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Simulating Macro-Level Effects from Micro-Level Observations

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Abstract. We consider the fruits of integrating agent-based modeling (ABM) with lab-based experimental research with human subjects. While both ABM and lab experiments have similar aims—to identify the rules, tendencies, and heuristics by which individual agents make decisions and respond to external stimuli—they work toward their common goal in notably different ways. Behavioral-lab research typically exposes human subjects to experimental manipulations, or treatments, to make causal inferences by observing variation in response to the treatment. ABM researchers ascribe individual simulated "agents" with decision rules describing their behavior and subsequently attempt to replicate "macro" level empirical patterns. Integration of ABM and lab experiments presents advantages for both sets of researchers. ABM researchers will benefit from exposure to a larger set of empirically validated mechanisms that can add nuance and refinement to their models of human behavior and system dynamics. Lab-oriented researchers will gain from ABM a method for assessing the validity and magnitude of their findings, adjudicating between competing mechanisms, developing new theory to test in the lab, and exploring macro-level, long-run implications of subtle, micro-level observations that can be difficult to observe in the field. We offer an example of this mixed-method approach related to status, social networks, and job search and issue guidance for future research attempting such integration.

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Introduction

Imagine a researcher, working with a representative sample of human subject participants in a laboratory setting, found that people, on average, displayed a slight preference—say, 55%—for having neighbors of the same race. What should we make of such a finding? To start, we might view the figure as modest, reflecting on the fact that few neighborhoods are as racially diverse as this reported preference would seem to suggest. In fact, using census data, we might even find that a full 95% of people have neighbors who are the same race as them. What does this discrepancy—55% preference versus 95% reality—reveal? On the one hand, we might conclude that the laboratory participants simply lied about their preferences and that the real preference for having racially similar neighbors is much higher than 55%. This may certainly be true. A more benign interpretation might be that people's reported preferences were accurate, but, because people tend to stay in their houses for long periods of time, the 95% statistic drawn from the census is most representative of historical preferences. In other words, even if people have preferences for *more* racial diversity in the places they wish to live, it is possible that the opportunities to find such diversity are limited.

Within the confines of the research lab, one might attempt to adjudicate between these two possible interpretations by comparing participants' responses in anonymous versus nonanonymous conditions, or perhaps by designing a study to measure implicit—i.e., outside of conscious awareness—versus explicit preferences for racial similarity. There is reason to believe that such steps, while perhaps interesting for other purposes, would lead our hypothetical researcher down an incorrect path. How do we know? To answer that question, consider instead a third possibility, drawn from Schelling's (1971) seminal work on racial segregation: employing an early, rudimentary approach to what is now commonly known as agent-based modeling (ABM), Schelling showed that even modest preferences—say, 55%—for having racially similar neighbors at the level of the individual result in nearly complete racial segregation (95%) in aggregate.[1] Schelling's result teaches us several things, including most strikingly that the whole is often far different than the sum of its parts. For our purposes here, however, Schelling's work is most exciting for pointing to a potentially fruitful integration of research methods—ABM and experimental social science with human subjects. The present paper considers this integration in detail and offers an example of what such integration might look like.

To preview our core motivation, we argue that social and organizational science researchers who conduct their research with human subjects in controlled laboratory settings should consider using ABM techniques to (1) analyze the "macro" implications of their "micro" findings (including, notably, the sorts of subtle phenomenon that are difficult to identify using archival data or even field-based experiments, yet may carry meaningful macro implications), (2) examine the sensitivity of those finding to factors not easily observed or manipulated in the lab, (3) develop additional theory to explore further in the lab, and (4) experiment with various interventions in a cost-effective way. Further, we believe that ABM researchers and modelers should pay closer attention to research happening in experimental labs as well, particularly when it comes to designing the decision rules that guide their simulated agents. Existing ABM research—including Schelling's early work[2]—typically ascribes agents with simplified decision rules based on casual observations, rational choice assumptions, and potentially outdated findings from prior behavioral research. As a result, even if an ABM supplies a *sufficient* explanation for a given outcome—for example, that small, homogenous preferences for having racially similar neighbors *can* generate empirically meaningful patterns of racial segregation—this does not imply that actors in the real world behave in similar ways. Using more specific, nuanced findings from behavioral research to program actors in a simulated world can enable ABM researchers to consider questions not only of (plausible) explanation but also empirical prediction (see Macy and Willer 2002).

While bringing these two modes of research together will involve overcoming social barriers (researchers typically do either lab experiments or simulation, but not both), educational barriers (lab experimenters will have to learn programming and vice versa, or else be willing to collaborate across disciplinary lines), and methodological barriers (methods need to be developed to calibrate models from experiments, and vice versa), we believe that the barriers represent relatively minor impediments in comparison to the value that integration can create. The value of bringing together experimental research with ABM is likely to come in two forms, at least. First, ABM research will benefit from exposure to a larger set of plausible, vetted mechanisms that can add significantly to the validity, nuance, and refinement of new and existing models of human interaction and collective outcomes. Increasing the accuracy and usefulness of computational simulations requires a strong understanding of human behavior that laboratory researchers are well positioned to provide. Second, ABM offers experimental researchers a method for investigating the validity and magnitudes of their findings in ways that lab research—and even field-based experimental research—does not typically allow. By allowing agents to respond to one another, as well as to changes in their environment, across time, ABM offers a way for researchers to assess aggregate and long-run implications of what are typically single-period observations of human behavior in a lab.[3]

By way of an example involving social status, social networks, and job loss, we offer guidance about how to move research findings from the behavioral lab to the computer lab and, to an extent, back again. We draw a contrast between "top down" and "bottom up" approaches to ABM and highlight one "bottom up" approach that we consider to be most promising for experimental researchers to pursue. Whereas many ABM researchers begin with an "already emerged collective phenomena"—in other words, an empirical observation—and then "seek microrules that can generate them" (Epstein and Axtell 1996, p. 20), the example we present here uses the results of an existing experimental research paper to construct a simulated world whereby individual agents are initially programmed to behave in a manner consistent with findings from a prior lab-based experiment. From this, we then observe an emergent collective phenomenon that serves as a baseline for further computational and experimental analyses. In other words, we start with the decision rules and move to an emergent pattern as opposed to the other way around. The result of this integration of research methods is the simulated projection of a question that we propose many experimentalists may often want to ask but, given the limitations of their methods, seldom do: *What are the macro implications of my micro findings*?

