others, Putnam (2000), Lin (2001) and Burt (2005) as well as with the partial empirical results due to, e.g., Knack and Keefer (1997), Inglehart and Baker (2000), Beugelsdijk and Smulders (2003) and Norbutas and Corten (2018). In particular Norbutas and Corten (2018), working with Dutch social media data, devise direct empirical measures of municipality-level network density and network modularity, e.g. frequency of local cliques. They find that network modularity is negatively associated with economic performance. They also find, however, to their own surprise and contrarily to the implications of our model, that network density is negatively associated with economic performance at the municipality level.

Other partial confirmation of our results can be found by looking at country–year averages from ESS data: a country's economic performance (average income) correlates strongly both with the average frequency of social contacts (0.4855***, $n = 63$) and social trust (0.8009***, $n = 63$).

Hence, our model delivers an empirically testable hypothesis that societies which form dense (r), inclusive (p) and diverse (λ) networks should be more trustful and more willing to cooperate, and thus exhibit better economic performance, than societies which are permeated by visible and invisible barriers, fragmenting the networks into locally dense cliques of individuals who think alike and have similar sets of information and other resources. Unfortunately, sufficiently detailed and internationally comparable data on social network structures are not yet available.

Fig. 2, in turn, presents the outcomes for social utility. Here we make three main findings. First, we observe that average social utility presents a $\cap$-shaped relationship with network density r, with a peak at $r^* = 3$ which corresponds to an average of 6 social ties per person. (The exact value of r^* may depend on network size, but only slightly: at most, it may increase from $r^* = 3$ when $N = 2048$ to 4 or 5 for very large networks.) This finding relates to Dunbar's (1992, 1993) observation that individuals' social networks tend to form "a series of concentric (and egocentric) circles of acquaintanceship containing, roughly, 5, 15, 50, 150, 500 and 1500 individuals, with their circles reflecting successively declining emotional closeness and frequency of contact." (Stiller and Dunbar, 2007, p. 94). The circle of approximately 5 people (i.e., between 4 and 7 people, reflecting individual differences) is the "support clique" in which the individual seeks support in her everyday life. Hence, our model extends these findings by predicting that in societies where people's social ties tend to be limited to their narrow "support cliques", the average social component of individuals' well-being is maximized: we find that maintaining social ties within the narrow circle of approximately 6 closest acquaintances is good for total social utility in a society, but all further social ties tend to be detrimental to aggregate social utility. In contrast, as shown above, the average economic component of well-being (i.e., the aggregate economic performance) increases with r also when $r > 3$. This creates a tension between aggregate social utility and economic performance.

Second, we find that average social utility increases with the share of local cliques that are family based (i.e., decreases with λ). This reflects the observation that greater family similarity makes social ties more efficient in satisfying the "safety drive" (Bowlby, 1969; Kadushin, 2002) and thus it is often the family to which we turn for support. However, a high frequency of kinship ties also comes in the way of the "effectiveness drive" because kinship ties are not particularly efficient in facilitating the flow of information and other network resources and often are found to reduce individuals' earnings (Franzen and Hangartner, 2006; Sabatini, 2009). This further strengthens the tension between aggregate social utility and economic performance.

Third, we find that average social utility has a mixed reaction to p (the probability of occurrence of local cliques), depending on ρ (the importance of family ties for social utility) and λ (the share of local cliques that are family based): (i) if ρ is small or λ is large then

