Individual risk preferences and collective outcomes in the evolution of exchange networks

Flache, A.

Published in:
Rationality and Society

Publication date:
2001

INDIVIDUAL RISK PREFERENCES AND COLLECTIVE OUTCOMES IN THE EVOLUTION OF EXCHANGE NETWORKS

Andreas Flache

ABSTRACT

Recent research argues that individual risk aversion favors cooperation in social dilemmas. The argument focuses on conditional cooperation in repeated interaction. The more risk averse actors are, the less they are inclined to put at risk ongoing cooperative relationships by attempts at unilateral exploitation. I argue that this reasoning may not suffice to capture risk effects in exchange networks, where actors face both decisions about cooperation and decisions about selection of new partners. I present a model that combines both decisions. Consistent with previous analyses, the model predicts that individual risk aversion favors rational cooperation in ongoing dyadic exchanges. However, simulations also reveal that risk aversion may negatively affect cooperation through reduced mobility in partner search. If actors consider partner change as risky, then risk-averse actors may stick to suboptimal relationships, even if better alternatives are available that allow for higher levels of cooperative exchanges. Further simulations show nonlinear effects of individual risk preferences on the density and efficiency of exchange networks.

KEY WORDS • computer simulation • exchange networks • micro–macro link • social dilemmas • social risk preferences

1. Introduction

In exchange relations, the actors involved often face a social dilemma. On the one hand, all participants benefit if they establish an exchange of, e.g. goods, services, or help. On the other hand, self-interested actors may face both incentives and have opportunities to 'free ride', that is, not to reciprocate others' contributions to the exchange. As a consequence, exchange relations can only be stable if participants cooperate, that is if they resist

Rationality and Society Copyright © 2001 Sage Publications (London, Thousand Oaks, CA and New Delhi), Vol. 13(3): 304–348. [1043–4631(200108)13:3; 304–348; 018285]

temptations to behave opportunistically. Clearly, this perspective suggests that individuals' preferences towards taking risks may affect cooperation in exchanges. For example, people who are more afraid of taking risks might be less willing to cooperate when this exposes them to the danger of exploitation by opportunistic partners. Conversely, one may expect that the less an actor is concerned by the possibility of exploitation, the more he will be ready to take the risk of cooperating, for example in order to secure future gains from receiving others' help. The intuitive argument sketched here draws on the notion that risk preferences affect cooperation because of particular forms of boundedly rational (Simon 1955) behavior in social dilemmas. More in particular, Lindenberg (1988) employs Kahnemann and Tversky's (1979) prospect theory to argue that cooperation in collective action may be explained by the motivating power of loss. This motivating power of loss derives from the assumption of prospect theory that individuals' risk preferences are risk-seeking in losses and risk-averse in gains. Then, actors can be expected to be more willing to take collective action, like mobilizing for a strike, when the goal is to avoid losses, such as fending off a wage cut, rather than to obtain gains (cf. Raub and Snijders 1997; Snijders and Raub 1998).

Recent analyses of risk effects in social dilemmas (Raub and Snijders 1997; Snijders and Raub 1998; van Assen 1998) argue both theoretically and based on experimental evidence that *risk aversion favors cooperation*, or, conversely, that *risk-seeking undermines cooperation*. Their argument departs from game theoretical analysis of conditions for cooperation in *repeated social dilemma interactions*. In this framework, standard rational decision theory suffices to derive effects of risk preferences. In repeated interactions, it may be rational for egoistic actors to cooperate based on strategies of *reciprocity* (Axelrod 1984; Friedman 1971; Taylor 1987). The central condition here is a sufficient 'shadow of the future'.[1] Under reciprocity, a sufficient shadow of the future deters rational participants of an exchange from unilateral defection in the present, because they anticipate the undesirable consequence of losing others' cooperation in the future. In this perspective, risk aversion favors cooperation, because in

> a repeated game-framework using the logic of conditional cooperation ... [t]he relevant problem for ... a rational actor is whether he should try a unilateral exploitation of partners who cooperate conditionally. He has to weigh the short-term incentive for an exploitation against the expected long-term costs of such a behavior. In a scenario of this type, risk aversion will favor

> own cooperation, while risk seeking preferences will tend to favor defection. (Raub and Snijders 1997: 279)

Furthermore, the game theoretical analyses of Raub, Snijders and van Assen show that the predicted *positive* effect of loss aversion on cooperation remains, even when the original standard rationality model is combined with Kahnemann and Tversky's (1979) assumption of S-shaped utility.

In this paper, I argue that game theoretical analyses of repeated exchanges may not suffice for us to fully understand the effects of individual risk preferences on collective outcomes in exchange networks. Previous studies model cooperative relations as *isolated exchanges* where actors have no possibility to leave ongoing relations and to seek new relationships. However, for a number of empirically relevant applications this seems an implausible assumption. For example, as social network analysts have observed, *exchanges of social support* tend to be embedded in *networks* of support relations (Hall and Wellman 1985). In these networks, actors often seem to strive for reciprocity, that is they select exchange partners partly on the basis of amount of resources they may expect to attain in the exchange (Komter 1996). Similarly, in certain industries, technology cooperations between firms constitute network patterns in which firms seek to establish relationships with partners based on both technological attractiveness and status in the industry of potential partners (Podolny and Page 1998). In other words, exchange networks often have the property that actors are at least to some degree free to change partners and that potential exchange partners also differ in their attractiveness, for example because of variation in the amount of material resources at their disposal. In such a network, the relevant decision problem actors face is not just whether to cooperate in a particular relationship. In addition, actors need to make decisions about whether and when to exit from relations with exchange partners and, moreover, they have to make choices between potential new exchange partners. In this perspective, members of an exchange network face both *cooperation decisions* and *partner selection decisions*.

The main point of my paper is that predictions about effects of individual risk preferences on cooperation may change considerably when partner selection is taken into account. I argue that risk preferences are particularly relevant for partner selection, because it is reasonable to assume at least a moderate degree of bounded rationality as soon as partner selection comes into play. Clearly, partner selection imposes a more complex decision problem compared to cooperation decisions. In partner selection, actors need to optimize their position in a network with numerous strategically interdependent potential exchange partners who differ in neediness. By contrast, the strategic problem in the cooperation decision involves only two actors in an ongoing relationship. Accordingly, it seems reasonable to employ in a model of exchange networks boundedly rational partner selection heuristics, but strict rationality is retained for modeling cooperation decisions. Partner selection heuristics, in turn, may entail effects of risk preferences that conflict with the effects on cooperation decisions predicted by the standard repeated game framework. For example, such a conflict occurs when actors employ the plausible heuristic that partner changes are a potentially risky course of action, whereas they underplay the risks involved in keeping the status quo. Then risk aversion may at the same time favor cooperation *within* ongoing exchange relations *and* reduce actors' readiness to take the risk of seeking new partners. As a consequence, a risk-averse actor may stay in suboptimal relationships where he attains lower levels of resource exchanges than he might achieve with alternative partners who have more resources to bring into the exchange. Hence, the less inclined an actor is to take risks, the more he tends to be a cooperative partner in present exchange relationships, but the less he may optimize his exchange network in terms of the total amount of exchanges he attains. In the end result, a more risk-seeking individual may actually cooperate *more* across all his relationships, not because he is less opportunistic, but because he is opportunistic *enough* to abandon present exchange partners in favor of new partners to whom he is willing to give more resources, because they are capable of giving more resources in return.

To analyse how risk preferences affect the interplay of cooperation decisions and partner selection, I draw, in the remainder of this paper, on a somewhat adapted version of Hegselmann's (1998) model of the dynamics of exchange networks (cf. Flache and Hegselmann 1999a, b). In this model, actors differ in their attractiveness as exchange partners and they have the possibility to change their relationships over time. To illustrate the model, I will talk about exchanges of help or social support. However, the scope of this analysis includes every form of exchange where actors face cooperation problems, differ in their attractiveness as exchange partners, and are to some degree free to change partners. The basic building block of the support network, the dyadic support relation, is modeled as in the previous game theoretical studies of repeated social dilemma games. In the next section, I combine this model with the repeated game approach of Raub and Snijders (1997) to analyse how risk preferences shape conditions for cooperation in isolated dyads. Then, I extend that model by including partner selection. This is followed by the presentation of computer simulations that show how individual risk preferences in combination with different partner search heuristics shape the dynamics and collective outcomes of exchange networks. The last section discusses results and puts forward conclusions.

2. Risk Preferences in Dyadic Support Relations

The dyadic exchange relation between two individuals, say Ego and Alter, is the basic building block of help exchange networks. In my analysis, the exchange outcomes that actors expect to arise from the dyadic relationship shape their perception of the attractiveness of potential partners. Accordingly, the analysis of exchange behavior *in the dyad* is the first step in modeling the partner selection process *in the network*. In this section, I therefore ignore for the moment the assumption that actors are free to change partners. I focus exclusively on ongoing exchanges in an isolated dyad. To include risk preferences, I follow the approach of Raub and Snijders (1997) and analyse how risk attitudes affect the conditions under which self-interested actors are willing to use *conditional cooperation* in ongoing help exchanges. Unsurprisingly, it turns out that my analysis of the *isolated dyad* is consistent with previous results. In the isolated dyad, risk aversion makes conditions for cooperation less restrictive. In particular, for a population in which actors differ in attractiveness as exchange partners, this implies that risk aversion makes actors less selective with respect to the attractiveness of partners with whom they are willing to cooperate. As a consequence, cooperation becomes feasible for a larger range of combinations of attractiveness levels as actors are more risk averse. I will demonstrate that how this affects the overall structure and the level of cooperation in the help exchange network as a whole depends on the partner selection strategies that actors use.

In the following sections, I present the model of help exchanges in the dyad. I model the exchange dyad as a repeated *support game*. Subsection 2.1 describes individual neediness and support actions in the game, and Subsection 2.2 specifies the incentive structure participants face. Finally, the game theoretical analysis of effects of risk preferences on individual exchange behavior in the repeated support game is presented in Subsection 2.3.

2.1 Individual Neediness and Support Actions

I assume that the participants in the exchange are fully characterized by a specific level of neediness. Neediness reflects both an actor's capability to provide help and his need for help. More precisely, I assume that the capability to provide help and the need for help are inversely related. The more help Ego needs in a certain period of time, the less help he can give to Alter in the same period.[2] I feel that this assumption is often plausible for social exchange relations. For example, consider the effects of variation in hunting skills on the individual neediness for food donation in a hunter-gatherer group. Skillful members may both have more food to share with others and less need for food support themselves, compared to weaker members. Similarly, in a rural village only some members may be wealthy enough to afford expensive farming machinery. These farmers do not need to borrow others' machines, but they might lend their machinery to less wealthy members. Technically, I model individual neediness *i*, n_i, as a number between zero and one ($0 \leq n_i \leq 1$). Conversely, *i*'s capability to provide help is $1 - n_i$. An actor who is maximally needy ($n_i = 1$) needs help 'all the time', but he is not capable of supporting his partner. By contrast, an actor who is minimally needy himself ($n_i = 0$) never needs support, but he is capable of providing a full unit of help per time unit.

I model the ongoing exchange between Ego and Alter as a repeated support game that consists of consecutive iterations of a constituent game. For simplicity, both actors have only two decision options in the constituent (one-shot) game, to provide help (*C*ooperate) and to not provide help (*D*efect). To further simplify, I assume that participants make these decisions simultaneously and independently.[3] The effects of cooperation and defection depend on actors' neediness levels. The smaller the neediness of Ego, n_i, and the larger the neediness of Alter, n_j, the larger the amount of help that Ego gives (and Alter receives) when Ego decides to support Alter (C). Technically, I assume that Ego's cooperation gives $n_j\ (1 - n_i)$ units of help to Alter in the corresponding iteration. However, when Ego fails to support Alter, Ego provides zero units of help. Conversely, Ego receives (and Alter gives) $n_i\ (1 - n_j)$ units of help if Alter supports Ego (C). At the same time, Ego receives zero units of help, when Alter gives no support (D).

