A Computational Model of Housing Segregation

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Thirty years ago, the economist Thomas Schelling suggested a theory to explain the persistence of racial segregation in an environment of growing racial tolerance (Schelling, 1971). Schelling posited a simple model that made a straightforward point: if individuals will tolerate racial diversity but will not tolerate being in a minority in their own neighborhood, then segregation will tend to be the only stable equilibrium.

Schelling's use of "micromotives" to explain "macro" phenomena has become a familiar concept, but it has not advanced very far as a practical tool. Mathematically, it is much easier to analyze the aggregate behavior of individuals in market models, in which everyone is engaged in the same transaction, than in Schelling's type of "tipping" models, in which individuals react to their local environment rather than an aggregated market. This has been changed, however, by the recent development of accessible computer software that permit the programming of complex computational models. In this paper, we use computational modeling to move the Schelling theory from a simple illustration to a more complex model of a biracial city. Our paper has three sections: (a) an explanation of the basic problem to be explained in housing segregation; (b) the steps we took to create a computational model illustrating the dynamics of modern segregation; and (c) our initial attempts to address the core problem of computational modeling, which is how to quantify its results and concretely test hypotheses.

The Paradox of Modern Housing Segregation

Housing segregation -- particularly of African Americans -- continues to be a dominant feature of most American cities, and it has been linked to a wide range of urban ills. Scholars in the field generally agree that income differences between blacks and whites only explain a small fraction of current segregation levels; but beyond this, there is no consensus and little in the way of convincing evidence to demonstrate why housing segregation has remained so high.

As an historical matter, it is obvious and widely agreed that black housing segregation came about through organized, mostly private efforts to ghettoize blacks in the early twentieth century -- particularly the years between the world wars (Sander, 1988). As late as the early 1960s, discrimination against blacks seeking to live in white areas was nearly universal. But two sea changes occurred in the 1960s. First, dramatic revolutions in the law banned most forms of housing discrimination (though the laws were very imperfectly enforced), and second, white attitudes moved sharply against the practice of housing discrimination and towards greater tolerance of housing integration. Systematic housing audits conducted since the 1960s have documented a broad, secular trend towards lower rates of housing discrimination.

In the wake of these changes, the character of black/white housing segregation changed sharply in the 1970s. Black housing prices, which had previously been much higher than prices for comparable housing in white areas, fell sharply in the 1970s. Blacks moved in huge numbers out of traditional ghettos. In a few cities, segregation levels (as measured by the index of dissimilarity) fell sharply. But in most American cities, black migration ultimately produced racial transition and resegregation, rather than integration. Thus the paradox: dramatic changes in the law and in the actual contours of urban housing markets have produced, in most cities, only small changes in segregation.

Scholars in the field have advanced three very different explanations for the persistence of segregation. Massey and others have argued that discrimination continues to be prevalent, essentially confining blacks to a few geographic areas. Muth and other economists have argued that aversion among most whites to integration led these whites, after the passage of fair housing laws, to bid up prices in white areas beyond what blacks were willing to pay. Clark and others have agreed with Muth's views of white behavior, but further suggest that blacks, too, generally prefer segregation to integration.

Proponents of each of these theories offer some empirical evidence to support their conclusions, but these are sketchy and incomplete at best, and it is doubtful that any of these tests have changed anyone's mind. This is partly because of a general lack of rigor in the field; only a few scholars have made even preliminary attempts to develop empirical tests that might differentiate among competing theories (Farley, 1992; Sander, 1999). But it is also due in large part to the complexity of housing segregation, and the interaction of many simultaneous phenomena operating at local levels within metropolitan areas.

Hence the appeal of computational modeling. By attempting to develop an explicit model of how housing segregation operates, using a large number of autonomous "agents" and observing the interaction of these agents over time, one can accomplish several things. First, building a model requires one to specifically operationalize theory: instead of asserting that "discrimination" prevents integration, one must specify exactly how discrimination might do this -- for example, how discrimination could be, on the one hand, sufficiently pervasive to keep segregation high, while on the other, it could be consistent with widespread penetration of small numbers of blacks into most previously all-white suburban enclaves. Second, a model allows one to test the interaction of multiple phenomena on a neighborhood level. One can thus directly observe the extent to which Schelling-type microdynamics dominate more conventional market equilibria. Third, computational models make it possible to directly test the sensitivity of results to variations in parameters. For example, how high does a preference for segregation have to be in order to "trip" a microdynamic that produces neighborhood segregation? At what point can the discrimination of individuals make an entire neighborhood exclusionary? Fourth, computational modeling produces outputs that can be subjected to empirical tests. Most obviously, one can look at the model's output and assess whether it comes close to capturing the actual evolution of cities; less obviously, the detailed results of a model can be subjected to more detailed forms of empirical analysis.

