

13 Relative deprivation *in silico*: agent-based models and causality in analytical sociology

Gianluca Manzo

Introduction

The concept of relative deprivation is one of the most frequently used notions in economics (see Clark *et al.* 2008), in social psychology (see Tyler *et al.* 1997: ch. 2; Walker and Smith 2001: ch. 1) and in sociology (see Cherkaoui 2001; Coleman 1990: ch. 8; Lundquist 2008). Despite its diffusion, formal analyses of the mechanisms generating rates and feelings of relative deprivation are far less common.¹

In sociology, the most notable exceptions are, on the one hand, Boudon's (1982: ch. 5; 1979: 52–6) analysis – later taken up by Kosaka (1986) and Yamaguchi (1998) – and, on the other, Burt's (1982: ch. 5, 191–8) contribution.

These analyses, however, have a different focus. The first group have the following characteristics:

1. They are interested in the rates of relative deprivation.
2. They tend to demonstrate that the relation between objective opportunity structure and proportion of dissatisfied actors can be both negative and positive.
3. They implicitly refer to actors who compare themselves with a given group as a whole (global comparisons).

By contrast, Burt's model can be characterized as follows:

1. It focuses on the individual feelings of deprivation.

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¹ Davis (1959) seems to be the first attempt to formalize the ideas at the heart of *The American Soldier*. His model is concerned with the proportion of deprived actors and it supposes completely socially unstructured comparisons between actors. The model, however, does not contain any generative mechanism of the rate of relative deprivation.

2. It does not address the question about the positive or negative nature of the relation between objective opportunity structure and the intensity of feelings of dissatisfaction.
3. It takes into account comparisons between people who are embedded in social networks (local comparisons).

My aim here is to develop a unified theoretical framework which enables us to analyze formally the relation between these different aspects at the same time. In particular, I will try to demonstrate two statements:

1. The four-way relation between the attractiveness of the goods at stake, the opportunity structure, the percentage of dissatisfied actors, and the intensity of their feelings of dissatisfaction may take a variety of forms except the most sought-after one, i.e. the “*more opportunities, less dissatisfied-and-less-intensely-dissatisfied actors*” pattern.
2. The presence of dyadic interactions can significantly modify certain aspects of this four-way relation such as it originally appears in a microcosm whose actors are entirely isolated and where only global comparisons are made.

Compared with the above-mentioned formal analyses, an additional distinctive trait here is that I have sought to solve these problems by programming and studying an agent-based model (Ferber 1999; Gilbert 2007; Miller and Page 2007).²

In the context of this book, this application serves a second purpose. The chapter is intended as an illustration of the potentialities of agent-based modeling as a methodological support for the two main aspects of the conception of causality analytical sociology is built on, i.e. “generativity” and “counterfactuality.”³

According to the first criterion, causal claims rest on the possibility to demonstrate that the relation between two happenings ultimately comes from an underlying bundle of structured triads “entities/

² This computational method has recently been singled out for its conceptual flexibility and computational power in economics (Axtell 2000; Epstein 2006; Tesfatsion and Judd 2006), finance (Mathieu *et al.* 2005), political science (Axelrod 1997; Cederman 2001), geography (Sanders 2007) and at least partially in sociology (Hummon and Fararo 1995; Macy and Flache 2009; Macy and Willer 2002; Sawyer 2003).

³ Agent-based methodology has recently been put on the analytical sociology agenda (Hedström 2005: ch. 6; Hedström and Bearman 2009). I discuss this link more deeply elsewhere (see Manzo 2007a, 2007b, 2010). Let us also notice that the elective affinities between generative epistemology and agent-based methodology have already been pointed out (Cederman 2005; Epstein 2006: chs. 1–2). By contrast, to my knowledge, no explicit bridge has yet been built between the counterfactual account of causality and agent-based models.

properties/activities,” that is to say a “mechanism” (see Machamer *et al.* 2000: 3). Such a conception of causality was first outlined by Harré (1972: 115–19, 136–7), who called it “generative theory of causality”; it then progressively spread in statistics (Cox 1992), economics (Simon 1979) and sociology (Boudon 1979; Fararo 1989, 2009; Goldthorpe 2001; Hedström 2004). Analytical sociology is programmatically building on this idea (see Hedström 2005: ch. 2; Hedström and Bearman 2009; Hedström and Swedberg 1998: 7).

On the other hand, the counterfactual account of causality basically states that the causal character of the relation between two happenings ultimately rests on the possibility to demonstrate that if, say, *X* had not occurred, *Y* would not have occurred. Deeply grounded in philosophy (see Lewis 1973 and, more recently, Woodward 2000), such a conception of causality has widely been accepted in economics earlier than in sociology (see Morgan and Winship 2007; Winship and Morgan 1999). As some recent contributions suggest (see Hedström and Udéhn 2009; Hedström and Ylikoski 2010), counterfactuals are also entering epistemological agenda of analytical sociology.

From a methodological point of view, “generativity” and “counterfactuality” raise two different, although related, problems. The generative criterion requires to demonstrate that a given set of loops between structures, behaviors and interactions produces the aggregate patterns of interest. An agent-based model allows to provide this demonstration. Its internal structure allows the design of multi-level artificial mechanisms while its dynamic makes it possible to transform the mechanism in a process, which is what one is looking for when one wants to determine what a mechanism is able to bring about.

On the other hand, the counterfactual criterion demands to evaluate the degree to which a given alteration of the mechanism at hand modifies the aggregate patterns of interest. Agent-based models allow to easily perform this task. When one explores the parameter space and the internal structure of an agent-based model, one is indeed studying the sensitivity of the outcomes to the mechanisms and its initial conditions. In this sense, this computational technique provides a powerful tool to create and analyze “potential outcomes” *in silico*.

It is worth noticing, however, that to claim that agent-based models represent flexible causally generative and counterfactual devices does not amount to state they are able to produce empirically validated causal statements on their own. In this regard, it is important to distinguish two steps:

1. the analysis of how posited mechanisms work and the high-level patterns they generate; and

2. the empirical validation of them.

The first task requires to construct microcosms which run in accordance with one or another set of rules capable of generating one or another set of individual and collective states. Here agent-based models are useful and necessary. By contrast, the second task is not specific to analytic sociology: it only requires injecting empirical information at the entrance to or exit from an agent-based model. We already have a broad spectrum of tools (qualitative and quantitative) for doing this.

To solve the problem of discovering real-world causal relations, we obviously have to integrate the two phases. But to claim that we should test a mechanism empirically before submitting it to rigorous formal study is to reverse the order in which the problems should be solved.⁴

The chapter is organized as follows. I first give an overview of the literature on relative deprivation and I posit some useful conceptual distinctions. I then present the theoretical structure of the agent-based model I built in order to study the rate and feelings of relative deprivation at the same time. Lastly, I discuss the computational results obtained by simulating this artificial society under several parameter settings. The conclusion summarizes the questions I have addressed as well as the main results and limitations of the analysis.

A useful analytical distinction: RD frequency and RD intensity

The empirical observations which gave rise to sociological literature on relative deprivation (hereafter noted RD) all noted an inverse relation between actors' perceptions of the conditions they act in and the "objective" quality of those conditions.⁵

Stouffer and his colleagues (1965 [1949]: vol. I, pp. 52, 125) were the first to use the concept explicitly to explain this seemingly paradoxical

⁴ I tried to satisfy both requirements in my analyses of educational inequalities in France and in Italy (see Manzo 2009a). Two other good examples of sociological empirically calibrated agent-based models are Hedström (2005: ch. 6) and Bruch and Mare (2006).

⁵ The most well-known is certainly the inverse correlation at the core of *The American Soldier* (Stouffer *et al.* 1965 [1949]: 251–2) between promotion rates in the army and subjective perception of opportunities for promotion. But, before *The American Soldier*, Tocqueville (1955 [1856]: bk. III, ch. 4, p. 176) had observed that "it was precisely in those parts of France where there had been the most improvement that popular discontent ran highest." Durkheim (1951 [1897]: bk. II, ch. v, p. 244) noted that "an unusual increase in the number of suicides is observed with this collective renaissance." After *The American Soldier*, Runciman (1966: 3) acknowledged that "dissatisfaction with the system of privileges and rewards in a society is never felt in an even proportion to the degree of inequality to which its various members are subject."

correlation. The hypothesis implicit in this “interpretative intervening variable,” as Merton (1957: 229) described it, is that actors’ assessments of their objective opportunities actually depend on their standards of comparison (Stouffer *et al.* 1965 [1949]: vol. I, p. 125).⁶

While empirical observation of a linear inverse relation between opportunity structure and people’s perceptions of those opportunities was what first motivated the use of the RD concept, the problem of how general that relation is has not yet been completely resolved.⁷

This problem is complex because it arises from two distinct but overlapping dimensions. On the one hand, the RD phenomenon involves two aspects; on the other hand, a large variety of mechanisms responsible for them can be at work.

On the first point, one should carefully distinguish between RD frequency – i.e. the proportion of actors who do not have what they want – and RD intensity: the strength of the feeling actors associate with this discrepancy (see Runciman 1966: 10; see also Elster 2007: 58). This suggests that the mechanisms that move a certain number of actors to perceive a discrepancy between reality and their desires may be different from those that engender their specific reactions to this assessment. From this in turn it follows that the relations between conditions of well-being and subjective perceptions of those conditions can take different forms depending on which aspect of RD is being studied and the type of mechanisms mobilized.⁸

⁶ Runciman (1966: 10) was the first to give a more developed definition: “We can roughly say that A is relatively deprived of X when (i) he does not have X, (ii) he sees some other person or persons, who may include himself at some previous or expected time, as having X (whether or not this is or will be in fact the case), (iii) he wants X, and (iv) he sees it as feasible that he should have X.” A pioneering definition developed in social psychology adds a fifth component: “lack[s] a sense of responsibility for failure to possess X” (Crosby 1976: Table 1).

⁷ The authors of *The American Soldier* themselves seemed aware of the problem: “To be conservative, we should limit our conclusion by saying that a force with relatively less promotion chances tended to have a larger proportion of men speaking very favorably of promotion opportunities than a force with greater promotion chances” (Stouffer *et al.* 1965 [1949]: 257). The point was mentioned in passing by Merton (1957: 237, n. 7): “presumably, the relationship is curvilinear, and this requires the sociologists to work out toward the conditions under which the observed linear relation fails to obtain.” Runciman (1966: 19–20) took up the point nearly ten years later: “this relation is both complicated and variable ... it can as well take the form of an inverse correlation as a direct one” (1966 247). In economics, the Easterlin paradox holding that “raising the incomes of all does not increase the happiness of all” (Easterlin 1973: 4) has been repeatedly analyzed (cf. Clark *et al.* 2008) to demonstrate that a positive relation between income and satisfaction with life does exist, not only at the individual level but also at the aggregate level and not only within a given country but also among countries (Wolfers and Stevenson 2008).

⁸ This analytic distinction appears clearly in contemporary social psychology definitions of RD: “a judgment that one is worse off compared to some standard; this judgment

On the second point, RD generative mechanisms can be inscribed in a basic analytic space using axes that correspond to the comparison reference points that actors choose (for a more specific analytical map, see Gambetta 1998: 114–19). Two main types are usually considered in social psychology (Tyler *et al.* 1997: ch. 2):

1. actor-specific reference points, namely one's own past condition or expectations (intrapersonal comparisons); and
2. reference points external to the actor, namely other individuals or groups (inter-individual and intergroup comparisons).