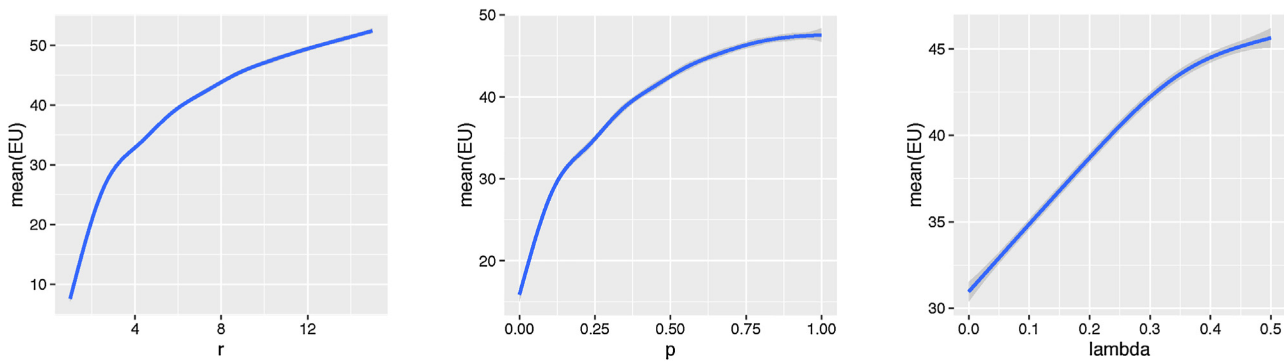

Fig. 1. The impact of network density (r), inverted probability of local cliques (p), and the inverted share of local cliques that are family-based (λ), on average economic performance in the society (EU).

average social utility is relatively low and increases with p; (ii) conversely, if ρ is large or λ is small then social utility is relatively high and decreases with p. The former case describes societies where family ties are not particularly valued or where local cliques are diverse and not limited to family members (such as, e.g., the societies of Nordic countries, cf. Alesina and Giuliano (2010)). In that case, the social benefits from having access to more information outweigh the costs of obtaining less family support and the society is better off with inclusive networks (high p) rather than with a multitude of local cliques. The latter case, in contrast, describes societies where family ties are valued highly or where local cliques tend to be limited to family members (such as, e.g., the societies of Mediterranean countries). In that case, the social benefits from obtaining more family support outweigh the costs of having worse access to information and the society is relatively better off with fragmented networks with many local cliques (low p).

The above findings are partly corroborated by country–year averages from ESS data. We find that average social utility correlates strongly with social trust (0.5585***, $n = 63$) but weakly (and insignificantly) with the average frequency of social contacts (0.2095, $n = 63$), exhibiting a $\cap$-shaped relationship somewhat resembling that for network density r in Fig. 2. Unfortunately, social utility is not directly measured in ESS data; thus we proxy it with residuals from regressing life satisfaction on incomes within a given country and year.

As a side remark, we also note that in our model, average social utility increases with the relative importance of family ties vs. contacts with "valuable", centrally located people (ρ). Values of other aggregate model variables are not affected by ρ. The role of the "prisoner's dilemma" parameters g_{nn}, g_{nc}, g_{cn} and ε is similarly unidimensional: they have a one-way influence only on economic performance (i.e., higher payoffs and a lower promise default rate lead to higher average economic performance).

5.3. Implications for network structure

Our results imply that there exists a clear trade-off between social utility and economic performance at the aggregate level, and both of them cannot be maximized at the same time. However, assuming a social welfare function which puts positive weights on both objectives, we can draw the following implications from the above results.

1. *Network density.* In real societies, average network density is never extremely low. For example, in our data for the Polish society (Growiec et al., 2017), respondents declare to have contacted, on average, 10.4 persons during the last week and 17.3 persons during the last month. Therefore we can safely discard the range of $r \leq 3$ in which both social utility and economic performance grow with r. For $r > 3$, however, there is a trade-off between both objectives. In consequence we expect that, even though in our model we do not directly take into account the costs of forming and maintaining social links, the optimal density of the network is bounded.
2. *Frequency of family-based local cliques.* Similarly, we expect that it is optimal for a society to keep a balance between cliques of friends consisting of family members and other acquaintances: λ has a different direction of influence on aggregate social utility and economic performance.
3. *Frequency of local cliques.* Finally, when we consider the frequency of local cliques in the network (parameter p), the situation depends on how much family ties are valued in the society. If contacts with the family are highly valued (or if local cliques are predominantly family based) then there is a trade-off between aggregate economic performance and social utility and we can expect that *small world* networks (moderate p) are optimal; however, if family ties are not highly praised in the society (or if local cliques are very diverse) then it is optimal for a society to form highly diversified, inclusive network structures (high p).