The model we have constructed, and describe here, is relatively crude, but we think it is real enough to illustrate the utility of this approach in understanding segregation.

Building a Computational Model of Segregation

Although Schelling described his segregation model as a "thought experiment" and focused on simple numerical examples, it lends itself so readily to computational modeling that it has been a standard computational demonstration for many years.

The core of Schelling's model is a binary utility function. There are two races of people -- say whites and blacks. On an open grid, each person is surrounded by eight squares, which are occupied by whites, blacks, or vacancies. Whites are "happy" -- which means they will stay put -- so long as the number of blacks on adjacent squares remains below some threshold. If this threshold is met or passed, the white becomes "unhappy", and will make a random move to any of the vacant squares in the grid. Blacks similarly have some threshold of tolerance for white neighbors, beyond which they, too, will move.

The surprising result from this simple model is that, for a wide range of tolerance levels, integrated neighborhoods will "tip" towards one group or another, leading the outnumbered group to flee and the neighborhood to become segregated.

The core innovation of our model is that instead of having a one-dimensional "switch" that causes whites or blacks to either move or stay-put, we use a multivariate utility function and a systematic process for our computational units (which we will call "reds" and "blues") to compare present utility with a selection of alternatives.

The main advantage of using a more complex utility function is that we can compare a wide variety of models within a single framework. Within this framework we can test results from the simple assumptions of Schelling against results for models with economic, psychological, and social factors. Changing the weights of the factors allows a researcher to easily operationalize a variety of thought experiments and compare their consequences.

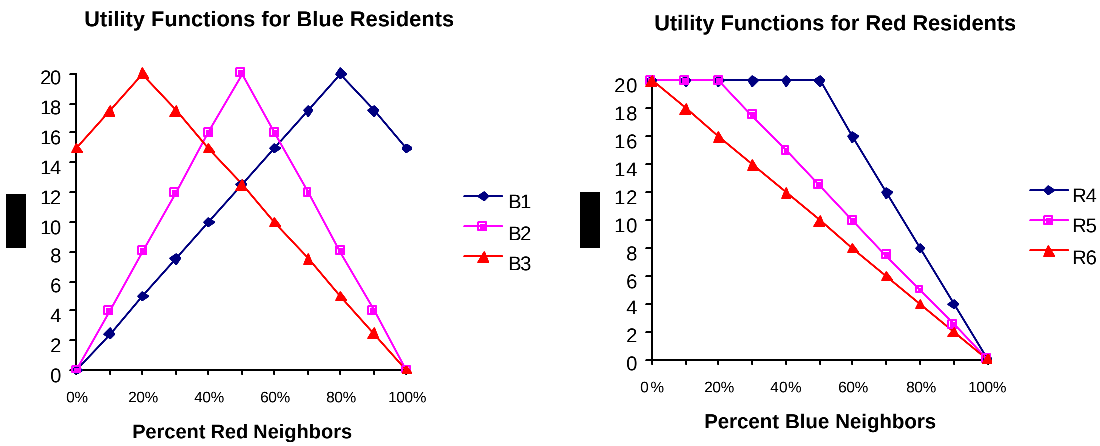
In this model, we allow our blue and red actors to have heterogeneous preferences for racial integration. Thus, some reds are more accepting of integration than others and some blues have ideal points with higher integration and some with lower. We enable agents to evaluate both their immediately adjacent neighbors as well as the racial balance of the community in which they live. The framework is also designed to allow a variety of starting points - segregated or integrated. Finally, we allow them to consider housing cost and social cost from moving greater distances.