Recent studies have attempted to show that these two types of comparisons actually proceed from a single, more general type known as counterfactual comparisons: “comparisons of one's current outcomes with outcomes that one might have obtained but did not” (Olson and Roese 2002: 266).⁹

Compared with the statistical analysis of observational data (see Clark *et al.* 2008: 111–15), constructing formal models of RD-generating mechanisms and analyzing them deductively seems an attractive way of trying to establish what the form of the relation between opportunity structure and RD frequency/intensity is. This strategy indeed enables us first to establish all the outcomes logically associated with a given mechanism (or several), and, then, to locate, within this range of possibilities, the section of the real world covered by the empirical data under study.

As I said, Boudon's formal model suggested that the relation between opportunity and individual satisfaction can be both negative and

is linked, in turn, to feelings of anger and resentment” (Tyler *et al.* 1997: 17); “a subjective state that shapes emotions and cognitions and influences behavior” (Pettigrew 2002: 353).

⁹ From an historical point of view, we find intrapersonal comparisons in Tocqueville's *Old Regime and the French Revolution* (1955 [1857]: 177): “Dazzled by the prospect of a felicity undreamed of hitherto and now within their grasp, people were blind to the very real improvement that had taken place and eager to precipitate events”; “Patiently endured so long as it seems beyond redress, a grievance comes to appear intolerable once the possibility of removing it crosses men's mind” (see Cherkaoui (2005: ch. 1) for a perceptive reading of these mechanisms in Tocqueville's work). We also find intrapersonal comparisons, with astounding parallelism, in Durkheim's thinking: “Thus, the more one has, the more one wants, since satisfactions received only stimulate instead of filling needs” (Durkheim 1951 [1897]: 248); and “The less limited one feels, the more intolerable all limitation feels” (Durkheim 1951 [1897]: 254). Durkheim also seems to have been sensitive to intergroup comparisons: “Lack of power, compelling moderation, accustoms men to it, while nothing excites envy if no one has superfluity” (Durkheim 1951 [1897]: 254). The social comparison reference points at the heart of *The American Soldier* (Stouffer *et al.* 1965: 251) prompted Merton's analysis (1957: chs. VII and VIII) of the concept of “reference group.” Runciman (1966: 24–5) combined the two, positing a loop between a rise in individual expectations and a rise in actor reference group level.

positive, a point that has been confirmed by Kosaka's and Yamaguchi's re-analyses of the model. The mechanism which generates this result is simple: a combined set of rules, individual reasoning and interdependence structure that lead a certain number of actors to rationally hope to obtain more than they could objectively obtain (according to Gurr's (1970: 51) typology, this is a "aspirational deprivation" mechanism). In terms of the above distinctions between RD frequency and RD intensity, however, all these authors were only concerned with RD frequency. But what is the form of the relation between opportunity structure and RD intensity? Moreover, how are these three elements linked to one another and how is this threefold relation modified when actors are embedded in some sort of relational structures?

An agent-based model of RD frequency and RD intensity

To answer these questions, I programed an agent-based model which contains six components. While the first five simply generalize Boudon's original model, the sixth one introduces a new module which quantifies the disappointment, envy and regret which dissatisfied actors may feel when intrapersonal comparisons, population-based or neighborhood-based inter-individual comparisons and counterfactual reasoning are at work.¹⁰

1. *Agents' opportunity structure.* It is specified by the following elements: (a) a population of N agents; (b) a limited numbers of two types of goods, G^1 and G^2 ; (c) the sum of G^1 plus G^2 is always equal to N ; (d) G^1 and G^2 differ in attractiveness in the sense that the benefit B^1 (> 0) associated with G^1 is higher than the benefit B^2 (≥ 0) associated with G^2 ; (e) G^1 and G^2 also differ in accessibility in the sense that G^1 can only be obtained if agent spends C^1 (> 0 and $< B^1$) whereas G^2 can only be obtained if agent spends C^2 (≥ 0 , $\leq B^2$ and $< C^1$); (f) all agents have enough resources to be able to spend C^1 or C^2 .
2. *Agents' beliefs.* They build on the following elements: (a) each agent knows the number of G^1 and G^2 available in society but does not know the number of agents $A(S^1)$ and $A(S^2)$ who will respectively adopt strategy S^1 (spending C^1 to obtain B^1) or strategy S^2 (spending C^2 to obtain B^2); (b) each agent must therefore estimate the gain expected from S^1 ($G[S^1]$) compared to the gain expected from S^2

¹⁰ Constructing and analyzing a multi-agent system is still a fairly costly operation (see Janssen *et al.* 2008). Here I used the agent-based simulation platform option (Railsback *et al.* 2006), specifically NetLogo 4.0.3 (Tisue and Wilensky 2004a, 2004b; Wilensky 1999).

($G[S^2]$) as a function of the number of agents $A(S^1)$ likely to opt for S^1 (and therefore the number likely to opt for S^2).¹¹

3. *Agents' desires.* Each agent wishes to obtain a net benefit from his choice so that, for each number of agents $A(S^1)$ likely to opt for S^1 , he will choose S^1 if and only if $G(S^1) - G(S^2) > r$ (where r is the minimum gain demanded).
4. *Agents' final choice.* Given the vector of choices for or against S^1 produced by the dynamic conjunction of an agent's beliefs and desire, the probability of the agent ultimately deciding for or against S^1 increases non-linearly as a function of the proportion of cases in which agent chooses S^1 . Specifically, I chose a logistic function discretized by 10-unit intervals.¹²
5. *Agents' final gain.* Once agents have made their definitive choice for S^1 or S^2 , G^1 and G^2 available in the system can be allocated to them. There are three possible situations:
 - (a) If the number of agents who definitively opted for S^1 is exactly equal to the number of G^1 , all agents are satisfied: those who wanted G^1 got G^1 ; the others, who wanted G^2 , got G^2 .
 - (b) If the number of agents who definitively opted for S^1 is greater than the number of G^1 , some of the agents who spent C^1 to obtain B^1 will actually only be able to obtain G^2 . As there are no individual or social screening traits in this artificial world, agents receiving the lesser benefit at the higher cost are determined by random selection.
 - (c) If the number of agents who ultimately opt for S^1 is below the number of G^1 , the number of agents opting for S^2 will be above the number of available G^2 . Given that the game rule stipulating

¹¹ In particular, as long as $A(S^1) < G^1$,

$$\begin{aligned} G[S^1] &= B^1 - C^1 & [1] \\ G[S^2] &= ((B^2 - C^2) * G^2) / A(S^2) & [2] \end{aligned}$$

Instead, when $A(S^1) > G^1$,

$$\begin{aligned} G[S^1] &= ((B^1 - C^1) * G^1) / A(S^1) + ((B^2 - C^1) * (A(S^1) - G^1)) / A(S^1) \\ &= ((B^1 - B^2) * G^1 / A(S^1)) + (B^2 - C^1) & [3] \\ G[S^2] &= B^2 - C^2 & [4] \end{aligned}$$

It is worth noticing that neither Boudon (1982: 117) nor Kosaka (1986: 36–40) considered the case where $A(S^1) < G^1$. This omission is probably due to the fact that both authors were studying the model only for $B^2 = C^2 = 0$ and $r = 0$. Under the condition $r = 0$, the case of $A(S^1) < L^1$ is not of much interest because S^1 will always be more advantageous than S^2 . But if the intention is to run the simulation on a vast range of parameter combinations, this generalization of agents' belief updating process has to be included.

¹² The two situations originally studied by Boudon (1979: 52–6) – S^1 is chosen in 50 percent of cases and S^1 is chosen in 100 percent of cases (S^1 as a dominant strategy) – thus

that B^1 cannot be obtained by spending only C^2 precludes allocating G^1 to these agents, the simplest solution is to randomly allot a zero-gain to the surplus of agents desiring G^2 .

Thus programed, Boudon's original model can now generate not one but two types of RD (hereafter indicated as RD^1 and RD^2), whose frequency can be studied (hereafter respectively indicated RD^1_{freq} and RD^2_{freq}). In particular, RD^1 affects agents who, having chosen G^1 , only got G^2 because there were not enough G^1 lots. By contrast, RD^2 affects agents who wanted G^2 but in fact got nothing given the rules of the game and because there were not enough G^2 lots.

6. *Agents' emotions.* The experience of RD^1 may generate a different bundle of feelings of dissatisfaction than the one generated by the experience of RD^2 . In this connection, I posit that:

- (a) Intrapersonal comparisons will be made in both cases. The strength of the disappointment they generate is proportional to the size of the difference between expected gain and gain ultimately obtained.
- (b) Inter-individual comparisons also exist for both RD^1 and RD^2 . The strength of the envy they generate is understood to be inversely proportional to the number of those who did not get what they wanted (i.e. RD^1_{freq} and RD^2_{freq}).¹³
- (c) RD^2 can also imply a specific source of dissatisfaction. Agents finding themselves in this situation may reason counterfactually as follows: "If the rules of the game were different, there wouldn't be a waste of G^1 ." They may think that non-allotted G^1 could be put back in the game at a lower price – exceptionally. My assumption here is that criticism of this kind, implicitly aimed at the rule system in effect, may give rise to regrets, and that the breadth of those regrets would be proportional to the number of non-allotted G^1 lots.¹⁴

become respectively the equilibrium point and the upper limit of a more general choice function. This choice then represents here the main source of heterogeneity among agents – a point Yamaguchi (1998) greatly insisted on. The sources of heterogeneity will be much more extensive in the sixth component of the model.

¹³ According to Elster (1999: 141), envy is one of the most frequent comparison-based emotions (the ones "triggered by favorable or unfavorable comparisons with individuals with whom we will never interact"). More specifically, I am quantifying here the strength of this emotion by a mechanism implicitly postulated by Stouffer *et al.* (1965: 251), where the intensity of individual feelings of dissatisfaction is inversely related to the diffusion of failure.

¹⁴ Elster (1999: 241–2) establishes a direct link between counterfactual reasoning and emotions: "Fifth, there are counterfactual emotions generated by thoughts of what

With $RD^1_{intensity}$ and $RD^2_{intensity}$ indicating the intensity of the dissatisfaction feeling perceived by agents experiencing respectively RD^1 and RD^2 , we have the following simple representation of these three hypotheses:

$$RD^1_{intensity} = \alpha[(B^1 - C^1) - (B^2 - C^1)] + \beta(1/ RD^1_{freq}) \quad [5]$$

$$RD^2_{intensity} = \gamma[(B^2 - C^2) - (0 - C^2)] + \delta(1/ RD^2_{freq}) + \lambda[\text{non-allotted } G^1] \quad [6]$$

where $\alpha, \beta, \gamma, \delta$ and λ are random values drawn from uniform distributions $[0, 0.5]$ that represent the idea that the three feeling-of-deprivation generative mechanisms operate differently from one individual to another.¹⁵

In truth, this formalization implies an additional supposition. The second term in [5] and [6] actually inversely links the intensity of envy felt by agents with the overall proportion of agents who find themselves in the same deprivation situation.