2.2 *The Incentive Structure*

The incentive structure of the support game reflects the preferences of self-interested actors. To facilitate the discussion, I distinguish between *outcomes* and the *utility* actors effectively derive from an exchange outcome. *Outcomes* express costs and benefits of the exchange outcome in terms of some objectively quantifiable commodity, say money. Consistent with standard utility theory, I assume that the *utility* that *risk neutral* individuals derive from an exchange is a linear function of the corresponding outcome and that the utility actors obtain is *always* a monotonous function of outcomes, regardless of individuals' risk preference. To model outcomes, mutual defection, DD, is used as the baseline outcome that yields zero to both participants. In DD, actors neither receive help nor provide support. Actors gain from being supported, compared to the baseline. At the same time, actors incur some loss if they provide help themselves. More precisely, the larger the amount of help Ego receives, the larger his gain is. Conversely, the more help Ego provides, the larger his loss. Technically, I model i's gain from receiving help from j, G_{ij}, and i's loss as a result of giving help to j, L_{ij}, as follows:

$$G_{ij} = n_i\,(1 - n_j)B \tag{1}$$

$$L_{ij} = (1 - n_i)n_jE$$

The parameters B and E are positive constants that weigh the benefit, B, of receiving one unit of help against the effort costs, E, of providing the unit. It is a central assumption in this analysis that self-interested individuals may in principle benefit from mutual support. To ensure this, I assume that Ego's benefits of receiving a unit of help exceed Ego's costs of 'producing' a unit, hence $B > E$. Table 1 illustrates the incentive structure that ensues for the constituent support game. For consistency with the literature, I use the standard notation for the Prisoner's Dilemma game (PD) to denote outcomes. However, notice that the support game is not necessarily a PD. I discuss the conditions under which the support game constitutes a PD further below. I denote the outcome corresponding with the strategy combinations CC, DC, CD, and DD as reward (R), temptation (T), sucker's payoff (S), and punishment (P), respectively. The subindices i and j indicate that outcomes vary for different combinations of neediness levels. For example, R_{ij} denotes the outcome that an actor of neediness level n_i attains from mutual cooperation with a partner of neediness level n_j. Notice that the game is not necessarily symmetrical. Players obtain different outcomes in symmetrical choice combinations, unless they are equally needy.

Table 1 shows that cooperation in the support game may conflict with self-interest. There is nothing that guarantees reciprocation within one iteration. Particularly in short-term relationships, actors might be tempted to withhold support. More precisely, not to help is always a dominant strategy in the constituent game, because $T_{ij} > R_{ij}$ and $P_{ij} > S_{ij}$. Exploiting a partner who provides help is the most profitable outcome for a selfish actor, and to be exploited by a partner who fails to help is least attractive, regardless of how needy the players are. Clearly, the support game may face self-interested actors with a PD structure. However, the game is not necessarily a PD. In a PD, both players prefer *mutual* cooperation (CC) to *mutual* defection (DD) despite incentives to defect *unilaterally.* In the support game, however, it is possible that only the weaker player may be interested in mutual support.[4] More precisely, when Alter is too weak in comparison with Ego, then Ego may not receive enough help from a weak Alter to compensate the investment in support of Alter ($G_{ij} < L_{ij}$). As a consequence, Ego may prefer mutual defection to mutual support ($P_{ij} > R_{ij}$). Accordingly, the constituent support game is a PD if, and only if, for both players it holds that $R_{ij} > P_{ij}$. Equation (1) implies that this is equivalent to $n_i\,(1 - n_j)B > n_j\,(1 - n_i)E$ for both players.

To introduce risk preferences in this model, I follow Raub and Snijders (1997) and assume that the function that maps outcomes on utilities is concave for risk-averse actors, linear for risk-neutral actors and convex for risk-seeking preferences. Raub and Snijders show that this qualitative distinction suffices to derive effects of risk preferences on the conditions for cooperation in a repeated game. However, for combining their analysis with assumptions about partner selection, it is useful to express the degree of risk aversion

Table 1. Outcomes in the constituent support game

	C		D	
C	$R_{ij} = G_{ij} - L_{ij}$	$R_{ij} = G_{ji} - L_{ji}$	$S_{ij} = -L_{ij}$	$T_{ji} = G_{ji}$
D	$T_{ij} = G_{ij}$	$S_{ij} = -L_{ji}$	$P_{ij} = 0$	$P_{ji} = 0$

quantitatively by a single parameter that controls the shape of the utility function. For this purpose, I introduce a utility function U with a *risk-parameter* ρ, such that negative values of ρ correspond to risk-aversion preferences, whereas $\rho = 0$ expresses risk neutrality and $\rho > 0$ yields a risk-seeking preference structure.[5] For the further model analysis, it is only necessary to define the function U for the range of positive outcomes of the support game. Moreover, only support games need to be considered that satisfy the conditions of a PD, that is, R > P for both players. Equation (2) formalizes the utility function U.

$$U(x) = T\left(\frac{x}{T}\right)^{2^{\rho}} \tag{2}$$

Figure 1 illustrates how the risk parameter ρ shapes the utilities of the outcomes of the constituent support game. The positions of the outcome values on the horizontal axis of Figure 1 correspond to the outcomes that an actor with neediness $n_i = 0.3$ obtains in a support game with a partner of neediness $n_j = 0.5$, where $B = 4$ and $E = 1$.

The figure demonstrates how increasing willingness to take risks shifts the relative values of the utilities corresponding to the outcomes. To understand why risk preferences shape the utility function in the way shown in Figure 1, consider an actor involved in a relationship of ongoing mutual cooperation. Suppose the partner's strategy is unknown, except for the fact that the partner is 'friendly', that is, he will never defect first. In every iteration, the focal actor obtains a certain outcome of R if he never tries to cheat

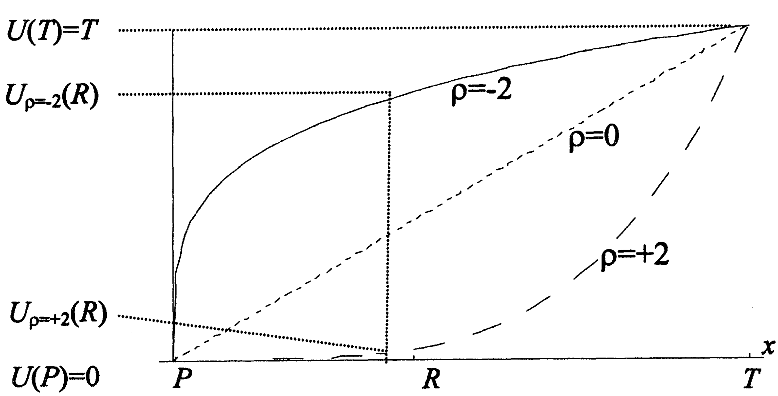


Figure 1. Convex ($\rho = +2$), linear ($\rho = 0$) and concave ($\rho = -2$) utility functions applied to the outcomes of the constituent support game for $n_i = 0.3$ and $n_j = 0.5$

on his partner. However, the focal actor might further improve his outcome from R to T by trying unilateral exploitation. But in doing so, he takes the risk that the opponent will retaliate in subsequent interactions. Somewhat simplified, the actor's decision problem may be characterized as a choice between the certain profit from mutual cooperation (R) and a gamble that may result in successful exploitation (T), but that may also entail mutual punishment (P). Figure 1 indicates how risk preferences affect the actor's decision-making in that choice situation. The figure shows that for the risk-averse actor ($\rho = -2$), the extra gain in utility that might be obtained by cheating on the partner, $U(T)-U_{\rho=-2}(R)$, is very small in comparison with the potential loss of future cooperation, $U_{\rho=-2}(R)-U(P)$. In other words, only if he expects a very small probability of his opponent's retaliation will an actor with a risk preference of $\rho = -2$ prefer the gamble of trying a unilateral exploitation to continuation of the cooperative relationship. However, the risk-seeking actor ($\rho = +2$), derives a large utility gain from reaping the best outcome rather than only the second best, $U(T)-U_{\rho=+2}(R)$, whereas he almost neglects the potential loss from deterioration of the cooperative relationship, $U_{\rho=+2}(R)-U(P)$. Clearly, for the risk-seeking actor only a small probability for successful exploitation suffices to make the risky gamble of unilateral defection preferable to the certain option of harvesting the benefits from cooperation.[6]

Figure 1 suggests that risk preferences may affect the conditions under which rational actors cooperate in a repeated PD. At the same time, variation in risk preferences does not change the social dilemma structure as such. As the function U is monotonous, the order of outcomes, S, P, R and T, is retained in the order of utilities, that is, $U(S)$, $U(P)$, $U(R)$ and $U(T)$ for every risk preference ρ. This implies, in particular, that changes in the risk parameter ρ do not affect the condition that is constitutive for a PD structure, namely $U(S) < U(P) < U(R) < U(T)$ for both players. This yields a first straightforward result for the effects of risk preferences on cooperation in the isolated dyad:

The support game for the neediness pairing (n_i, n_j) is a Prisoner's Dilemma for risk-seeking ($\rho > 0$) and risk-averse ($\rho < 0$) actors if, and only if, the game constitutes a Prisoner's Dilemma also from the point of view of risk-neutral actors ($\rho = 0$).

2.3 Risk Preferences, Cooperation, and Partner Attractiveness in the Repeated Support Game

The constituent support game is a one-shot situation in which both actors have the dominant strategy to not support their partner. However, for social interactions in general and help exchange relations in particular it is more plausible to assume that actors expect to have at least a certain probability of future encounters. To model the 'shadow of the future' in support relations, I assume that it is common knowledge for all players that after one iteration of the constituent support game, the game continues with probability α and the game ends with probability $(1 - \alpha)$. Clearly, the larger the continuation probability α, the longer the common future that rational actors can expect. This implies that in computing the expected utility of a particular payoff stream, actors use exponential discounting of future payoffs, where α is the discount rate.

To specify the conditions for individually rational cooperation in the repeated support game, I use the solution concept of subgame perfect equilibrium (SPE). Broadly, to say that actors choose strategies that constitute a SPE is to say that they act individually rational. In a SPE, none of the players faces an incentive to unilaterally change his strategy as long as all other players also follow their respective equilibrium strategy. Moreover, even if some deviation from the equilibrium path occurs, following the equilibrium strategy still is the mutual best response strategy for every player in the ensuing subgame (for a formal definition and a detailed discussion, see Kreps 1990: ch. 12). Friedman (1971) applied the SPE-concept to indefinitely repeated games like the support game. To identify prerequisites for conditional cooperation, he considered a class of extreme strategies that are easy to analyse, so-called *trigger strategies*. A player following a trigger strategy always supports his partner in the first iteration of the game, but in subsequent iterations support is only given on the condition that the partner gave support in *all* preceding iterations. Hence, eternal punishment follows any deviation from cooperative behavior. Clearly, the trigger strategy represents an extreme form of conditional cooperation. Obviously, more forgiving strategies, such as Tit-for-Tat, may be an empirically more plausible model of reciprocity, particularly in settings where imperfect information about others' behavior requires a certain degree of lenience with unintended defections (Kollock 1993; Wu and Axelrod 1995). However, the present analysis assumes perfect information about actors' past behavior. In this context, extreme trigger strategies are a useful instrument for identifying the boundary conditions for cooperation. To explain, trigger strategies impose the largest punishment possible, eternal damnation. Only when this punishment suffices to deter defection, may a less restrictive strategy also support cooperation (cf. Myerson 1991: 327–8). Accordingly, effects of risk preferences on cooperation that are predicted on the basis of trigger strategy models are likewise an indication of the effects that risk preferences may have on any form of individually rational cooperation.

Friedman's analysis showed that mutual conditional helping on the basis of trigger strategies constitutes a SPE when the probability α for continuing the relation in the next period is not lower than a certain threshold value α'. In that case, the loss that a defector faces from his opponent's retaliation in the future is not compensated by the short-term gain in the present iteration. For trigger strategies, the corresponding threshold continuation probability can easily be computed on the basis of the utilities of the constituent Prisoner's Dilemma game (cf. Friedman 1986: 77–89). Applied to the support game, this result yields the following theorem.

The cooperation condition. Mutual conditional cooperation on the basis of trigger strategies is a SPE[7] of the repeated support game when for both actors the continuation probability α is larger than or equal to α'_{ij} where:

$$\alpha'_{ij} = \frac{U(T_{ij}) - U(R_{ij})}{U(T_{ij}) - U(P_{ij})} = 1 - \left(\frac{Bn_i(n_j - 1) - En_j(n_i - 1)}{Bn_i(n_j - 1)}\right)^{2\rho} \qquad (3)$$

Proof: Friedman 1986: 77–89 and appendix.