6. Results for individual-level correlations

The second group of simulation results quantifies the impact of social network structure on individual-level correlations. In this way we address the micro–macro linkages, i.e., we investigate the degree to which individual-level incentives are affected by country-level averages. These findings are helpful for understanding which correlations are robust and expected to hold in all societies, and which are specific to a given network structure.

The results are presented in Table 4 and can be summarized in the eight points provided below. We note that the first three of them are supported by ESS data, whereas empirical verification of the latter five ones is not possible on the basis of cross-country panel survey datasets so far due to the lack of information on the key variables in question.

1. *In dense networks, social ties are individually less valuable.* ESS data strongly suggest that in countries where social contacts are relatively frequent on average, individuals' social ties are less correlated with incomes (−0.3960***), social utility (−0.6340***), and overall life satisfaction (−0.5310***). They are also less tightly linked to social trust (−0.4135***). In these countries, social trust is also visibly less correlated with incomes (−0.2909***). (The reported numbers are correlation coefficients for cross-country data on (i) the average frequency of social contacts in a given country and (ii) the within-country correlation coefficient between the individuals' frequency of social contacts and their incomes).

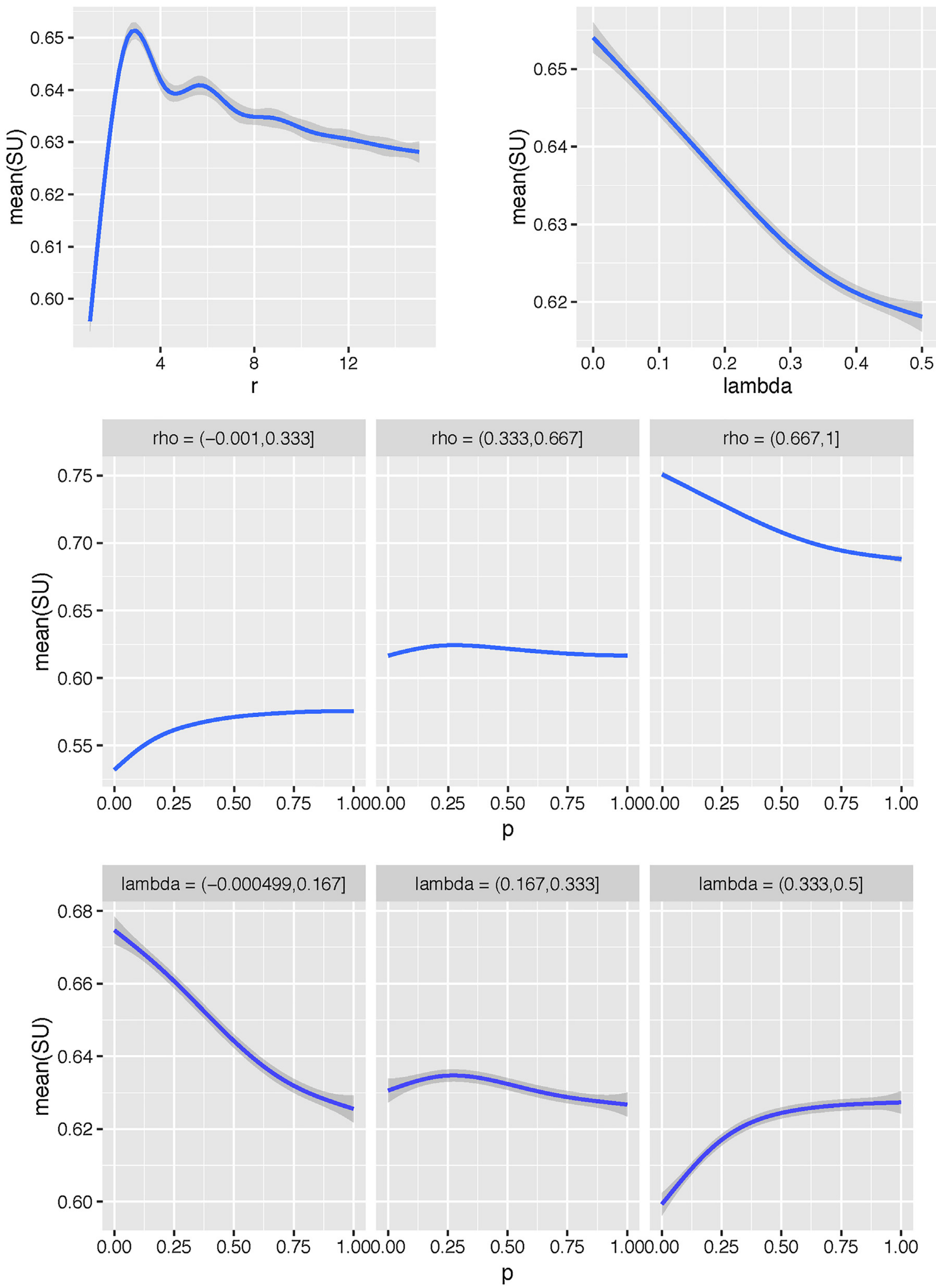

Fig. 2. The impact of network density (r), the inverted share of local cliques that are family-based (λ), and inverted probability of local cliques (p) on average social utility (SU).

Table 4