But we could reasonably allow that when agents are determining how strongly they think they have been penalized in not getting what they want compared to those who spent as much as they did and *did* get the desired lot, they only take into account local diffusion of RD^1 and RD^2 . While this hypothesis seems reasonable – one point in its favor is that it does not require us to suppose that agents have permanent knowledge of the overall state of the system – it also raises the problem of defining what is “local.”

As indicated by the second term of [7] and [8], my hypothesis here is that what makes up the horizon within which agents assess the diffusion of RD situations is the set of dyadic ties they are embedded in (“neigh” refers to agent’s “neighborhood”; i.e. the agents he is in direct contact with).¹⁶

$$RD^1_{intensity} = \alpha[(B^1 - C^1) - (B^2 - C^1)] + \beta(1/ RD^1_{freq}[\text{neigh}]) \quad [7]$$

$$RD^2_{intensity} = \gamma[(B^2 - C^2) - (0 - C^2)] + \delta(1/ RD^2_{freq}[\text{neigh}]) + \lambda[\text{non-allotted } G^1] \quad [8]$$

might have happened but didn’t – regret, rejoicing, disappointment, elation – and wistful subjective emotions generated by thoughts of what might still happen, albeit with insufficient probability to generate hope or fear.”

¹⁵ To obtain $RD^1_{intensity}$ and $RD^2_{intensity}$ values that vary between two given extremes, we can standardize each term of [5] and [6] (see below note 21). It would also be useful to study how the model behaves if we substitute a “ratio” (or a “log-ratio”) for the difference in the first term of [5], [6], [7] and [8], since the algebraic properties of this functional form are considerable (see Jasso 2008). Finally, notice that the first term of equations [5] and [6] can be simplified, respectively, to $(B1-B2)$ and to $(B2)$, so expressing the idea that the strength of the disappointment generated by intrapersonal comparisons is supposed to be proportional to the size of the expected benefit that the actor ultimately does not obtain.

¹⁶ As Gartrell (1987) remarked, the literature on relative deprivation tends to ignore that ego-centered social networks are a powerful source which determine “who compares

Formally speaking, this second definition of persons “in the same boat,” to borrow Stouffer’s expression, raises a problem we do not encounter with the “global comparisons” implied by [5] and [6]: how are we to handle the situation where RD^1_{freq} or RD^2_{freq} are nil in the agent’s neighborhood? To remain consistent with the posited mechanism, an agent’s feeling of envy can only be maximal here (since in this situation he would be the only one who did not get what he wanted). To represent this idea – i.e. “zero neighbors experiencing RD” – I have changed 0 into 0.01 when the situation presents itself (otherwise computation would be impossible), thereby providing maxima that vary with size of agent’s neighborhood.¹⁷

Simultaneously generating RD frequency and RD intensity patterns

The sensitivity analysis that follows aims to demonstrate that within the artificial society driven by the mechanisms just described, the four-way relation between the attractiveness of goods at stake, the “wealth” of the opportunity structure, the quantity of dissatisfied agents (RD^1_{freq} and RD^2_{freq}) and the intensity of this dissatisfaction ($RD^1_{\text{intensity}}$ and $RD^2_{\text{intensity}}$) assumes multiple forms that are not independent of the interaction configuration linking agents to each other.¹⁸

To prove it, I first consider a microcosm without dyadic interactions between agents, and then I introduce these interactions, first in the form of a random network, then a scale-free network.¹⁹

with whom.” In particular, Gartrell (2001: 173–5) demonstrated that dyadic properties such as frequency, “multiplexity” and strength of contacts are especially important in predicting the reference point of a given agent. As I said in my introduction, among formal analyses of relative deprivation, only Burt (1982) explicitly takes into account the role of social networks. In particular, he posits that actors compare with one another if they are structurally equivalent. Assuming that actor’s significant others are his direct contacts, I am positing a more general dyadic rule of comparison.

¹⁷ As I noted above, Elster (1999: 141) presents “envy” as a comparison-based emotion, and so did I in Equations [5] and [6]. In Equations [7] and [8], by contrast, where I posit agents to be embedded in a network of dyadic links, “envy” is considered as an interaction-based emotion (emotion that arises “only when there is social interaction,” see Elster (1999: 141)).

¹⁸ The attractiveness of G^1 over G^2 is measured by $R(B) = (B^1 - C^1) / (B^2 - C^2)$ and $R(K) = [(B^1 - C^1) - (B^2 - C^2)] / (C^1 - C^2)$ (see respectively, Boudon (1982: 118) and Kosaka (1986: 38)); on the other hand, the “wealth” of the opportunity structure is represented by the percentage of goods with the highest benefit, i.e. goods G^1 .

¹⁹ In a previous analysis (see Manzo 2009b), I explored in depth only the relation between the first three elements. The main computational results obtained by analyzing approximately 26,000 parameter combinations concerning both the zero and non-zero-second alternative cases (i.e. respectively, the situation in which $B^2 = C^2 = 0$ and $B^2 \neq 0$ and $C^2 \geq 0$) can be synthesized as follows: (a) the relation between an

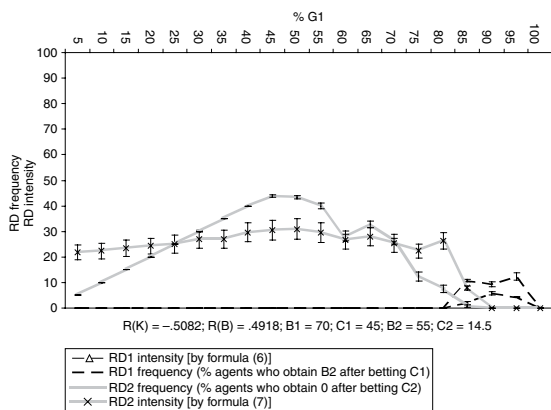
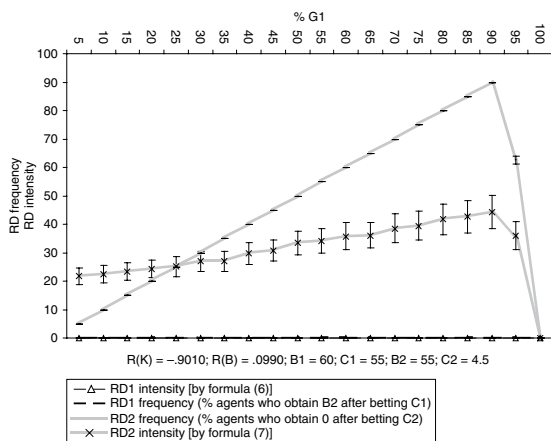


Figure 13.1 Relative deprivation in an artificial society, situation 1 percentages (95% confidence intervals) of agents who finally obtain B2 or nothing after betting C¹ or C² (y-axis) and average values of RD¹ and RD² intensity (average 95% confidence intervals) for these agents (y-axis) as a function of the percentage of available G¹ (x-axis) and different levels of G¹ attractiveness (see R(K) and R(B) values).

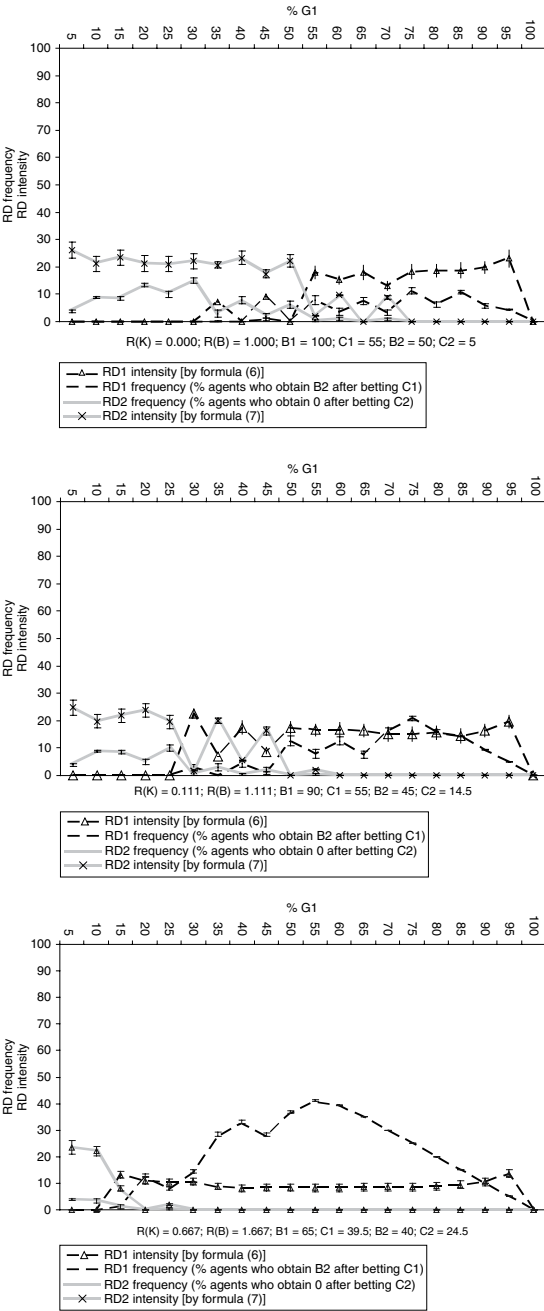


Figure 13.1 (cont.)

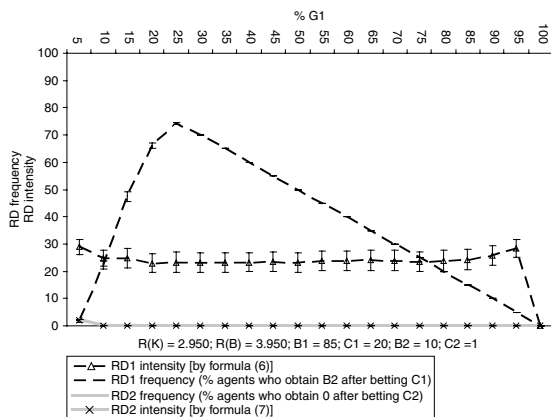
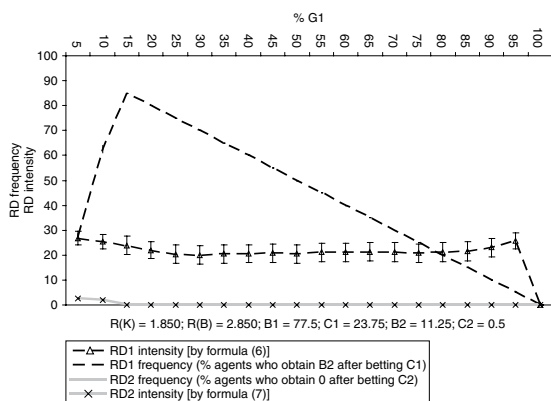
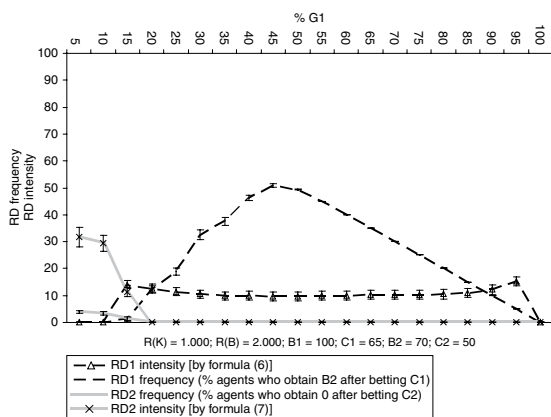


Figure 13.1 (cont.)