The condition expressed by Equation (3) has a straightforward interpretation. The larger the short-term gains of defection (numerator) and the smaller the long-term costs of punishment (denominator), the larger the probability of future interactions, α, that an actor requires for cooperation. Or, only when actors expect a sufficient probability of future interactions, then the punishment of their opponent's eternal defection is severe enough to deter them from attempts at unilateral exploitation in the present. The result of Equation (3) can immediately be applied to derive effects of risk preferences on the conditions for cooperation in the repeated support games. To simplify this analysis, I employ in the following section the assumption that every actor in the population has the same risk parameter ρ. The ensuing result is consistent with the previous literature.

The effect of risk preferences on the cooperation condition. If the support game is a PD, then the larger the risk parameter ρ, the larger for both actors the threshold continuation probability α'_{ij}, that is, the more restrictive are the conditions for mutual cooperation. More technically,

$$\frac{\partial \alpha'_{ij}}{\partial \rho} > 0, \text{ if } R_{ij} > P_{ij} \text{ for both actors.} \tag{4}$$

Proof: See appendix.

To illustrate the result, Figure 2 visualizes the effects of the risk preference, ρ, on the cooperation condition. To compute the figure, I assumed that the benefit of receiving a unit of help, B, is 4 times as large as the effort required to produce the unit, E. More concretely, $B = 4$ and $E = 1$. The subfigures chart the largest of the threshold continuation probabilities α'_{ij} and α'_{ji}, as a function of the combination of neediness levels n_i and n_j. Between figures, I increase the risk parameter from strong risk aversion ($\rho = -2$) to risk neutrality ($\rho = 0$) up to high readiness to take risks ($\rho = +2$). The white space in the figures indicates the range of (n_i, n_j) combinations where at least one of the continuation probabilities exceeds a level of $\alpha = 0.903$. I choose this particular level of α because it corresponds to the continuation probability in a situation where both players continue the game only with probability 95% after a particular iteration, hence they have a small 5% chance of leaving the relationship. This corresponds with the standard assumptions of the simulations presented in Section 4. Accordingly, the white space in the figures represents those pairings of neediness levels for which the condition $\alpha = 0.903$ is too restrictive to sustain individually rational cooperation.

Figure 2 shows that the more different the neediness levels of the actors involved, the larger the continuation probability α that is required for conditional cooperation. At every level of the risk parameter ρ, the cooperation condition reflects the cost–benefit considerations of the less needy player. The less help he receives compared with the help he gives, the longer the expected duration of the exchange relationship required to deter this player from defection. The white range in the figures indicates that sufficient stability is no longer attainable, as players' neediness levels are too dissimilar. Although these properties of the cooperation condition are stable against variation of actors' risk preferences, Figure 2 illustrates that the *range of pairings* (n_i, n_j) for which

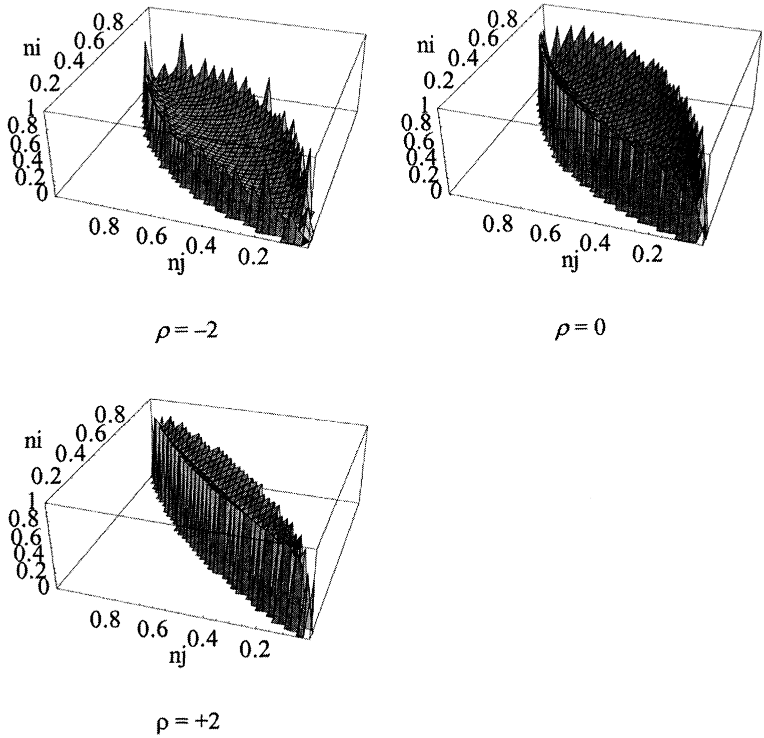


Figure 2. Threshold continuation probability α'_{ij} as a function of combination of neediness levels (n_i, n_j) for three different levels of the risk parameter ρ

cooperation can be attained at $\alpha = 0.903$ shrinks, as actors' willingness to take risks increases. The range of pairings (n_i, n_j) for which cooperation can be attained becomes narrower between $\rho = -2$ and $\rho = 0$ and it shrinks considerably between $\rho = 0$ and $\rho = +2$. At the same time, comparison of the three graphs shows that the height of the surface increases, as actors become more risk-seeking. This demonstrates that for a particular pairing of actors, the increasing willingness to take risks makes the conditions for cooperation more restrictive. Finally, the graphs show that for high readiness to take risks ($\rho = +2$), only those pairings that are very similar in their neediness can still attain cooperation. Moreover, even for these pairings the threshold continuation probability is very large in comparison with the lower levels of the risk parameter shown in Figure 2.

Figure 2 demonstrates how risk preferences shape the conditions for cooperation. However, to assess how this affects partner selection in support networks, assumptions about the attractiveness of particular exchange partners are required. To model partner attractiveness, I assume that actors compare partners on the basis of the utility they expect to derive from the support relation with a potential partner *j*. Clearly, the longer the expected duration of the relationship for both parties, the better are the prospects that cooperation can be attained and the more attractive is a potential partner. Expected duration, in turn, depends on future alternatives for oneself and the partner, and on the partner selection strategies of the players. Obviously, a perfectly rational assessment of partner attractiveness is very complicated, because it involves prediction of possible future developments of the exchange network, together with an assessment of the associated probabilities. Accordingly, I deliberately simplify the decision model at this point and assume that actors follow a boundedly rational heuristic. In this heuristic, actors make a pessimistic 'baseline guess'. This guess is that they and their neighbors will use every option to leave. Knowledge about the migration process in the network then leads actors to a commonly expected shadow of the future. To explain, the model assumes that partner selection options only arise with an exogenously given probability m per period. I assume that this rate is common knowledge, because it represents publicly known structural characteristics of the society, such as average mobility costs or the strength of family bonds in support relations. As a consequence, all actors expect the same subjective continuation probability in every support game. This is the probability that both Ego and Alter get no chance for partner change in the next iteration, hence $\alpha = (1 - m)^2$. While the baseline guess is in fact wrong when the network stabilizes, the bias introduced by the assumption is conservative in the sense that the model never predicts too much rational cooperation in support relations. The reason is that the shadow of the future can never be shorter than actors expect in this model. Hence, actors never overestimate possibilities for support exchange or the attractiveness of their potential exchange partners.

With the assumption of a commonly known shadow of the future, a rational actor i uses the *cooperation condition* to predict whether cooperation can be attained with a particular partner *j*. Actor i expects to attain the reward of support exchange with *j*, $\mathrm{U}(R_{ij})$, if the cooperation condition is satisfied for the pairing (ij). At the same time, i expects zero utility in a relation with a partner with whom cooperation is unattainable. These assumptions suffice to strictly derive an intuitively straightforward result.

The effect of risk preferences on partner attractiveness. Consider the range of partners for whom the cooperation condition is satisfied for a focal actor i. The attractiveness of a potential partner j for i decreases with j's neediness. This is true for all risk preferences ρ. More technically, this follows from:

$$\forall \rho: \frac{\partial R_{ij}}{\partial n_j} < 0, \text{ if } R_{ij} > P_{ij} \text{ for both actors.} \tag{5}$$

Proof: See appendix.

Figure 3 illustrates the implications for the effect of risk preferences on partner attractiveness for the case represented by Figure 2 (B = 4, E = 1, $\alpha \leq 0.903$).

Figure 3 shows that, within the range where cooperation is feasible, actors prefer exchange relations with partners that need as little help as possible, regardless of their risk preference. At the same time, the range of actors who are more attractive than no support exchange at all gradually shrinks as the risk parameter ρ increases. To illustrate partner attractiveness, I discuss the effect of Alter's neediness, n_j, on Alter's attractiveness, for the case of Ego's neediness fixed at n_j. Figure 3 demonstrates that with $\rho = -2$, potential partners of Ego have zero attractiveness as soon as their neediness falls below approximately $n_j = 0.2$ or it exceeds $n_j = 0.8$. Ego may be too needy relative to Alter's neediness ($n_j > 0.2$), so that a shadow of the future of $\alpha = 0.903$ is not large enough to deter Alter's defection. Conversely, Alter may be too needy relative to Ego's neediness ($n_j > 0.8$), so that Ego fails to resist the temptation. Between these extremes, Figure 3 reveals a negative slope for the effect of Alter's neediness, α, on Alter's attractiveness. For $n_i = 0.5$ and $\rho = -2$, Alter's attractiveness declines from $R_{ij} = 1.7$ at $n_j = 0.2$ to approximately $R_{ij} = 0.01$ at $n_j = 0.8$. The figure shows that the same qualitative effect obtains regardless of Ego's level of neediness and regardless of the risk parameter ρ. At the same time, the range of neediness levels that are attractive as partners from Ego's point of view shrinks as ρ increases. Moreover, the difference in attractiveness between the best partner and no support at all declines with increasing ρ. With $\rho = 0$, only partners between approximately $n_j = 0.22$ and $n_j = 0.78$ are attractive for an Ego with $n_i = 0.5$ (as compared to approximately $n_j = 0.2$ and $n_j = 0.8$ for ρ =

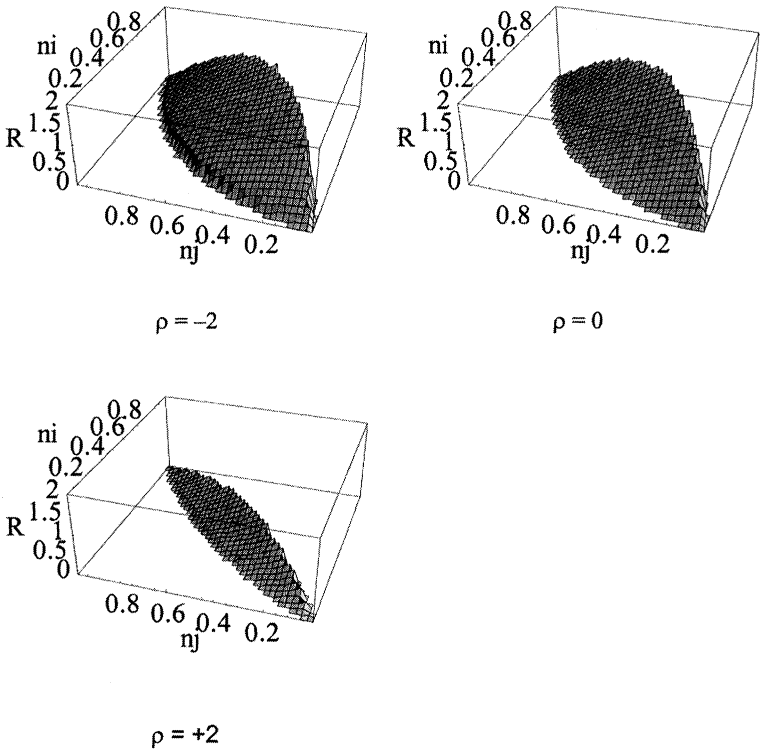


Figure 3. Partner attractiveness in terms of the expected outcome from an exchange relation, charted as a function of combination of neediness levels (n_i, n_j) for three different levels of the risk parameter ρ

–2). With $\rho = 2$ this range shrinks further to the region between about $n_j = 0.36$ and $n_j = 0.64$. Correspondingly, the difference in utility obtained with the best and the worst partner available declines from 1.69 for $\rho = -2$ to 1.42 for $\rho = 0$ and 0.69 for $\rho = +2$.

