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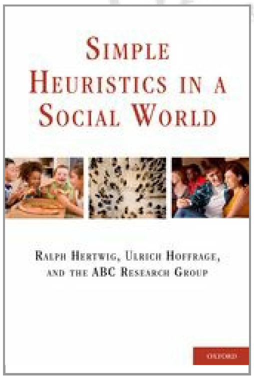

Simple Heuristics in a Social World

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Fast Acceptance by Common Experience: Augmenting Schelling's Neighborhood Segregation Model With FACE-Recognition

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[–] Abstract and Keywords

Schelling (1969, 1971a,b, 1978) observed that macro-level patterns do not necessarily reflect micro-level intentions, desires or goals. In his classic model on neighborhood segregation, which initiated a large and influential literature, individuals with no desire to be segregated from those who belong to other social groups, nevertheless, wind up clustering with their own type. Most extensions of Schelling's model have replicated this result. There is an important mismatch, however, between theory and observation that has received relatively little attention. Whereas Schelling-inspired models typically predict large degrees of segregation starting from virtually any initial condition, the empirical literature documents considerable heterogeneity in measured levels of segregation. This chapter introduces a mechanism that can produce significantly higher levels of integration

and, therefore, brings predicted distributions of segregation more in line with real-world observation. As in the classic Schelling model, agents in a simulated world want to stay or move to a new location depending on the proportion of neighbors they judge to be acceptable. In contrast to the classic model, however, agents' classifications of their neighbors as acceptable or not depend lexicographically on recognition first and group type (e.g., ethnic stereotyping) second. The FACE-recognition model nests classic Schelling: when agents have no recognition memory, judgments about the acceptability of a prospective neighbor rely solely on his or her group type (as in the Schelling model). A very small amount of recognition memory eventually leads to different classifications that, in turn, produce dramatic macro-level effects resulting in significantly higher levels of integration. A novel implication of the FACE-recognition model concerns the large potential impact of policy interventions that generate modest numbers of face-to-face encounters with members of other social groups. The model describes a new co-evolutionary process in which individual-level classifications of others and the macro-structure of the social environment jointly and substantively influence one another.

Keywords: ethnic, discrimination, agent based, computational economics, stereotypes, recognition, lexicographic, noncompensatory, heuristic, urban economics, institutional design, social judgment

> Contrary to general belief, I do not believe that friends are necessarily the people you like best, they are merely the people who got there first.
>
> *Peter Ustinov (1979)*

In *The Adventures of Huckleberry Finn*, Mark Twain's (Twain, 1884/2006), Huck Finn demonstrates two sharply contrasting attitudes toward black slaves. When Huck considers blacks as an abstract group, his thinking follows ugly pro-slavery norms, affirming the view that slaves are the rightful property of their owners. In one infamous passage, Huck confesses that he expects to “go to hell” for helping the escaped slave, Jim, to elude recapture:

> And then think of ME! It would get all around that Huck Finn helped a nigger to get his freedom; and if I was ever to see anybody from that town again I'd be ready to get down and lick his boots for shame.… I was stealing poor old woman's nigger that hadn't ever done me no harm.… (p. 137)

In contrast to his views of blacks in general, Huck adopts a very different attitude toward Jim when interacting face-to-face on their journey down the Mississippi River. After only a small amount of shared experience, Huck makes a choice, incurring a large personal cost, to help Jim escape. Feeling conflicted, Huck describes his decision-making process in the following passage, in which he **(p.226)** considers sending a message written on a piece of paper that would have turned Jim in, returning him to his owners:

> [I] set there thinking—thinking how good it was all this happened so, and how near I come to being lost and going to hell. And went on thinking. And got to thinking over our trip down the river; and I see Jim before me all the time: in the day and in the night-time, sometimes moonlight, sometimes storms, and we a-floating along, talking

> and singing and laughing…. and then I happened to look around and see that paper. It was a close place. I took it up, and held it in my hand. I was a-trembling, because I'd got to decide, forever, betwixt two things, and I knowed it. I studied a minute, sort of holding my breath, and then says to myself: "All right, then, I'll GO to hell"—and tore it up. (pp. 137–138)

This tension—between Huck's affirmation of the "moral correctness" of respecting slave owners' property and his choice to help Jim escape—is interesting sociologically and psychologically, but also with respect to the standard decision-making model of constrained optimization, which requires self-consistent beliefs and actions. If asked to explain Huck's use of two very different rules of engagement, a Bayesian might try to identify some piece of information about Jim that Huck had acquired in the course of their adventures. This Bayesian rationalization would require that Huck behave generously to Jim only after conditioning on a signal indicating that Jim is a high-valued outlier in a distribution of black slaves whose qualities do not generally merit such generosity and consideration.

One finds little support in Twain's novel for this Bayesian interpretation to harmonize Huck's negative view of blacks in general with his distinctly enthusiastic view of Jim in particular. The Bayesian view interprets Huck's decision to help Jim as the result of belief updating and conditional probabilities.[1] Huck thinks of Jim very differently than he does about the average person drawn from the population of black slaves. And this shift occurs on the basis of almost no evidence in favor of Jim's specialness. In the story, just as in many real-life instances, Huck's general and specific decision rules remain conflicted. They remain unresolved, and need not be resolved, because Huck applies different rules of social interaction depending on a critical contextual cue: whether **(p.227)** the situation requires judgments about abstract groups or about individuals situated face-to-face in an everyday encounter.

What makes the difference for Huck in his decision to help Jim is not information about Jim's characteristics, but a shift in the environment that allows Huck and Jim to deal with each other one-on-one and accumulate a stock of mundane experiences in common. Twain's text supports the speculation that if Jim were replaced by a randomly drawn slave, Huck would have developed similar affection for him, too, leading to the same set of conflicting views, cued by the contextual factor of abstract generalization versus face-to-face interaction.

The possible consequences of Huck's decision were enormous: the prospect of punishment for helping an escaped slave and the perceived certainty of going to hell versus a chance at a reward for turning him in. Huck's decision was momentous for Jim, too, implying certain punishment and continued slavery versus a chance at freedom. In this chapter, we focus on a far less dramatic, but still important, decision: choosing a location.[2] There is a wide range of factors that people consider when choosing where to reside, including price, distance to work, school quality, physical features of houses and apartments, and, not least, what housing economists refer to as neighborhood quality. In our analysis, we isolate and focus on one key component of perceived neighborhood quality: demographic information about neighbors' ethnic types. As in Huck's dilemma, such information could be abstract (e.g., neighbors' ethnicity or social status), or it could be relational—whether or not there is a history of shared experience, and, if so, whether this experience was positive or negative. We compare two different decision rules: one that assesses the desirability of locations solely on the basis of neighbors' ethnic type (or group membership), and one that also takes relational information into account. To study the impact of these two decision rules on location choice, we build on what is one of the most famous models of ethnic-group interaction in the social sciences, Thomas Schelling's model of neighborhood segregation (1969, 1971a, 1971b, 1978).

A jointly causal loop connects micro and macro levels (Coleman, 1994), structured by the co-evolution of individual behavior and the external environment. The macro pattern in the neighborhood influences the level of happiness experienced at the micro level. In other words, who your neighbors are determines whether you want to stay or move. These decisions made on the micro level, in turn, shape macro patterns by reformulating the composition of neighborhoods. The investigations reported in the present book and its predecessors (Gigerenzer, Todd, & the ABC Research Group, 1999; **(p.228)** Todd, Gigerenzer, & the ABC Research Group, 2012) focus on how the macro-level environment influences the micro-level (i.e., how the structure of information in the environment influences the performance of individual decision strategies). In the present chapter, we will consider the other direction as well, describing how micro shapes macro (i.e., how decision rules shape the environment). Specifically, we propose a simple, lexicographic decision rule in which positive, shared experience trumps aversion to others based on different group identity.

The chapter will proceed as follows: We motivate this decision rule by drawing on previous theoretical and empirical research. Subsequently, we fully specify the recognition-augmented Schelling model, which uses contextual information given by shared experience in the decision maker's environment. This augmentation leads to an encompassing model that includes the classic Schelling model as a special case. We then present results from a series of agent-based simulations. Finally, we discuss interpretations of these results, their implications for institutional design in the real world, and the possibility of future empirical tests of the recognition-augmented Schelling model.[3]

FACE-Recognition: *F*ast *A*cceptance by *C*ommon *E*xperience

If there were no constraints in the social world, we could form our attitudes towards others by collecting all the possible information about them. Yet, time and processing constraints often do not allow for such a luxury, and thus we are forced to use only a very limited set of information about others, to categorize them with the help of stereotypes and behave accordingly (Dovidio, Glick, & Rudman, 2005). Such use of fast and frugal heuristics in a social world may not necessarily lead us astray—to the contrary, some scholars (e.g., Schneider, 2004) have suggested that cognitive mechanisms underlying stereotyping also produce beneficial results in certain contexts. In a similar vein, in their meta-analysis, Ambady and Rosenthal (1992) concluded that people appear to make surprisingly accurate social judgments based on "thin slices" of information.

A fundamental distinction when categorizing others is between "us" and "them"; that is, between in-group and out-group members (Esses, Jackson, Dovidio, & Hodson, 2005; Sherif, Harvey, White, Hood, & Sherif, 1961; Tajfel, Billig, Bundy, & Flament, 1971; Tajfel & **(p.229)** Turner, 1979; Turner, Hogg, Oakes, Reicher, & Wetherell, 1987). There is, however, abundant evidence demonstrating that people are not locked into their prejudices and stereotypical thinking. Let us consider some examples from history and literature illustrating that people commonly make exceptions for some out-group members without changing their attitude toward the out-group as a whole.