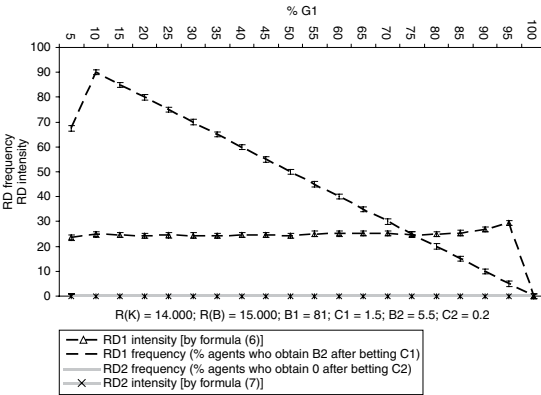
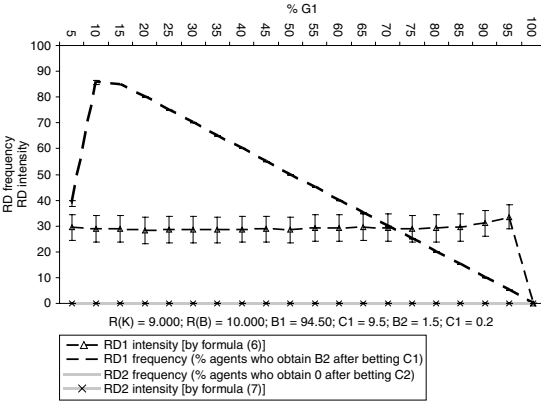
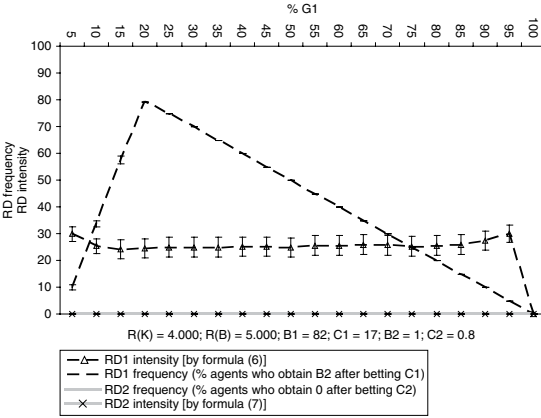


Figure 13.1 (cont.)

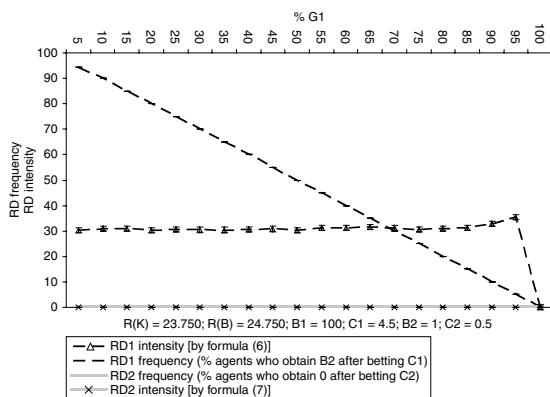


Figure 13.1 (cont.)

The population-based inter-individual comparisons case

Figure 13.1 presents the $RD_{intensity}^2$ and $RD_{intensity}^1$ generated by the model for each level of RD_{freq}^2 and RD_{freq}^1 . To improve graph readability, I have omitted trends in percentages of agents obtaining what they want.²⁰

improvement in the opportunity structure and the percentage of dissatisfied agents may take a positive linear form (*more opportunities, more dissatisfied agents*), a negative one (*more opportunities, fewer dissatisfied agents*), or both forms at once; (b) we get closer to the negative linear form (*more opportunities, fewer dissatisfied agents*) as attractiveness of the higher-returning goods makes each agent's choice insensitive to that of others; (c) this multiplicity of forms and the underlying dynamic do not vary relative to population size as long as size change is proportionate to number of higher-returning goods; in the opposite case, the "*more opportunities, more dissatisfied agents*" relation reappears at a rate proportionate to how limited opportunity structure range is relative to population size. These results thus confirm and extend Boudon's, Kosaka's and Yamaguchi's original result (they only studied indeed the situation in which $B^2 = C^2 = 0$), which is that the positive linear form designated by "*more opportunities, more dissatisfied actors*" – i.e. the take-off point of sociological literature on RD – is only validated in a specific region of the parameter space.

²⁰ I am presenting here a set of typical patterns generated by the model for a specific series of $R(B)$ and $R(K)$ values. In fact, I explored about 1,976 different combinations of B^1 , C^1 , B^2 and C^2 values (varying respectively between 10 and 100; 1.5 and 95; 5 and 90 and 0 and 50) producing G^1 attractiveness levels ranging from $(R(K)) = -0.90$ to $(R(K)) = 98.5$, or, alternatively, $(R(B)) = 0.09$ to $(R(B)) = 99.5$. Taking into account also the variations of the percentage of G^1 lots, I simulated the model for 20,700 parameter combinations, for a total of 207,000 simulations, since each combination was simulated ten times to assess the model behavior variability linked to its random elements (for the sake of brevity, I omitted here the values of ten seeds I used). All the simulations consider populations of 100 agents demanding a minimal gain of $r = 1$. This sensitivity analysis was performed using the NetLogo 4.0.3 "BehaviorSpace" module.

We see that RD^2_{freq} and $RD^2_{\text{intensity}}$ are more likely to move in the same direction than are the curves relative to RD^1_{freq} and $RD^1_{\text{intensity}}$. In the first case, an increase in the proportion of agents aiming for G^2 but getting 0 tends to go together with a more intense feeling of deprivation, and vice versa. In the second case, on the contrary, an increase in the proportion of agents aiming for G^1 but only getting G^2 tends to go together with a less intense feeling of deprivation, whereas that intensity increases when the number of these agents falls.

The aggregate RD^2_{freq} quantity and the individual $RD^2_{\text{intensity}}$ thus seem linked by a positive relation ("more more-intensely-dissatisfied individuals" or "fewer less-intensely-dissatisfied individuals"), whereas RD^1_{freq} and $RD^1_{\text{intensity}}$ seemed linked by a negative one ("more less-intensely-dissatisfied individuals" or "fewer more-intensely-dissatisfied individuals"). This reflects the fact that the mechanisms I posited as generating the dissatisfaction associated by agents respectively with RD^1 and RD^2 are not the same (compare Equations [5] and [6]).

The case of RD^1 is simple. The feeling of deprivation is assumed here to derive from two sources: a feeling of disappointment whose intensity is proportionate to the size of the gap between expected gain and gain actually realized, and a feeling of envy of an intensity inversely proportional to the rate of deprivation in the population. Under this condition and for a given value of $R(K)$, whereas the value of the term quantifying the first source is stable, the value of the term quantifying the second falls as RD^1_{freq} increases, and vice versa. This means we are first adding a gradually falling quantity, then a gradually rising quantity, to a fixed quantity. In all situations where RD^1_{freq} increases at first and then declines, the result will be a flattened U-curve for $RD^1_{\text{intensity}}$. However, as we near the negative form of the relation between opportunity structure and RD^1_{freq} , $RD^1_{\text{intensity}}$ will increase more or less slowly, because in this case RD^1_{freq} is only falling.

The case of RD^2 is slightly more complex. Here the feeling of deprivation is understood to derive from a third mechanism, in addition to the other two sources allowed for RD^1 ; namely, that agents experiencing RD^2 reason counterfactually, and this in turn generates a feeling of regret whose intensity is proportionate to the number of wasted G^1 . Under this condition, even though the value of the term quantifying the effect of interpersonal comparisons falls as RD^2_{freq} increases, the value of the term quantifying the effect of the counterfactual reasoning tends to increase. This means that the more abrupt the rise in RD^2_{freq} and the greater its breadth, the more likely it is for a concomitant increase in $RD^2_{\text{intensity}}$ to set in. On the other hand, when RD^2_{freq} is low and rises little, $RD^2_{\text{intensity}}$ is more likely to be stable (the effects of the two mechanisms cancel each other out) or even to vary inversely with RD^2_{freq} (and

here we come back to the situation characterizing $RD^1_{intensity}$, where the inter-individual comparisons takes precedence).²¹

As soon as we combine the plural forms of the two groups of relations studied thus far – on the one hand, the relation between an improved objective opportunity structure and percentage of dissatisfied agents (RD^2_{freq} and RD^1_{freq}) (see above note 19); on the other, the relation linking percentage of dissatisfied agents with intensity of agents' feelings of deprivation ($RD^2_{intensity}$ and $RD^1_{intensity}$) – the following general result appears: enriching the opportunity structure can indeed maintain a virtuous relation between that structure and both the quota of dissatisfied agents (“more opportunities, fewer dissatisfied individuals”) and the intensity of individual feelings of dissatisfaction (“more opportunities, weaker dissatisfaction”). The problem is that if interpersonal comparisons are operative which inversely link the feeling of dissatisfaction to “scarcity” of deprivation experiences, then the regions where these two relations obtain may well fail to overlap. Under these conditions, dissatisfaction intensity will indeed tend to go down when the number of dissatisfied agents increases, whereas when that number falls, dissatisfaction intensity will tend to rise.

The neighborhood-based inter-individual comparisons case

If we now introduce a dyadic tie structure linking agents to each other within the artificial microcosm (see Equations [7] and [8]), how will this change the complex relation between the opportunity structure (here number of G^1), percentage of dissatisfied agents (RD^2_{freq} and RD^1_{freq}), and feeling-of-deprivation intensity ($RD_{intensity}$)?

The relation between G^1 and RD^2_{freq} – RD^1_{freq} should not be affected. In the present version of the model, dyadic agent interactions determine only the set of agents with whom an agent experiencing RD compares himself. $RD^2_{intensity}$ and $RD^1_{intensity}$, therefore, are what may be affected by such interactions.

To see how fully this is confirmed, I put agents into a random network with a slight spatial bias (the average network degree here is 10).

²¹ The profile of the curves just discussed and interpreted is stable when we simulate the model after eliminating the source of inter-individual variability I applied to each of the three mechanisms responsible for $RD^1_{intensity}$ and $RD^2_{intensity}$. And their form is not even linked to the range of the three terms that formalize the action of these mechanisms. I also simulated the probabilistic and determinist versions of the model, standardizing each of these terms, by relating it to the difference between its minimal and maximal theoretical values. While this standardized version is unquestionably more elegant formally, it does not change the profile of the curves presented in Figure 13.1, except to further flatten the shape.