In what follows, we briefly highlight the epistemological foundations of laboratory-based experimental research and ABM, highlighting both differences and similarities with respect to assumptions, methods, trade-offs, and goals. Next, we discuss the integration of ABM and experimental methods, highlight the empirical and theory-building payoffs that can come by way of their integration, and offer practical guidance for scholars to consider when employing these complementary approaches in their own work. This section (as well as Online Appendices B and C) represents a first pass at articulating the conditions and topic areas that we believe to be most receptive to integrating human subjects experiments with ABM (see also Roth and Murnighan 1978, Kenrick et al. 2003). We readily acknowledge that future research may and indeed should critically assess many of the boundary conditions that we put forth here. Finally, we offer an example of our proposed mixed-methods approach. Using the results from a recently published experimental paper, we build an ABM to assess the feasibility of that paper's findings, explore temporal, macro-level implications of the paper's micro-level observations, assess various proposed mechanisms for the paper's findings that are either difficult or impossible to study in the lab, and generate additional hypotheses to further test in the human-subjects lab. We do not intend our analysis to represent a comprehensive investigation of an empirical phenomenon. Instead, our example is deliberately broad and meant to highlight four different pathways by which experimental and ABM methods may best complement one another.

Controlled, Behavioral Experiments with Human Subjects

Experimental approaches in the social sciences date back to the late 19th century with Wihelm Wundt founding the first experimental laboratory devoted to psychological research at the University of Leipzig in 1879, and Norman Triplett's early experimental studies of social facilitation, first published in 1898. Following on this early work, experimental methods have since become a maxim of social psychological research, offering researchers a powerful way to observe human behavior and make causal inferences. With some exceptions, most experimental research operates by subjecting some human participants, but not others, to certain stimuli—or alternatively, subjecting human subjects to the stimuli at one point in time but not another—and observing differences in outcomes, such as their emotional, preferential, or behavioral responses. By randomly assigning individuals to either receive the stimuli or not—and then verifying that the groups are in fact not significantly different on any important dimension, by chance—researchers may infer that any observed differences in outcomes can only be attributed to the presence and/or absence of the stimuli itself. Extraneous factors that commonly complicate nonexperimental research—e.g., nonrandom selection effects, noncomparability of treated and untreated groups, unobserved variable bias, etc.—are rendered largely irrelevant by the experimental approach.[4]

For its many benefits, however, experimental methods also have several natural shortcomings. First, given the overly constructed nature of laboratory-based experiments, researchers must be cautious around matters of validity—i.e., to what extent do concepts, measures, and conclusions accurately correspond to the things they are meant to represent—and generalizability—i.e., to what extent can the observations from the experimental research be applied in other settings. While we acknowledge that the goal of experimental research need not always be to uncover general principles of behavior (see Mook 1983),[5] we also note that a core goal of most experimental research in social and organizational psychology, in particular, is to elucidate general principles of human cognition and human behavior that maintain real-world complements and can subsequently inform empirical research outside the context of the lab. Aiding the experimentalist in assessing both validity and generalizability is a worthy undertaking, especially in light of recent calls for replication and greater transparency in experimental research (e.g., Finkel et al. 2015).

Second, lab-based experimentalists are often poorly equipped to assess the magnitudes of their empirical findings and account for issues related to time and space. Each of these shortcomings is a direct consequence of a primary benefit of lab-based experimentation, which is to offer the researcher the maximum amount of control to isolate causal, and oftentimes subtle, effects. To be sure, these specific shortcomings have not gone unnoticed. Some, in fact, have gone as far as to question the utility of lab-based experimental research altogether, arguing as do Levitt and List (2008, p. 910), that "to be empirically relevant, the anomalies that arise so frequently and powerfully in the laboratory must also manifest themselves in naturally occurring settings of interest." We find such extreme a view to be an overstatement, reflecting not only on several of the insights made by Mook (1983), but also when acknowledging the strides experimental researchers have already taken to remedy the inherent limitations of their primary method. With respect to time, for example, researchers have advocated using within-subject experimental designs that require the researcher to observe participants over more than one time period, typically subjecting those participants to a stimuli or treatment in some periods and removing it in others (e.g., Hsee et al. 1999). With regard to effect magnitudes and context, recent years have seen a notable increase in the tendency to supplement lab-based experiments with experiments conducted in the "field," whether factories (e.g., Bloom and Van Reenen 2007, Bernstein 2012), firms (e.g., Cable et al. 2013), countries (e.g., Paluck 2009), or even more specialized locations such as gyms (e.g., Milkman et al. 2014), hotels (e.g., Goldstein et al. 2008), and hospitals (e.g., Grant and Hofmann 2011). While we anticipate seeing even more of this sort of work moving forward, we also view ABM, with its unique and cost-effective ability to account for time and space, as adding significantly to the experimentalist's toolkit.

Agent-Based Modeling

ABM is a research tool that allows investigators to observe and analyze aggregate phenomena by simulating the behavior of individual "agents," where agents are typically, though not always, understood to be people or organizations (Epstein and Axtell 1996, Gilbert and Troitzsch 2005, Holland 1995, Miller and Page 2009, LeBaron 2000).[6] As a research method, ABM initially emerged, at least partially, in opposition to deductive, analytical modeling, which often requires researchers to ignore or assume away heterogeneity among actors with respect to their beliefs, preferences, and behaviors (for the sake of solving a given differential equation). By comparison, a principal benefit of ABM is that it can be used to show how complex social phenomena can emerge from heterogeneous individuals who learn, adapt, interact, and behave according to specified, idiosyncratic, and even dynamic decision rules. Like Schelling's (1971) segregation model, ABM is at its best when demonstrating the conditions under which the outcomes of aggregated individual actions differ markedly from the nature of each underlying action.

Generally speaking, there are two basic approaches to computational simulation and ABM. The first, which we will call a "top down" approach, "involves pointing to some empirical phenomenon . . . and asking: 'can you grow it?"' (Duffy 2006, p. 953). For Schelling's segregation model, for example, this approach might begin with the observation that communities are racially segregated and attempt to generate a system with comparable patterns of segregation by way of affixing many different decision rules to individual agents—e.g., "I will remain in my current home when at least two of my neighbors are the same race as me" or "I will move after a neighbor of the same race moves"—and then investigating which decision rules, if any, produce the observed empirical pattern. The second approach, which by comparison we will call "bottom up," is more exploratory, as it begins not with a macro-level observation to reproduce, but a specified set of micro-level decision rules to investigate—e.g., what happens when all people have a slight preference for racial homophily and will move until those preferences are satisfied? Whereas the "top down" approach is best motivated by questions of "how" (e.g., "how can this outcome be reproduced?"), the "bottom up" orientation is the most natural outcome of questions beginning with "what" (e.g., "what are the group, community, or societal implications of this kind of individual behavior?").