To summarize, results of the game theoretical model of risk effects in the repeated support game *without partner selection* are in line with earlier analyses. The more risk averse actors are, the less restrictive are the conditions under which they can attain conditional cooperation. The model also indicates how risk preferences might shape partner selection. The more ready actors are to take risks, the smaller is the range of partners that they find attractive enough to embark on any support exchange at all. This suggests that risk preferences may have a profound effect both on the level of spontaneous cooperation and on structural characteristics of a help exchange network. However, to assess these effects, assumptions are required that specify how individuals make partner selection decisions.

3. Models of Partner Selection in Support Networks

This section presents the model of the partner selection process in a social support network. In 3.1, I discuss the general framework that I use, the cellular automata framework. Section 3.2 specifies assumptions about interaction structure and partner selection options in a support network. Finally, in 3.3, I describe the assumptions about actors' actual partner selection strategies. In this approach, partner selection is not modeled as a strictly rational decision. Instead, I describe in 3.3 two different partner selection *heuristics* that I will compare in the simulations, the *best outcome heuristic* and the *lottery heuristic*.

3.1 The Cellular Automata Framework

To model partner selection, I employ a *cellular automata* (CA) framework (cf. Hegselmann and Flache 1998). In this framework, the support network is embedded in a *two-dimensional cellular grid*. The neighbor cells of a particular location constitute the occupant's neighborhood. I assume that actors simultaneously play support games with all neighbors in their neighborhood. However, not all sites on the grid are occupied. This allows partner selection to be modeled in terms of migration. More precisely, I assume that actors attain a migration chance from time to time. A migration chance is the opportunity for an actor to leave his present location and to move to a free location in a neighborhood with more attractive partners. Finally, I use computer simulation to derive from actors' repeated migration decisions the dynamics and structure of the emergent support network.

I employ the CA framework because it provides an easy to handle tool by which to capture three characteristic features of support networks: locality, overlapping neighborhoods, and interdependence of numerous individual partner choices (cf. Hegselmann and Flache 1998). Support networks are characterized by *locality*, because actors' outcomes are primarily affected by the small fraction of network members that are directly related to a focal individual. Moreover, partner selection may be locally restricted to a certain degree, because both accessibility of information and costs of migration may increase with actors' distance from a potential new position in the network. At the same time, local *neighborhoods* in support networks may often *overlap*, because actors may be directly or indirectly related to the same exchange partners. Finally, support networks may confront actors with *interdependence of numerous individual partner choices*. For example, relationships with strong members may be a scarce good in support networks, because the number of actors competing for these relationships may exceed the number of partners that strong actors are willing to support. As a consequence, an actor occupying a 'slot' in the personal network of a strong member may restrict the partner choices of numerous others and vice versa. While the CA framework allows locality, neighborhood overlap and interdependence of individual choices in a support network to be modeled straightforwardly, the framework also imposes a number of potentially restrictive simplifications. For example, the model assumes homogeneity in the maximal number of neighbors of an individual actor. I discuss in the concluding section how simplifications like this one may affect the analysis. In the remainder of this section, I describe how I use the CA framework to model support networks.

3.2 Interaction Structure and Partner Selection Options

Interaction Structure. In the cellular world, actors 'live' at the surface of a *torus*, so their world can be represented as a checkerboard without borders. Individuals simultaneously and independently participate in a repeated support game with every member of the *interaction window* of their present cell. The total outcome they attain in one iteration of the game is simply the sum of the outcomes of all support games they are involved in. I call this sum the *location outcome* Γ. Below, I discuss how risk preferences affect the utility that actors effectively derive from the location outcome. Figure 4 illustrates the interaction window. The interaction window is modeled as a von Neumann neighborhood, that is, neighbors are the adjacent cells in the west, north, east, and south of the focal cell. However, cells in the interaction window are not necessarily occupied with individuals. To model migration opportunities, I assume that there are fewer group members than there are locations on the checkerboard. Accordingly, the 'game' Ego plays with an empty cell always yields a utility of zero per iteration.

Partner Selection Options. From time to time individuals get the chance to select new partners, that is, to migrate to a new neighborhood. More precisely, the simulation consists of a number of consecutive periods. In every period, every individual receives a migration option with an *exogenous migration probability m*. Migration options are evaluated and/or used in *sequential* order according to the results of the lottery. Individuals who do not receive a migration option play one iteration of all their support games in the corresponding period. Individuals who have the chance to migrate may move to a new location *and* then immediately play the first iteration of the support games with their new neighbors. However, individuals may also decide not to make use of the migration option and just continue the support games with their present neighbors. To model locality and scarcity of partners, I assume that migration can only occur within a certain *migration window* and *only to vacant destination cells*. Moreover, the information that actors have about location and neediness levels of other members is restricted to the migration window. As Figure 4 shows, an individual that received a migration option is located in the center of its migration window. For simplicity, I assume that the window is a square of an odd size that is equal for all individuals.

3.3 Migration Heuristics: Best Outcome versus Lottery

To model boundedly rationality in migration behavior, I assume that actors follow plausible heuristics rather than perfectly rational migration strategies. As assumptions about behavioral heuristics

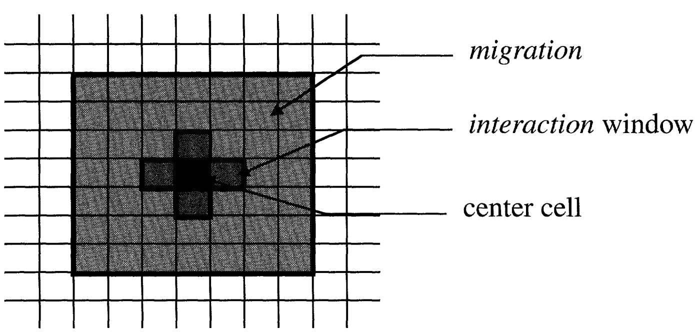


Figure 4. Basic windows in the cellular world

are necessarily to some degree arbitrary, I decided to compare two different heuristics that vary in the degree to which risk preferences affect migration behavior. Broadly, both migration heuristics apply a rule that may be characterized as myopic optimization: 'move to the network position that maximizes utility in the *present* network structure and neglect possible future changes in the network'. The main difference between the two heuristics lies in how actors' risk preferences affect utility comparisons individuals make between potential new locations and their present position in the network. The *best outcome heuristic* assumes that actors always prefer a location with a higher location outcome to a position with a lower location outcome, regardless of whether comparisons concern their present position in the network or only potential new locations. In this model, risk preferences only affect *how much* utility actors actually expect to gain from a particular migration move, but there is no doubt that they will move if they find a location with a higher outcome. In the *lottery heuristic*, I implement the assumption that the actors' decision is only partly determined by comparison of outcomes. In addition, risk-averse actors have a conservative bias towards staying at their present location, whereas risk-seeking actors are more inclined towards changing their network position.

Both migration heuristics assume that actors do not anticipate their own and their neighbors' migration behavior when they assess the shadow of the future in support games. Instead, actors use the pessimistic baseline guess that every migration option will be seized. Every player i then checks whether the cooperation condition is satisfied for the ensuing shadow of the future of $\alpha = (1 - m)^2$ with respect to a particular neighbor j. If the cooperation condition is satisfied for the combination of neediness levels (n_i, n_j), the neighbors will support each other and expect to be supported in the next iteration. Otherwise, both players will defect and expect each other to defect. I assume that actors use the pessimistic guess of α to anticipate whether potential new neighbors will cooperate in future support relationships. More precisely, in this analysis every actor knows instantly and perfectly *all individuals' positions and the neediness levels of all (real or potential) neighbors in the migration window*. Moreover, actors are aware of the outcomes and utilities of the repeated support game both from their own and their partners' point of view. In the migration heuristics, actors make use of this knowledge to assess and compare exchange outcomes at their present location and potential future positions in the network.

The Best Outcome Heuristic. The best outcome heuristic assumes that risk preferences shape the utility function U' that maps the location outcome Γ on the utility an actor obtains from a particular location. In principle, this is the same function that was used in Section 2 for modeling the effects of risk preferences on the utilities obtained from the support game. The only difference is the interval $[\Gamma_{min}, \Gamma_{max}]$ in which the location outcomes are defined. The outcome for the worst possible case, $\Gamma_{min} = 0$, is obtained when an actor occupies a position where he has no neighbors at all or only neighbors with whom no cooperation can be established. The best outcome, Γ_{max}, arises when an actor is surrounded by four members of the lowest neediness level with which cooperation is still available for him. Obviously, Γ_{max} varies with both actors' own neediness and the common risk parameter ρ. Equation (5) formalizes the function. Figure 5 shows how the risk parameter ρ affects the shape of the utility function $U'(\Gamma)$.

$$U'(\Gamma) = \Gamma_{max}\left(\frac{\Gamma}{\Gamma_{max}}\right)^{2\rho} \qquad (6)$$

The basic rule of the best outcome heuristic is extremely simple: 'move to the location with the highest location utility $U'(\Gamma)$ that is available in your migration window'. There are two further specifications: 1) only move if the best alternative is strictly better than your present location and 2) if there is more than one equally good best alternative then pick one of the best alternatives at random. These rules immediately imply that under the best outcome heuristic the outcome of a migration decision is completely determined by the location outcomes that are involved. More precisely, if an actor compares two locations with different location outcomes, then he will always prefer the location with the higher outcome, regardless of his risk preference. The reason is that under the best outcome heuristic, location utilities are strictly increasing in location outcomes. Hence, risk preferences affect partner selection only through their effect on the location outcomes themselves, which – in turn – ensue from the effect of risk preferences on the conditions for cooperation in the repeated support game.

The Lottery Heuristic. The lottery heuristic models the assumption that actors perceive of their present location as a relatively stable 'safe bet', whereas they consider alternative positions as risky gambles that contain unknown probabilities for both considerable improvements or severe losses after migration. This heuristic may be justified with the assumption that actors' behavior reflects previous experiences with support networks that are more or less in equilibrium. In such networks, most actors are in positions that can no longer be improved by changing partners. Migrants have small chances of improving their network position, but they may face a considerable risk of ending up with a location that is worse than the one they abandoned.

To model the lottery heuristic, I use again the utility function U'. I then assume that the location utility $U'(\Gamma)$ yields the utility that actors derive from the outcome of their present location, Γ. However, with respect to alternative locations, actors are assumed to take the location outcome after migration to the alternative, Γ', to estimate the *expected utility* of the related gamble. Accordingly, the basic rule of the best outcome heuristic is this: migrate to the alternative location with the largest location outcome Γ', if the *estimated expected utility* Γ' of this location is larger than the utility you derive from the outcome of your present location, Γ, that is, $\Gamma' > U'(\Gamma)$. Otherwise, stay at your present location. Again, I assume that if there is more than one equally good best alternative, actors pick one of the best alternatives at random. Obviously, the best outcome heuristic and the lottery heuristic are equivalent for the case of risk-neutral preferences ($\rho = 0$).

For illustration of this migration rule, consider the following simplification of the actors' decision situation. Think of the alternative location as a gamble G with an unknown probability p to 'win' after migration the best outcome available, Γ_{max}, and probability $(1-p)$ to end up with the worst possible outcome $\Gamma_{min} = 0$. I assume that actors do not know the probability p, but they use the outcome they would attain immediately after migration, Γ', as an indicator of the expected outcome of the gamble. Hence, actors assume $\Gamma' = p\,\Gamma_{max}$, or $p = \Gamma'/\Gamma_{max}$. With this assumption, the *expected utility* of this gamble is $EU(G) = (1-p)U'(\Gamma_{min}) + pU'(\Gamma_{max}) = \Gamma'$. By contrast, the present location represents a subjectively safe bet with the certain 'price' of $U'(\Gamma)$. Hence, the actor prefers the new location if $\Gamma' > U'(\Gamma)$ and otherwise he stays at the present location.