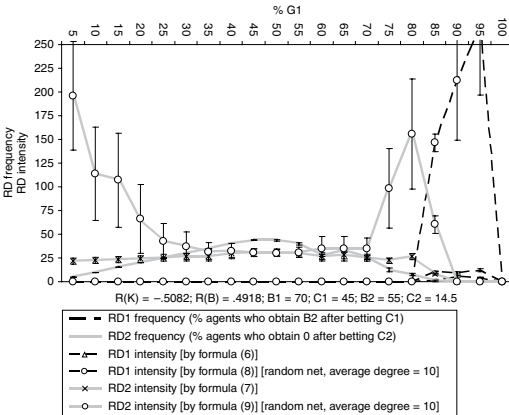
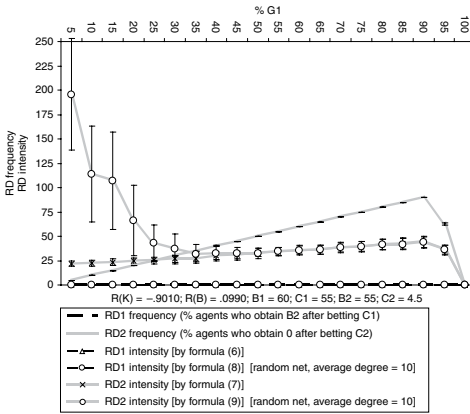


Figure 13.2 Relative deprivation in an artificial society, situation 2 percentages (95% confidence intervals) of agents who finally obtain B2 or nothing after betting C^1 or C^2 (y-axis) and average values of RD^1 and RD^2 intensity (average 95% confidence intervals) for these agents (y-axis) in a no-network world and in a random-network world (average degree = 10) as a function of the percentage of available G^1 (x-axis) and G^1 attractiveness (see $R(K)$ and $R(B)$ values).

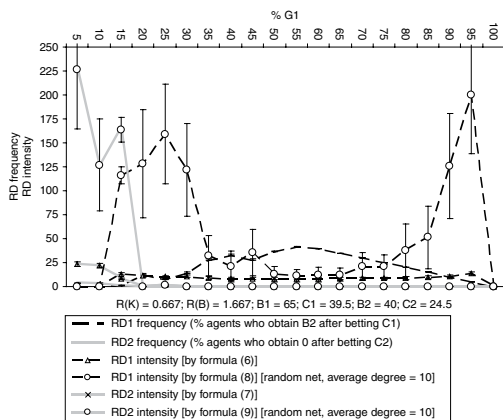
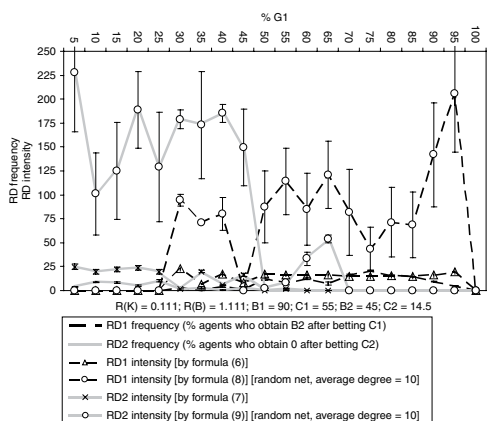
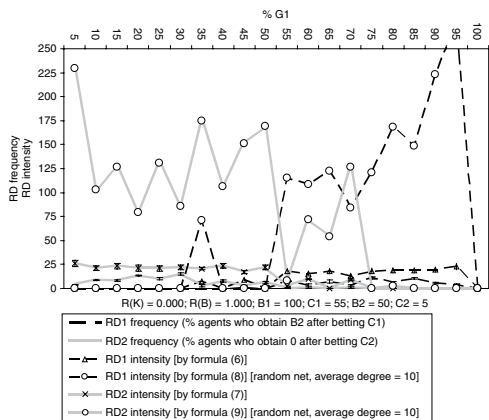


Figure 13.2 (cont.)

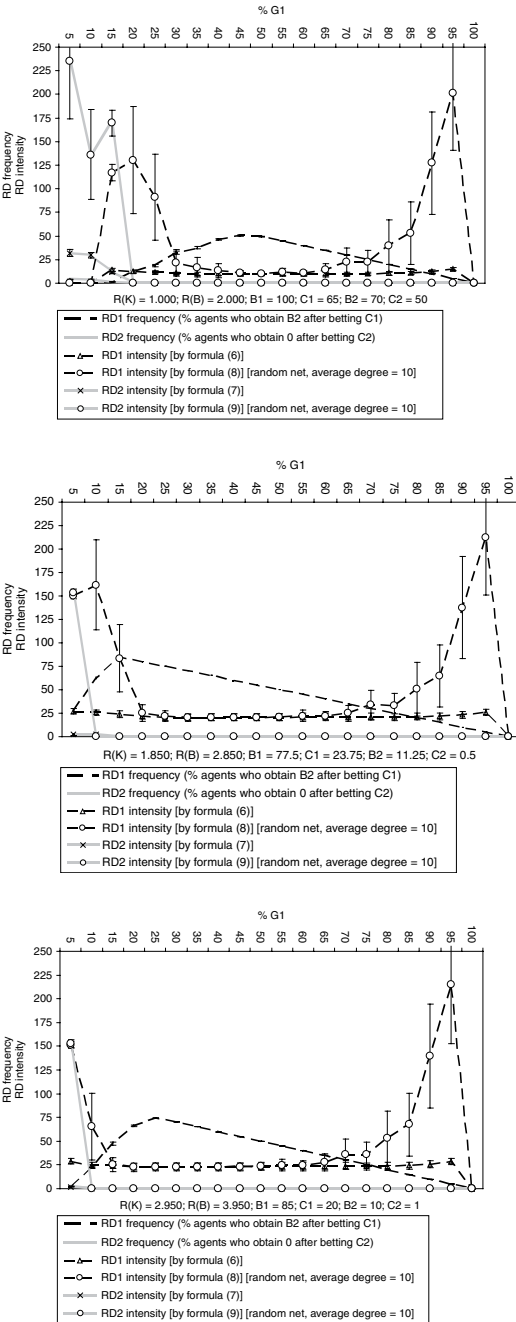


Figure 13.2 (cont.)

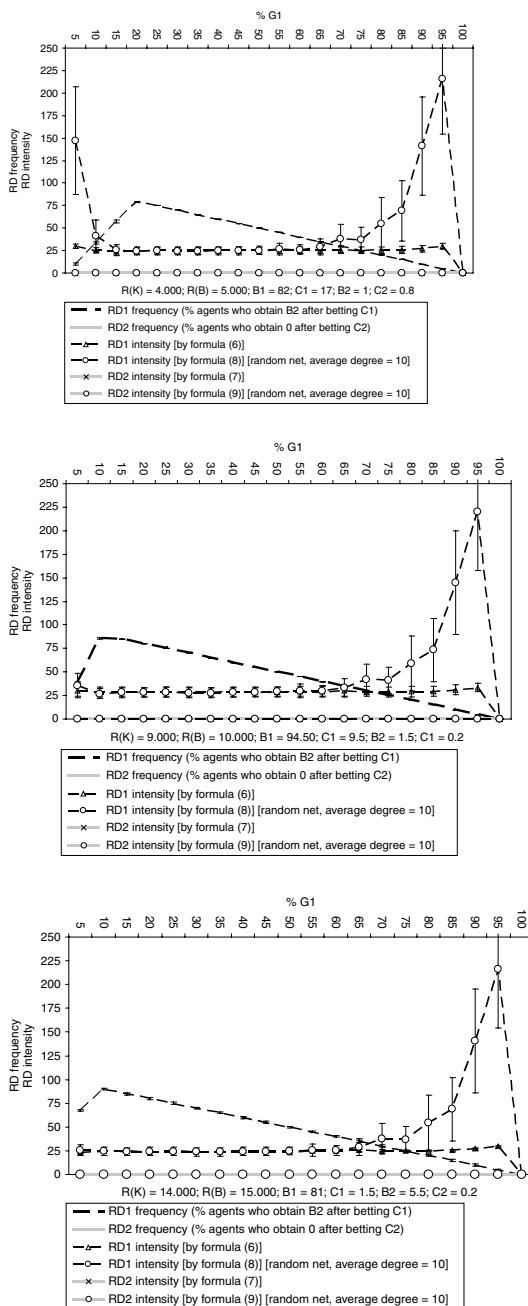


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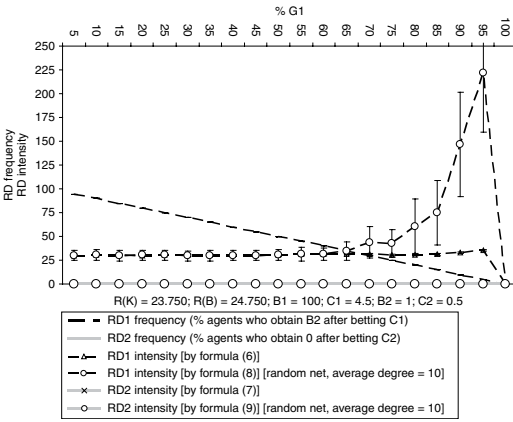


Figure 13.2 (cont.)

Figure 13.2 introduces into Figure 13.1 the $RD^2_{intensity}$ and $RD^1_{intensity}$ values I got by simulating the model under this new condition.²²

We can first consider situations where G^1 attractiveness is weak, leading, as we now know, to an extremely high level of RD^2_{freq} . In this case we observe that in comparison to an artificial world in which there is no network:

1. the relation between an increase in G^1 and $RD^2_{intensity}$ is not exclusively positive but rather both negative and positive;
2. when RD^2_{freq} is low, $RD^2_{intensity}$ level is a great deal higher, but as RD^2_{freq} increases $RD^2_{intensity}$ gets considerably closer to the level observed when there were no ties between agents.

What accounts for these differences? Given that agents embedded in dyadic interactions compare themselves to immediate neighbors experiencing RD^2 , the probability of an agent finding other agents around him in the same situation is low when RD^2_{freq} is low. This implies that the term of Equation [7] quantifying the interpersonal comparison will take on extremely high values for many agents, generating a particularly high level of $RD^2_{intensity}$. As RD^2_{freq} increases, this condition disappears: the term relative to interpersonal comparisons will take on increasingly low values while the term relative to counterfactual reasoning will increase continuously. This is why average $RD^2_{intensity}$ levels can fall first, then rise.

²² To construct the network, I used an algorithm that has only been available in NetLogo since version 4.0.3 (Stonedahl and Wilensky 2008). The algorithm works as follows: (a) we take a randomly chosen agent; (b) we determine the agent closest to him (Euclidian distance); (c) we create a link; (d) we reiterate these operations until the average network degree reaches the average degree chosen at the outset.

If we now consider situations where RD^1_{freq} replaces RD^2_{freq} because G^1 attractiveness is stronger, we observe equally significant modifications. Compared to the no-network artificial world, the form of the relation between an increase of G^1 and $RD^1_{\text{intensity}}$ does not change – we move gradually from a mixed negative/positive relation to an entirely positive one (“more opportunities, stronger dissatisfaction”) – but the levels of $RD^1_{\text{intensity}}$ are much higher at the extremes; that is, when RD^1_{freq} is low. This is because, here again, the overall “scarcity” of RD^1 implies the presence of many “neighborhoods” in which agents experiencing RD^1 have no neighbors in this same deprived situation. Since this agent is the only one not to get what he wanted, he feels maximum envy.²³

As Figure 13.3 shows, that this structural condition exists is attested by the results of simulations where the average network degree went from 10 to 50. Under this condition, the differences in average $RD^1_{\text{intensity}}$ and $RD^2_{\text{intensity}}$ levels that existed between societies with and societies without random networks tend to disappear. This is because given that agents’ “neighborhoods” have been extended, an agent in RD^1 or RD^2 is more likely to meet someone among the neighbors he is linked to who is also experiencing RD , despite the fact that the overall rate of RD^1 and RD^2 are low. The effect is to contain quite firmly the spectacular rise of the term quantifying neighborhood-based inter-individual comparisons.