The impact of model parameters on individual-level correlations.

Correlation between	Average correlation			Impact of parameter			
	PL data	ESS	Model	r	p	λ	ρ
D_i and C_i	0.8387*		0.8661†	0.5146	0.3656	0.0000	0.0002
D_i and Bo_i	−0.0986*		−0.0138†	−0.4164	0.3875	0.3017	−0.0006
D_i and Br_i	0.2100*		0.2248†	0.0493	0.1299	−0.0002	0.0002
D_i and SU_i	0.1540*	0.2095	0.1934	−0.6019	0.1754	0.0872	0.0002
D_i and Tr_i	0.0578	0.4795*	0.3655	−0.4470	0.5631	−0.1756	0.0008
D_i and Co_i	0.0387		0.3449	−0.1004	0.2379	−0.0001	0.0003
D_i and EU_i	0.0360	0.4855*	0.4026	−0.1806	0.1826	−0.0718	0.0004
C_i and Bo_i	−0.1325*		−0.0327†	−0.2760	0.4924	0.4592	0.0000
C_i and Br_i	0.2100*		0.2599†	0.1022	−0.0222	−0.0001	0.0001
C_i and SU_i	0.1119*		0.4132	−0.2489	−0.3691	0.0379	−0.5221
C_i and Tr_i	0.0385		0.3416	−0.1050	0.6834	−0.1298	0.0012
C_i and Co_i	0.0460		0.3782	−0.0261	0.0868	0.0001	0.0003
C_i and EU_i	0.0333		0.4078	−0.0745	0.1218	−0.0383	0.0004
Bo_i and Br_i	−0.0898*		0.0339†	−0.5023	0.2156	0.0685	−0.0007
Bo_i and SU_i	0.0164		0.3573	−0.1490	0.2239	0.0612	0.8555
Bo_i and Tr_i	−0.0373		−0.8194	−0.5774	0.2080	0.0414	0.0003
Bo_i and Co_i	−0.0080		0.0154	−0.4635	0.3125	0.1591	−0.001
Bo_i and EU_i	−0.1207*		−0.3806	−0.1239	0.4727	0.2456	−0.0003
Br_i and SU_i	0.0693		0.1918	−0.3102	−0.0531	0.0065	−0.1712
Br_i and Tr_i	−0.0360		0.1141	−0.3580	0.2240	−0.0146	0.0009
Br_i and Co_i	0.1196*		0.9752	0.5225	0.0520	0.0011	−0.0014
Br_i and EU_i	0.1350*		0.7056	0.8706	0.2259	0.1557	0.0000
SU_i and Tr_i	0.0402	0.5585*	−0.1171	−0.4127	0.0078	−0.0075	−0.7273
SU_i and Co_i	0.2163*		0.2394	−0.4723	−0.0415	0.0170	−0.2483
SU_i and EU_i	0.0000	0.5551*	0.0685	−0.3621	0.0069	0.0483	−0.6104
Tr_i and Co_i	0.2653*		0.1876	−0.5442	0.1221	−0.0356	0.0014
Tr_i and EU_i	0.2972*	0.8009*	0.5799	−0.7808	−0.2019	−0.2291	0.0007
Co_i and EU_i	0.1912*		0.7592	0.8046	0.2630	0.1761	0.0007