Survey research has shown that whites and blacks are not homogeneous in their preferences for the racial makeup of their neighborhoods (Clark, 1986; Farley, 1994). While blacks are consistent in preferring racially mixed neighborhoods, they vary in their view of the ideal mix of whites and blacks. Some blacks are comfortable as a minority in a predominantly white neighborhood, but would not like to be the only black family in an area. Others would rather be in the majority, but are tolerant of a few whites. Whites, on the other hand, tend to have a threshold for acceptable integration; past that point they become increasingly dissatisfied with more diversity. This threshold varies and some whites are very accepting of integration while others are not. We have approximated the preference functions below; mathematically in Table 1 and graphically in Figure 1. In the model, we have followed empirical evidence and created three single-peaked preference functions for our minority blue agents and three sloping preference functions for our majority red agents. To determine their utility, our actors look at the racial makeup of the surrounding neighborhood and compare it with their preference function.

Table 1

Blue Agents	
Type 1	Utility=20-(25 * abs(0.2-fractionOf))
Type 2	Utility=20-(40 * abs(0.5-fractionOf))
Type 3	Utility=20-(25 * abs(0.8-fractionOf))
Red Agents	
Type 4	If (fractionOf<=0.5) then Utility=20 else Utility=20 - (40 * (fractionOf - .5))
Type 5	If (fractionOf<=0.2) then Utility=20 else Utility=20 - (25 * (fractionOf - .2))
Type 6	Utility=20 - (20 * fractionOf)

Figure 1



In Schelling's model, the agents only evaluate the locations immediately adjacent to their own [the Von Neumann neighborhood (N,S,E,W) or Moore neighborhood (Von Neumann plus (NE, NW, SE, SW)] when deciding whether to move. However, empirical evidence suggests that individuals consider the broader community as well as immediate neighbors in making housing decisions. In our model, square "tracts" of locations can approximate this community consideration. For instance, if 10x10 tracts are used, a 50x50 city grid can be divided into 25 separate tracts. The individual will then compare his racial preference function with the racial balance of the tract in which he resides. We can also set relative weights in running the simulation, so that total utility is 60% of the utility from the racial balance of the immediate neighborhood and 40% of the utility from the racial balance in the tract (See Figure 2). With this feature, we can easily compare the implications of theories about the relative importance of neighbors versus communities. Additionally, the definition of tracts is essential for calculating the dissimilarity index, a standard measure of racial segregation.[2]

[2] See (Duncan and Duncan, 1955). The dissimilarity index is calculated as

Figure 2

$$Utility = w_1 * neigh\_pref + w_2 * tract\_pref$$

Another difference with Schelling is our ability to vary the initial starting conditions. In Schelling's model, the starting point was a grid with the two races randomly distributed. As the algorithm runs, the micro-level preferences lead to macro-level phenomena of segregation. The initial chaos becomes ordered.

A principal concern of the investigators in this project has been to create a model that could account for periods of integration as well as segregation. Thus, our model allows the researcher to specify a square "ghetto" that will only be inhabited by the minority blue agents (See Figure 6 below). In the Schelling model, an initial condition of segregation would be in equilibrium, a result contradicted by empirical evidence. In our model, we can confine the minorities to a particular area of the grid in the initial setup in a manner akin to discriminatory housing laws. We then allow the minorities to leave the ghetto and observe the interplay of the agents' preferences.

As described above, one empirical result of discriminatory housing laws was an artificial elevation of housing costs in minority neighborhoods because the inability to relocate caused pent-up housing demand. As a result, minorities often paid a premium for substandard housing. It is easy to see that the incorporation of housing cost as a factor in housing decisions is an important feature of a segregation model.

In this model, housing cost is calculated by weighting the occupancy rate for the particular tract. Therefore, consistent with the laws of supply and demand, a tract where all the

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dissimilarity= $\frac{1}{2}\sum_{i=1}^{N}\left|\frac{black_i}{black_{total}} - \frac{nonblack_i}{nonblack_{total}}\right|$, for all N subareas i with black population $black_i$ and non-black population $nonblack_i$.

possible locations are occupied will have a maximum housing cost and a completely empty tract will have the minimum. The intermediate values are calculated as a linear function of the occupancy rate.