We can obtain more direct proof of this phenomenon by introducing a scale-free network (rather than a random one) into the model. The purpose of doing this is to construct by default a situation with a great number of small “neighborhoods,” thereby structurally multiplying situations where an agent experiencing RD^1 or RD^2 is unlikely to find another in the same situation. This should greatly amplify average $RD_{\text{intensity}}$ levels.²⁴

Figure 13.4 show that this is exactly what happens. Regardless of G^1 attractiveness, $RD^2_{\text{intensity}}$ or $RD^1_{\text{intensity}}$ are indeed regularly higher in the artificial society based on a scale-free network than they are in

²³ This aggregate effect will, of course, appear more or less sharp depending on the functional form chosen to formalize the term quantifying interpersonal comparisons in the case where agent has no neighbors in the same deprivation situation as his. It can be almost entirely effaced, for example, by applying a logarithmic transformation to this term in Equations [7] and [8]. Having studied the behavior of the model under that alternative condition, I conclude, however, that this type of manipulation conceals the presence of a significant theoretical phenomenon.

²⁴ To construct this network I used an algorithm available in NetLogo (Wilensky 2005) based on a formalization of the “preferential attachment” mechanism first put forward by Barabasi and Réka (1999). Researchers are currently at work constructing algorithms formalizing mechanisms that will generate scale-free (and small-world) networks that are sociologically more significant than the one implemented with the algorithm I used (see, for instance, Pujol *et al.* 2005). Here, however, what interests me are the structural characteristics of a scale-free network, not the process by which it emerges.

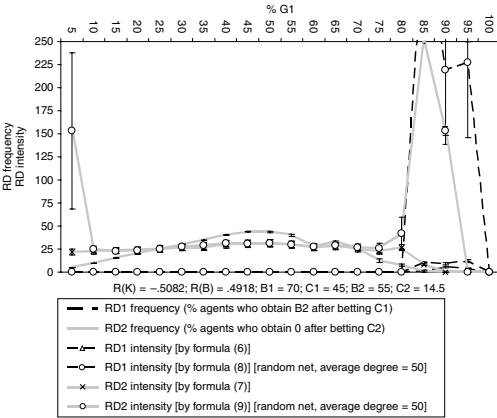
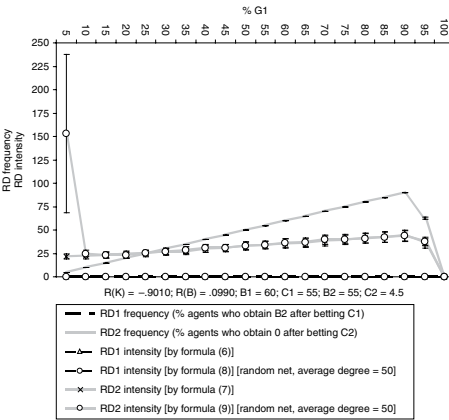


Figure 13.3 Relative deprivation in an artificial society, situation 3 percentages (95% confidence intervals) of agents who finally obtain B² or nothing after betting C¹ or C² (y-axis) and average values of RD¹ and RD² intensity (average 95% confidence intervals) for these agents (y-axis) in a no-network world and in a random-network world (average degree = 50) as a function of the percentage of available G¹ (x-axis) and G¹ attractiveness (see R(K) and R(B) values).

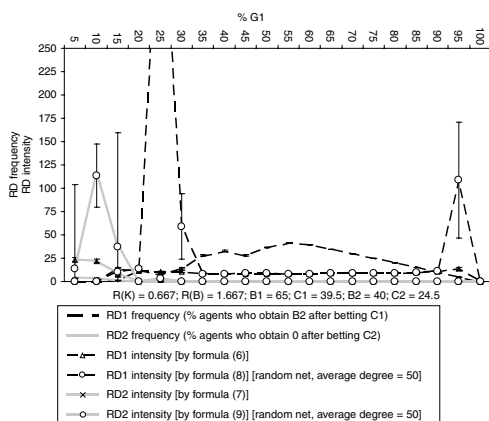
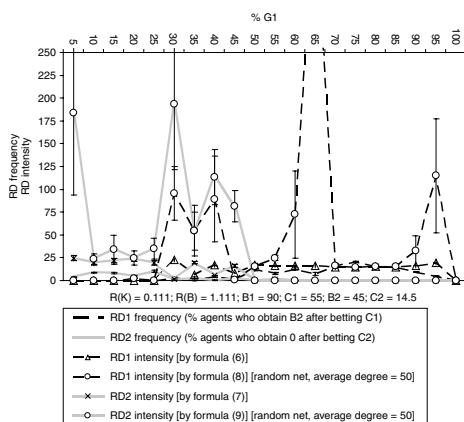
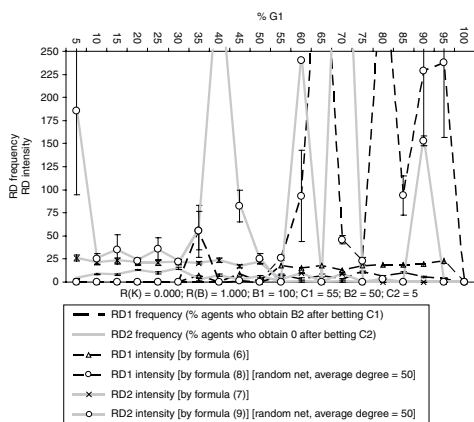


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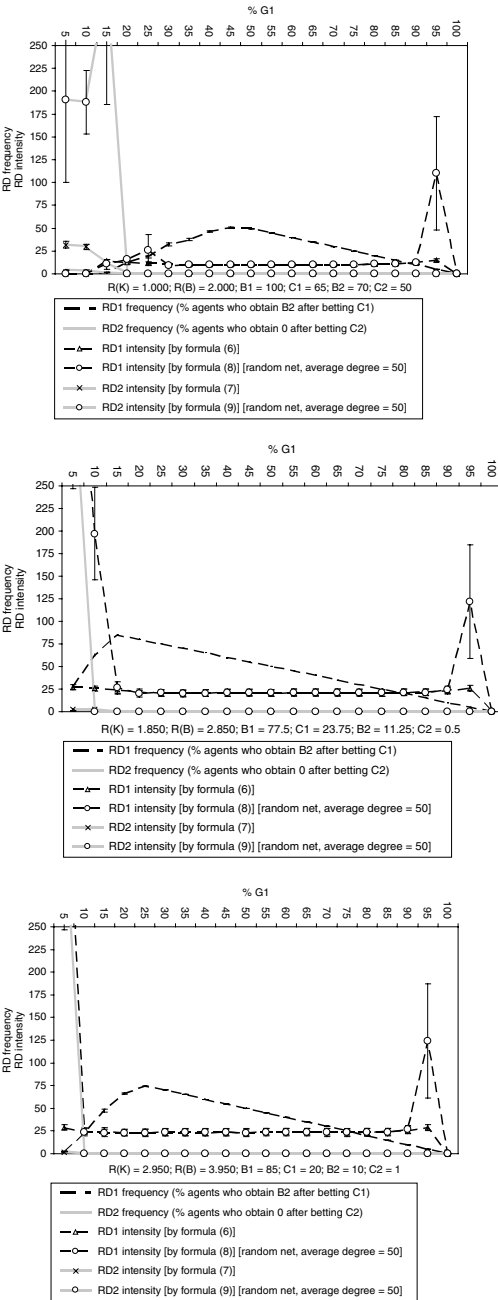


Figure 13.3 (cont.)

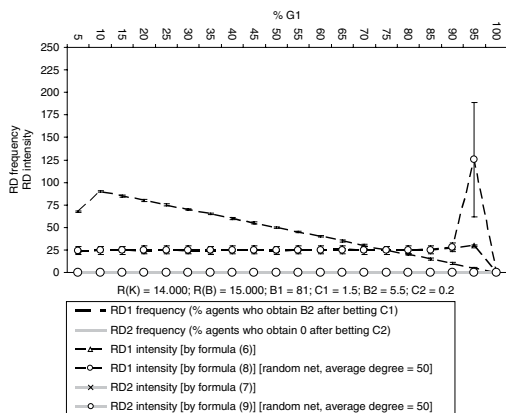
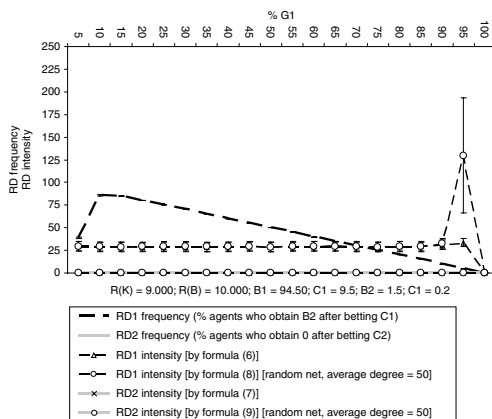
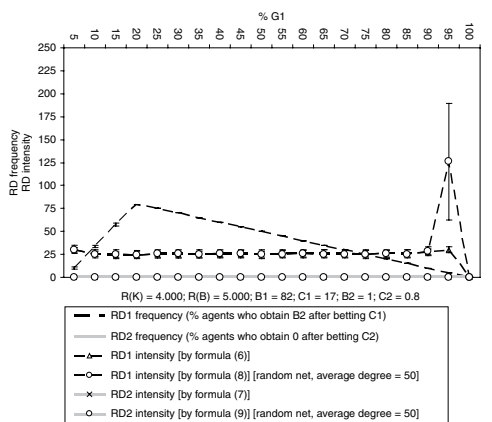


Figure 13.3 (cont.)

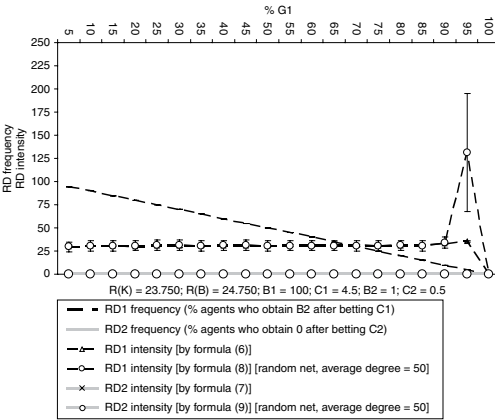


Figure 13.3 (cont.)

an artificial society without dyadic interactions that delimit the set of agents with whom one compares oneself. The same is true if we compare the scale-free network microcosm with the random network society (see Figure 13.2), except for the extreme situations, i.e. where RD^2_{freq} or RD^1_{freq} is low.

This is readily explained. Though there are indeed a great many small “neighborhoods” with the scale-free network – and this increases the probability that agents experiencing RD will not meet another agent in their neighborhood who is also experiencing RD – these same limited neighborhoods mean that the agent is alone among a low number of satisfied fellow agents. Despite the fact that dissatisfaction is maximal here compared to the situation where one has at least a few neighbors who are also experiencing RD, this maximum will be lower compared to the random-network artificial society (comprising an average degree of 10) where one may be alone among a higher number of satisfied agents.