The Roma, or Gypsy, minority in Europe faces widespread discrimination in contemporary Europe. In the documentary film *Roma and Stereotypes* (2000),[4] Danish journalist Jerry Bergman describes an extreme opinion, uttered by a taxi driver who suggested that the furnaces at Auschwitz should be reopened to exterminate the Roma people. However, Bergman's comment reveals that this shocking and seemingly absolute statement does not reveal the full picture: "But, yes, of course he does have several friends who are Gypsies.… These few he knows should be left in peace, but the rest of course should be exterminated." Thomas Jefferson is another figure who had no qualms with being inconsistent. In his writing, he showed little hesitation in comparing African Americans to animals. Jefferson also wrote abhorrently of interracial unions, describing them as a "degradation to which no lover of his country, no lover of excellence in the human character can innocently consent" (Jefferson, 1784/1905, vol. 11, p. 418). However, his obvious prejudice against blacks and interracial relationships in general did not limit an intimate face-to-face relationship with a slave, Sally Hemmings. Finally, in what is probably the most famous fictional love story of all time, *Romeo and Juliet*, Shakespeare (1595/1997) portrays the conflict between different decision procedures used when dealing with individuals from a despised group. The feud between the Montague and the Capulet families, which their children take part in, stands in stark contrast to the romance between Romeo Montague and Juliet Capulet. Romeo and Juliet valued their romantic love more than their parents' expectation that members of the other family should be regarded as enemies.

These examples illustrate what seems to be a regularity of human social dynamics: People show blanket disdain for other groups, from avoidance to full-blown hatred directed at despised groups such as blacks, whites, Jews, Muslims, poor people, or homosexuals, to name only a few. At the same time, these examples demonstrate that people with deep prejudices are often willing, and even enthusiastic, to build friendships across group boundaries. Minard's (1952) account of white mine workers willingly interacting with black miners below ground while reestablishing racial divisions above ground is as relevant today as it was half a century before, documenting that physical **(p.230)** proximity serves as a cue for switching on and off the relevance of anti-group sentiments (Hewstone & Brown, 1986).

Although there are certainly additional factors that could account for switching on and off anti-group sentiments as a basis for decisions in different contexts, we focus on the one we already mentioned in the example of Huckleberry Finn. We propose a simple, lexicographic heuristic. Its lexicographic structure derives from the fact that an individual's positive or negative face-to-face experience can completely overrule general beliefs such as ethnic stereotypes. We refer to this heuristic as the *FACE-recognition heuristic*, where the acronym FACE encompasses its literal meaning (i.e., recording faces into recognition memory) as well as other contexts with small numbers of individuals in which *Fast Acceptance by Common Experience* allows relationships to form that defy generalized antipathy or affection according to group identity. When there is only a small amount of shared experience, then the quality of that person-specific shared experience determines the result of classification (Figure 8-1, left tree, right branch), overruling any other classification that would have resulted based on group identity. However, when the other person is unrecognized, the FACE-recognition heuristic reduces to the classic Schelling model, classifying people solely on the basis of group identity (Figure 8-1, left tree, left branch; also see below).

One of the predecessors of the FACE-recognition heuristic is *contact theory* (Allport, 1954; for more recent work, see Pettigrew, 1998; Pettigrew and Tropp, 2006). This theory describes how face-to-face interactions between members of different groups holding negative stereotypes of each other can limit prejudice. It suggests one mechanism that can transform face-to-face meetings of different group members into an integration device that results in durable social ties. A key difference between contact theory and the FACE-heuristic is that the contact theory literature generally seeks conditions under which contact categorically shifts beliefs about the other group (i.e., reduces the general level of prejudice) well beyond particular situations or person-specific relationships.

There is little consensus among psychologists and sociologists about how and whether generalized shifts in beliefs about other types can be achieved. The originator of contact theory (Allport, 1954) predicted that positive effects of contact in the above sense could be achieved only if interacting groups had equal status, common goals, participated in cooperative joint action, and if their integration was institutionally sanctioned. Later theorists working in the tradition of contact theory elaborated additional conditions aimed at making positive contacts more frequent and long-lived, although critics questioned whether they could possibly be implemented as real-world institutions (Dixon, Durrheim, & Tredoux, 2005). There is **(p.231)**

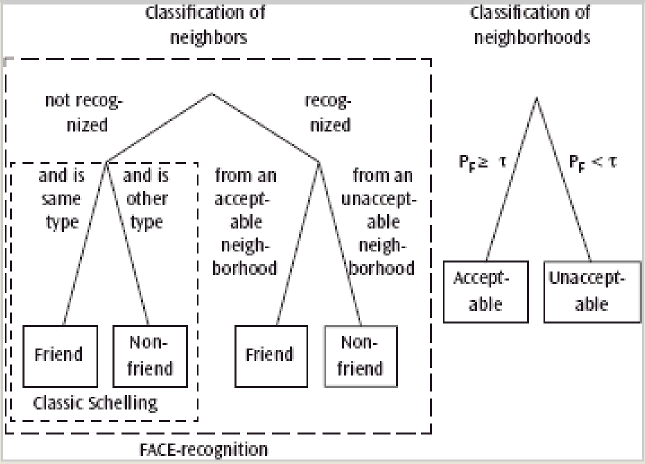

Figure 8-1: Classification of neighbors (left tree). In the classic Schelling model, the classification of neighbors is exclusively based on their group membership (right branch). When equipped with FACE-recognition memory, neighbors who are recognized are classified based on whether the most-recent previous encounter with them was in an acceptable or unacceptable neighborhood, whereas unrecognized neighbors are classified as in classic Schelling. Classification of neighborhoods (right tree) is the same for both models and depends exclusively on whether the proportion of friends among the neighbors (P_F) is above the acceptability threshold τ. (*Source*: This and the following figures were adapted from "Fast Acceptance by Common Experience: FACE-recognition in Schelling's model of neighborhood segregation" by N. Berg, U. Hoffrage, & K. Abramczuk (2010), *Judgment and Decision Making, 5*, 391–410. Copyright by the authors.)

fairly widespread agreement that even when some key conditions are lacking, moderate contact can still increase tolerance, as measured variously in the related literatures.[5] One interesting finding is that repetitive exposure to people (and abstract symbols, too!) appears to increase favorable sentiment (e.g., Bornstein, 1989; Homans, 1950; Zajonc, 1968). A recent experimental study finds that spatial proximity alone substantially increases the likelihood of friendship in **(p.232)** at least one important real-life context, confirming Peter Ustinov's belief that opened the present chapter (Back, Schmukle, & Egloff, 2008). Several researchers also report that personalized interaction appears to give people a stronger sense of individual identity, reducing the importance of group membership in the formation of opinions about others and decisions to interact with them (Ensari & Miller, 2001; Miller, 2002; Rothbart & John, 1985).

The FACE-recognition heuristic is similar, but not identical, to the recognition heuristic studied in Goldstein and Gigerenzer (1999, 2002). Goldstein and Gigerenzer proposed that recognition is an evolved capacity that can be used to make judgments whenever there is a correlation between recognition and a criterion with respect to which objects are to be ranked. Reasoning according to the recognition heuristic is a one-step process: If one of the two objects is recognized and the other is not, the one that is recognized is judged to have greater value. An important feature of the recognition heuristic is the fact that it is noncompensatory. The moment that one object is recognized and the other not, the decision, or choice, or classification is determined. No other information enters the decision process, and therefore no further information needs to be weighted, or has the potential for overruling the recognition-based decision. (Some have questioned whether recognition is indeed used in a noncompensatory manner, which is addressed by Gigerenzer & Goldstein, 2011, in their review of this literature; see also Hoffrage, 2011a.) We use the same noncompensatory, or lexicographic, mechanism in the FACE-recognition model. The difference is that for the FACE-recognition heuristic, mere recognition does not necessarily lead to a positive appreciation; instead, the attitude towards someone else is modified by whether the shared common experience had a positive or a negative flavor.

The FACE-recognition heuristic is also related to Aktipis's (2006) evolutionary game theory model in which agents repeatedly play Prisoner's Dilemma while using different decision rules for choosing with whom to play in each round. Numerous strategies in such population games have been studied in an attempt to explain the real-world observation that people, even in anonymous one-shot games, often play non-Nash strategies to achieve greater cooperation than is predicted by standard game theory (see, for example, Bowles & Gintis, 2004; Nakamaru & Kawata, 2004; Sudgen, 1986; chapter 5). Aktipis (2006) considers two simple strategies that rely on recognition to choose with whom to play the game: D-mem and C-mem. The D-mem strategy for accepting partners is always to accept an unrecognized individual as a playing partner and then cooperate. Whenever a partner defects, D-mem records that individual's name on the defector list, thereby excluding this individual as a partner in the future. Once **(p.233)** the agent's memory limit is reached, D-mem removes the oldest defector from the list to record new ones. The second strategy in Aktipis is C-mem, which remembers only the names of recent cooperators, and once its memory capacity is full, it accepts playing partners only from the names of cooperators on that list. A key similarity between our model and Aktipis's is that attitudes towards others are determined by simple memories based only on recognition and the outcome of previous encounters. Moreover, for both models it can be shown that their very modest memory requirements and very simple decision rules lead to large-magnitude population-level effects.