No matter the approach, ABM, too, is not without its own shortcomings. As Duffy (2006, p. 953) noted, "more precise and careful empirical support, using field data or other observations could be brought to bear in support of a particular phenomenon, but this is not (yet) the standard practice." In other words, ABM suffers from its own set of complications when it comes to matters of both validity and generalizability. Because a simulation is only as accurate as the parameters that go into it, most ABM researchers adopt the approach of assessing their model over as many possible combinations of parameters as possible. Given the vast number of combinations in even the most modest ABMs (e.g., a simple model with only five parameters, each having five values yields 3,125 unique combinations, each of which could require hundreds or even thousands of simulated trials), it should be unsurprising that ABM works best when the researcher has specific knowledge of as many micro-level behavior rules as possible. Without this knowledge, rules often take the form of hypotheses and educated guesses and have historically resulted in an overreliance on rational-actor assumptions. To continue Duffy's commentary, "The processes by which agents in [ABM] models form expectations, choose actions or otherwise adapt to a changing environment is not typically based on any specific micro evidence" (p. 953). As we come to argue in the following section, lab-based experimental research is an ideal candidate for offering that "micro evidence."

Integrating Experiments and ABM

For their many similarities (e.g., both operate with a degree of researcher control that is uncommon in other methodological approaches, both are inherently experimental as they involve systematically altering one thing to analyze its effects on another, both acknowledge and allow for significant heterogeneity among people, and so on), experimental research with human subjects and ABM use notably different approaches to test the validity of a hypothesized mechanism. Whereas lab research uses mediation and moderation, ABM often employs an "if X, then Y approach" to assess mechanisms by examining their implications. When a model produces an outcome, Y, that is infeasible, then a researcher may conclude that X is in need of additional refinement. Despite this difference (and in ways that we explore below, because of it), ABM and human subjects experiments are also particularly well positioned to alleviate many of the shortcomings unique to each research method. Here, we consider first the benefits ABM can bring to human subjects experiments and then the reverse.

ABM Benefits for Lab Experiments. The first benefit that ABM brings to lab-based experimental research is a platform for addressing the question, "What are the macro implications of my micro findings?" Exploring the aggregate and long-run findings of (typically one-shot) human subject experiments should be a worthy and important goal of social scientific research. Behavioral labs seldom afford researchers such an opportunity, however. ABM offers a low cost way for lab researchers to ask and assess such questions. In this way, ABM can help generate external validity and generalizability—or undermine those very things if and when the results of the ABM are entirely incongruent with any empirically observed regularities—for lab-based experiments.

Second, by shedding light on the role of interdependence among actors (whether direct or indirect), ABM research can lead to new hypotheses that have not been tested or confirmed in either experimental or empirical work. In other words, ABM can aid in theory development and motivate future experimental research. Third, ABM offers a powerful tool for deciphering between multiple mechanisms. This contribution of ABM is particularly important in the face of mounting criticisms of experimental research for generating an overabundance of plausible mechanisms (e.g., Levitt and List 2008). For many social scientific researchers, such an overabundance presents an acute problem as it implies a level of interpersonal heterogeneity that can be difficult to account for, especially in closed-end analytical modeling (see Murnighan and Roth 2006 for an extended and entertaining discussion of this issue). ABM, on the other hand, is an ideal research method for capturing heterogeneity among both agents and mechanisms alike. By experimenting with certain parameters of an ABM (e.g., affixing a behavior to varying percentages of agents in a simulation, or adding a stochastic input to dictate the frequency at which a certain decision rule is activated) and pitting competing mechanisms against one another (and then seeing what aggregate-level outcome best represents a familiar picture of the real world), ABM affords experimentalists a method for testing the sensitivity of their proposed mechanisms and arranging those mechanisms in order of significance.

Lab Experiment Benefits for ABM. The most important thing that lab-based experimentation can offer ABM research is tested, identified, and verified mechanisms. According to Rand and Rust (2011), ABM researchers should strive to establish four kinds of validation for their models: (1) micro-face validation, (2) macro-face validation, (3) empirical input validation, and (4) empirical output validation. Macro-face validation and empirical output validation involve ensuring that nothing unrealistic happens in the macro patterns of a model or in the relationships among the model's output values, respectively. By comparison, micro-face and empirical input validation involve ensuring that the parameters and the relationships among the parameters of the model correspond to the real world, respectively. This is precisely the role that behavioral lab experiments can and should play in the development of ABM.[7] The data generated from human-subjects experiments is ideally suited to designing and calibrating the decision rules used by ABM researchers and affixed to the agents who are active in their ABM simulations. After all, as Simon (1982, p. 120) pointed out, "Armchair speculation about expectations . . . is not a satisfactory substitute for factual knowledge as to how human beings go about anticipating the future, what factors they take into account, and how these factors, rather than others, come within the range of their attention." The findings of lab-based experimental research are excellent candidates for becoming that "factual knowledge."[8]

In the remainder of this paper, we present an example of integrating ABM and experimental research. Specifically, we build an ABM using the results from a recent experimental paper by Smith et al. (2012, hereafter SMT) on social status, social networks, and job search (see also Jackson 1988 for a nonexperimental investigation of a related phenomenon). As we alluded to in the introduction, the purpose of this example is not to produce a thorough empirical analysis of job search, but rather to highlight four different approaches for integrating ABM with a set of behavioral findings from an experimental study. We classify these four approaches as: (1) Macro Exploration—do the micro effects aggregate to recognizable macro outcomes? (2) Sensitivity Analyses—does increasing or decreasing the weights associated with different mechanisms alter the hypothesis? (3) Theory Testing—what happens when the assumptions underlying the hypothesis or mechanisms are changed? (4) Intervention Testing—what changes to the simulated environment are most likely to alter agents' behaviors and collective outcomes? Because our example touches on only one topic area, Online Appendix Table C.1 includes a list of several additional areas of study that may be well suited to our proposed multimethod approach. For readers interested in learning more about designing and implementing ABM, we also provide technical details of our example model and pseudocode to reproduce it using the software package NetLogo in Online Appendix A. Finally, Online Appendix A also includes several links to informational resources that should prove valuable for interested researchers to learn more about ABM. The full model code and documentation will be made available via OpenABM.org on publication of this paper.