Figure 3

$$HousingCost_i = w_3 * \left(\frac{occupancy_i}{totalhousing_i}\right)$$

Like housing cost, distance is frequently cited as a factor in relocation decisions. Other things equal, people would prefer to relocate closer to their existing social and work centers. In this model, we operationalize that preference with a distance cost that is a function of a weight and the Euclidean distance from the current location (A) to the new location (B) being considered.

Figure 4

$$DistanceCost = w_4 * \sqrt{(x_A - x_B)^2 + (y_A - y_B)^2}$$

The combination of each of the factors described above leads to the general utility function in Figure 5. The four weights mean that the researcher can easily investigate a wide variety of model specifications by only changing a few values. For instance, we can set w_1 to 1.0 and all the others to 0.0 and view the result of a model akin to Schelling's original in which only the immediate neighbors are considered. Or, we can give non-zero values for each weight and have a variety of more complex models.

Figure 5

$$Utility = w_1 * neigh\_pref + w_2 * tract\_pref + w_3 * \left(\frac{occupancy_i}{totalhousing_i}\right) + w_4 * \sqrt{(x_A - x_B)^2 + (y_A - y_B)^2}$$

At the start of each run of the simulation, the user specifies the value of each of the four weights. The user also specifies the size of the city grid, the size of the tracts, the portion of empty locations, the ratio of blues to reds outside the ghetto, the position and size of any ghetto, and fraction of all agents who are allowed to move each turn. Finally, the user sets a seed for the pseudo-random number generator.[3]

Initially, the program follows the user's input and creates the city grid. The three types each of reds and blues are randomly distributed as instructed and a ghetto is created with an equal amount of each blue preference type distributed randomly. At each turn, a portion of the agents is given the opportunity to move.[4] In a random sequence, each of those agents randomly selects five currently empty locations to compare. The agents calculate their current utility at the present location and assess the utility at the possible new locations (including any distance cost). If a new location would be better, the agent picks the best location and moves there.

After all of the moves for the turn are completed, the program updates the display of the map and graphs a variety of outputs. One output is a graph for the dissimilarity index over time. We also get the average housing cost, average utility, and the portion of agents who moved in dynamic graphs with lines for all agents, red agents, and blue agents. Additionally, we can output a variety of data for analysis with conventional statistical tools.

<u>An Illustrative Run of the Model.</u>

In Figure 7, we can see the first step of a simulation run. In this model, the utility function for each individual follows the form:

[3]A psuedo-random number generator is a computer algorithm that takes a "seed" and generates a long series of digits that can be treated as random numbers for most purposes. The twin benefits of psuedo-random numbers are that they are easy to generate and that you always get the same string of digits from the same seed. This way, a simulation is easy to reproduce and verify.

[4] The total list of agents is divided into equal parts specified by the user. At each turn, one of the subsets of the agent list is given the opportunity to move. This simulates the reality that not all people constantly consider moving and slows the model to make it easier to monitor the trends as they develop.

$$Utility = 1.0 * neigh\_pref + 0.0 * tract\_pref - 50 * (\frac{occupancy_i}{totalhousing_i}) - 0.01 * \sqrt{(x_A - x_B)^2 + (y_A - y_B)^2}$$

The three types of preference functions for each color are represented with differing shades of red and blue. The darkest blue are the agents with preference type 1, whose ideal is to have blues constitute 80% of their neighbors. The lightest blue has type 3; their ideal being 20% blue neighbors. The truest red agents have preference 6; they are the least tolerant of blues. The brown looking reds have preference 4 most tolerant of blues.

We can see the large ghetto of blues in the center of Figure 6, representing the conditions immediately after legalized racial housing segregation ends. The housing cost for blues is very high and the dissimilarity index is above 70%. Already in time 1 we can see that about 18 blues have moved from the ghetto and we have at least a few vacancies. At time 10 (Figure 7), the model has already changed dramatically. The blue agents who prefer to be around other blues most now dominate the ghetto. The blues who appreciate integration most have moved from the ghetto. Also, we have the reds of preference type 4 moving to the border areas of the ghetto.

For blues at time 10, the average total utility has increased from -40 to about -32. The housing cost for blues dropped to a minimum at time 4 and now is slowly climbing. And, the overall dissimilarity index has declined to about 52%. Much of the action is driven by the movement of blues, who consistently move in higher rates than the reds.