Neighborhood Segregation: Schelling's Classic Model and a Recognition-Augmented Variant

The intellectual father of attempts to model neighborhood segregation, Nobel laureate Thomas Schelling (1969, 1971a, 1971b, 1978), made an intriguing observation: Even in a population of individuals who have no desire for segregation and no strict aversion to out-group members, the goal of simply avoiding being a relative minority in one's respective neighborhood leads to surprisingly high levels of segregation that no individual (in Schelling's model) desires or strives to achieve. This incongruity of macro consequences that do not reflect the primary goals of the individuals whose decision rules nevertheless cause the macro pattern is a key theme in Schelling's work and led to the title of his book, *Micromotives and Macrobehavior* (Schelling, 1978).

Neighborhood segregation continues to be a relevant public policy issue (Alesina, 1999; Baughman, 2004; Brender, 2005; Musterd, Priemus, and van Kempen 1999; Nechyba, 2003), and recent work in economics, sociology, and mathematical social sciences (Fossett, 2006; Pancs & Vriend, 2007; Vinković & Kirman, 2006; Zhang, 2004) indicates that Schelling's ingenious model continues to play a very important role in the theoretical approaches offered today.[6] In fact, the mathematical social sciences are rich with analyses that build on and modify Schelling's spatial proximity model. Some of them explore parameters and features already present in Schelling's model. Others introduce new elements that attempt to capture additional features **(p.234)** from the spatial dynamics of real cities. Modifications include alternate definitions of the spatial environment, neighborhoods, rules for moving (e.g., simultaneous versus sequential), numbers of and overlap among group types, noise, vacancy rates, and so on.

Schelling's classic paper on segregation consisted of a thought experiment showing that, even when no individual has a preference for segregation (i.e., an aversion to living near members of a different ethnic group), high levels of unintended segregation are very likely to occur. This basic result has been confirmed by many researchers working with theoretical extensions that add new features to Schelling's model. For example, Fossett (2006) and Gilbert (2002) added information about the cost of residing at a particular location and produced similar theoretical results predicting large degrees of segregation. Gilbert also considered models where neighborhood characteristics depended on recent histories, allowing agents to switch group membership (e.g., switch ethnic identity), leading again to high levels of segregation. Scope of vision (i.e., how agents view the boundaries of their own neighborhoods) was analyzed in Fossett and Waren (2005) and Laurie and Jaggi (2003), leading again to segregation. A rather large literature has investigated different utility functions (Bøg, 2005, 2006; Bruch & Mare, 2003; Pancs & Vriend, 2007), almost always reinforcing Schelling's prediction of high levels of segregation. Other notable extensions include Vinković and Kirman (2006), drawing on techniques borrowed from physics; analytical models using stochastic stability as an equilibrium concept (Bøg, 2005, 2006; Young, 1998, 2001; Zhang, 2004); and the continuum models of Yizhaq, Portnov, and Meron (2004). The vast majority of these extensions generalize or reinforce the original result of highly segregated end-state geographies that are unintended and do not require any individual to prefer segregation.

Parallel to these studies, a growing body of literature relates Schelling's model to real-world data (Bruch & Mare, 2003; Clark, 1991; Fossett, 2006; Portugali, Benenson, & Omer, 1994), revealing an interesting clash between models and reality. Even though there is overwhelming conformity in the theoretical literature with extensions of Schelling's model that predict high levels of segregation from virtually any starting condition, empirical measures of segregation in cross-sectional studies of cities, countries, and other social groupings show remarkable heterogeneity (Huttman, Saltman, Blauw, & Saltman, 1991; and references in Berg, Hoffrage, & Abramczuk, 2010). Disparity between the Schelling model's predictions and wide variation in integration in the real world is frequently overlooked. Instead, the segregation literature tends to focus on social problems stemming from segregation—and with good justification, given the seriousness of these problems. These include **(p.235)** long-term joblessness, single-parenthood, school dropouts (Cutler & Glaeser, 1997; Nechyba, 2003), problems in tax collection (Brender, 2005), and reduced chances of positive economic outcomes among the poor, together with alienation among the well-off (Atkinson & Flint, 2004).

To be sure, segregation exists in the real world. The practical importance of attenuating its detrimental social effects motivates ongoing public policy attempts to nurture civic society. Therefore, it is understandable that the Schelling model, which predicts the segregation that these policies aim to assuage, plays a prominent role in this literature. But there is a problem in terms of discord between theory and observation. The Schelling model predicts high levels of segregation starting from virtually anywhere within a very large set of initial conditions and parameter values. But the empirical literature reveals that cities, countries, academic departments, and other social configurations vary in the extent to which social groups engage in inter-group mixing at the aggregate level. This raises an interesting question: How can the Schelling model be squared with real-world data? Are there extensions of the Schelling model that come closer to reality by predicting various degrees of segregation that vary systematically with other observable factors in the environment?

Drawing on a large literature in psychology and biology concerning face- and name-recognition (e.g., Berg & Faria, 2008; Bruce & Young, 1986; Moscovitch, Winocur, & Behrmann, 1997; Schweinberger, Pickering, Burton, & Kaufmann, 2002; Semenza & Sgaramella, 1993; Semenza & Zettin, 1989) we conducted a series of computer simulations aimed at demonstrating how the FACE-recognition heuristic can produce a much wider variety of spatial patterns of integration and segregation that are systematically linked to parameters in the model. We next sketch the classic Schelling model before detailing how the FACE-recognition heuristic performs in this context.

The Classic Schelling Model

Consider a $G \times G$ square lattice with a total number of G^2 locations, inhabited by agents. If there are only two groups, a majority and a minority, and if each agent belongs to only one group, then the total number of agents, N, equals $N_{MAJ} + N_{MIN}$, with $N_{MAJ} \geq N_{MIN}$. In each period, each agent has to make a binary decision: to stay at the current location or to move somewhere else. To make this decision meaningful, there must be unoccupied locations available for agents who want to move, which implies strictly more locations than total number of agents ($G^2 \rangle N$). Whether an agent wants to stay or to move depends on whether he is satisfied with his current location, which, in turn, depends on the proportions of **(p.236)** same-type and other-type agents in his immediate neighborhood. Schelling defined an agent's *neighborhood* as the locations directly proximal, or surrounding, an agent's location. Thus, for an interior agent, his neighborhood consists of the eight locations that form a small box around his location.[7] Agents located at the edges have smaller neighborhoods, although alternative definitions of “neighborhoods” have appeared in this literature.[8] An agent is happy with his current location as long as the proportion of same-type agents in the neighborhood is at least as large as the acceptability threshold τ (Figure 8-1, right tree). Larger values for this threshold impose more stringent homogeneity requirements in order to classify locations as acceptable.

A sequential process then unfolds by which unhappy agents move from unacceptable to acceptable locations, with movers picked at random from the list of all unhappy agents and then moving to the nearest acceptable location. Whenever an agent moves, it changes the spatial distribution of types in other agents' neighborhoods. This, in turn, causes other agents to transition from happy to unhappy, or the reverse. This feedback loop—in which individuals' happiness about their current location and the spatial geography of the environment are jointly causal—is a primary reason why this simple model has generated such enduring interest. Changes in the spatial distribution of types affect individuals' decisions about whether they want to move, and individuals' decisions about whether to move affects the spatial distribution of types. The distribution of types reaches a terminal state, which completes a single run of the Schelling model, when one of the following three conditions is met: (a) All agents are happy and thus nobody wants to move; (b) some agents are unhappy, but no improving moves are possible because none of the unoccupied locations are acceptable from the points of view of the unhappy agents; or (c) the maximum number of iterations is reached, indicating either very slow convergence to a happy or unhappy ending, or the presence of a cycle **(p.237)** that will never converge to a terminal state, which we refer to as an *indeterminate ending*.[9]

For a population with two group types and equal numbers of each type, one can intuitively see that maximal integration is achieved by a perfect checkerboard pattern such as the one depicted in Figure 8-2, Panel A. In that panel, the neighborhood grid is 8 × 8 (with corner locations unoccupied), implying a total of 60 possible locations, occupied by 30 "–" type and 30 "+" type agents. Negative and plus signs represent ethnic or group identity. Each agent not located on an edge has an equal number of neighbors of each type. Now imagine this perfectly integrated grid is subjected to a spatial shock[10] in which 20 of the 60 agents disappear at random, chosen uniformly from all occupied locations without regard to type.[11] Then five new agents of random type appear at randomly chosen locations, drawn uniformly from among the 24 unoccupied locations (4 unoccupied corners plus 20 newly unoccupied locations after the disappearance of 20 agents). A single run of the Schelling model continues by forming a list of unhappy agents, that is, agents who want to move. A single unhappy agent is selected at random (from the list of unhappy agents) to actually move to the nearest location at which he is happy. If there are two or more desirable locations that are equally near, then one is chosen at random, and the list of unhappy agents is then updated. This process of picking unhappy agents one at a time continues until a terminal state is reached (see above).