Integrating Experiments and ABM in Practice: Status, Job Threat, and Social Networks

If people turn naturally to friends and close confidants when they feel threatened (Jackson 1988), *and* if people are indeed more likely to find employment via structurally "weak" social network ties (Granovetter 1974), then what happens when the threat one encounters is job loss? Do people trim their "weak" network ties at the very moment when those ties are the most important? Moreover, do different kinds of people differ in the way they mentally construct or "cognitively activate" their networks following the onset of job threat? These are the questions posed in SMT. According to the authors' arguments, variation in the way people think about their networks following the threat of job loss should carry over to have an impact on how people engage with or "mobilize" their social networks (Small 2013, Small et al. 2015, Smith 2005, Menon and Smith 2014, Srivastava and Banaji 2011), impacting people's success in finding subsequent employment.[9]

To address these questions, the authors first used data from the General Social Survey (GSS), a large-scale national probability sample survey run out of the University of Chicago. Their analysis revealed significant associations among the size and composition of respondents' reported social networks, their levels of self-reported socioeconomic status, and their responses to the question, "How likely is it that you will lose your job in the next 12 months?" Specifically, the data indicated that respondents who self-identified as having low socioeconomic status who also perceived a moderate to significant threat of job loss reported having smaller and denser networks than like-status respondents who felt no such threat. Among high-status respondents, by contrast, moderate to significant job threat was associated with the recall of larger and less dense social networks. Unable to address issues of reverse causality with a cross-sectional database (whether the fear of job loss led respondents to recall different networks, as the authors' theory proposed, or the network, or a separate variable correlated with the network, in fact affected the perception of job threat), the authors next tested their hypotheses in an experimental laboratory using a sample of human subjects. To do this, they measured participants' perceptions of their social status, randomly assigned them to experience simulated feelings of either high or low job-related threat, and then asked them to recall their social network contacts. The findings were consistent with the data from the GSS—low-status (high-status) people reported having smaller and more dense (larger and less dense) networks when under threat than when not under threat—and now causal, because of the random assignment of threat.

The findings in SMT present a handful of potentially important implications, empirically, theoretically, and for public policy. Empirically, an intriguing follow-up question is what would the world look like if high-status people consistently widened their social networks in the face of job threats and low-status people winnowed theirs? What if participant's behavioral intentions as reported in the lab—what the authors call "cognitive network activation"—turned into behavioral facts—what the authors call "network mobilization"? Would the resulting patterns of social interaction, social connectedness, and employment approximate anything resembling empirical observations at more macro levels? Theoretically, the findings in SMT speak to several different plausible mechanisms that ABM can be used to explore further. For instance, are the differences between high- and low-status people reflective of cognitive biases and individual differences, or are they more likely the result of rational adaptation to prior (successful and unsuccessful) attempts at network*ing*? Shifting finally to policy considerations, what sorts of interventions might effectively prevent low-status people from shifting their attention to the core of their social networks following the onset of job loss, if indeed such reactions are counterproductive? Although lab settings *can* be ideal for testing interventions designed to change the way people make decisions (e.g., experimental research has convincingly shown that presenting a decision as loss prevention is more effective than presenting the same decision as generating a gain (e.g., Kahneman and Tversky 1984)), ABM offers a powerful tool for assessing how interventions can affect more aggregate-level outcomes such as income distributions and social welfare.

To identify in the real world the sorts of behaviors SMT observed in the laboratory would be extremely complex. To start, one would need to (1) reliably measure individuals' full social networks (what the authors refer to as people's "potential networks") so as to know to whom the individual *could* turn following the onset of job threat or job loss, and (2) gather a sufficiently large sample of individuals to ensure that a reasonable number of those individuals would at some point lose (or at least be at risk of losing) their jobs—the large N would be necessary to control for the fact that job loss may not be randomly or uniformly distributed across the entire population—*and* respond to that loss in sufficiently varied, yet measurable ways. While online social media and social networking sites render these two objectives more feasible now compared to, say, 10 years ago, the availability of big, electronic data sets are in no way a cure-all. As Simon (1987) pointed out, it is simply very hard, and will likely always be very hard, to use real-world empirical data to analyze the link between individual cognition and behavior, and more macro, society-level patterns and outcomes.

This difficulty does not mean, however, that social science researchers should narrow their focus to a single level or immediately adjacent levels of analysis. Economists, notably, have long analyzed how individual behavior and psychological orientation—especially, utility maximization—may aggregate to explain macro-level phenomena by way of formal, closed-end mathematical modeling and by solving for steady state, long-run equilibria. ABM, too, offers tools by which to examine the effects of individual behaviors on macroscopic patterns, though unlike the closed-end models typically used by economists, ABM needs not converge to any equilibrium state and allows for significantly more heterogeneity among individual "agents."

Macro Exploration: The Effects of Network Winnowing and Widening on Employment Demographics and the Distribution of Wealth

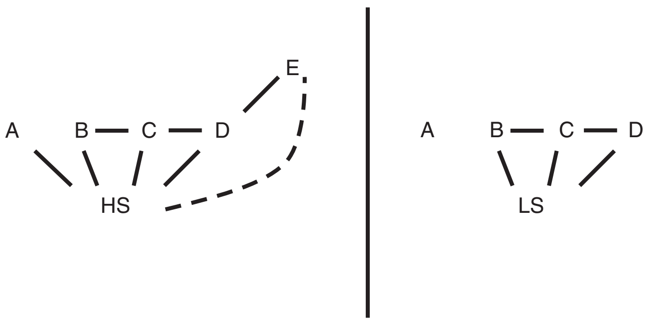
What would happen if low-status people systematically narrowed and high-status people systematically widened their social networks following *actual* job loss?[10] How would the network structure of a community or society evolve? What would happen to the overall distribution of earnings and wealth in that society? Would the long-run macroscopic outcomes of these individual network winnowing and widening behaviors produce anything that resembles the real world? To address these questions, we constructed an ABM to explore the potential macro implications of the micro observations in SMT. In doing so, we wondered whether the aggregation of low-level decision rules that most closely correspond to the authors' findings could create patterns of employment behavior similar to real-world patterns, reproducing, for instance, status-based wealth gaps. This is not to say, of course, that status-based wealth gaps necessarily result entirely from differences in the way people engage with their social networks following job loss. Rather, the implication of such a finding is best thought of as an existence proof regarding the possibility that differences in individual-level networking behavior may help to account for some of the wealth gap.