By time 20 (Figure 8), the ghetto has homogenized and is now almost entirely populated by the blues of preference type 1. The dissimilarity index has dropped to 47%. The average utility of the blues has stabilized around -31. Housing cost is fluctuating, but still significantly lower for blues than for the reds.

If we skip ahead to time 100 (Figure 9), we see that the ghetto has shrunk considerably.

Some blues have formed small clusters in other areas of the grid. Surrounding the blue clusters and the ghetto we see the most tolerant reds. We also continue to see a continuing decrease in the dissimilarity index, now down to 40%. The housing costs for blues fluctuate, but the trend is increases and a convergence toward the housing costs for reds. The average utility remains at a plateau with minor fluctuations.

With time 500 (Figure 10), we had two noticeable changes. First, further shrinkage of the ghetto has atrophied its shape to a more elongated region with fewer vacancies. And second, the small clusters of time 100 are now larger and typically located at the perimeter of the grid. Also, it seems that we have fewer blues that are not part of a cluster. However, the continuing trend of the dissimilarity index shows that the net effect is a new low at 35%. There is still a pattern towards less aggregate segregation.

Housing costs for blues and reds finally converge at time 1000 (Figure 11). Although some fluctuations persist, the variance has greatly diminished. The blue ghetto is now still smaller and has a long vertical shape. Many of the former ghetto residents are now on the outskirts of the grid. But, the breakup of the central ghetto has caused the dissimilarity index to bottom out at around 25%. So, we have persistent clustering of blues, but the changes means that the overall measures of segregation are down.

In Figures 12 through 14 we can see the long trends in the key variables. Blues begin by paying a higher premium for housing and then have the values of their homes plummet with the removal of housing segregation laws. Over the long term, we see the housing cost to blues converge back to that of reds. The impact of the initial change in housing costs is that the average utility for blues climbs rapidly. However, it appears that only minor fluctuations occur over the remainder of the simulation. As noted above, this model shows a long and steady trend toward greater integration. Overall, the model travels from a dissimilarity index of 75% to

25%. Small clustering of blues persists, but now the enclaves are spread across the grid.

The Model and "Reality".

Though relatively simple, this model looks enough like an actual urban setting to aid our understanding of urban segregation. Consider the following examples:

--*Housing prices*. It has been well established empirically that housing prices in the ghetto fell sharply after the passage of fair housing laws (Sander, 1999). The cause is probably exactly what we see in the simulation: a significant number of blacks seeking integration move out of the ghetto quickly, but the remaining concentration of blacks in the ghetto is dense enough to deter even the most tolerant reds from moving in. This produces a vacuum in the ghetto, and declining prices. It also puts a bound on the number of blacks who will actually depart the ghetto, since they soon find that housing prices in white neighborhoods exceed those in the predominantly black areas. An original insight suggested by the model is that this black/white gap in housing prices will gradually erode over time, as the ghetto is, in effect, reshaped to make more of its housing accessible to whites and restore equilibrium in the housing market.

--*The migration of blacks.* The movement of blacks out of the ghetto produces, in the model, three generic types of result: widely-scattered blacks (the most tolerant) in most white neighborhoods, living in concentrations too low to provoke white flight; "nodes" of black concentration outside the ghetto, where black pioneers cluster in concentrations large enough to produce fleeing by some whites and migration by some less-tolerant blacks; and expansions of the ghetto, where migration by blacks from the original ghetto is nonetheless close enough to the old ghetto that it is, in effect, "reabsorbed". These three types of integration outcome are exactly those observed in real metropolitan areas. This model suggests characteristics of those neighborhoods -- prices, satisfaction, and the attitudinal distribution of residents -- that should be testable with actual data.

--*Segregation within the white community.* The model shows clearly that whites separate from each other, just as most of them separate from blacks. That is to say, the three types of whites rearrange themselves relatively early in the model towards clusters of similar "tolerances" among their white neighbors. This has interesting implications for the political structure of metropolitan areas. Again, it should be feasible to empirically test whether these attitudinal differences really occur across different white communities -- varying with the level of integration -- and how this, in turn, relates to other political attitudes.