The three panels to the left of Figure 8-2 display three states of one run of the classic Schelling model: initial checkerboard (Panel A), subsequent spatial shock in which 11 "–" types and 9 "+" types disappeared and 1 "–" type and 4 "+" types appeared (Panel B), and end-state spatial distribution (Panel C). Following the initial shock to the spatial distribution, the first period in a single round begins with decisions made by each agent about whether he wants to move. Panel B **(p.238)**

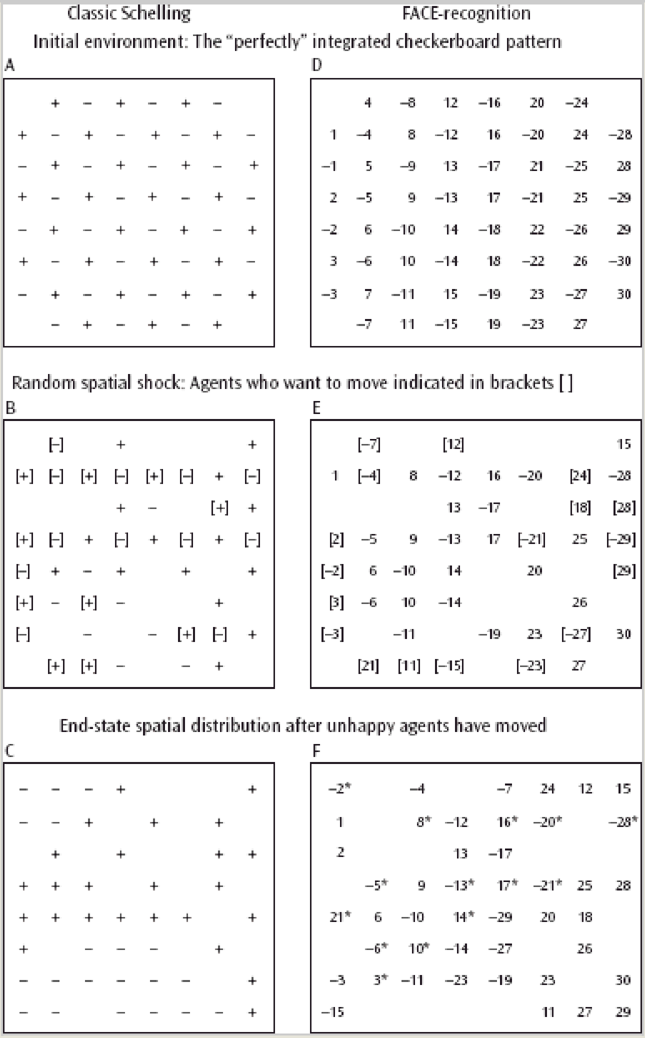

Figure 8-2: A single run of the classic Schelling model (the three checkerboards displayed to the left) and of the FACE-recognition model (the three displayed to the right). In the classic model, agents are only distinguished by their type ("–" vs. "+"), whereas in the FACE-recognition model, faces are identified with numerical IDs, positive for majority and negative for minority types. Starred agents in Panel F are made happy because of memory.

(p.239)

Table 8-1: Key Parameters in the Classic Schelling Model

Size and shape of the spatial environment, measured by edge length G in the case of a square lattice (which also gives the number of possible locations = G^2);
Group type distribution (either given in frequencies, N_{MAJ} and N_{MIN}, or, equivalently, as a total population size, $N = N_{MAJ} + N_{MIN}$, plus a minority rate, N_{MIN}/N). (Adding a general number of groups is possible, but complicates the notation considerably without adding anything to the two-group analysis adopted in the present chapter);
Density, or fullness, of the environment (sometimes referred to as occupancy rate) N/G^2;
Acceptability thresholds (i.e., the minimum fraction of same-type agents required to classify a location as acceptable) τ_{MIN} and τ_{MAJ}, for minority and majority agents, respectively;
Procedure for generating the initial distribution;
Definition of neighborhood;
Other parameters needed to implement agent-based simulation; e.g., number of runs, and maximum number of moves allowed before a single run of the model terminates.

indicates with brackets the agents who are unhappy and want to move. With both types' acceptability thresholds set to 1/2, not all agents were happy in the initial state, although the post-shock spatial distribution has a much larger number of those who want to move: 22 of the 45 agents who populate the environment. Panel C shows the classic result of segregation; that is, agents have very few or even no single other-type agents as neighbors. Note that this final result occurred despite of the fact that all agents are as happy to live in a neighborhood that is 50% different from themselves as in a neighborhood that is all their own type, and despite the fact that the initial state was near-perfect integration. The resulting segregation was unintended because it does not reflect the micromotives of any single agent in the model.

As we already mentioned, various authors have investigated virtually all parameters in the classic Schelling model (Table 8-1). One surprising finding is that its basic prediction—high levels of segregation starting from virtually any initial condition—is incredibly robust over a very large set of parameter configurations and modifications to the model.

Extending the Classic Schelling Model by FACE-Recognition

In the classic Schelling model, a given location is acceptable if and only if the proportion of friends in the neighborhood, $N_{friends}/N_{neighbors}$, exceeds that agent's acceptability threshold τ, and is unacceptable otherwise. A *friend* is simply defined as a “same-type agent.” In the FACE-recognition version of the model, the same threshold rule for **(p.240)** determining whether a location is acceptable provides the crucial behavioral element (Figure 8-1, right tree), but with one important modification concerning the definition of friends and non-friends. The recognition-augmented Schelling model assumes that agents are endowed with a small amount of memory about the faces of recently encountered agents. Each agent's memory stores information about which faces are recognized from the K most recent neighborhoods and also records whether recognized faces are most recently recognized from an acceptable or unacceptable neighborhood. Agents who are recognized from an acceptable neighborhood in the past are counted as friends, no matter whether they are same-type or other-type. Conversely, agents who are recognized from an unacceptable neighborhood in the past are counted as non-friends, no matter whether they are same-type or other-type (Figure 8-1, left tree). When encountering unrecognized agents, the FACE-recognition model reduces to the classic Schelling model (which is, therefore, nested in the FACE-recognition model: see Figure 8-1, left tree). When encountering agents who are recognized from both good and bad neighborhoods, only the quality of the most recent memory matters for classification, although cases of remembering another agent from two previous neighborhoods in the past K periods are extremely rare.

This nested structure of the two models can be formalized using a memory parameter, which specifies how many previous periods are stored into each agent's memory. The classic Schelling model is then recovered from the FACE-recognition model if this memory parameter is set to zero, which implies that each agent recognizes no other agents and, consequently, all friend/non-friend classifications are based solely on group identity. When evaluating the acceptability of neighborhoods with one or more recognized agents, the changes that take place are few and mostly very local. The results below, however, show that these small, local changes lead to surprisingly large macro-level changes in the spatial geography of the environment.

The three panels to the right in Figure 8-2 show a single run in the FACE-recognition model, like for the classic Schelling model: first the initial state of checkerboard integration (Panel D); then the post-shock spatial distribution, with brackets indicating those who are unhappy and want to move (Panel E); and, finally, the terminal-state spatial distribution after all unhappy agents have moved to a location they find acceptable (Panel F). In contrast to classic Schelling, now faces can be identified. In Panels D, E, and F, these are coded as numbers—positive numbers for majority-type agents and negative numbers for minority agents. Agents are endowed with a single period of memory that generates two short lists (possibly empty) of friends and non-friends. These recognized agents (who number no more than eight when the memory parameter is set to 1 period) are classified (in terms of who makes a potentially good neighbor) by a **(p.241)** classification rule in which recent face-to-face experience absolutely overrules group identity.

An important feature of the FACE model visible in Figure 8-2 is that recognition memory can make agents happy or unhappy, and that these states of happiness can differ from those in the classic Schelling model. It is important to note that the new way for agents to be happy about a particular location (namely through FACE recognition) does not trivially lead to more happiness and therefore more integration—simply because there is also a new way to be unhappy (again, through FACE recognition). A priori, the recognition step in the classification of locations could just as well lead to more unhappiness and segregation.

To see this, compare the two checkerboards in the middle of Figure 8-2. The spatial shocks, represented as the difference between Panel B and Panel E, are exactly the same. Still, the agents who want to move right after the shock (indicated through brackets) are not the same in these two panels, because of one-period memories held over from the perfectly integrated checkerboard that slightly changed counts of friends and non-friends. Consider the top-most agent along the western edge who is identified as face "+1" (Panel E). Agent "+1" is surrounded by two other-type agents, "–7" and "–4." In the FACE-recognition model, agent "+1" remembers "–1" and "–4" (but not "–7") from the pre-shock checkerboard and, consequently, regards "–4" as an acceptable neighbor, but not "–7." Because agent "+1" views half of his neighbors as acceptable, and because his acceptability threshold of 1/2 requires only that half or more of his neighbors be friends, "+1" is happy with his post-shock location. In subsequent periods, "+1" will come to regard "–7" as a friend, too, because the face of "–7" will be recognized from a happy neighborhood.

Agent "–23," located at the right of the southern edge in Panel E, is another interesting case because, after the shock, she has two same-type and two other-type neighbors. Her acceptability threshold (like that of all agents in this run of the model) is set to 1/2. Therefore, in the standard Schelling model, she would not want to move. But in the FACE-recognition model, agent "–23" is made unhappy, because a memory of unacceptable neighborhoods in the past causes reclassification of a few same-type agents as non-friends (who would otherwise be classified automatically as friends if they were unrecognized). Similarly, agent "+24," who has three of five neighbors of the same type (and would therefore be happy in the classic Schelling model), is nevertheless unhappy and wants to move because same-type neighbor "+28" is recognized from an unacceptable neighborhood.

In the end-state, spatial distribution displayed in Panel F, all agents are happy. Starred agents are those who would be unhappy in their end-state position (because the majority of their neighbors are other-type **(p.242)** agents) if the classic Schelling classification rule based on group identity were used instead of the FACE-recognition heuristic. The reason that they are happy with their end-state neighborhoods is because they have accepted one or more other-type agents as a friend based on a shared experience from an acceptable neighborhood in the past. For example, the minority agent "–2" did not think of the majority agent "+1" as a friend in the beginning periods of the model. But somewhere along the way, "–2" moved to a neighborhood that was acceptable despite the presence of non-friend "+1" and, consequently, agent "–2" recorded "+1" as a friend. Note, too, from Panel E that "–2" coded some same-type agents, such as "–5" and "–6," as non-friends. Thus, along the adjustment path toward the terminal state, switches in classifications—from friends to non-friends, and non-friends to friends—result in evaluations of neighborhoods (as acceptable or unacceptable) that are substantively different from those of the classic Schelling model, even with a very small amount of recognition memory and consequently very short lists of recognized faces.