Figure 5 demonstrates how risk preferences shape migration decisions under the lottery heuristic. The figure represents actors' comparison of a present location with location outcome Γ_+ to an alternative position with a higher location outcome Γ_{+}. As the figure shows, a risk-averse actor may not necessarily prefer the alternative location, despite its higher outcome. In the example, the estimated expected utility of the alternative location, Γ_+, clearly falls below the utility that a risk-averse actor with $\rho = -2$ derives from his present location, $U'_{\rho=-2}(\Gamma)$. Moreover, the smallest location outcome for which the actor is at least indifferent between his present position and the alternative, $\Gamma_{indiff(\rho=-2)}$, clearly exceeds the outcome of his current position by far. By contrast, as Figure 5 shows, a risk-seeking actor with $\rho = +2$ clearly prefers the alternative position to his present one, that is, $U'_{\rho=-2}(\Gamma) < \Gamma_+$. Moreover, for the risk-seeking actor even locations with a considerably smaller location outcome than the present one are attractive enough to let him migrate. Even for an alternative location with an outcome as small as $\Gamma_{indiff(\rho=+2)}$ in Figure 5, a risk-averse actor still is at least indifferent between his present position with outcome Γ and the potential alternative.

Risk Preferences and the Dynamics of Support Networks: Simulation Results

This section presents computer simulations of the dynamics of support networks. The central question I tackle here is whether and how variations in individual risk preferences affect the level of cooperation in a help exchange network and the structure of the network. For comparison, the simulations use a baseline scenario where risk-neutral actors ($\rho = 0$) can attain an extended support network that is characterized by a relatively high degree of stability.

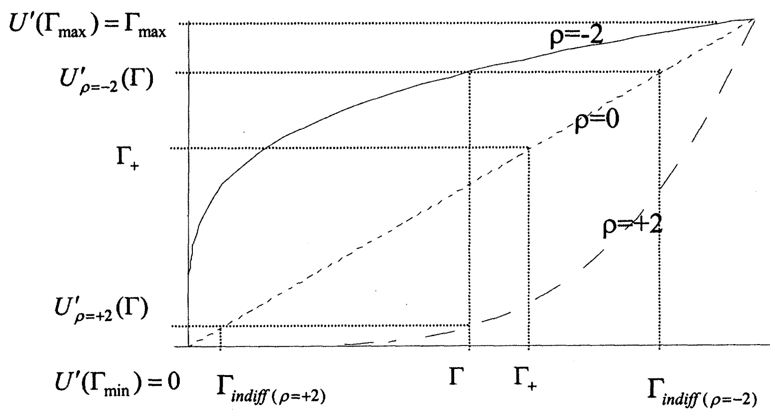


Figure 5. Comparison of a present location and an alternative position under the *lottery heuristic*

For this scenario, I assume a migration probability of $m = 0.05$ per period.[8] Furthermore, in every simulation run all individuals are initially randomly distributed in the cellular grid. Finally, for simplicity I assume that the population of the group consists of only a small number of different *neediness classes*. All members within neediness class i have equal neediness, n_i. More concretely, the group comprises nine neediness classes with $n_1 = 0.1$, $n_2 = 0.2, \ldots,$ $n_9 = 0.9$. Table 2 summarizes assumptions underpinning the simulations.

To assess the effects of risk preferences, first I use the model with the best outcome heuristic (4.1) and then apply the model in combination with the lottery heuristic (4.2).

4.1 The Best Outcome Heuristic: Results

In this analysis, I proceed in two steps. First, I compare selected scenarios representing qualitatively different levels of the risk parameter. Then I present an overview of the effects of risk preferences. For this, I show how outcome variables such as the density of the support network and the collective outcome from support exchanges are affected when the risk parameter gradually shifts across the range between strong risk aversion ($\rho = -3$) and high readiness to take risks ($\rho = +3$).

4.1.1 Scenarios. As a baseline, I simulate the scenario of risk-neutral actors ($\rho = 0$). Note that the results for this scenario are the same for the best outcome heuristic and the lottery heuristic. Subsequently, I compare the two extreme cases of strong risk-aversion ($\rho = -3$) and high readiness to take risks ($\rho = +3$). In these simulations, I evaluate networks in terms of the aggregated outcome, A, that is, individual outcomes per iteration summed across all dyads in the

Table 2. Assumptions of the simulations

Basics:	
interaction window:	von Neumann neighborhood
migration window:	11×11 with the focal individual in the center.
world:	21×21 (torus)
Class structure:	35 individuals per neediness class $\Rightarrow$
	a total of 315 individuals / 136 empty sites.
	All individuals have the same risk-parameter ρ.
Outcomes:	$B = 4, E = 1 \Rightarrow$ *benefit / effort* $= 4$
Probability for getting migration option:	$m = 0.05 \Rightarrow \alpha = 0.903$

network. Aggregated outcome is an indicator of the degree of cooperation in the network as a whole. To explain, with $B > E$ every unit of support exchanged in some dyad of the network increases aggregated outcome, because the benefit of the help exchange to the recipient exceeds the costs of the helper. Hence, the larger the aggregated outcome, the more support group members receive on average from their peers.

Figure 6b represents the pattern of a support network as it typically emerges under risk neutrality ($\rho = 0$) from the initial random configuration after 1,000 simulation periods. For interpretation of Figures 6 and 8, note the following:

(i) White cells are empty cells.
(ii) Short white lines connecting two actors indicate bilateral cooperation.
(iii) Different gray levels represent different neediness classes, as described by the legend at the bottom of the figures ($n_1 = 0.1$, $n_2 = 0.2, \ldots, n_9 = 0.9$).

Risk neutrality ($\rho = 0$). Figure 6b demonstrates that a *dense solidarity network* can arise under risk-neutral preferences. The density of the support network is seen in that almost every member of the population has one or more support relationships with some other actor. Under risk neutrality, the average individual has 3.52 of 4 possible support partners (mean value of 10 replications with a standard deviation of 0.06). In particular, even most of the 'unattractive' actors with high neediness are embedded in support relations. On closer inspection, however, the network reveals a distinct *onion-like segregation pattern.* Clusters of members of the least needy Class 1 tend to form the core of the 'onion', around which a 'shell' has emerged that primarily consists of members of neediness Class 2. This shell, in turn, is surrounded by a further shell consisting of members of Classes 3 and 4, and so forth. The further the distance from the core of the network, the larger the degree of neediness of the individuals located at this distance. At the periphery of the network, we almost exclusively find members of the highest neediness Classes 8 and 9. The network structure reflects the pattern of partner attractiveness under risk neutrality represented in Figure 3. All classes strive to occupy neighborhoods with a maximal number of members of the least needy class with whom support exchange is attainable. With the exception of the most attractive Class 1, however, the 'target classes' are searching for better partners as well. Needy classes are satisfied with neighboring stronger classes, but it is just that which makes the stronger classes willing to move. Eventually, a stable configuration arises when members of Class 1 flock together in a cluster surrounded by members of the next attractive Class 2. Members of the core cluster then have no further incentive to move, because they have already found the most attractive partners available. At the same time, members of the surrounding shell are not capable of invading the core cluster. As a consequence, they fail to find a better position than they already have. Similarly, the best that members of Class 3 can attain in this situation is a position close to the members of Class 2, and so on.

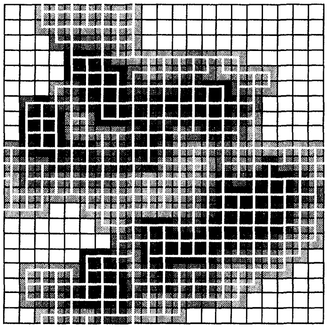
In terms of aggregated outcome, this patterns yields $A = 642$ in simulation period 1000. On average, an individual attains in this situation an outcome of approximately 0.6 per neighboring cell in the network of Figure 6b. For comparison, notice that a maximally needy player ($n = 1$) attains an outcome of 4 when he receives help from a player who is maximally capable of providing help ($n = 0$).

While the support network of Figure 6b shows that there is a considerable amount of cooperation between self-interested actors, it also indicates that the emerging network structure tends to exclude actors who have a high level of neediness. Broadly, the onion-like pattern resembles the 'Matthew principle' that seems to be reflected by the exchange patterns found in empirical research (Komter 1996). 'The less needy you are, the more you will be related to exchange partners who can give a lot of help.'

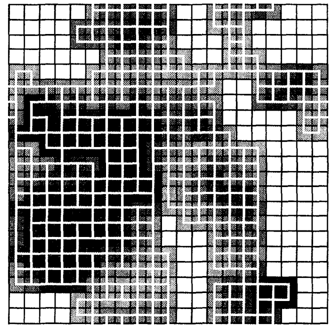
Strong Risk Aversion ($\rho = -3$). In line with previous analyses, the simulations show that risk aversion favors cooperation in the support network. Figure 6a reveals that the network structures for strong risk aversion and risk neutrality are similar. At the same time, there is a slight decline in the aggregate outcome from $A = 661$ under strong risk aversion towards $A = 642$ under risk neutrality. The explanation for the similarity in network structures can be found in the relatively small effect of risk preferences on the cooperation condition. There are only two pairings of neediness levels for which cooperation is attainable under strong risk aversion but not under risk neutrality. These are the combinations of Class 2 with 4 and 8 with 9. This small change in the network pattern also explains the decline in aggregate outcomes. The loss of the two combinations results in a network with a larger tendency towards similarity in neediness between exchange partners. However, the more dissimilar two exchange partners are in their need for help, the more help can in total be exchanged in a dyad (cf. Flache and Hegselmann 1999b: 81). The reason is that dissimilar dyads tend to match those actors who need much help with those who are best capable of providing help. Accordingly, the decline in aggregate outcome between strong risk aversion and risk neutrality goes in line with a slight decline in the average difference in neediness between exchange partners, from 0.15 under strong risk aversion down to 0.12 under risk neutrality.

High Readiness to Take Risks (ρ = +3). The simulations of this scenario confirm the trend indicated by the comparison of risk neutrality with strong risk aversion. Broadly, the more risk-seeking actors are, the less cooperation takes place in the support network and the more similar actors are in their neediness. Figure 6c shows that with $\rho = +3$ a 'class segregation' pattern emerges where actors exchange help exclusively with members of their own neediness class. The explanation of this can be found in the cooperation condition for $\rho = +3$. At this high level of the risk parameter, the condition is only satisfied for pairings with equal neediness class. Clearly, this considerably reduces the amount of help exchanged between partners as compared to risk neutrality and strong risk aversion. This is indicated by the decline in aggregate outcome down to $A = 501$, from the level of $A = 661$ and $A = 642$ under strong risk aversion and risk neutrality, respectively.

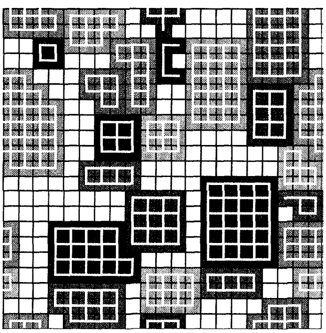
4.1.2 Systematic Variation of the Risk Parameter. I conducted a series of simulations where I vary the risk parameter in the interval between strong risk aversion ($\rho = -3$) and high readiness to take risks ($\rho = +3$) in steps of 0.5. At every level of ρ, I computed a number of outcome variables on the basis of the mean values of 50 replications, measured after 1000 simulation periods. To show how risk preferences shape cooperation, Figure 7 charts the effect of ρ on the aggregate outcome A as an indicator of the overall amount of exchange. To measure effects on the network structure, I use two indicators, the density of the support network and the average difference in neediness between exchange partners. Density is computed as the total number of mutually cooperative relations in the network divided by the maximal number of neighbors. In this simulation, the maximal number of neighbors is four times the number of inhabitants of the world. Note that density can never obtain its



a) (ρ = -3). Aggregated outcome A = 661.



b) (ρ = 0). Aggregated outcome A = 642.



c) (ρ = +3). Aggregated outcome A = 501.

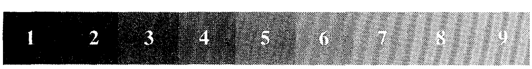


Figure 6. Support networks after 1000 simulation periods for three different levels of the risk-parameter. *Best outcome heuristic*

theoretical maximum of 1, because in a world with empty space there are always some actors who have fewer than four neighbors. The average difference in neediness is computed as the mean value of $|n_i - n_j|$ of all mutually cooperative relationships.