The Systematic Interpretation of a Computational Model

The examples offered above illustrate the usefulness of computational modeling in aiding one's intuition about what is going on in the real world. But one of the seeming drawbacks of these models is the difficulty of making firm, quantitative statements about the outputs of the models. How can one measure, for example, the effects of particular variables if the model operates all factors simultaneously to produce output? In this last section, we explore how the model's output can be subjected to more systematic analysis.

One of the hurdles to gaining wider acceptance for agent-based modeling among political scientists is the absence of a universal terminology for reporting results (Axelrod 1997; Johnson, 1999). It is largely a graphical endeavor, difficult to quantify, and lacking accepted meaning. The model outcomes are often reported (as we have above) by employing multiple images of the grid to illustrate the movement of agents over time. Just as often, plots of summary population statistics are provided to give some sense of the underlying dynamics as the agents evolve (see Kollman, Miller and Page, 1992; Martin and Quinn, 1996; and Miller and Stadler, 1998, for examples).

As best as we can determine, the lack of sophisticated statistical analysis is indicative of the relative youth of the technology, rather than any fundamental flaw with agent-based modeling as a methodology. Scholars in other disciplines, using other simulation methods, have harnessed the individual-level data in their experiments for rigorous examination (Naylor, Wertz and Wonnacott, 1969; Sherif and Le Minh, 1991). In political science not much has been done in this regard. The questions asked do not naturally lend themselves to rigorous statistical treatment. Kollman, Miller, and Page (1997), for example, ask an institutional question about sorting in a Tiebout model. Miller and Stadler (1998) and Kollman, Miller, and Page (1992) are similarly interested in the institutional outcomes of micro-level decisions, rather than in the decision-making process itself. These "what-if" scenarios are designed for macro understanding.

We are interested in both the macro- and micro-levels of activity, in the institutional outcomes (housing patterns) and in the individual dynamics that underlie them. The institutional outcomes were treated above; this section discusses the micro-level "decision" to move or stay put. The analytical paradigm we employ is drawn from survey research; we are treating the data as a panel survey of n agents over t periods (n= 2,405 and t=39), with 100% response rate and 0% panel mortality. The use of survey methodology and experimentation to analyze race and society is well-founded (e.g. Sears, Sniderman, Sidanius, etc.)

Space does not allow for a full treatment of the issues involved in the analysis of such data, nor for much beyond a bivariate examination of the model's dynamics. Two issues should be raised, however, in the interest of completeness. First, just as with real world data, the errors from our experimental trend data are probably correlated; the model therefore requires special treatment before multivariate analyses can be conducted (Greene, 1993). Second, since we are essentially studying a binary decision over time, to move or stay put, event-history analysis or some similar engine should be used to control for the fact that most agents do not move most of the time (Blossfeld and Rohwer, 1995). We point out these issues to introduce them to the analytical toolkit that will allow us to expand our model to include an otherwise unmanageable number of parameters.

Our motivation for analyzing individual-level behavior is two-fold. The first is exploratory. We have certain expectations about how agents are supposed to behave. If they behave in some other fashion we may have a problem with the programming, or an interesting finding. Second, to the extent that the model is correctly programmed we want to know what kinds of individual-level decisions result in the neighborhood patterns we witness. Of immediate interest to us is how often the agents move; how moving affects the utility of each agent; and how the various utility parameters–neighborhood utility, distance to a vacant space and housing density/price–are related. The results reported here are from a single run of the model, and should be viewed with reservation; they need to be replicated under multiple runs with alternate random seeds.

We find that the frequency of movement within the model space is dependent upon both the agent's level of tolerance for integration and its majority or minority status. The most tolerant blue agents are the most likely to move. Ninety-one percent were able to increase their utility by moving more than once, compared to 67% and 60% of those less comfortable in an integrated environment (Table 2). Among the majority red agents fewer than one-half moved more than once.

There is a deterministic quality to this pattern. The least tolerant blue agents begin in an environment (the ghetto) that is ideal to them, so movement is unlikely to increase their utility in the short run; the same can be said of the least tolerant red agents. Among the tolerant reds, however, the lack of movement relative to tolerant blues is not intuitive. We expected that their preference for an integrated neighborhood would lead to more activity; but unlike the minority blue agents, the overt behavior of the most tolerant reds mirrors that of the least tolerant of their kind. Apparently the shuffling of agents in majority neighborhoods is widespread amongst all preference types, rather than concentrated among only the least or most tolerant of integration.