Note: (i) *$p < 0.01$; †correlation used for model construction; (ii) in our Polish data, *SU* is computed as residuals from regressing life satisfaction (a combination of *SU* and *EU*) on relative incomes (*EU*). Zero correlation between *EU* and *SU* follows by construction; (iii) in ESS data, *SU* is computed as residuals from regressing life satisfaction (*stflife*) on incomes (*hinctnt*) within a given country and year. There is zero correlation at the individual level within each country-year cell but not across cells.

Our model reproduces all these findings qualitatively and also provides a few more detailed predictions. We find that an increase in r, mapping to the average number of social ties per agent, reduces the individual-level correlation of:

- Agent degree D_i versus social trust, willingness to cooperate, social utility and economic performance.
- Bonding social capital Bo_i versus social trust, willingness to cooperate, social utility and economic performance.
- Agent centrality C_i versus social utility and trust.
- Bridging social capital Br_i and social trust.
- Social trust and economic performance.

2. *Social trust is a functional substitute to social networks.* In trustful societies, social ties are individually less valuable, whereas in dense networks, the same follows for social trust. This pattern is clear in ESS data: in countries with a high average level of social trust, the frequency of social contacts is less correlated with individuals' incomes (-0.5406^{***}), social utility (-0.4173^{***}), and overall life satisfaction (-0.4339^{***}). By the same token, in distrustful societies, individuals' social ties are relatively more important for generating social utility and economic performance.

Our model correctly represents these relationships qualitatively. However, unlike network density r, aggregate social trust *Tr* is endogenously determined within the model, which allows us to provide a number of more detailed predictions. Having observed that aggregate social trust is positively related to both network density r and the (inverted) probability of occurrence of local cliques, p, we investigate the relationships between aggregate social trust and individual-level correlations by looking at the respective impacts of r and p. The key comparative statics for both parameters, however, are opposite in sign. This indicates the relatively dominant role of variation in r as well as underscores that both parameters influence social trust through different channels.

We find that an increase in p, i.e., a reduction in the frequency of local cliques, raises social trust but *increases* the individual-level correlation of:

- Agent degree D_i versus social trust, willingness to cooperate, social utility and economic performance.
- Bonding social capital Bo_i versus social trust, willingness to cooperate, social utility and economic performance.
- Agent centrality C_i versus social trust and economic performance.
- Bridging social capital Br_i versus social trust and economic performance.

3. *In dense networks and trustful societies, there is a trade-off between individuals' social utility and economic performance*, and conversely, in sparse networks and distrustful societies, social utility and economic performance are positively correlated in the cross section. Looking at ESS data, we find that individual life satisfaction is less dependent on incomes if the society supports frequent social contacts (-0.3097^{***}) or is generally trustful (-0.4540^{***}).

Our model reproduces this finding. We find that (i) on average, looking across all the considered model parameterizations, social utility and economic performance are essentially uncorrelated, but (ii) an increase in network density r unambiguously reduces the individual-level correlation between social utility and economic performance. Hence, in line with the empirical regularities we find that for low r (sparse networks), social utility and economic performance go hand in hand while for high r (dense networks), they present a trade-off.

Additional simulation results regarding the trade-off between SU_i and EU_i are included in Appendix C.