Tables 13.1 and 13.2 directly demonstrate (for the two extreme values of $R(B)$ – $R(K)$) these structural bases of the differences in average $RD^2_{\text{intensity}}$ or $RD^1_{\text{intensity}}$ levels that emerge in the artificial society with a random network and the society with a scale-free network. In the simulations just commented on, we see on the one hand that degree of agents experiencing RD^2 and RD^1 is on average lower in the scale-free network than in the near-random one, and on the other, the percentage of agents who are the only ones in their neighborhood experiencing RD is on average higher in the first case than in the second.

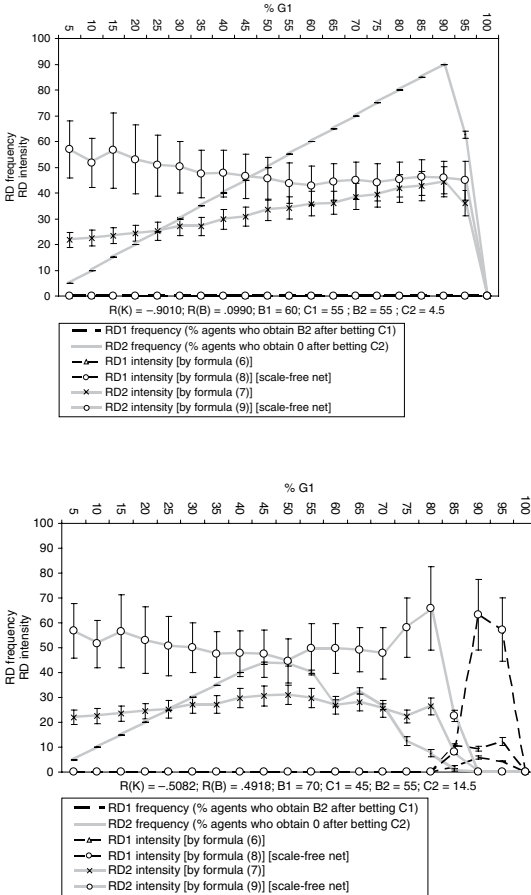


Figure 13.4 Relative deprivation in an artificial society, situation 4 percentages (95% confidence intervals) of agents who finally obtain B2 or nothing after betting C^1 or C^2 (y-axis) and average values of RD^1 and RD^2 intensity (average 95% confidence intervals) for these agents (y-axis) in a no-network world and in a scale-free-network world as a function of the percentage of available G^1 (x-axis) and G^1 attractiveness (see $R(K)$ and $R(B)$ values).

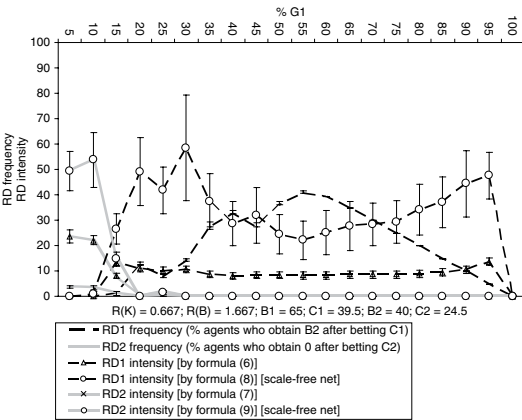
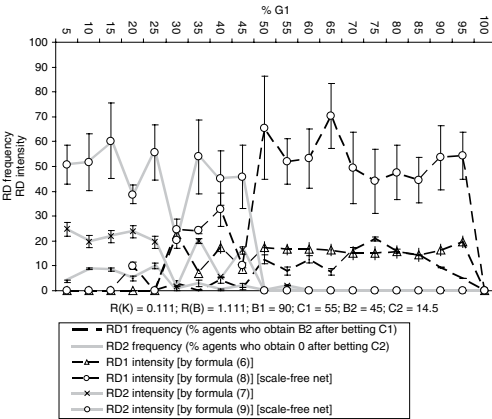
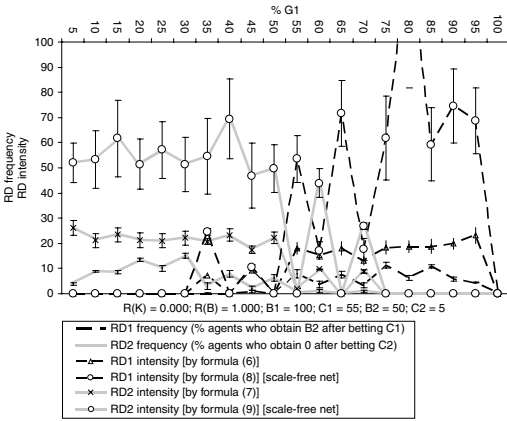


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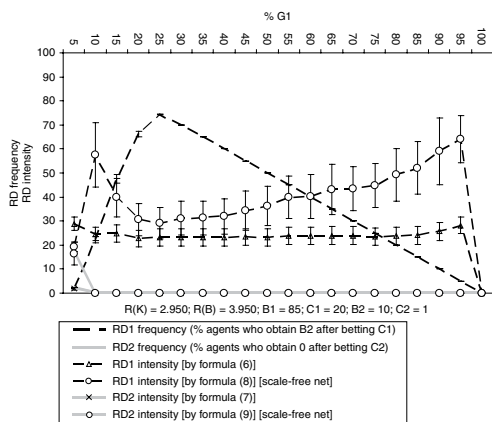
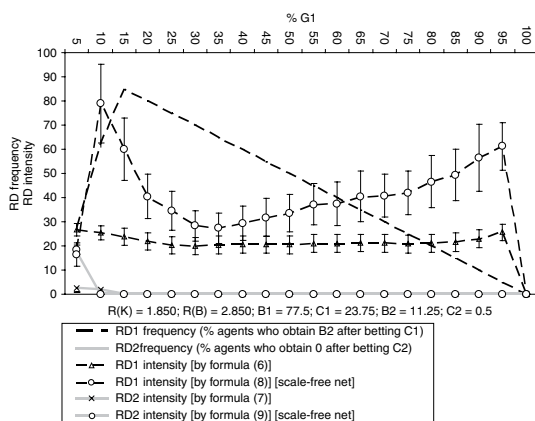
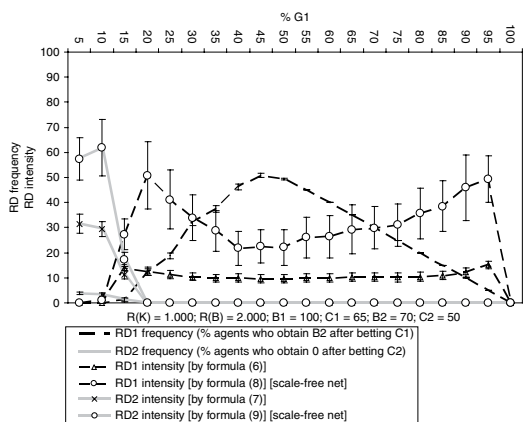


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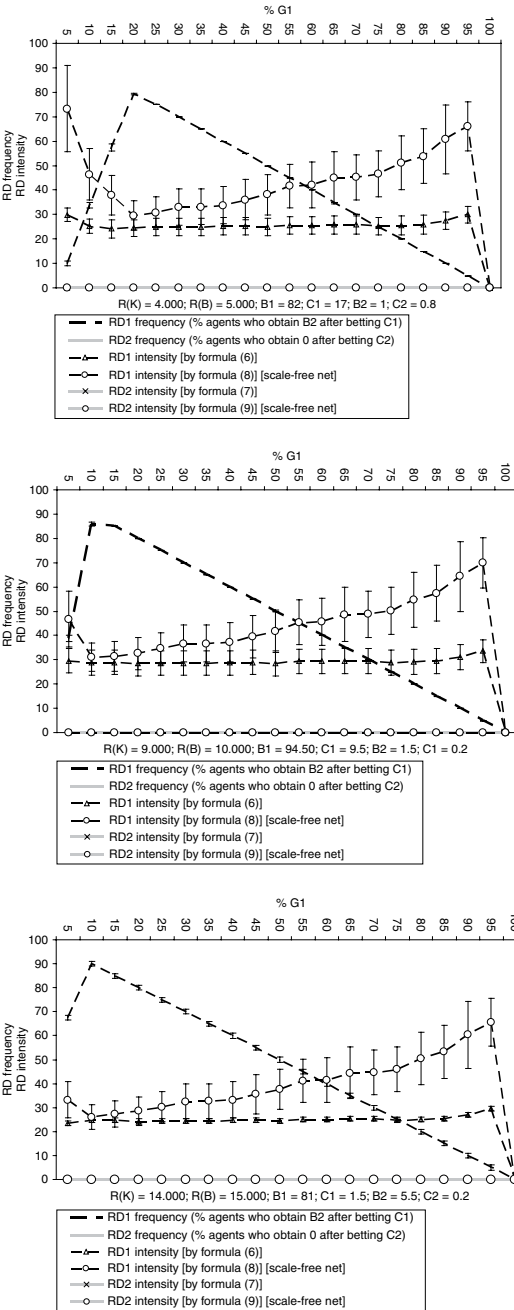


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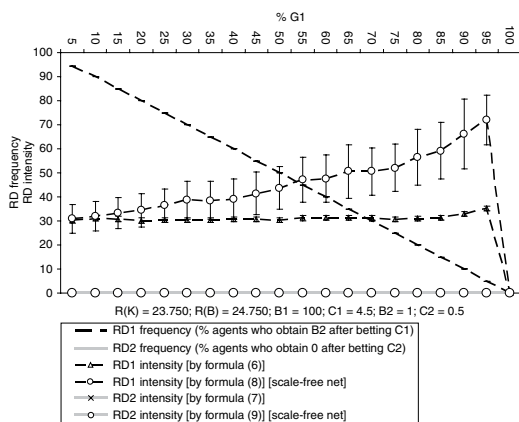


Figure 13.4 (cont.)

These results suggest that dyadic interactions matter. In my minimalist hypothetical schema – my only assumption was that network influences actors' points of comparison – these simulations indicate that the presence of interactions can significantly modify the individual dissatisfaction levels which characterize a microcosm whose agents are entirely isolated. Restricting the bases for inter-individual comparisons amounts, paradoxically, to increasing the probability of individual dissatisfaction being stronger. The more the dyadic interaction configuration multiplies the number of neighborhoods where the agent is the only one not to have what he wants, the further we move away from the dissatisfaction levels that appear for an artificial world where the agent compares his deprivation situation to the global diffusion of deprivation in the population at large.

Concluding remarks

This chapter has aimed to sketch a unified theoretical framework which links two classes of problems: on the one hand, the one of simultaneously generating variable quantities of dissatisfied actors and heterogeneously intense individual feelings of dissatisfaction; on the other hand, the one of determining how this dissatisfaction is modified when, instead of taking into account overall success rates, individuals only consider the success rate of their closest contacts.