Table 2. Frequency of movement, by agent type and tolerance for integration.

	Tolerance for integrated neighborhood						
	Low	Moderate	High		Moderate	Low	Total
Agent color	Blue	Blue	Blue	Red	Red	Red	Red
Number of Moves							
0	6%	8%	0%	19%	24%	20%	18%
1	34%	26%	9%	33%	32%	35%	32%
2 – 4	60%	67%	91%	48%	45%	44%	32%
N	249	110	97	991	591	367	2405

We also found that large movements across the grid are the result of small gains in utility. Most agents who move increase their neighborhood utility by less than two points, and the predominant change in the housing price/density is near zero, yet these small gains result in a broad range of distances moved (Fig. 15). This suggests two things. First, that the costs of changing locations in our present model are low, and therefore that the patterns that evolve are driven less by the affordability of *physically moving* than by the price and preference structures of the model. Second, it suggests that we need to do further experiments with the weights we place on our distance measure to see how neighborhoods develop when relocation costs are increased.

[FIGURE 15 HERE]

One surprising (but in hindsight foreseeable) result from the experiment was the relationship between the change in housing prices/density and the distance an agent moved. As might be expected, those in the densest areas would on average move farther away to find new housing, since their own neighborhood is, by definition, densely populated. What we didn't expect to find is that those agents who moved farthest away did not gain any utility from changed housing prices (Fig. 16). They traded one level of density for another of equal density, their only gain coming (apparently) from the change in the makeup of their neighborhood. But further examination revealed that there is no systematic relationship between the distance moved and integration preferences. This is something else that we didn’t expect to find in the experiment, and that bears further examination.

[FIGURE 16 HERE]

The apparent unimportance of distance in the utility calculus suggests that only two parameters are driving the model: neighborhood utility and housing price/density. We expect that these are positively correlated; we programmed it that way. An agent that maximizes its utility will, on average, trade off housing prices for a more/less integrated neighborhood, and vice-versa. It makes these trades based upon the decisions of the other agents, and not a pre-determined formula, thus the relationship is quite noisy (Fig. 17). There are four regions of interest in this figure, A, B, C and D. In region A, the agents have realized a loss in housing price utility in exchange for neighborhood utility. Region B illustrates gains in both utilities. More agents fall into this quadrant than any of the others. Region C is the mirror-image of region A; it represents a loss in neighborhood utility and a gain in housing price utility.

[FIGURE 17 HERE]

Region D is the most interesting; agents are losing both housing price and neighborhood utility. This should be an impossible outcome, since agents are programmed to move only if their utility is increased in one or both dimensions. We think, but are not sure, that it is an artifact of how neighborhoods change in between the reporting periods for each agent. For example, an agent who moved in accordance with the maximizing rules may find itself in a declining neighborhood, the qualities of which would not be measured again until the neighborhood had already reached a new level. Alternatively, it may be that this region represents the influence of the distance moving function, which is otherwise unimportant; but we can't test this hypothesis without a more rigorous statistical analysis and more iterations of the model.

Conclusion.

Our segregation model is still in its infancy. But like an infant, we would assert that the key components of a working computational model of segregation are in place. The fleshing out and development of our model will proceed, we hope, along three lines. First, we want to develop models that clearly embody distinct, alternative theories of how segregation operates in particular contexts. Second, we want to test these theories against specific historical contexts, and compare the predictions of the models with actual demographic outcomes. Third, we intend to refine further our diagnostic tools for interpreting model output, and begin testing these outputs against real-world empirical data. Our hope is that, before long, we will be able to raise and focus the debate on the causes of housing segregation, and demonstrate the viability of computational modeling as a versatile tool for comprehensively understanding social phenomena.