4. *In dense networks, there is a clearer trade-off between bonding social capital and other forms of social capital.* The model implies that an increase in r, mapping to the average number of social ties per agent, systematically reduces the individual-level correlation of bonding social capital Bo_i versus degree, centrality, and

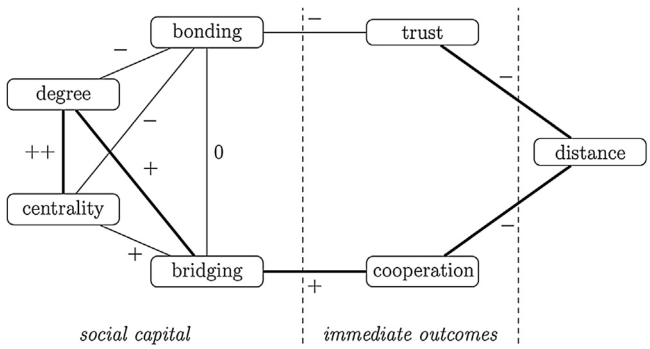

Fig. 3. Empirical relationships between the four dimensions of social capital as well as their immediate outcomes (social trust and willingness to cooperate), and network distance. *Note:* ++ strong positive correlation, + positive correlation, − negative correlation, 0 statistically insignificant correlation. Thick lines denote robust correlations, i.e. the ones which survive also when controlling for the simultaneous effects of other social capital dimensions. "distance" measures the length of path between two given individuals in a network and is a feature of the theoretical model that has not been tested empirically.

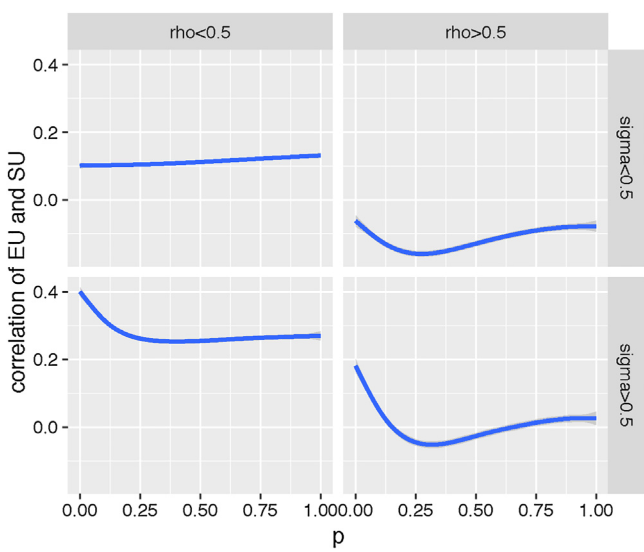

Fig. 4. The relationship between p, ρ, σ and the correlation between individuals' social utility and economic performance.

bridging social capital. The more social ties people have on average, the less of a difference there is between the ones who contact primarily with kin and the ones who have a more diversified network structure.

5. *In dense networks, bridging social capital is more conducive to cooperation and economic performance.* An increase in r strongly increases the individual-level correlation of bridging social capital Br_i versus willingness to cooperate Co_i and economic performance EU_i, as well as between Co_i and EU_i themselves. Social ties with dissimilar others and cooperative behaviors are individually profitable only if there is a sufficiently high chance that a random stranger will also play cooperatively.
6. *In societies with more local cliques (low p), individuals' economic performance is less tightly linked to their bridging social capital and cooperation, but more strongly linked to social trust and more strongly negatively linked to bonding social capital.* In societies where local cliques are frequent, social ties with dissimilar others and cooperative behaviors provide relatively less individual profit; on the other hand, engaging in economic interaction is relatively more profitable because there is quite a large chance of interacting with agents who are distant in one's network (high $L_{i,j}$).
7. *In societies where local cliques are predominantly family-based (low λ), the impact of individuals' bonding social capital on their social utility and economic performance is relatively small.* In societies where local cliques are frequent (low p), they may provide economic advantages to their members. In such a case, individuals whose social ties are mostly limited to kin will likely not belong to such cliques unless they are family-based. This creates a trade-off between ties with kin, which provide safety and support, and non-kin, which provide economic resources. In societies with many family-based cliques, however, this trade-off between ties with kin and non-kin is less pronounced.
8. *Social norms on family importance (ρ) affect only social utility.* If family is perceived as very important for social utility, as e.g. in the Mediterranean countries (Alesina and Giuliano, 2010), then it comes at the cost of lower trust, cooperativeness, and economic performance. In such case, social utility is also inversely related to centrality and bridging social capital.