The full list of parameters for all versions of the model is included in Table 1. The full technical details and documentation of our simulations are included in Online Appendix A. Here, we will summarize key steps and alterations. To begin, we built a model where individuals make decisions on how to search for jobs based on their socioeconomic status. After becoming unemployed, individuals with high socioeconomic status attempted to find a new job by initiating a new, weak tie with a friend of a friend, while individuals with low socioeconomic status relied only on their immediate connections (see Figure 1).[11] To set up the model, we assigned all agents an initial wealth, W_i, and earning rate, E_i, drawn at random from normal distributions (with a minimum value of one). W_i increases over time as a function of E_i, or $W_i = W_{i,t-1} + [E_{i,t-1} * W_{i,t-1}]$. In this simple model, there is no accounting for expenses, and all wealth is earned through labor (i.e., there is no investment income). Next, we connected the agents to one another in such a way that they formed what is known as a "preferential attachment" network similar to the one shown in Figure 2. At each time step[12] in the model, a specified percentage of agents lose their jobs at random, thereby setting their unique earning rates to zero. To reenter the labor market, and reestablish an earning rate other than zero, unemployed agents search for new jobs using the method dictated by their socioeconomic status. When agents find a new job, they gain the earning

Table 1. Parameters of the Simulation

Parameter	Macro exploration Figures 3 and 4	Sensitivity Figures 5–7	Theory development Figure 8(a)	Theory development Figure 8(b)	Theory development Figure 8(c)	Intervention testing Figure 9
Initial wealth	Normal distribution $\mu = 100$, $\sigma = 50$ (≥1)					
Initial earning rate	Normal distribution $\mu = 10$, $\sigma = 1$ (≥1)					
Number of agents	100					
Length of run	750 Timesteps					
Wealth threshold	1 (2 in Fig. 4, lower right)	1, 2, 3, 4, 5	N/A; search depends on experience			1
Unemployment rate	0.1	0.1, 0.2, 0.3, 0.4, 0.5	0.1			
Minimum degree (k)	2	1, 2, 3, 4, 5	2			
Number of replications	100	20	100			
Initial network search probability	Depends on socioeconomic status		1.0		0.0	Depends on socioeconomic status
Learning rate	0.0		0.01			0.0
Baseline hiring probability	1.0		0.5			1.0
Wealth power	N/A since hiring prob. is 1.0		0	10		N/A since hiring prob. is 1.0
Intervention time	No interventions					375
Intervention effect	No interventions					0, 0.5, 1.0, 1.5, 2

Figure 1. Network Winnowing and Network Widening

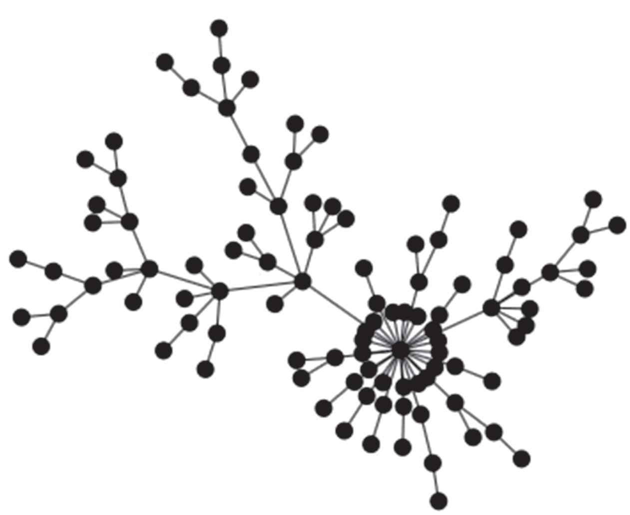


Notes. High-status people (left) search for employment by scanning friends of friends and creating a new tie with the wealthiest friend-of-a-friend contact, here E. Low-status people (right) respond to job loss by cutting their "weakest" tie and gaining employment from the contact with the maximum earning rate among those strong ties remaining.

rate of the person who hired them.[13] The cycle repeats indefinitely.

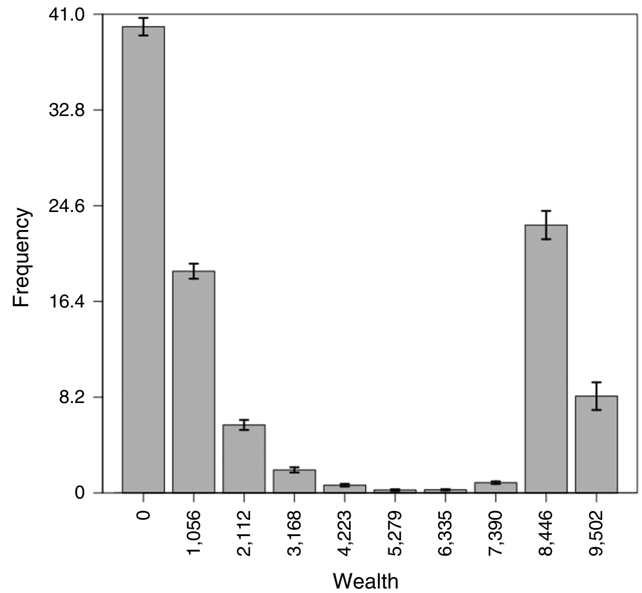
In the experiments described below, we simulated 100 agents initially connected to each other via a preferential attachment social network with a minimum degree (k) of 2 (Barabási and Albert 1999). At each time step, 10% of the population became unemployed,[14] and had to search for a job using the method dictated by their socioeconomic status. Individuals were considered to have high socioeconomic status if their wealth was more than one standard deviation above the mean wealth of all agents. Individuals were considered as having low socioeconomic status if they were below this threshold. We ran the model 100 times. Figure 3 shows the resulting distribution of wealth within each trial, averaged across all trials, after 750 time steps. Recall that the beginning wealth distribution for each trial was a normal one. By comparison, the distribution of wealth that emerges from our first model is strikingly bimodal with a large percentage of low-wealth individuals and smaller but still substantial percentage of high-wealth individuals.