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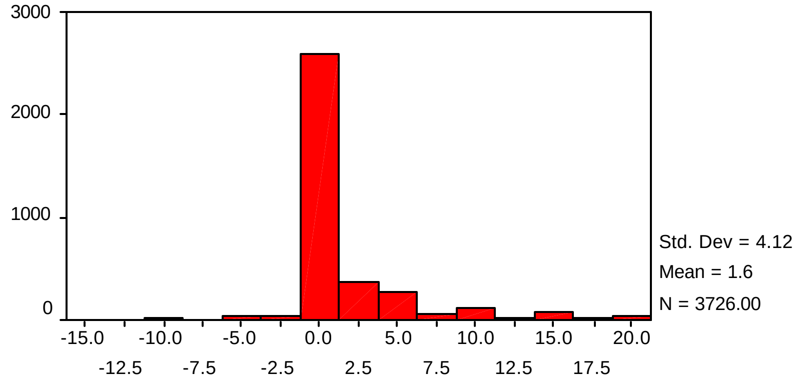
Figure 15

Change in neighborhood utility for

agents who have just moved.

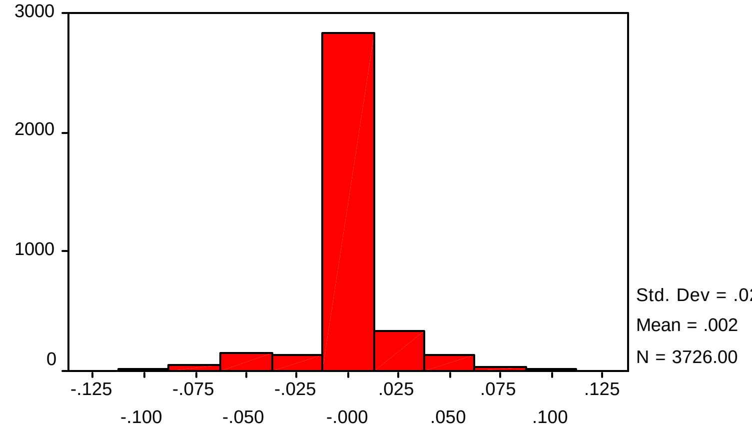
Maximum change +/- 20



Change in neighborhood utility

Change in housing price for

agents who have just moved.

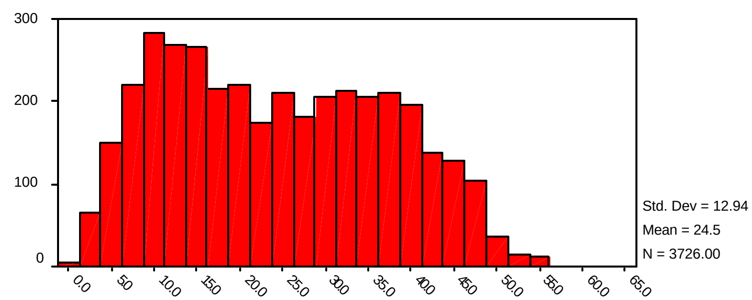


Change in tract density/housing price

Distance traveled for agents who

have just moved (distance = hypotenuse)

Maximum distance = 70 units



Distance moved

Figure 16

Change in housing price/density

by distance moved

Moving agents only

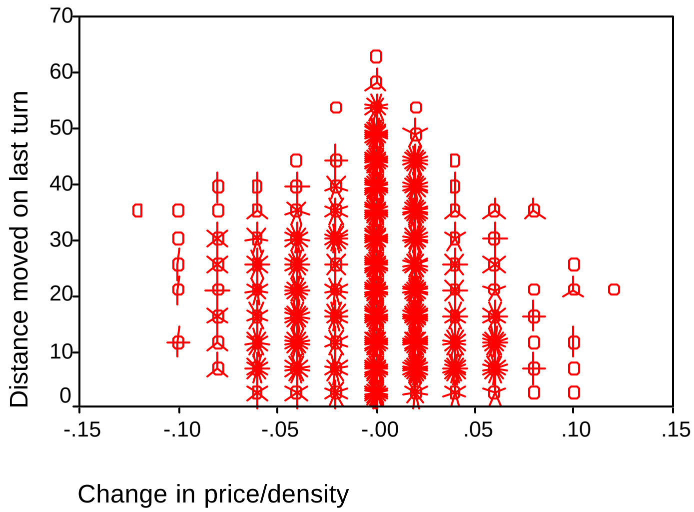


Figure 17

Plot of change in neighborhood utility

by change in housing price/density

Movers only