Figure 7 confirms the trend indicated by the above comparison of scenarios. Clearly, increasing readiness to take risks is detrimental to cooperation in the support network. The graph shows a continuous decline in aggregated outcome from approximately A = 660 at $\rho = -3$ to a level of about A = 500 at $\rho = +3$, a loss of 25% of all exchanges. The figure also shows that the decline is relatively small in the region of risk-aversion preferences, whereas the effect of ρ is stronger for risk-seeking preferences. Again, these trends can be explained by the effect of ρ on the cooperation condition. As also indicated by Figures 2 and 3, the range of combinations of neediness levels for which cooperation can be attained shrinks only slightly for negative values of ρ, whereas this range narrows down considerably as ρ increases in positive values. These effects on the cooperation condition correspond with the changes that risk preferences cause in the network structure. Figure 7 indicates that with increasing risk parameter, the network density gradually declines from approximately 0.9 to about 0.7. At the same time, partners in exchange relations become more alike in their neediness levels, as indicated by the shift from a difference of about 0.15 for $\rho = -3$ towards a difference of only 0.08 for $\rho = +3$. Clearly, the larger actors' risk preference, the less exchange relations they have on the average and the less help is exchanged in the average support relationship. This suggests that increasing readiness to take risks strengthens the tendency of support networks to exclude weak actors.

4.2 The Lottery Heuristic: Results

I proceed again in two steps, comparing selected qualitatively different levels of the risk parameter in the first step, and giving an overview of the effects of risk preferences in the second step.

4.2.1 Scenarios. The baseline scenario of risk-neutral actors ($\rho = 0$) is equivalent for the best outcome heuristic and the lottery heuristic.

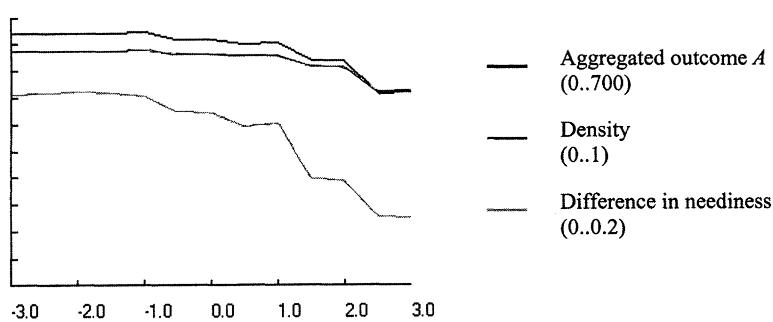


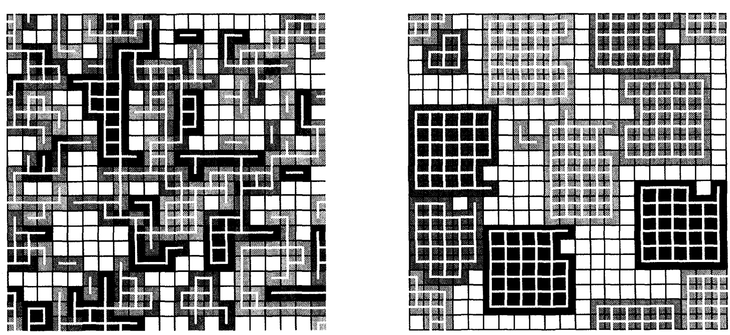
Figure 7 Effects of risk preference ρ on cooperation and network structure. *Best outcome heuristic*

Accordingly, I present here only the two extreme cases of strong risk aversion ($\rho = -3$) and high readiness to take risks ($\rho = +3$) and compare them to the results for risk-neutrality discussed above (Figure 6).

Strong Risk Aversion ($\rho = -3$). In contradiction to previous analyses, the simulations show that under the lottery heuristic risk aversion may have detrimental effects on cooperation. In a population of strongly risk-averse actors, the aggregate outcome is only $A = 465$, as compared to an aggregate outcome of $A = 642$ for risk-neutral actors. Inspection of the difference in neediness between exchange partners shows that the reason for this decline is not that actors tend to seek similar partners if they are risk averse. On the contrary, the average difference in neediness in an exchange relation drops from about 0.2 for risk-averse actors to approximately 0.15 for risk neutrality. This shows that exchange relations do not generate less exchanges, *if* actors find cooperative partners. However, comparison of the network densities indicates that finding partners is the real problem for actors with high risk aversion. The network is much sparser for risk-averse actors than for risk-neutral individuals, with a density of about 0.6 for $\rho = -3$ compared to a density of about 0.8 for risk-neutral preferences $\rho = 0$. The explanation for this trend lies in the contradicting effects that risk preferences have on the conditions for cooperation on the one hand and actors' 'mobility' in partner search on the other. As shown above, higher readiness to take risks reduces possibilities for cooperation between dissimilar neediness levels, creating a negative effect of ρ on cooperation in the network. At the same time, the lottery heuristic implies that with $\rho = -3$, risk-averse actors are easily 'satisfied' with their present position in the network. As Figure 8a shows, most actors found only one or two exchange partners. In fact, in the simulation run that generated this network, no further migration took place after only about 200 simulation periods. This indicates that after they found at least one or two exchange partners, strongly risk-averse actors hardly ever find alternative positions in their migration window that they deem attractive enough to move.

High Readiness to Take Risks ($\rho = +3$). The simulations of this scenario show that under high readiness to take risks, the networks emerging under the lottery heuristic and under the best outcome heuristic tend to converge. At this high level of ρ, the cooperation conditions allows only pairings between actors with equal neediness, as exemplified by the networks of the best outcome heuristic (Figure 6c) and by the lottery heuristic (Figure 8b). Moreover, risk-seeking actors are extremely mobile under the lottery heuristic. As a consequence they continue to migrate until a network structure emerged in which further migration can only result in considerable losses in outcome. A comparison of the aggregate outcomes between the two heuristics shows that this high mobility results in networks that are more optimized compared to the results of the best outcome heuristic (A = 550 vs. A = 501). Remarkably, the lottery heuristic implies that despite the strong reduction of cooperation possibilities between $\rho = -3$ and $\rho = +3$, the disadvantages of low mobility for highly rise-averse actors are so severe that the aggregate outcome of their network falls below the level obtained by their risk-seeking counterparts (A = 465 vs. A = 550).

4.2.2 Systematic Variation of the Risk Parameter. Again, the risk parameter is varied in the interval between strong risk aversion (ρ = –3) and high readiness to take risks (ρ = +3) in steps of 0.5. Outcome variables are computed in the same way as in the simulation series for the best outcome heuristic. Figure 9 shows the effect of ρ on the aggregate outcome A, the density of the support network, and the average difference in neediness between exchange partners.



a) (p = -3). Aggregated outcome A = 465. b) (p= +3). Aggregated outcome A = 550.

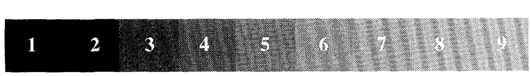


Figure 8. Support networks after 1000 simulation periods for two different levels of the risk-parameter. *Lottery heuristic*

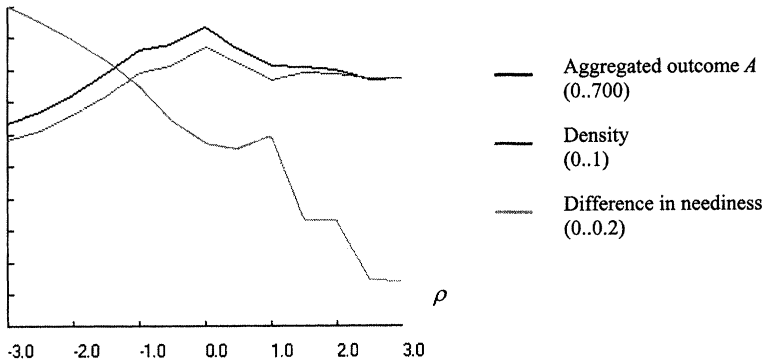


Figure 9. Effects of risk preference ρ on cooperation and network structure. *Lottery heuristic*

Figure 9 confirms the effects found in the comparison of scenarios. The figure shows that there are non-linear effects of risk preferences under the lottery heuristic. Broadly, two different regions of the parameter space can be distinguished. In the range of risk-aversion preferences, the dominant effect is that increasing ρ makes actors more mobile, but the related reduction in cooperation possibilities has only a relatively weak impact. As Figure 9 shows, this results in both an increasing density of the network and a higher level of cooperation as actors become more risk-seeking. Conversely, in the range of risk-seeking preferences, further increases in mobility cannot outweigh the negative effects of an increasingly restrictive cooperation condition. As a consequence, aggregate outcome and the density of the support network decline as individuals become even more risk-seeking. Comparison of Figures 7 and 9 makes clear that in this region of the parameter space the implications of the lottery heuristic and the best outcome heuristic are consistent, but the two models generate conflicting results for the range of risk-aversion preferences. Finally, the effects of ρ on the difference in neediness in Figure 9 indicate that there is a consistent trend towards similarity between neediness partners. For $\rho < 0$, this cannot outweigh the positive effects of more mobility on the level of cooperation. However, for $\rho > 0$ this results in fewer exchanges in the network, reducing the aggregate outcome.

5. Discussion and Conclusion

Risk-seeking preferences of individuals may support cooperation between actors in social dilemma situations. This argument has been put forward in the discussion of conditions for collective action (Lindenberg 1988). The underlying reasoning focuses on Kahnemann and Tversky's (1979) bounded rationality assumption that individuals are risk-seeking in losses and risk averse in gains, which may make them more willing to dare cooperation when avoidance of losses is at stake. However, following Raub and Snijders (1997), game theoretical analyses of cooperation in repeated games question this intuition. They draw on a perfect rationality framework to point out that in a repeated social dilemma situation, conditional cooperation is individually rational, as long as actors face a sufficient shadow of the future. In conditional cooperation, the relevant decision problem for a rational actor is whether he should try to unilaterally exploit a partner with whom he successfully cooperates, at the danger of losing future benefits from cooperation. In this perspective, risk-seeking actors are less cooperative than are risk-averse actors, because they are more inclined to put cooperative relationships at risk.

In this paper, I show that risk aversion may have both positive and negative effects on cooperation in networks of exchange relations. Following previous game theoretical analyses, I model dyadic exchange relations between two partners, Ego and Alter, as repeated social dilemma games. However, hitherto game theoretical analyses of risk effects within the perfect rationality framework have neglected two conditions that often characterize the social dilemmas occurring in networks of exchange relations. First, actors may differ in their attractiveness as exchange partners, and second, actors may to some degree be free to change partners. Accordingly, I used a model that adds these two conditions to the analysis of dyadic exchange relations and incorporates assumptions about the boundedly rational heuristics actors apply in the search for attractive exchange partners.

My analyses of the *isolated exchange relation* are in line with results of previous game theoretical studies. The more risk averse actors are, the less restrictive are the conditions for individually rational cooperation in repeated exchanges. I show that, with respect to partner search, this implies that individual risk aversion widens the range of potential exchange partners. Conversely, the more risk-seeking actors are, the narrower is the spectrum of attractiveness levels from which they are willing to choose partners.

To combine cooperation decisions with partner search, I use an adapted version of Hegselmann's (1998) cellular automaton framework (cf. Flache and Hegselmann 1999a, b). In this framework, actors maintain a number of exchange relations simultaneously. From time to time, actors can change all or at least some of their partners by migration to a new location on the cellular grid. The model assumes that migration strategies are based on boundedly rational heuristics of myopic optimization, because of the high complexity of the decision problem actors face. Simulations show that under risk-neutral preferences a dense exchange network with a distinct segregation pattern arises. Broadly, in this onion-shaped network actors tend to exchange with those who are similar in attractiveness. Actors who are most attractive form the core of the network, whereas the least attractive individuals are driven to the margin where they find mainly members of their own kind to exchange with. I then used two different assumptions about partner selection heuristics to assess the effects of risk preferences on this pattern of exchanges. In the best outcome heuristic, I assume that actors strictly prefer positions with a higher aggregate outcome. In the lottery heuristic, I assume that actors conceive of their present position in the network as a relatively safe bet, whereas they consider alternative locations as risky gambles.