Figure 2. Preferential Attachment Network



Notes. The distribution of links in a preferential attachment network follows a power-law distribution, meaning that few people have a lot of links and most people have a just a few links.

Figure 3. Wealth Distribution of 100 Agents Averaged Over 100 Runs

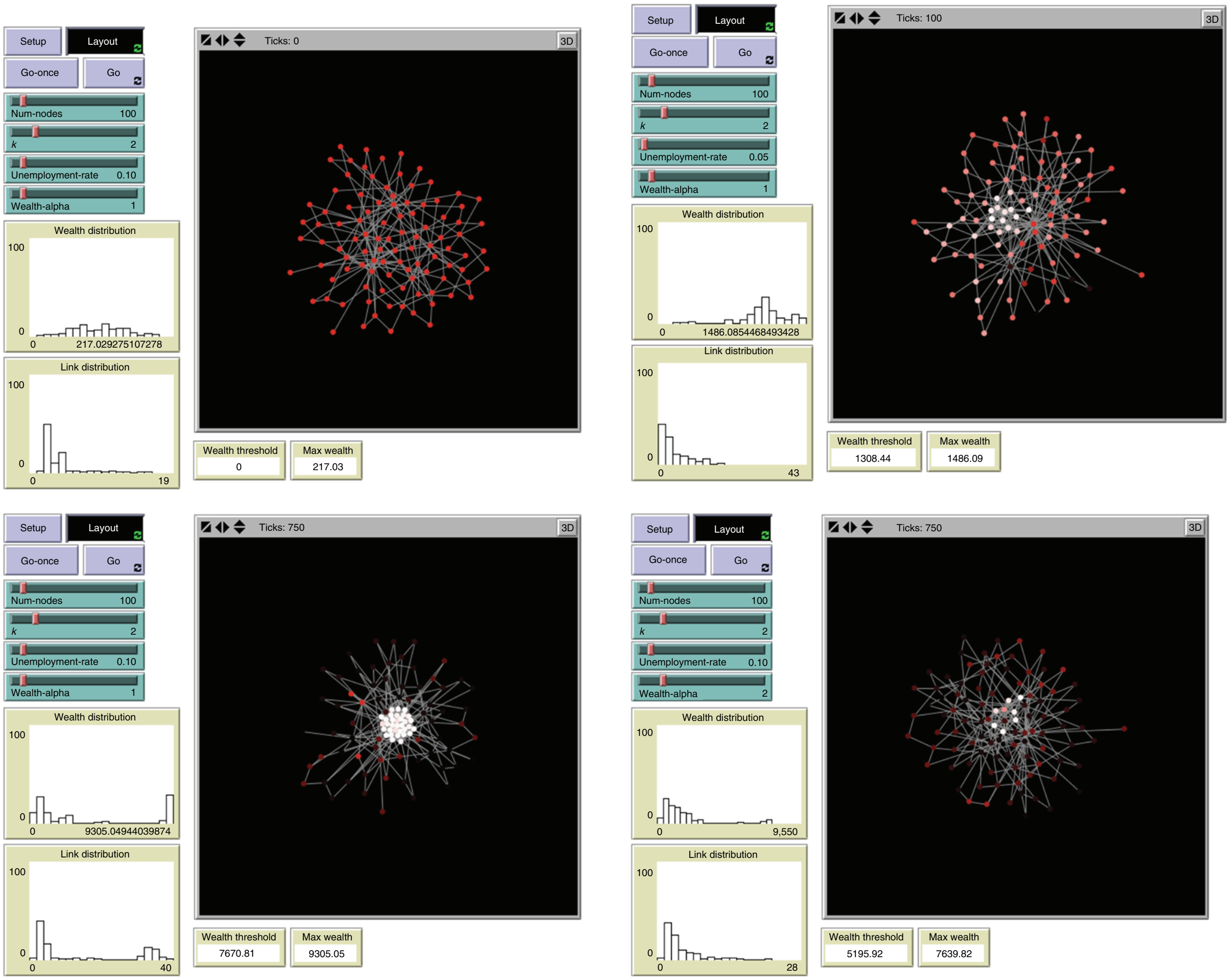


Notes. Error bars in all simulation figures indicate one standard error (i.e., the sample standard deviation divided by the square root of the number of replications).

The first three panels in Figure 4 show the starting, short-run, and long-run states of our model using screen output from the ABM software, NetLogo. What does the output reveal? First, differences in networking responses to job loss had a dramatic effect on the overall structure and connectivity of the community. Second, the initial normal distribution of wealth ultimately transitioned into a bimodal distribution of rich and poor over the long run. Third, the short-run effect of agents' networking behavior had a positive effect on the median amount of wealth earned and shifted the entire wealth distribution to the right. Even low-wealth agents tended to benefit from networking when their networks were still sufficiently broad. We did not anticipate this short-run effect, which may be best characterized by the emergence of an upper-middle class (see the top right panel of Figure 4). Over the long run, however, the networking outcomes, and thus the earning opportunities, of high- versus low-wealth people diverged, and the once growing upper-middle class began a swift breakdown into the bimodal distribution that characterizes the long-run outcome.

We view these initial results as evidence that even simple network rules may help explain patterns that

Figure 4. (Color online) Simulation Results, NetLogo Screenshots



Source. Wilensky (1999).
Notes. Upper left: Setup. Upper right: Short-run outcome. Lower left: Long-run outcome. Lower right: Long-run outcome when a smaller percentage of people are defined as high status. The buttons in the upper-left corner of each of the screenshots set up and run the simulation. The four sliders control the number of agents, the beginning distribution of network links, the unemployment rate, and the wealth threshold used to differentiate high and low status. The top histogram shows the distribution of wealth. The bottom histogram shows the distribution of links. The larger window shows the network of agents. Agents are shaded according to their relative wealth.

other researchers have observed empirically—namely, the growing disparity in wealth (Kenworthy 2014, Autor et al. 2008, Reardon and Bischoff 2011) and growing wealth-based disparity in social connectedness (Putnam et al. 2012). In much the same way that Schelling showed that even small biases can result in significant patterns of segregation, small differences in the way individuals respond to job loss and search for employment can result in dramatically different employment patterns, social connectedness, and wealth distributions. To be clear, we are not and would not argue that differences in people's networking response to job loss is the only mechanism at work in determining distributions related to wealth and social connectedness (our model does not account for any macroeconomic factors that impact wealth distributions, for example), but this model serves as an existence proof (Epstein 1999, Holland 2012) that such a mechanism can be a sufficient driver of wealth disparity.