Pitting the FACE-Recognition Model Against the Classic Schelling Model: Simulation Results

Procedure and Measures of End-State Integration

The single runs depicted in Figure 8-2 show a stark contrast in end-state spatial distributions of the two models (Panels C and F). To make sure that this contrast is systematic and not the result of mere chance occurrences, we repeated our simulations and report empirical distributions for our measures of end-state integration across many runs. Each run included (as a control condition) the classic Schelling model with no recognition memory and (as a treatment condition) the FACE-recognition model with at least one period of memory. In every run, the two conditions began with the same integrated checkerboard and were then subjected to the same spatial random shock. This enabled us to compare the macro-level consequences of the FACE-recognition heuristic starting in exactly the same initial world. Following this common spatial shock, the lists of agents who want to move was deterministic. In any given period of a single run, however, the issue of who among those who want to move was chosen to actually move results from chance, leading to different end-state spatial distributions.

To describe such end-state distributions, Pancs and Vriend (2007) use six segregation measures, recognizing that they are highly correlated, while emphasizing different aspects of inter-group mixing in the lattice environment. We turned their segregation measures into integration measures; that is, our coding was such that high values **(p.243)** indicated high integration rather than high segregation. We focus on three of these measures: other-type exposure, contact with at least one other, and switch rate.

Other-type exposure (OT) is the mean fraction of other-type agents as neighbors, averaged over agents. To compute OT on a spatial distribution, one computes for each agent, i, the number of other-type agents in the neighborhood, $N_{OT,i}$, and the total number of neighbors, N_i. Agent i's fraction of other-type agents in his neighborhood is simply $N_{OT,i}/N_i$, and OT is computed as the average across agents: $\Sigma_i(N_{OT,i}/N_i)/N$. In both Panel A and Panel D of Figure 8-2, OT begins at 53% in the initial checkerboard environment and rises to 55% immediately after the shock. In the classic Schelling model's end-state distribution (Figure 8-2, Panel C), OT integration falls sharply from 55% to 17%, but remains much higher at 45% in the FACE-recognition model (Panel F).

Contact with at least one other (COO) measures the fraction of agents whose neighborhood includes at least one other-type agent. To calculate COO, let $COO_i = 1$ if $N_{OT,i} \rangle 0$, and $COO_i = 0$ otherwise. Then $COO = \Sigma_i COO_i/N$. The complement, $1–COO$, is the fraction of agents who are absolutely segregated; that is, live entirely isolated from other-type agents. In both models displayed in Figure 8-2, the initial COO is 100% (Panels A and D), because all agents have at least one other-type neighbor. In the run of classic Schelling, the end-state distribution's value of COO falls to exactly 50% (Panel C), while remaining much higher at 87% for the FACE-recognition model (Panel F).

Finally, the *switch rate* (SR) is the average number of switches of type encountered in a 360-degree panoramic scan of each agent's adjacent locations, first normalized to a range between 0 and 1 within each agent, and then averaged across agents. SR captures a distinct aspect of inter-group spatial mixing. For example, a black agent surrounded entirely by whites would have a switch rate of 0 because looking around would not reveal one single switch from same-type neighbor to other-type neighbor. Empty locations do not count as neighbors. To calculate the switch rate over all agents in the environment, let

S_i represent the number of switches of neighbor's types from agent i's perspective, and let $MaxS_i$ represent the number of theoretically possible switches of this agent (which is identical with his number of neighbors). The switch rate is $SR = (\Sigma_i\ S_i/MaxS_i)/N$. For both models, the switch rate in the initial checkerboard is 95% (Panels A and D), falling to 70% immediately following the shock. In the terminal-state distribution of the classic Schelling model, SR falls dramatically to 22% (Panel D), while remaining at 67% in the FACE-recognition model (Panel F).

For a given parameterization of the model, there is considerable variability in the three integration measures, mostly due to random **(p.244)** selection of agents from the list of those who want to move. This selection mechanism is independent in control and treatment runs. Once the terminal state is reached in control and treatment runs, a single observation of the three integration measures is recorded for both control and treatment runs, resulting in a total of six observations. Thus, after 100 runs, six histograms are available, each displaying the distribution of 100 observations.

End-State Integration as a Function of Memory Size

We start our investigations with the question of how different quantities of recognition memory affect end-state integration. We implemented six memory treatments, starting with zero memory (which corresponds to the classic Schelling model), followed by the first treatment condition (FACE-recognition with a memory span of one period), and ending with a memory span of 30 periods. A *memory span* is the number of periods that an agent is able to look back over to determine whether or not a current neighbor was already a neighbor in the past, and if so, whether this was an acceptable or unacceptable neighborhood. If a recognized individual was a neighbor more than once within the agent's memory span, only the most recent memory associated with this agent is used.

Figure 8-3 shows histograms of end-state integration for the four memory conditions. Large differences are visible in the end-state integration distributions between control and treatment runs, indicating a large effect that is both statistically and substantially significant. Another striking feature of Figure 8-3 is that lots of memory has almost the same effect as a single period of FACE-recognition memory. In other words, introducing a small amount of recognition memory leads immediately to a large change in the end-state spatial distribution's level of integration. Additional amounts of memory have very limited effects on integration. (In fact, we also ran the simulations with memory spans of 2 and 10, but the resulting histograms looked like random variations of those for the parameters 1, 5, and 30, and were thus omitted for space reasons.)

When interpreting Figure 8-3, it is useful to be clear about the benchmarks. The vertical lines in the first row of histograms, at 0.53, 1.00, and 0.95, respectively, show the levels of integration in the "perfectly integrated" checkerboard neighborhood before the random shock (the same applies to Figures 8-4, 8-5, and 8-7). In the post-shock neighborhood, these upper bounds are not always attainable, because the number of agents has typically changed. Better as a benchmark, therefore, are the starting levels of integration directly following the initial shocks—these had ranges of 40% to 55% (with mean of 48%)

for Other-Type exposure, 82% to 100% (with mean of 94%) for Contact with at least One Other, and 41% to 81% (with **(p.245)**

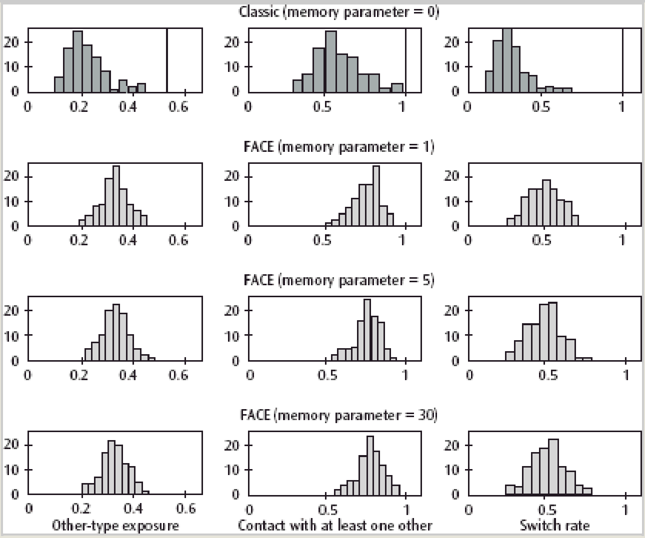

Figure 8-3: Histograms of end-state integration in six memory treatments. Unless otherwise stated, the parameter values here and in the following figures are: 8 × 8 grid, 30 of each type in the initial checkerboard, 20 randomly disappearing and 5 reappearing, acceptability threshold τ = 1/2.

mean of 65%) for switch rate. For other-type exposure and contact with at least one other, the median of the FACE-recognition extension falls about in the middle between the median of the classic Schelling and the respective benchmark, and for the switch rate, it is located at about one-third of the way to the benchmark.

End-State Integration as a Function of the Acceptability Threshold

We now turn to the question of whether small, local changes in the classification of locations (as acceptable or not) generate sizable changes in end-state integration relative to the control runs generated by the classic Schelling model. Again, we ran the simulations with memory spans of 1, 2, 5, 10, and 30, and again, we found virtually no effects of memory size. For space reasons, here and for all further analyses, we show the histograms only for memory sizes of zero (the classic model) and five (for the FACE-recognition model). As Figure 8-4 shows, a **(p.246)**

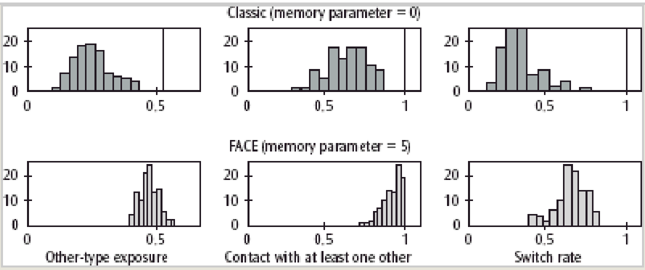

Figure 8-4: Histograms of end-state integration when agents have a lower acceptability threshold τ. Parameter values are the same as in Figure 8-3, except for τ which is set to 2/5.

slight relaxation of all agents' acceptability thresholds from 0.5 to 0.4 has enormous effects. With this slightly more tolerant threshold, the classic Schelling model's end-state integration shifts very slightly upward (compared with Figure 8-3), continuing to reflect the "unraveling" from perfect integration to unintended segregation. In contrast, the FACE-recognition model shows a strong sensitivity to reductions in intolerance, which shift the integration distributions shown in the histograms to near maximal levels, with large clusters concentrating around (and sometimes scattering above!) the initial-state levels of integration. These initial-state levels of integration, often regarded as benchmarks for maximal or perfect integration, are shown in the first row of the histograms. They are never achieved as levels of end-state integration in the classic Schelling model, but are regularly achieved, and sometimes even surpassed (in the case of the OT integration measure), by the FACE-recognition model.