7. Conclusion

The purpose of the current study has been to identify the key mechanisms allowing the social network structure to affect individuals' social trust, willingness to cooperate, economic performance and social utility, and to trace how these individual-level outcomes aggregate up to the society level. To this end, we have constructed a novel computational multi-agent model, building on Watts and Strogatz (1998) network structure but incorporating also a number of additional agent characteristics and accommodating a range of findings from the associated socio-economic literature. The model setup also draws from our empirical findings for the Polish society based on a unique, detailed survey dataset. Implications of the model, however, reach beyond the specificities of this particular society and have been tested at the cross-country level. They are presented in the form of aggregate-level comparative statics and individual-level correlations.

At the macro level, we have found that: (i) societies that either are globally better connected, exhibit a lower frequency of local cliques, or have a smaller share of family-based cliques, record relatively better economic performance; (ii) social utility presents a ∩-shaped relationship with network density and a positive relationship with the frequency of family-based local cliques; (iii) if contacts with family are highly valued in the society, then there is a *trade-off between aggregate social utility and economic performance*, and then *small world* networks are socially optimal, otherwise they are outperformed by highly diversified, inclusive networks.

At the micro level, in turn, we have found that (iv) in dense networks, social ties are individually less valuable; (v) social trust is a functional substitute to social networks: in trustful societies, social ties are individually less valuable, and vice versa; (vi) in dense networks and trustful societies, there is a *trade-off between individuals' social utility and economic performance*, and otherwise both outcomes are positively correlated in the cross section; (vii) in dense networks, there is a clearer trade-off between bonding social capital and other forms of social capital; (viii) in dense networks, bridging social capital is relatively more conducive to cooperation and economic performance.

The current study can be extended in various directions. The first item on our research agenda is to build a dynamic version of the considered model in order to allow individuals to endogenously form and dissolve social ties. This would allow us to identify the social network structures which will be formed in the long-run equilibrium, depending on the deep characteristics of the social capital formation process. One could then also study the age profiles of the considered variables as well as the relationships between the formation process of social capital, trust and cooperation, and the ultimate outcomes such as aggregate social utility and economic performance. In relation to this challenge, one could also exploit the dataset provided by Growiec et al. (2017) in order to base the assumptions on patterns of social formation on available empirical evidence.

Another important extension of the current study would be to collect and study more detailed, internationally comparable data on social capital variables. Ideally, questions on such variables could be included in large survey datasets such as the ESS or the World Values Survey. However, even more modest extensions of our related empirical study to other countries could be helpful for verifying (or falsifying) the computational model presented here.

Appendix A. Definitions of concepts

Table 5
Key concepts of the paper: model-based definitions and our preferred empirical operationalizations.

Variable	Model definition	Empirical operationalization
Individual-level variables		
Degree D_i	Number of social ties of agent i	Reported number of social ties of an individual
Centrality C_i	Eigenvector centrality of agent i	Reported ability to act like a bridge between otherwise disconnected sub-networks, interacted with the number of social ties
Bridging Br_i	Average level of type distance $d_v(i, j)$ across all agent i's social ties	Maintaining social ties with dissimilar others (several specific items)
Bonding Bo_i	Average level of family similarity $s_f(i, j)$ across all agent i's social ties	Percentage of family members among the individual's social ties
Trust Tr_i	Probability that agent i will enter economic interaction	Should most people be trusted, or one cannot be too careful (with other people)?
Cooperation Co_i	Probability that agent i will declare to cooperate with a random other agent	Behaving honestly and obeying rules (several specific items)
Social utility SU_i	Non-economic resources drawn from agent i's social ties: family ties and ties with central agents	Residual from regressing self-reported life satisfaction on individual incomes
Economic performance EU_i	Expected aggregate payoff from economic interactions of agent i with all other agents	Individual incomes (subject to usual measurement caveats)
Network-level variables		
Network density r	2r is the average number of social ties per agent	Average number of social ties per person
Rewire probability p	(Inverted) probability of occurrence of local cliques	*Difficult to obtain from survey data*[a]
Non-family-based cliques λ	(Inverted) share of local cliques that are family based	*Difficult to obtain from survey data*[a]

Source: Section 3 of this paper and Growiec et al. (2017).