Sensitivity Analysis: Exploring the Robustness of the Model Results to Perturbations in Parameter Values

It is likely that most readers will have already thought of a handful of changes to our initial, simplified model. For instance, what happens as the number of agents increases or the beginning distribution of links is altered? Alternatively, how might altering the unemployment rate or the nature by which agents become unemployed—perhaps a function of their current earning rate, their accumulated wealth, or even their network position—affect the macro-level outcomes? Each of these changes amounts to a kind of sensitivity analysis that can enable researchers to assess the robustness of their results to perturbations in the input parameters (Wilensky and Rand 2015) and analyze the importance of individual parameters for the model overall. Importantly, as the number of parameters increase, researchers can begin to pinpoint which parameters are central to emerging trends and which result in only trivial differences, or alternatively, create patterns that are illogical and contrary to existing empirical observations. While such analyses are often impossible to run in the behavioral lab or the real world, they constitute little more than a coding challenge for ABM research.

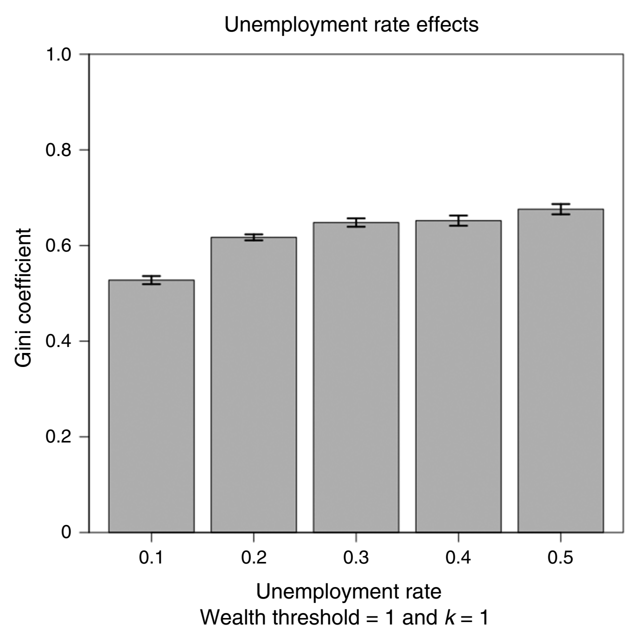
Typically, there are four different criteria by which parameters should be chosen for sensitivity testing: (1) Model-Altering—parameters that have a potentially dramatic effect on a model's behavior, as opposed to parameters that might just alter the surface aspects of a model; (2) Uncertain—parameters that are difficult or impossible to validate empirically; (3) Controlling—parameters that have the potential for policy interventions, as these may lend insight into how the complex system under investigation might react to different interventions; and (4) Environmental Dynamic—environmental parameters that are not typically fixed in the real world, but rather change both temporally and contextually. While assessing all parameters of a model is important, testing the sensitivity of model alternating, uncertain, controlling, and environmental dynamic parameters especially can lend credence to the validity of the model results.

The specific parameters in our model that are good candidates for sensitivity analysis are (1) the unemployment rate, which controls the fraction of individuals who become unemployed in each time period; (2) the link distribution, which dictates how agents are initially connected; and (3) the wealth threshold for assigning high versus low status. As mentioned previously, in our initial model we set the unemployment rate at 10%, assumed a sparsely connected preferential attachment-type network with a minimal degree (k) of 2 (Barabási and Albert 1999), and assumed a high wealth threshold of 1 standard deviation above the mean. We can test how sensitive the model is to these assumptions by altering the value of these parameters and observing the associated outcomes.

To examine these alternatives, we reran our model but varied the three parameters in the following ways: (1) the link distribution we varied by changing the minimum degree (k) from 1 to 5 by increments of 1, (2) the unemployment rate we varied from 0.1 to 0.5 at 0.1 increments, and (3) the wealth threshold we varied from 1 to 5 standard deviations above the mean by increments of 1.[15] These changes amount to 125 different combinations of parameters. For each set of parameters, we ran the model 20 times, resulting in 2,500 iterations of the model all told. We then calculated a Gini coefficient[16] of the resulting wealth distribution for each of the different parameterizations and present the results in Figures 5–7. Online Appendix B further contains several additional sensitivity analyses.

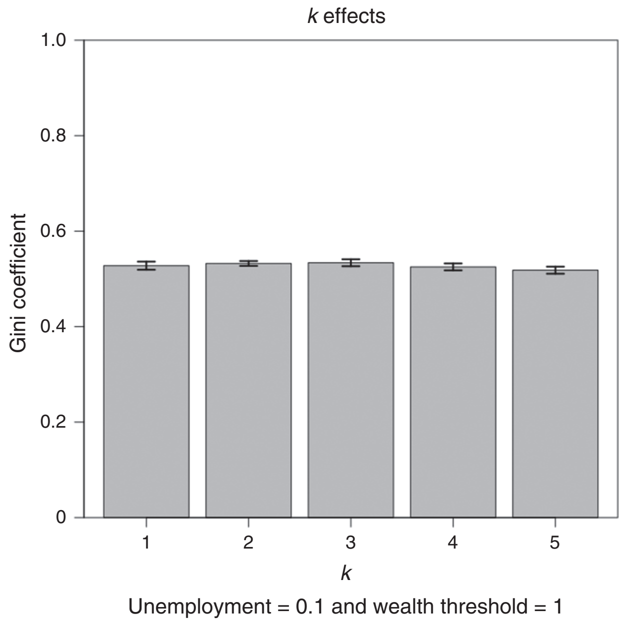
Results of these additional tests indicated first that our model is in no way sensitive to initial network density, a surprising and promising finding given that this parameter is difficult to validate using real-world data. By comparison, the model does appear to be sensitive to changes in the wealth threshold and unemployment rate. Whereas increasing the wealth threshold parameter decreases the wealth disparity, increasing the unemployment rate to particularly high levels increases that disparity. The first of these results indicates that wealth equality increases as high-status individuals become more discriminating in who they consider to be other high-status individuals. This appears counterintuitive at first, as one might expect a higher wealth threshold to exacerbate wealth-based inequality. Assessing the underlying distributions, however, clarifies that increasing the wealth threshold simply creates more low-status, low-wealth individuals in the population, decreasing overall inequality not by decreasing the difference in wealth between the rich and the poor, but by simply increasing the number of agents with little wealth. With respect to the

Figure 5. Unemployment Rate vs. Gini Coefficient



Note. Average of 20 runs.