Next, we introduce differences between majority agents' and minority agents' acceptability thresholds. Figure 8-5 presents four configurations of acceptability thresholds. In the first configuration ($\tau_{MIN} = \tau_{MAJ} = 2/5$), both minority and majority agents are more tolerant (than the $\tau = 1/2$ benchmark case), which produces a large difference between control and recognition treatments. In the second configuration ($\tau_{MIN} = 3/8$ and $\tau_{MAJ} = 5/8$), minority types are more tolerant and majority types less tolerant, which produces another large treatment effect (even larger than the first configuration in many runs), but with slightly lower levels of end-state integration in both cases. In the third configuration ($\tau_{MIN} = 5/8$ and $\tau_{MAJ} = 3/8$), minority agents are less tolerant and majority types are more tolerant. Because, by definition, most agents are majority types, and because they are more tolerant in this third configuration, the control runs have much higher levels of end-state integration and therefore produce smaller treatment effects **(p.247)**

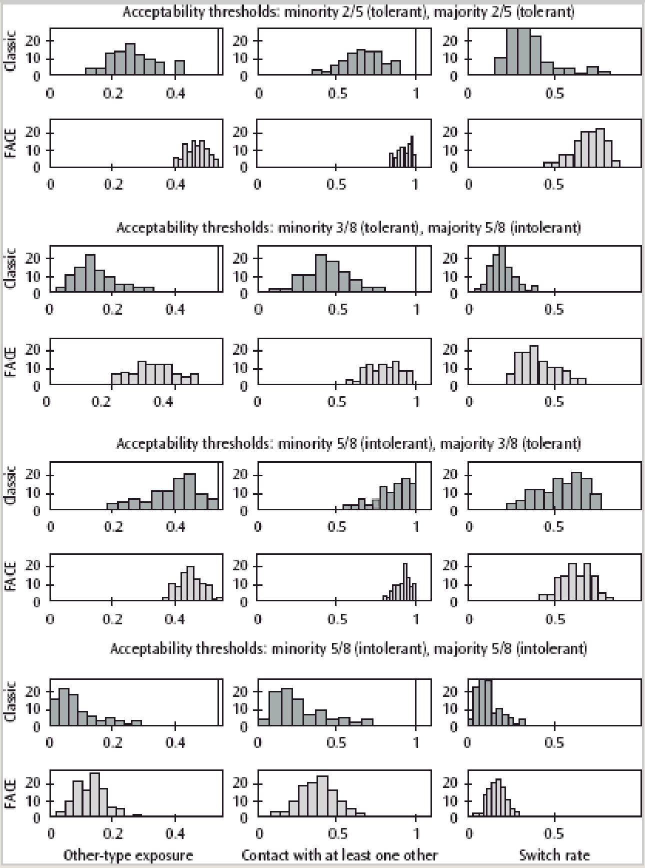

Figure 8-5: Integration measures as a function of acceptability thresholds (memory span = 5).

(end-state integration in recognition runs minus end-state integration in control runs). In the fourth configuration ($\tau_{MIN} = \tau_{MAJ} = 5/8$), both types are less tolerant, which produces lower levels of end-state integration in all cases, but a still noticeable treatment effect.

We measured treatment effects in a variety of other configurations of acceptability thresholds, which confirmed two key findings **(p.248)** visible in Figure 8-5. First, as soon as there is enough intolerance to produce unraveling of integration to segregation in the classic Schelling model, the effect of memory on end-state integration is large, decreasing steadily as all agents become less tolerant (i.e., holding both types' τ thresholds equal and increasing them toward 1). The second interesting result is the asymmetric effect of heterogeneous intolerance. When minority agents are more tolerant and majority agents are less tolerant,[12] the treatment-control difference is much larger than if the intolerance parameters are switched between types (so that minorities are less tolerant and majorities are more tolerant). One reason why the treatment-control difference is small when only majorities are more tolerant is that tolerant majorities push the control-treatment levels of integration higher, thereby reducing the difference due to floor effects. Another reason is that most available locations tend to be majority-type heavy, by definition of there being more majority types. Therefore, when minority agents are less tolerant, more moves are required to find acceptable neighborhoods for all agents, and greater spatial concentrations of minorities are produced than would be the case for the same-sized decrease in tolerance among majority types.

Dispersion and Time to Reach Convergence

Another interesting feature is that, in every single treatment- control comparison reported so far and for each of our three integration measures, the runs with recognition memory produced dramatically less dispersed distributions (visible in Figure 8-3). In many cases, the classic Schelling model's end-state integration distributions were more than twice as dispersed as the treatment distributions. This reduction in dispersion in the FACE-recognition model is important because it strengthens the link between model parameters and the dependent variables. In other words, the FACE-recognition model provides a much higher signal-to-noise ratio, where “signal” is interpreted as a change in the model's parameters and “noise” is the dispersion in end-state integration due to random effects such as the random spatial shock, random ordering of when unhappy agents get to move, and random choice of locations when a mover has more than one minimum-distance acceptable location.

Related to the reduction of dispersion in the variables measuring end-state integration, the introduction of recognition memory in the model also led to a dramatic reduction of the dispersion of the **(p.249)** number of iterations needed to reach convergence. Fewer moves were needed to reach convergence in the FACE-recognition model, and the distribution of number of moves to convergence was far less dispersed than in the classic Schelling model. As can be seen in the first column in Figure 8-6, the range of number-of-moves-to-reach-convergence shrank from roughly (0, 30) to (10, 20). That 2/3 reduction in range coincided with a clear reduction in the modal number of moves—from more than 20 in the classic Schelling model to somewhere around 15 or 16 once recognition memory was introduced.

Comparing the two histograms within the first row of Figure 8-6, one sees that reducing the acceptability threshold reduces the number of moves needed to reach convergence in the classic Schelling model by roughly 5. However, this reduction in moves needed to reach convergence is modest when compared to the dramatic decrease in the recognition memory treatments resulting from the same reduction of the acceptability threshold (comparison within columns, across rows). Thus, adding recognition memory to the Schelling model increases end-state integration, reduces dispersion of integration measures, and dramatically reduces the number of moves to reach convergence.

Recall that the dynamics come to a terminal state in one of three ways: (a) All agents find their neighborhoods acceptable (i.e., happy convergence); (b) at least one agent wants to move, but no unoccupied locations are acceptable to any of those agents who want to move (i.e., unhappy convergence); and (c) the maximum number

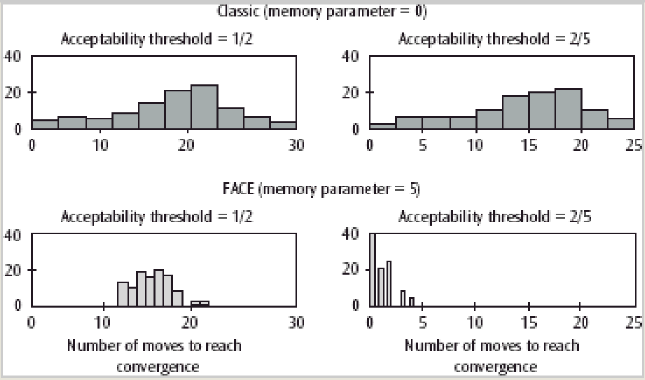

Figure 8-6: Histograms of number of moves to reach convergence, by memory and acceptability threshold τ.

(p.250) of iterations allowed by the program is reached without achieving convergence (i.e., indeterminate outcome, because we do not know whether convergence could be achieved or not). An important difference between control and treatment runs is the relative frequency of happy versus unhappy convergent outcomes. In the classic Schelling model, 10% to 90% of runs ended in unhappy convergences (not indeterminate) depending on acceptability thresholds and neighborhood density, typically where minorities could not find any available locations with enough minority neighbors. In the recognition treatments (i.e., memory parameter 〉 0), unhappy convergence occurred 1 to 3 out of a total of 100 runs across all parameterizations.

Integration as a Function of the Number of Locations

Skeptics might worry that FACE-recognition is more important in small places because the fraction of all residents who are recognized is higher. As the number of locations increases, the fraction of all agents that any one particular agent recognizes goes to zero, and one might reasonably question whether recognition effects could withstand the test of scaling up to larger and larger environments.