Methodologically, the point here has been to suggest that this undertaking can now benefit from a computational tool – agent-based

Table 13.1 *Average degree of agents experiencing RD^2 and percentage of these agents who do not have any neighbors in RD^2 (average values with standard deviation in parentheses) for each of the three network structures used (case of $R(K) = -0.09$. See Figures 13.2, 13.3 and 13.4 for RD frequency and RD intensity trends)*

G1	Random network (average degree = 10)		Random network (average degree = 50)		Scale-free network	
	RD^2 agents' average degree	% of agents who do not have any neighbors in RD^2	RD^2 agents' average degree	% of agents who do not have any neighbors in RD^2	RD^2 agents' average degree	% of agents who do not have any neighbors in RD^2
5	9.9 (1.5)	52.0 (24.0)	52.5 (5.2)	0.0	1.7 (0.8)	88.0 (18.3)
10	10.2 (0.8)	35.0 (18.6)	51.2 (3.3)	0.0	1.7 (0.7)	80.0 (15.5)
15	9.9 (0.7)	16.7 (10.4)	50.9 (3.3)	0.0	2.1 (1.0)	74.0 (18.2)
20	9.9 (0.5)	13.0 (6.0)	49.7 (2.6)	0.0	2.0 (0.8)	71.5 (14.8)
25	9.9 (0.5)	10.0 (6.5)	49.9 (2.2)	0.0	1.9 (0.6)	66.0 (13.4)
30	9.9 (0.4)	4.7 (3.4)	49.6 (2.6)	0.0	2.0 (0.5)	59.0 (12.3)
35	10.0 (0.24)	1.7 (1.9)	49.0 (2.3)	0.0	2.0 (0.4)	52.0 (9.7)
40	10.0 (0.2)	0.5 (1.0)	49.5 (2.1)	0.0	2.0 (0.3)	49.8 (12.2)
45	10.0 (0.2)	0.9 (1.5)	49.9 (2.0)	0.0	2.0 (0.2)	42.4 (8.6)
50	10.0 (0.2)	0.0	49.7 (1.4)	0.0	2.0 (0.2)	36.4 (7.3)
55	10.0 (0.2)	0.0	50.0 (1.1)	0.0	2.1 (0.2)	28.4 (7.1)
60	10.0 (0.2)	0.0	49.9 (1.2)	0.0	2.1 (0.1)	25.8 (7.7)
65	10.0 (0.2)	0.0	49.9 (1.0)	0.0	2.1 (0.1)	22.3 (4.8)
70	10.0 (0.1)	0.0	49.8 (0.8)	0.0	2.1 (0.1)	20.6 (4.5)
75	10.0 (0.1)	0.0	49.9 (0.7)	0.0	2.1 (0.1)	17.7 (4.1)
80	10.0 (0.1)	0.0	49.8 (0.8)	0.0	2.1 (0.1)	13.8 (5.5)
85	10.0 (0.1)	0.0	49.7 (0.6)	0.0	2.1 (0.1)	9.4 (3.8)
90	10.0 (0.1)	0.0	49.8 (0.5)	0.0	2.1 (0.1)	6.8 (4.1)
95	9.9 (0.2)	0.0	49.7 (0.8)	6.0 (12.8)	2.1 (0.1)	25.3 (7.9)
100	—	—	—	—	—	—

Table 13.2 *Average degree of agents experiencing RD¹ and percentage of these agents who do not have any neighbors in RD¹ (average values with standard deviation in parentheses) for each of the three network structures used (case of $R(K) = 23.75$. See Figures 13.2, 13.3 and 13.4 for RD frequency and RD intensity trends)*

G1	Random network (average degree = 10)		Random network (average degree = 50)		Scale-free network	
	RD ¹ agents' average degree	% of agents who do not have any neighbors in RD ¹	RD ¹ agents' average degree	% of agents who do not have any neighbors in RD ¹	RD ¹ agents' average degree	% of agents who do not have any neighbors in RD ¹
5	10.0 (0.1)	0.0	50.0 (0.3)	0.0	2.0 (0.1)	3.7 (2.4)
10	10.0 (0.1)	0.0	50.0 (0.3)	0.0	2.0 (0.1)	7.2 (4.3)
15	10.0 (0.1)	0.0	49.7 (0.5)	0.0	2.0 (0.1)	9.6 (5.6)
20	10.0 (0.1)	0.0	49.7 (0.7)	0.0	2.0 (0.1)	12.6 (6.5)
25	10.1 (0.2)	0.0	49.7 (0.7)	0.0	2.0 (0.2)	18.5 (9.4)
30	10.1 (0.2)	0.0	50.2 (0.9)	0.0	2.0 (0.2)	22.4 (10.4)
35	10.1 (0.2)	0.0	50.3 (1.1)	0.0	2.0 (0.2)	24.3 (10.8)
40	10.1 (0.2)	0.0	50.2 (1.2)	0.0	2.0 (0.2)	26.0 (10.5)
45	10.1 (0.3)	0.0	50.1 (1.2)	0.0	2.0 (0.3)	32.0 (14.5)
50	10.1 (0.2)	0.4 (0.8)	50.1 (0.9)	0.0	2.0 (0.4)	37.6 (17.1)
55	10.3 (0.2)	0.4 (0.9)	50.0 (1.7)	0.0	2.0 (0.4)	41.6 (16.0)
60	10.3 (0.3)	0.8 (0.1)	49.8 (2.0)	0.0	2.1 (0.4)	44.0 (12.9)
65	10.4 (0.3)	1.4 (1.8)	49.7 (2.0)	0.0	2.0 (0.5)	50.0 (14.2)
70	10.4 (0.4)	1.7 (1.7)	49.6 (2.5)	0.0	2.1 (0.6)	55.3 (16.6)
75	10.3 (0.4)	5.6 (3.7)	49.5 (3.2)	0.0	2.1 (0.7)	57.6 (13.5)
80	10.4 (0.4)	9.0 (6.2)	49.6 (3.2)	0.0	1.8 (0.6)	70.5 (14.2)
85	10.5 (0.5)	18.7 (8.8)	49.6 (3.3)	0.0	1.8 (0.5)	72.7 (16.5)
90	10.4 (0.7)	32.0 (19.4)	49.1 (4.6)	0.0	1.8 (0.6)	78.0 (18.3)
95	10.3 (1.1)	60.0 (32.2)	50.0 (0.3)	10.0 (13.41)	1.5 (0.3)	92.0 (16.0)
100	—	—			—	—

modeling – that allows both for specifying in a highly flexible way the conceptual structure of a bundle of mechanisms and exploring their aggregate causal effects under a large range of conditions.

Introducing at the same time generative mechanisms of relative deprivation rate and feelings thus allowed to establish that an improving opportunities system may go along with two different situations. On the one hand, it can produce a “*more opportunities, more dissatisfied-*

yet-less-intensely-dissatisfied agents” pattern; on the other hand, it may go together with a *“more opportunities, fewer dissatisfied-yet-more-intensely-dissatisfied agents”* pattern. The condition under which the model studied here leads to the emergence of these complex relations is the presence of interpersonal comparisons that inversely tie individual dissatisfaction to the diffusion of deprivation situations.

The theoretical interest of these computational results is that they circumscribe the extension of the classic *“more opportunities, higher dissatisfaction levels”* pattern, showing that the inverse pattern, i.e. *“more opportunities, lower dissatisfaction levels,”* is equally possible. However, they also signal that the two patterns might be incompatible. This incompatibility is exemplified in the extreme case where all actors want to obtain the most attractive goods regardless of how many competitors they think they have. In this case, as opportunities improve, the quantity of dissatisfied agents falls while the intensity of deprived agents’ dissatisfaction can only grow. According to the absolute intensity of this feeling, society’s level of individual dissatisfaction could ultimately fall (if these agents are not intensely dissatisfied) or, on the contrary, rise (if these agents, while few in number, are also intensely dissatisfied).

Dyadic interaction configuration then can play a decisive role in the appearance of one or another systemic equilibrium. The last variant of the model simulated here suggests that if we suppose that actors take account of deprivation diffusion within their local neighborhood rather than throughout the population, individual dissatisfaction levels tend to soar. If the network contains few low-degree-nodes, this explosion is primarily verified when the global quota of dissatisfied agents is reduced; by contrast, the rise tends to become general if there are many low-degree-nodes. In this case, regardless of the global proportion of dissatisfied agents, the probability that each will be the only one among his contacts not to have what he wants rises.

The theoretical interest of introducing several structures of dyadic ties, which has been greatly facilitated by agent-based modeling, is considerable. First, even though the idea is an old one – Merton had already distinguished comparisons of self “with those men who are in some pertinent respect of the same status or in the same category” from comparisons “with the situation of others with whom [one was] in actual association, in sustained social relations” (Merton 1957: 231) – a formal model of relative deprivation implementing this distinction was still missing. This seems to represent real progress because, as (Gartrell 1987: 49) noticed, “the network approach will help to resolve fundamental, unanswered questions about social evaluation first raised in 1950 by Merton and Rossi – specifically, the

origins of comparative frameworks and the relation between individual and categorical or group reference points.” Second, introducing neighborhood-based comparisons gives us the occasion to refine some existing conceptual distinctions. On the one hand, insofar as the last version of the model conceives “envy” as a by-product of comparisons that are driven by dyadic links between actors, it seems reasonable to introduce a hybrid category, i.e. what one can call “comparison–interaction-based emotions,” in Elster’s (1999: 141–2) original typology, which distinguishes between comparison-based emotions and interaction-based emotions (see above note 17). On the other hand, this concept tends to make more complex Hedström’s (2005: ch. 3, fig. 3.2) typology of social interactions. In addition to “desire-mediated,” “belief-mediated” and “opportunity-mediated interactions,” we should indeed also take into account the possibility of “emotion-mediated interactions.”

The main limitations of the results discussed are equally obvious. First, the model presented here is still excessively simple compared with the mechanisms which we imagine generate both dissatisfied actor rates in a given society and the intensity of their feelings of dissatisfaction. Second, whatever the degree of theoretical complexity we grant these mechanisms, we would have to demonstrate that they are operative in real societies. What I was looking for in this preliminary analysis was simply material that would serve to convince the reader that agent-based simulation constitutes a particularly well-adapted tool for analytical sociology, enabling sociologists in this field to study as completely as possible the causal implications of the models they aspire to analyze.

With regard to theoretical enrichment, it should be evident that this type of analysis can be pushed as far as we like. But the technique can also be extremely useful when the objective is to link the model to reality. It is perfectly capable of handling fine empirical data on reasoning, comparisons, feelings and/or specific objects grounded in individual states of deprivation. Likewise, the regularities discussed here can easily be compared with empirical quantifications of dissatisfied actor rates as well as of components of the individual feeling of dissatisfaction.

From this perspective, agent-based models offer an additional general benefit: they pinpoint just where our empirical data are deficient, thereby suggesting how to reorient our collecting procedures.

So let us conclude this chapter by emphasizing the importance of pursuing that connection between analytical sociology, agent-based models and more traditional quantitative techniques.

In the minds of many quantitative sociologists, analytical sociology is merely an empty shell. Morgan (2005: 26), for example, wrote as follows of the contributions assembled by Hedström and Swedberg (1998): “Without a doubt, they correctly identified a major problem with quantitatively oriented sociology. But, they did not offer a sufficiently complete remedy.” Pisati (2007: 7–8) recently wrote: “It is not clear how the explanation strategy in question can be applied in practice to explain complex systems – which is what social phenomena constantly are.”

Though we can agree that “there is no method, let alone a logic, for conjecturing mechanisms ... this is an art, not a technique” (Bunge 2004: 200), it seems to me urgent to have the “art” give way to agent-based modeling when we study such mechanisms. If we cannot resolve to take this step, then this false definition of the situation – i.e. “analytic sociology is an empty shell” – could become true.

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