Computer simulations show that under both heuristics individual risk preferences have a profound effect on the overall level of cooperation in the network and on the network structure. Under the best outcome heuristic, increasing readiness to take risks gradually reduces the range of cooperation possibilities for partners of different neediness. As a consequence, partners in exchange relations become more and more alike in attractiveness. This reduces both the density of the network and the overall amount of cooperation in the network. The reason is that according to the model most cooperation takes place between partners with different attractiveness levels. The more dissimilar actors are, the more those who need a high amount of resources, but have little to give, are matched with those who can give a high amount of resources, but have little need for it. In the end result, the aggregate outcome (as an indicator for overall cooperation) declines by about 25% in the simulations, when individual risk preferences shift from highly risk-averse to highly risk-seeking. Clearly, these results are consistent with previous game theoretical studies. However, with the assumption that actors apply the lottery heuristic, I find non-linear effects of risk preferences that were not anticipated by previous research. More precisely, under the lottery heuristic, risk-averse actors tend to stick to present relationships, even if better positions in the network could still be attained. As a consequence, strongly risk-averse actors fail to optimize their exchange network in terms of the amount of cooperative exchanges they conduct. If actors become more risk-seeking, this has two opposing effects. On the one hand, the range of partners shrinks with whom actors are willing to cooperate, but on the other hand individuals are more ready to change partners and thereby to optimize their exchange relations. The interplay of these two mechanisms generates a tipping point, approximately at the level where actors are risk-neutral. Below the tipping point, increasing readiness to take risks raises cooperation; beyond the tipping point, cooperation declines as actors become more risk-seeking.

The non-linear effects of individual risk preferences hypothesized by this study invite speculations of substantive interest for the analysis of solidarity in social support and research in interfirm relations. A recurring subject in the study of solidarity is the effects of decreasing individual embeddedness into local communities in modern societies. Classics such as Durkheim (1964) or Tönnies (1887) formulated concerns that this development could put traditional forms of solidarity under pressure. More recently, these concerns are reflected by the emphasis that communitarian theoreticians put on communities as the basis of social solidarity (Etzioni 1988). Societal and geographical mobility in particular are factors that reduce individuals' local embeddedness. The present study highlights potential interaction effects of these factors with the risk orientations that are prevalent in a society. In populations where actors are moderately risk averse or risk neutral, higher mobility may mainly lead to a reshuffling of solidarity relations that eventually optimizes overall efficiency of social support exchanges. In Durkheim's (1964) terms, this may be interpreted as a form of a successful transition from 'mechanic solidarity' to 'organic solidarity'. At the same time, the simulations of this paper suggest that this transition may be less successful in societies with predominantly risk-seeking individuals. Here, higher mobility may disrupt solidarity networks, because the possibility of profitable partner change undermines actors' willingness to invest in present exchanges. Clearly, this argument focuses on structural variation in risk preferences in terms of differences between populations rather than on differences between individuals within populations. Such structural differences in risk preferences, in turn, can be tied to empirically measurable differences in wealth between societies. The more wealthy members of a society are on average, the less they may be inclined to take risks in seeking for profitable social support exchanges and the less disruptive may mobility be for solidarity in social support.

In interfirm relations, effects of constraints on mobility may likewise be moderated by the overall level of risk aversion in an economy, which in turn may be tied to the overall level of capital available. The recent change in German tax laws on the sale of cross company holdings may provide an illustration (Beck 2000). Until recently, Germany imposed a prohibitive capital gains tax of 50% that was effective in discouraging changes of cross company holdings. This was generally seen as a measure that increased stability of the economy. In light of the present analysis, a reason for this might have been that with the relatively low after war capital stock, German firms might otherwise have been inclined to pursue risky merger strategies at the expense of collective efficiency. However, 'in recent years, [the cross holdings] have become less of an asset and more of a liability, but the capital gains tax discourages companies from unwinding them' (Beck 2000: 32). This led the German government to abolish the tax recently, with the expectation that this measure will increase the competitiveness of the German economy, because it will trigger a restructuring of cross holdings towards a more efficient system of interfirm relations. In terms of the present model of risk effects, abolishment of the tax may be interpreted as a response to decreasing risk-seekingness in a maturing economy. The expected effects of the reform may reflect the shift towards more profitable relational structures in moderately risk-averse populations that the simulation suggested with respect to effects of increasing migration chances.

The results of this analysis suggest that predictions about the effects of individual risk preferences on cooperation may change considerably when the dimension of partner selection in exchange networks is taken into account. In a similar vein, Flache and Hegselmann (1999b) showed that effects of individual altruism on cooperation strongly vary when partner selection is introduced to the analysis. That study argued that individual altruism favors cooperation in isolated dyads, whereas there are non-linear effects of individual altruism in exchange networks. Higher levels of altruism may foster social support in weakly altruistic groups, because individual altruism reduces the restrictiveness of conditions for cooperation. However, in strongly altruistic groups, altruism may actually reduce exchanges of social support. Strong altruistic motivations may drive overly compassionate weak members into mutual help, excluding stronger partners from support relations, at the expense of an efficient allocation of collective resources for social support. More in general, both the present analysis and Flache and Hegselmann's study of altruism indicate that the dimension of partner selection in exchange networks cannot be safely neglected when effects of individual preferences on cooperation in social dilemmas are addressed. The underlying reason, I argue, is the fundamental difference in the logic of cooperation decisions and partner selection decisions. In partner selection decisions, some degree of individual opportunism may be required to lead actors away from suboptimal exchange relations into more attractive positions in an exchange network. However, in this context, 'more attractive' also means that actors actually cooperate more, because they can attain higher profits from the exchange as compared to less attractive network positions. If only isolated exchanges are considered, this possibility cannot come into play. Here, higher levels of individual opportunism are always detrimental for cooperation.

The results of this study also provide additional support to the claim that slight variations in assumptions about individual preferences and decision mechanisms may have a profound effect on predictions of collective outcomes. Rational choice theorists tended to ignore this possibility for a long time, arguing both that small unsystematic deviations from rationality would cancel out in the aggregate (Hechter 1987) and that selective pressure and imitation would drive individuals to behave 'as if' they were rational (Friedman 1953). However, recently adherents of rational choice theory have become increasingly aware of the fact that macro predictions may often be highly sensitive to variation in micro assumptions. Voss (1990) has forcefully argued that taking into account 'bounded rationality' in rational choice analyses may considerably change outcomes of the analysis. A number of studies show strong effects on collective outcomes in social dilemmas of variation between (boundedly) rational decision-making and a simple model of reinforcement-driven behavior (Flache 1996; Flache and Hegselmann 1999a; Flache et al. 2000; Macy 1990). Finally, the analyses of effects of risk preferences of Raub and Snijders (1997; Snijders and Raub 1998) and van Assen (1998) and the present paper have demonstrated a similar sensitivity of macro outcomes with respect to variation in individual risk preferences.

I believe this accumulating evidence suggests that the systematic analysis of the effects of variation in micro assumptions on macro predictions should take a more prominent place in rational choice studies.

Although I believe that careful exploration of the sensitivity of rational choice explanations to changes in micro assumptions is warranted, I feel that this does not imply that we can have no general theories of collective behavior in a rational choice framework. All of the above-cited studies that revealed effects of micro assumptions on macro outcomes showed at the same time that important regularities of interest can be robust. A further example is Olson's (1965) prominent negative effect of group size on collective action. This effect can be derived both from backward-looking stochastic learning models (Macy 1991) and from game theoretical analyses in the orthodox rational choice framework (Raub 1988). In a similar vein, the present study shows that both variation in risk preferences and migration heuristics may leave important properties of the emerging exchange structures unchanged. In particular, the onion-like exchange patterns predicted by the simulations emerged under a large range of conditions together with the highly stable regularity of a negative correlation between individual neediness and the attractiveness of support relations attained by an actor.

Clearly, this study relies on a number of assumptions and simplifications that are potentially restrictive for the conclusions. In particular, the posited non-linear effects of risk aversion only occur under the assumption that individuals tend to perceive partner change as a risky decision. However, I believe that this assumption has some empirical plausibility. As discussed above, such a heuristic may be the result of the generalization of experiences that actors make with networks close to equilibrium, where members adopt more or less optimal positions in the exchange structure. In such networks, partner change is indeed a risky course of action. Moreover, it seems plausible that actors have more information about their present relations than about potential new partners. Accordingly, they can make a more accurate assessment of the range of possible outcomes of their current exchanges as compared to potential new relationships. Again, this might make partner change more risky than continuation of ongoing exchanges.

A second set of simplifications in this analysis relates to the modeling framework. My analysis uses a cellular automata framework that is characterized by a two-dimensional social space, a von Neumann neighborhood structure and a regular cell grid. I believe that the number of dimensions of the CA has little effect on the results. The dynamics of partner selection that generate non-linear effects of risk preferences are primarily driven by the logic of mutual selection in a population where actors differ in attractiveness and compete for scarce optimal exchange relations. This logic is independent of the number of dimensions of the social space in which networks are embedded. At the same time, outcomes might be affected by the assumption of a regular grid. To explain, it seems empirically plausible that network positions in exchange structures vary in their structural constraints on access to partners. For example, population density or access to transportation may vary between neighborhoods in a city. As a consequence, individuals may need more support per relation (and give more support per relation) in regions where fewer potential partners are accessible. In collaboration with other researchers, I began to use *irregular* grids in cellular modeling, grids that comprise cells with varying numbers of next neighbors (cf. Flache and Hegselmann 2000; Hegselmann et al. 2000). This work showed that the effects of heterogeneous structures of social support networks can be easily addressed in the CA framework. At the same time, we found that basic implications of the partner selection model, like the emergence of onion-like segregation patterns, are not affected by the assumption of irregular grid structures.

The assumption of a von Neumann neighborhood is potentially critical for the results of this study, because it precludes transitive exchange networks. If A is a neighbor of B and B is a neighbor of C, then in a von Neumann neighborhood A can never be a neighbor of C. However, in the present analysis I assumed independence of Ego's support exchanges with different Alters. Accordingly, the outcome of A's exchange with B is the same, whether A may also exchange with C or not. Clearly, the independence assumption may itself be regarded as implausible for exchanges of social support. Nevertheless, for the moment I plan to retain independence. The assumption greatly facilitates the game theoretical analysis, though there is no indication that substantive model implications change considerably, when a more complicated model with interdependent transitive exchange relations is employed. To explain, transitivity and interdependence may imply that exchanges are mutually exclusive to some degree. That is, if A helps B, A cannot help C any more. Or, if C receives support from A, C does not need support from B. However, even then cooperation in exchanges benefits from a longer shadow of the future, less needy actors are more attractive and the logic of partner selection still drives actors to compete for positions in neighborhoods with 'good partners'. Accordingly, I expect that the main conclusions of the simulation of risk effects do not change under transitivity and interdependence of exchanges.

While careful exploration of model limitations is required, I believe that this study revealed an interesting possibility. The effects of individual risk preferences on cooperation in exchanges may sensitively depend on the degree to which exchange relations are embedded in networks where actors vary in attractiveness and are to some degree free to change partners. This embeddedness seems empirically plausible for areas as different as exchanges of social support and technology cooperation between firms. In these areas, I argue, risk preferences that sustain cooperation in the isolated exchange between Ego and Alter may at the same time hamper cooperation in the network as a whole. Overly risk-averse actors may be highly cooperative in ongoing exchange relations but they may fail to optimize their relationships in terms of the overall amount of cooperative exchanges they can make.

NOTES

This study derives from earlier research financed by a grant from the German Science Foundation (DFG) to Rainer Hegselmann (University of Bayreuth, HE-1412/4–1). I am indebted to him for his inspiring remarks and our fruitful collaboration. The work that led to the present analysis and the compilation of the manuscript was made possible through a fellowship of the Royal Netherlands Academy of Arts and Sciences granted to the author. Furthermore, I thank Michael W. Macy, Marcel van Assen, and two anonymous reviewers for helpful comments.