To the extent that the rationale behind this concern is intuitive, the simulation results are counterintuitive. Figure 8-7 shows that the larger the grid is, the more dramatic the effect of recognition. This figure was constructed as follows. Grid-size took on the values 4, 8, 10, and 16, resulting in numbers of locations of 16, 64, 100, and 256. The numbers of agents who randomly disappeared and reappeared in creating initial spatial shocks were in all cases proportional to the benchmark of Schelling's 8 × 8 setup, with 20 of 60 (33%) disappearing, 5 of 60 (8%) reappearing; arriving at a total number of agents equal to 45 of the original 60 (or 75%) of the cornerless checkerboard population. Thus, as the grid size ranges over 4, 8, 10, and 16, the parameter indicating the post-shock number of agents takes on the values 9 [$= 0.75(4^2–4)$], 45 [$= 0.75(8^2–4)$], 72 [$= 0.75(10^2–4)$], and 189 [$= 0.75(16^2–4)$]. The resulting histograms show large, persistent, and ever-more precise differences in end-state integration (precise in the sense that differences in the positions between histograms become less and less a result of noise from randomization steps in the simulation as integration measures are averaged over larger numbers of individuals and therefore become less variable). Thus, the large recognition effects reported earlier should not be dismissed as mere small-world phenomena and, instead, can be viewed as broadly applicable to groups of varying sizes—quite possibly including large metropolitan cities. **(p.251)**

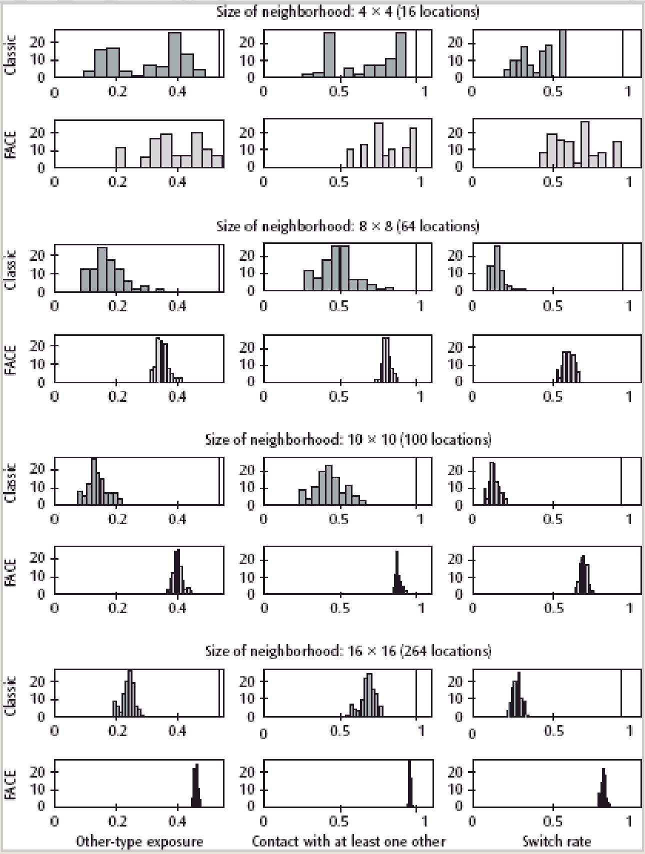

Figure 8-7: Effect of recognition memory on end-state integration increases with neighborhood size (memory span = 5).

End-State/Initial-State Preservation of Integration as a Function of Shock Size

The results presented so far share one important feature, which is the magnitude of the spatial shock (1/3 of the agents randomly moved at the initial stage). In this section, we examine the sensitivity of our reported treatment-control differences with respect to shock size. Schelling emphasized that even very small shock sizes could **(p.252)** produce dramatic unraveling of the checkerboard into stark segregation. At the other extreme, as the shock size approaches 100%, the post-shock spatial distribution becomes increasingly close to a uniform distribution in which agents are placed in random locations without regard to group type.

Figure 8-8 shows the fraction of post-shock integration that is preserved in end-state integration as a function of shock size. The x-axis shows shock sizes of 0.1, 0.2, 0.33, 0.5, 0.66, 0.8, and 0.9, ranging from nearly perfect integration to nearly random initial conditions. The y-axis shows end-state integration divided by post-shock integration, which measures the percentage of integration preserved in the process of moving to a convergent end-state spatial distribution. The median value of the percentage of integration preserved is indicated by "F" for the FACE-recognition treatment and "C" for the classic Schelling, or control, treatment, with 80% confidence bands (10th and 90th percentiles) for each set of 100 runs. In each set of 100 runs, the control and treatments began with the same spatial shocks but evolved according to classic-Schelling or recognition-augmented rules for classifying locations as acceptable or not. For the shock size of 0.1, the distributions of preserved integration were far apart, with entirely non-overlapping 80% confidence bands in all three integration measures.

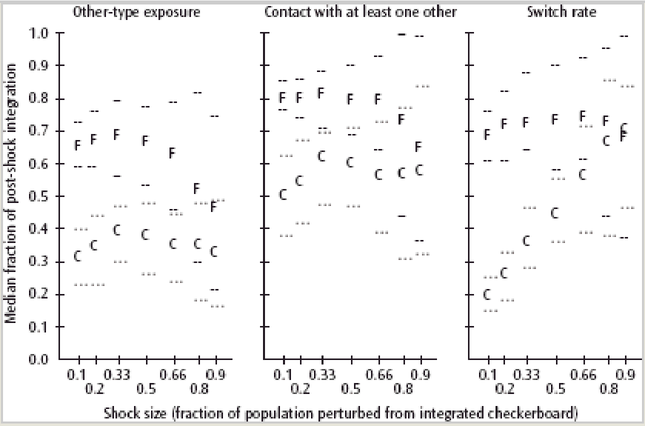

Figure 8-8: Median fraction of post-shock integration preserved in end-state indicated by “r” for FACE-recognition treatment and “c” for classic Schelling model, with 80% sample-distribution intervals (memory span = 5).

(p.253) As shock size increases, two countervailing effects are noteworthy. First, because the post-shock (initial) distribution gets further away from perfect integration, end-state integration must be further away from perfect integration as well. All else being equal, this would reduce the level of end-state integration. But because post-shock (initial) integration is the denominator of the ratio depicted on the y-axis of Figure 8-8, and it is negatively affected by shock size as well, this would increase the values plotted on the y-axis, all else being equal. As shock size approaches 1 and the initial post-shock distribution becomes completely random, the treatment effect disappears, as intuition would suggest, indicated by increasing overlap between control and treatment distributions. Nevertheless, large differences between treatment and control persist even for very large magnitude shocks (e.g., affecting half or more of the population with an involuntary move).

Effects of FACE-Recognition on the Micro Level

Up to this point, we have adopted a macro-perspective and analyzed spatial distributions in the environment. The models, however, also allow for adopting the perspective of individual agents. We restrict ourselves here to short summaries, in particular as we reported the effects of recognition memory on this level in more detail and with graphical illustrations in Berg et al. (2010). The results summarized below are, once again, obtained from simulations with a grid size of 8, with 45 post-shock agents on a lattice with 64 possible locations, acceptability thresholds set to 1/2, and a memory size of five.

The time path of the number of agents who want to move shows an interesting asymmetry between minority and majority movers. When this analysis is performed across members of the majority and the minority, there is little difference in the numbers of movers between control and treatment for a given period. When analyzed separately, however, significant control versus treatment differences can be obtained. Once recognition memory is introduced, there are significantly more unhappy majority agents in early rounds (because there are more negative shifts from friend to non-friend among same-type neighbors) and significantly fewer unhappy minority agents (because there are more ways to be a happy minority agent as the result of non-friend-to-friend shifts among other-type agents, thanks to recognition memory). The number of unhappy majority agents decreases rapidly in treatment runs, however, resulting in faster convergences and an increased rate of happy convergences.

Finally, we determined how many agents, in their end-state locations, would have wanted to move in the classic Schelling model but are made happy thanks to recognition memory. The number of such **(p.254)** agents is about 9 out of 45 (i.e., about 20%). Consistent with results reported above, we found that this number is largely independent of the amount of memory with which the agents are endowed.

Discussion

We introduced the FACE-recognition model (Fast-Acceptance-by-Common-Experience), which extends the classic Schelling model of neighborhood segregation by giving agents a small amount of FACE-recognition memory. In this extension, agents classify neighborhoods the same way as in the classic Schelling model, by computing the fraction of all neighbors who are friends and comparing this fraction with an acceptability threshold. As in the Schelling model, unrecognized neighbors are classified as “friends” if they are same-type agents, and as “non-friends” if they are other-type agents. Unlike in the Schelling model, however, recognition-augmented agents are able to recognize agents who were neighbors in previous periods and classify them as friends if they were neighbors in acceptable neighborhoods and non-friends if they were neighbors in unacceptable neighborhoods. This classification of recognized agents lexicographically overrules classifications based on group identity. Even though this extension of the classic Schelling model leads to only a small number of reclassifications of nearby agents in which group identity is overruled, it nevertheless results in large-scale shifts in end-state spatial distributions. End-state distributions in the model feature much higher levels of inter-group mixing as measured by three quantitative measures of integration, faster convergence to stable states, and higher signal-to-noise ratio in terms of the influence of changes in model parameters versus noise from randomization steps in the sequence of moves. The effects persist across various acceptability thresholds, grid sizes, and shock sizes.

From Simulations to the Real World: FACE-Recognition and Institutional Design

A key result of our simulations is that a very small amount of recognition memory can produce surprisingly durable levels of integration. Thus, when comparing environments where agents have opportunities to recognize even a handful of other-type neighbors with environments whose agents do not have this opportunity, our model identifies a new variable capable of explaining observed differences in levels of integration. Beyond its more realistic range of predictions and new explanation for places with low versus high levels of integration, the FACE-recognition model implies that institutions that promote face-to-face mixing can have large effects on long-run integration. This stands in marked contrast to the classic Schelling model's rather pessimistic **(p.255)** and unconditional prediction that virtually all integrated groups will unintentionally unravel into high levels of segregation. Regarding the literature concerning policy tools aimed at fostering integration, our extended Schelling model suggests a new theoretical account for explaining why cities and other social spheres of interaction differ so dramatically in terms of inter-group mixing. The model generates the hypothesis that locations whose histories created above-average levels of inter-group face-to-face interaction in the past—by historical accident or by intentional institutional design—should have above-average levels of integration in the present.