[a] Therefore, we perform robustness analysis for $p, \lambda \in [0, 1]$, i.e. their entire domain.

Appendix B. Additional empirical results

In our related empirical paper (Growiec et al., 2017), we use a novel survey dataset on a representative sample of the Polish population ($n = 1000$) to draw a detailed map of the four social capital dimensions and their links to social trust and willingness to cooperate (which we view as immediate social capital outcomes) as well as economic performance and subjective well-being (the ultimate outcomes). In this paper, these individual-level results are used in the specification of model setup and its parametrization.

The key findings are summarized in Fig. 3. We find that degree (number of social ties) strongly and robustly positively correlates with centrality; it also robustly correlates positively with bridging social capital. In simple Pearson correlations, degree also correlates negatively with bonding social capital whereas centrality correlates positively with bridging and negatively with bonding social capital. Bridging and bonding social capital are, in turn, essentially uncorrelated in our data. All these relationships are well approximated by our computational multi-agent model, both qualitatively and quantitatively, even though we do not calibrate any of the model parameters to match these correlations directly (see Table 2 in Section 4 on simulation experiment design).

The empirical study of Growiec et al. (2017) also confirms a robust positive link between bridging social capital (social ties with dissimilar others) and willingness to cooperate, and between social trust and willingness to cooperate, as well as points at a negative relationship between bonding social capital (strong kinship ties) and social trust. These findings are in line with bulk of the associated literature and are accordingly reflected in the assumptions of our model.

Appendix C. Additional simulation results for the trade-off between social utility and economic performance

The current appendix presents additional results on the relationship between individual-level economic performance and social utility. As mentioned in the main text, when the results are averaged over all considered model parameterizations, both outcomes are essentially uncorrelated. We shall investigate, however, how this relationship might be affected by changes in model parameters. All the values reported below are average correlations over all considered parameterizations of the model conditional on the assumed values of given parameters.

The strongest impact on the relationship between individual EU_i and SU_i is observed for ρ (the importance of kinship ties for social utility): Kendall's τ correlation is approximately equal to −0.49. The higher the value of family ties in the society (higher ρ), the lower the correlation coefficient between social utility and economic performance. For a low ρ, both outcomes are positively correlated: there are both social and economic advantages of being better connected. For a high ρ, however, both outcomes are negatively correlated: agents derive their social utility primarily from strong family ties, so the ones who have primarily family-based networks, have to accept lower economic performance.

A strong impact is also observed for σ (Kendall's τ approximately 0.27). This means that if the process of tie formation in a given society is strongly dependent on the intrinsic value of an agent (high σ), the correlation between agents' economic performance and social utility is positive. In contrast, in societies where tie formation is relatively unrelated to agents' characteristics (low σ), correlation between economic performance and social utility becomes negative.

Lastly, an interesting result for the correlation between social utility and economic performance is obtained with the probability of occurrence of local cliques (p). It is shown in Fig. 4. If family ties are relatively unimportant (low ρ) and network formation is not strongly directed by the intrinsic value of an agent (low σ) then p is relatively unimportant. In all other scenarios, a low p – meaning that there are relatively few people in the society with long-distance connections – implies that these people enjoy relatively higher levels of both social utility and economic performance; this leads to a relatively higher correlation of EU_i and SU_i. Moreover, in the societies where family ties are relatively important ($\rho > 0.5$), if the network starts to be very inclusive (a low number of local cliques, high p) we observe that the correlation between economic performance and social utility starts to grow as well. The reason for such a situation is that in such societies the individuals who have a large number of contacts (high D_i) naturally have a high EU_i but also they have a relatively high SU_i as they are likely to have more connections with family members.

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