1. Axelrod's term 'shadow of the future' refers to the expected duration of a future relationship from the point of view of the participants.
2. With this assumption I focus on situations where needy actors can reciprocate 'help' only in terms of a comparable sort of help, but not in terms of some *other* commodity valued by less needy partners. This precludes exchanges like that of care for affection (or reproduction chances) between parents and their children. While this assumption limits the scope of the analysis, I argue that it applies to a considerable range of social support situations. Moreover, for the present analysis it suffices to assume that there is one dimension along which actors vary in their attractiveness as exchange partners.
3. With this assumption, the support game used here is different from the original support game used in Hegselmann (1998). The main difference is that *bilateral* help is always possible in the game I use here, though the degree varies for different neediness class combinations. By contrast, the support game of Hegselmann (1998) allows in each period only *unilateral* help. As a consequence, that game

imposes *imperfect* information, which greatly complicates the game theoretical analysis. Obviously, there are different plausible approaches to model what in daily life is known simply as *mutual help*.

4. More precisely, the support game always guarantees $R > P$ for the player who is less needy, regardless of the combination of neediness levels. The proof is straightforward and will be supplied by the author on request.
5. A similar approach has been used by van Assen (1998). Strictly, the definitions of concave (convex) require that the utility function is twice differentiable and that the first derivative is larger than zero and the second smaller (larger) than zero. In the appendix I prove that the function U in Equation (2) satisfies these requirements.
6. The standard literature on utility theory shows rigorously that a utility function is concave (convex) if and only if actors always prefer (do not prefer) the certainty of obtaining some amount x to a gamble with the expected outcome of x (Kreps 1990).
7. The equilibrium is not necessarily a unique SPE. That is, I assume that players solve the problem of equilibrium selection and coordinate on this SPE.
8. Flache and Hegselmann (1998) and Hegselmann (1998) studied the effects of the migration rate, m, on the pattern of support networks between pure egoists. These studies find that increasing migration rates reduce the density of support networks and, eventually, lead to the total collapse of support relations when the migration rate exceeds a critical level. In the present paper I keep m constant, because I focus on the effects of risk preferences.

REFERENCES

Axelrod, R. 1984. *The Evolution of Cooperation*. New York: Basic Books.

Beck, B. 2000. 'Germany Surprises Itself.' In *The World in 2001*, ed. D. Fishburn, pp. 29–32. London: The Economist Newspaper Limited.

Durkheim, E. 1964 [1893]. *The Division of Labour in Society*. New York: The Free Press.

Etzioni, A. 1988. *The Moral Dimension. Toward a New Economics*. New York: The Free Press.

Flache, A. 1996. *The Double Edge of Networks. An Analysis of the Effect of Informal Networks on Cooperation in Social Dilemmas*. Amsterdam: Thesis Publishers.

Flache, A. and R. Hegselmann. 1999a. 'Rationality vs. Learning in the Evolution of Solidarity Networks: A Theoretical Comparison.' *Computational and Mathematical Organization Theory* 5(2):97–127.

Flache, A. and R. Hegselmann. 1999b. 'Altruism vs. Self-Interest in Social Support. Computer Simulations of Social Support Networks in Cellular Worlds.' *Advances in Group Processes* 16: 61–97.

Flache, A. and R. Hegselmann 2000. Final Report of the DFG Research Project 'The Dynamics of Social Dilemma Situations' [Abschlussbericht zum DFG Projekt 'Dynamik sozialer Dilemma-Situationen]. University of Bayreuth, Department of Philosophie. Available at: (http://www.uni-bayreuth.de/departments/philosophie/deutsch/dfg).

Flache, A., M.W. Macy and W. Raub 2000 'Do Company Towns Solve Free Rider

Problems? A Sensitivity Analysis of a Rational-Choice Explanation', in W. Raub and J. Weesie (eds) *The Management of Durable Relations: Theoretical and Empirical Models for Households and Organisations*. Amsterdam: Thela Thesis.

Friedman, M. 1953. *Essays in Positive Economics*. Chicago, IL: University of Chicago Press.

Friedman, J. W. 1971. 'A Non-Cooperative Equilibrium for Supergames.' *Review of Economic Studies* 38: 1–12.

Friedman, J. W. 1986. *Game Theory with Applications to Economics*. New York: Oxford University Press.

Hall, A. and B. Wellman. 1985. 'Social Networks and Social Support.' In *Social Support and Health*, eds S. Cohen and S. L. Syme, pp. 23–41. New York: Academic Press.

Hechter, M. 1987. *Principles of Group Solidarity*. Berkeley, CA: University of California Press.

Hegselmann, R. 1998. 'Experimental Ethics – A Computer Simulation of Classes, Cliques and Solidarity.' In *Preferences*, eds. C. Fehige and U. Wessels, pp. 298–320. Berlin: De Gruyter.

Hegselmann, R. and A. Flache. 1998. 'Understanding Complex Social Dynamics – A Plea For Cellular Automata Based Modelling.' *Journal of Artificial Societies and Social Simulation* 3: http://www.soc.surrey.ac.uk/JASSS.

Hegselmann, R., A. Flache and V. Möller. 2000. 'Cellular Automata as a Modelling Tool: Solidarity and Opinion Formation.' In *Tools and Techniques for Social Science Simulation*, eds. R. Suleiman, K. G. Troitzsch and N. Gilbert, pp. 151–78. Heidelberg: Physica.

Kahneman, D. and A. Tversky. 1979. 'Prospect Theory: an Analysis of Decision under Risk.' *Econometrica* 47: 236–91.

Kollock, P. 1993. 'An Eye for an Eye Leaves Everyone Blind: Cooperation and Accounting Systems.' *American Sociological Review* 58: 768–86.

Komter, A. 1996. 'Reciprocity as a Principle of Exclusion.' *Sociology* 30 (2): 299–316.

Kreps, D. M. 1990. *A Course in Microeconomic Theory*. New York: Harvester.

Lindenberg, S. 1988. 'Contractual Relations and Weak Solidarity: The Behavioral Basis of Restraints on Gain Maximization.' *Journal of Institutional and Theoretical Economics* 144: 39–58.

Macy, M. W. 1990. 'Learning Theory and the Logic of Critical Mass.' *American Sociological Review* 55: 809–26.

Macy, M. W. 1991. 'Learning to Cooperate: Stochastic and Tacit Collusion in Social Exchange.' *American Journal of Sociology* 97: 808–43.

Myerson, R. B. 1991. *Game Theory. Analysis of Conflict*. Cambridge, MA: Harvard University Press.

Olson, M. 1965. *The Logic of Collective Action*. Cambridge, MA: Harvard University Press.

Podolny, J. M. and K. L. Page. 1998. 'Network Forms of Organizations.' *Annual Review of Sociology* 24: 57–76.

Raub, W. 1988. 'Problematic Social Situations and the Large Number Dilemma.' *Journal of Mathematical Sociology* 13: 311–57.

Raub, W. and C. Snijders. 1997. 'Gains, Losses and Cooperation in Social Dilemmas and Collective Action: The Effects of Risk Preferences.' *Journal of Mathematical Sociology* 22: 263–302.

Simon, H. A. 1955. 'A Behavioral Model of Rational Choice.' *Quarterly Journal of Economics* 63: 129–39.

Snijders, C. and W. Raub. 1998. 'Revolution and Risk. Paradoxical Consequences of Risk Aversion in Interdependent Situations.' *Rationality and Society* 10: 403–25.

Taylor, M. 1987. *The Possibility of Cooperation.* Cambridge: Cambridge University Press.

Tönnies, F. 1887. *Gemeinschaft und Gesellschaft. Grundbegriffe der reinen Soziologie.* Leipzig.

Van Assen, M. 1998. 'Effects of Individual Decision Theory Assumptions on Predictions of Cooperation in Social Dilemmas.' *Journal of Mathematical Sociology* 23 (2): 143–53.

Voss, T. 1990. *Eine Individualistische Theorie der Evolution von Regeln und einige Anwendungsmöglichkeiten in der Organisationsforschung* [An individualistic theory of the evolution of regulations and some applications to organization research]. München: Sozialwissenschaftliche Fakultät der Universität München (Habilitation).

Wu, J. and R. Axelrod. 1995. 'How to Cope with Noise in the Iterated Prisoner's Dilemma.' *Journal of Conflict Resolution* 39: 183–9.

ANDREAS FLACHE is currently postdoc at the ICS at the University of Groningen. His present research is made possible by a fellowship of the Royal Netherlands Academy of Arts and Sciences. In 1996, he took his PhD in sociology at the ICS. From 1996 to 1999 he worked at the Department of Philosophy of the University of Bayreuth, Germany. His present research addresses the relationship of network embeddedness with group solidarity. His further research interests concern micro foundations of solidarity, game theoretical modeling and computer simulation of co-operation and solidarity in groups as well as experimental research in sociology.

ADDRESS: ICS – University of Groningen Grote Rozenstraat 31. NL-9712 TG Groningen. The Netherlands [email: a.flache@ppsw.rug.nl]

Appendix

Proposition A1: The function $U(x) = T\left(\frac{x}{T}\right)^{2^\rho}$, $x > 0$ (see Equation (2)) is concave for $\rho > 0$ and convex for $\rho < 0$.

Proof: The first derivative of U in x is $\frac{\partial U(x)}{\partial x} = 2^\rho \left(\frac{x}{T}\right)^{2^\rho - 1}$. This term is always larger than zero by virtue of the assumption $x > 0$. The second derivative is $\frac{\partial^2 U(x)}{x^2} = \frac{2^\rho (2^\rho - 1)\left(\frac{x}{T}\right)^{2^\rho - 2}}{T}$. It is negative, if

$2^{\rho} < 1$, which is equivalent to $\rho < 0$. Accordingly, it is positive if $\rho < 0$. *Q.E.D.*

Proposition A2: The cooperation condition
The proof for the general form $\alpha'_{ij} = \frac{U(T_{ij}) - U(R_{ij})}{U(T_{ij}) - U(P_{ij})}$ has been given by Friedman. Applying the function U of Equation (2) to this result yields $\alpha'_{ij} = \frac{T_{ij} - T_{ij}(\frac{R_{ij}}{T_{ij}})^{2\rho}}{T_{ij}} = 1 - (\frac{R_{ij}}{T_{ij}})^{2\rho}$. Substitution of T and R by the definitions of Table 1 and Equation (1) yields the r.h.s. of Equation (3) in the cooperation condition. *Q.E.D.*

Proposition A3. Effects of risk-preferences on the cooperation condition.
The first derivative of α'_{ij} by ρ is
$\frac{\partial \alpha'_{ij}}{\partial \rho} = -2^{\rho}(\frac{B' - E'}{B'})\,\mathrm{Log}(2)\mathrm{Log}(\frac{B' - E'}{B'})$, where $B' = Bn_i(n_j - 1)$ and $E' = En_i(n_j - 1)$. We know that $0 < \frac{B' - E'}{B'} < 1$, because 1) $0 \leq n_i, n_j \leq 1$ implies that $B' < 0$ and $E' < 0$ and 2) the precondition $R_{ij} > P_{ij}$ is equivalent to $-B' > -E'$, which in turn implies $B' - E' < 0$. Hence, $\mathrm{Log}(\frac{B' - E'}{B'}) < 0$. Together, this implies that the term for $\frac{\partial \alpha'_{ij}}{\partial \rho}$ is positive, because it contains two negative and two positive subterms. *Q.E.D.*

Proposition A4. Effects of risk preferences on partner attractiveness.
In the range of partner neediness levels n_j where the cooperation condition is not satisfied, actor i obtains 0 utility from the exchange, that is, he is indifferent between partners. In the range where the cooperation condition is satisfied, partner attractiveness is equivalent to $U(R_{ij})$. The first derivative of $U(R_{ij})$ by n_j is
$\frac{\partial U(R_{ij})}{\partial n_j} = -\frac{(B' - E' + E(n_i - 1)2^{\rho})(\frac{B' - E'}{B'})^{2^{\rho} - 1}}{n_j - 1}$. with $B' = Bn_i(n_j - 1)$ and $E' = En_i(n_j - 1)$. As $0 < \frac{B' - E'}{B'} < 1$ (see proof of proposition A3), and $n_j - 1 < 0$, the first derivative of $U(R_{ij})$ by n_j is smaller than zero if the subterm $(B' - E' + E(n_i - 1)2^{\rho})$ is smaller than zero. This is the case because $B' - E' < 0$ (see proof of proposition A3) and $E(n_i - 1)2^{\rho} < 0$. *Q.E.D.*