Given the policy goal of maintaining a given level of integration, a large fraction of any achieved level of integration can be maintained in the FACE-experience model by fostering very modest quantities of face-to-face experience across social groups. Small amounts of recognition robustly maintain integration when buffetted by spatial shocks. This finding also lends theoretical support to designed institutions in smaller-scale settings whose aim is to maintain integration even when shocks to group membership occur. One example is the prosaic-sounding coffee-and-cake institution cultivated at the ABC Research group (every day at 4:00 p.m.: see Gigerenzer, 2006), which is one part of a designed institution that attempts to generate a high frequency of face-to-face encounters among members of large and interdisciplinary research teams. Other examples of environments designed to facilitate random encounters among different group members include parks, bars, restaurants, and road systems that feature unavoidable meeting locations generating high levels of face-to-face contact across groups, accumulating experience performing normal, mundane activities on a regular basis. Nyden, Lukehart, Maly, and Peterman (1998) note that the existence of such places is a regular characteristic of integrated neighborhoods.

Avenues for Future Research

In the real world, inter-group dynamics are affected not by a single shock, but by a sequence of occasional shocks. These occur when institutions change or other large-magnitude shifts in the environment take place. Sometimes, the moves that people make are caused by other factors, such as changing family structure, changes in school quality, or job changes. It would therefore seem worthwhile to investigate whether the large-magnitude effects of recognition memory on end-state integration are attenuated or accentuated by repeated shocks.

Another simplification in the FACE-recognition model that might be relaxed to better map onto real-world group dynamics is the friend-making process. In fact, the spatial channels through which the friend-making process unfolds could be entirely separate from **(p.256)** the choice of location and subject to its own set of institutional variables, while preserving the fundamental dependence of classification of locations on personal lists of friends and non-friends. One might replace the binary friend-making process with a probabilistic spatial structure in which nearby agents are more likely to become friends. Such stochastic variants would extend the geographic range of effects of friend and non-friend lists beyond immediately surrounding locations, although the large macro effects of small local shifts in lists of friends and non-friends are already impressive.

A third extension of the FACE-recognition model concerns the question of designing institutions that promote integration and their often unintended consequences. One thinks of school busing programs in America, and the possibility of embedding more specific geographic and institutional structure in the model to analyze the consequences of introducing new institutions concerning inter-group mixing. One might investigate the degree to which institutions introduced in the real world, after being introduced in the model, could produce simulated differences in integration that match observed differences, say, among regions in the United States or within cities in the American South (e.g., Dallas and Atlanta compared with Memphis and Jacksonville). Deeper differences in spatial mixing can be observed in countries like Israel, where cosmopolitan cities such as Haifa and Hadar enjoy modest Arab–Jewish mixing, in contrast to nearly all-Jewish cities such as Lod and Ramle, and all-Arab cities such as Nazareth and Shfa Amer.

Finally, FACE-recognition's positive effects on integration are also likely to be observable in other macro-systems, such as markets. The economic relevance of face-to-face encounters in cultivating near-instantaneous sympathy and its connections to the functioning of markets were discussed by Adam Smith (1759/2010). Smith can be interpreted as hypothesizing that markets may fail to function well as they become globalized or administered in a way such that transactions become detached from ongoing face-to-face relationships (Berg & Maital, 2007; Harpham, 2004). Interestingly, online auction platforms such as *eBay* seem to function well only because they institutionalized a procedure to build the reputations of agents, allowing participants to share their personal categorizations of their trade partners as trustworthy or not-trustworthy (Bolton, Katok, & Ockenfels, 2004).

Rationality and Internal Inconsistency

One widespread methodological norm in economics is to derive equations describing behavior as the solution to a constrained optimization problem. Indeed, even the very simple location-choice rule in the classic Schelling model has been given utility-maximizing **(p.257)** "foundations" (see, for example, Bruch & Mare, 2003; Pancs & Vriend, 2007). Our methodological approach drops the utility maximization hypothesis and goes instead for an empirical modeling strategy that examines macro dynamics as a function of a precisely specified heuristic. Compared to the classic Schelling model, the FACE-recognition model produces very different and more interesting, aggregate-level dynamics in terms of measurable ethnic integration. In addition to providing a new explanation for widely different historical trajectories of segregation through time, the model's dynamics allow individual decisions about whether to move and the spatial environment that influences those decisions to co-evolve in a jointly endogenous process.

An added advantage of dropping the utility-maximization hypothesis is that the model more accurately reflects the reportedly self-conflicted experiences of real decision makers, and those dramatized in literature, like Huck Finn, whose decision to help free Jim did not, as we tried to show above, require or precipitate any change in Huck's generally racist views.

In our interpretation, internal inconsistency between rules of engagement used in face-to-face situations and rules used in abstract classification tasks has no inherent or essential normative value. The examples discussed in this chapter dealt with attitudes and behaviors that are indeed immoral and disturbing. We want to emphasize that it is not logical inconsistency that leads to moral problems or bad behavior. Imposing consistency as a normative requirement would select equally for agents who consistently hate all "+" types as well as those who consistently love all "+" types. Therefore, inconsistency is not the problem. Instead, we prefer to describe inconsistency as a human capacity, following observers such as Kitcher (1992) who argue that holding sets of inconsistent beliefs in one's mind plays a genuinely positive role in creativity and scientific discovery. Cautiously yet optimistically, we wish to extrapolate from the fundamental result in this chapter: By occasionally allowing generalized beliefs based on stereotypical thinking to be overruled by entirely inconsistent rules of engagement in face-to-face settings, the inconsistent micro-motives at the heart of the recognition-augmented Schelling model allow for clear-cut improvements in macro patterns. This result ought to give us pause before rushing to define rationality merely in terms of internal consistency (Berg, 2003; Berg & Gigerenzer, 2010). Inconsistent micro behavior, systematically defined in the FACE-recognition heuristic, can generate positive externalities based on proximity that lead to desirable macro patterns. To the extent that we value integration complementarities generated by our differences and serendipitous discovery thanks to interaction across groups, then our inconsistent behavior that results from conditioning strongly on FACE-recognition can indeed make the world a better place. **(p.258)**

Notes:

([1].) The distinction between Bayesian integration of conditional-probability-weighted valuations versus categorical decision-tree models is treated at length by Rothbart (1981). Although we find very little other than analytical tractability to speak in favor of the Bayesian model as applied to the real-world phenomenon of stereotyping, Krueger and Rothbart (1988) present some evidence in terms of statistical fit for such models. Earl (2011) argues for the relevance of fictive data sources, such as Twain's novel, in social science research.

([2].) "Location" here can be interpreted not only in geographical terms but also as a position within any network in which proximity can be identified.

([3].) This model and parts of the simulation results reported in this chapter have been published by Berg, Hoffrage, & Abramczuk (2010) in the journal *Judgment and Decision Making*. Parts of the present text and figures have been adopted from this publication.

([4].) The documentary film *Roma and Stereotypes* by Katarzyna Kotula was made for

Polish television in Krakow in 2000.

(5.) When conditions facilitating positive relationship formation are altogether absent, contact theory predicts that contact may intensify prejudice. There is some empirical support of this; for example, Brooks' (1975) work on black workers entering London's public transportation labor force.

(6.) In addition to the nonlinear dynamics that lead to counterintuitive mappings from individual behavioral rules into macro structure, which is the focus of Schelling's work and of this chapter, multiple factors have been identified as jointly causing persistent segregation (Fossett, 2006), which include differences in income (Bayer, McMillan, & Rueben, 2004), housing discrimination (Nyden, Lukehart, Maly, & Peterman, 1998), and related forms of social disorder (Musterd et al., 1999).

(7.) This is sometimes referred to as a *Moore neighborhood*, following Edward F. Moore's work in cellular automata theory, which is distinct from *von Neumann neighborhoods* consisting only of adjacent locations that share an edge (e.g., interior locations on the checkerboard square lattice have only four adjacent locations that share an edge).

(8.) Some researchers eliminate the effect of edges by defining “neighborhoods” and “distance” in a way that measures opposite edges as adjacent. This is something like walking on a globe, where one can never bump into an edge (or walk off the face of the earth). For cities and other physical spaces where integration is a real concern, edges seem to be an important real-world feature that we intentionally preserve in all models presented here.

(9.) Imagine agent A moves, which makes happy agent B transition to unhappy; B in turn moves, which makes the newly happy A transition back to unhappy; but when A moves to make himself happy again, it makes happy B transition back to unhappy, and so on.

(10.) Real-world equivalences of such shocks are any events that affect the ethnic composition of cities and neighborhoods. Examples include (a) a meat-packing company opens in a small Kansas town and hires 200 Latino workers; (b) housing prices in the South fall relative to the North, attracting a disproportionate influx of non-white (i.e., lower-income) Americans; (c) affirmative action policy is changed at a university or department, and the ethnic composition of the group begins to change; (d) Hurricane Katrina displaces mostly black residents from New Orleans because of the random locational strike of the hurricane.

(11.) Schelling (1971b, 1978) begins with a perfectly integrated checkerboard as the initial state, whereas Schelling (1971a) begins with a random spatial distribution as the initial state.

(12.) It is interesting to note that the first of these two schemes (i.e., majority type being less tolerant than minority types) is what Clark (1991), for example, suggests is found in real-world settings.