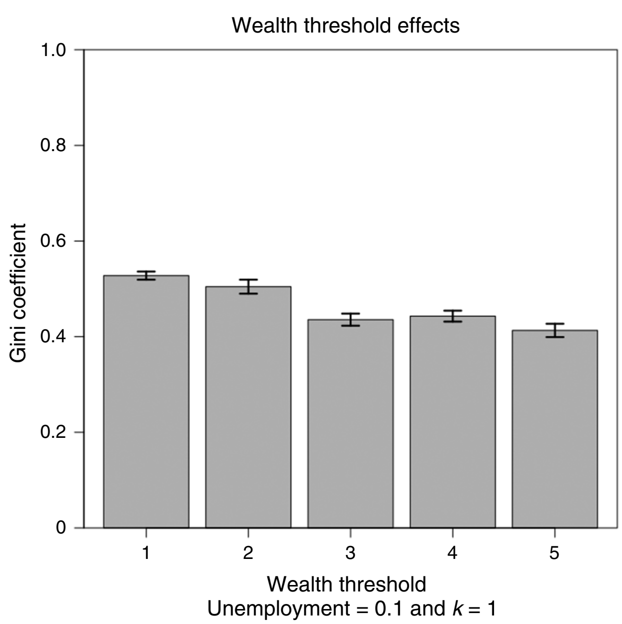
Figure 6. Network Density vs. Gini Coefficient



Note. Average of 20 runs.

unemployment rate, our results suggest a new testable hypothesis regarding the effects of real unemployment, which varies over time, on both social connectedness and the distribution of wealth. Our results indicate that as unemployment goes up, so should inequality of wealth. At first blush, this result seems to contradict the fact that wealth inequality tends to decrease when unemployment increases (Meyer and Sullivan 2013). Recent research, however, has also shown that the negative relationship between unemployment and

Figure 7. Wealth Threshold vs. Gini Coefficient



Note. Average of 20 runs.

inequality tends to be short-term, and that wealth inequality may in fact increase in the wake of recession (Maloney and Schumer 2010). Our result may help to shed some light on a potential mechanism—one involving people's networking behaviors during a recession—underlying this important but understudied long-run trend.

Theory Development: The Creation of Generative Theories

One might also consider more complex versions of our model that intend not to test the feasibility, validity, and macro-level aggregations of the experimental findings, but help construct new theory by which to explain the origins of certain behaviors, possibly leading to new hypotheses for additional exploration back in the behavioral lab. For example, our initial model presupposed that high- and low-status people follow fixed yet contrasting rules of behavior following the event of job loss. While this may in fact be true, and is all that the experimental design in SMT was able to reveal, it tells us little about how these behavioral trends might come to be. Here, too, ABM can be useful.

Imagine that instead of following predetermined rules, all actors, regardless of their wealth, react to job loss the way high-status actors do in the description above, scanning the networks of their friends and attempting to secure a new job from a wealthy friend-of-a-friend. For this alternative model, we might also relax the assumption that all tie formation attempts (i.e., gaining a new job) are successful and instead calculate a probability that the target accepts a job seeker's invitation to form a tie as a function of the seeker's wealth, the wealth gap between the seeker and target, or the strength of the tie between the seeker and target. In making these adjustments, we set the stage for agent learning or adaptation; for example, we may design the model such that the more often a seeker is rejected by a target, the more likely the seeker is to turn toward "strong" network ties in the future, thereby learning to use the method employed by low-status individuals from the initial results in SMT.

Indeed, a major advantage of ABM is that it allows simulated agents to learn as a function of their experiences and make different decisions over time, even when faced with the same situation (Rand 2006, Holland 1995). This is particularly important when one acknowledges that agents in the real world often lack information about what the outcomes of their actions may be (Simon 1955). Accordingly, an important question relating to our model here is whether or not it is possible to generate the same patterns of behavior, and same long-run distributions of wealth and social connectedness, using adaptive agents.[17] This sort of analysis can enable researchers to move beyond static theories to consider the dynamic processes that support and generate them.

To explore learning and adaption in the context of networks and job search, we made three important changes to our initial model, all of which we have alluded to already. First, we dictated that all unemployed agents, regardless of their wealth, seek new employment using the high-status method—i.e., scanning friends of friends—at least initially. Second, we relaxed the assumption that all job search attempts are successful. The second change is necessary given the first, as making the first change without the second quickly results in a fully connected network. To make the second change, we assigned a probability of being rejected by another agent. As part of this change, we set a baseline probability of being hired to 50%, regardless of their wealth or the wealth differential between themselves and the target of their search. Third, we added a mechanism by which job seekers would update which method they used based on their own past experiences. In particular, if they attempted to get a job using the high-status method and it failed, then they would be less likely to use that method in the future, and vice versa for the low-status method.

As illustrated in Figure 8(a), these adjustments resulted in a single-peaked wealth distribution, which is highly right skewed (i.e., has a large percentage of wealthy individuals) and thus did not recreate the bimodal distributions from our original model. Next, we altered the model such that the probability of receiving a job from a weak tie—a friend of a friend—was a function of the difference in wealth between the job seeker and target. The probability of receiving a job from a strong tie, should the agent choose this path, remained fixed at 50%, regardless of the wealth differential between seeker and target. Under these specifications, a more dispersed, almost bimodal, wealth distribution began to emerge but was again skewed unrealistically toward the wealthy, as shown in Figure 8(b). Finally, we altered the initial settings such that instead of having all agents attempt to use the high-status method of job search, all agents, regardless of wealth started out using the strong-tie, low-status job search method. Under this final specification agents still learned and adapted their behavior over time, revealing their learned preferences for one type of search versus the other. The final model resulted in the more recognizable, bimodal wealth distribution with a significant left-tail skew (see Figure 8(c)). These results best indicate that it is possible to start from the assumption that all individuals behave in a similar manner initially, and still generate the bimodal wealth distribution that we saw previously using nonadaptive agents. Importantly, the models reveal the significance of an additional parameter, a wealth-differential parameter, which controls the likelihood that a person is hired by a "weak" tie (see Smith 2005 for related, ethnographic evidence consistent with this conclusion).

Intervention Testing: Exploring How Policy Can Alter Emergent Outcomes

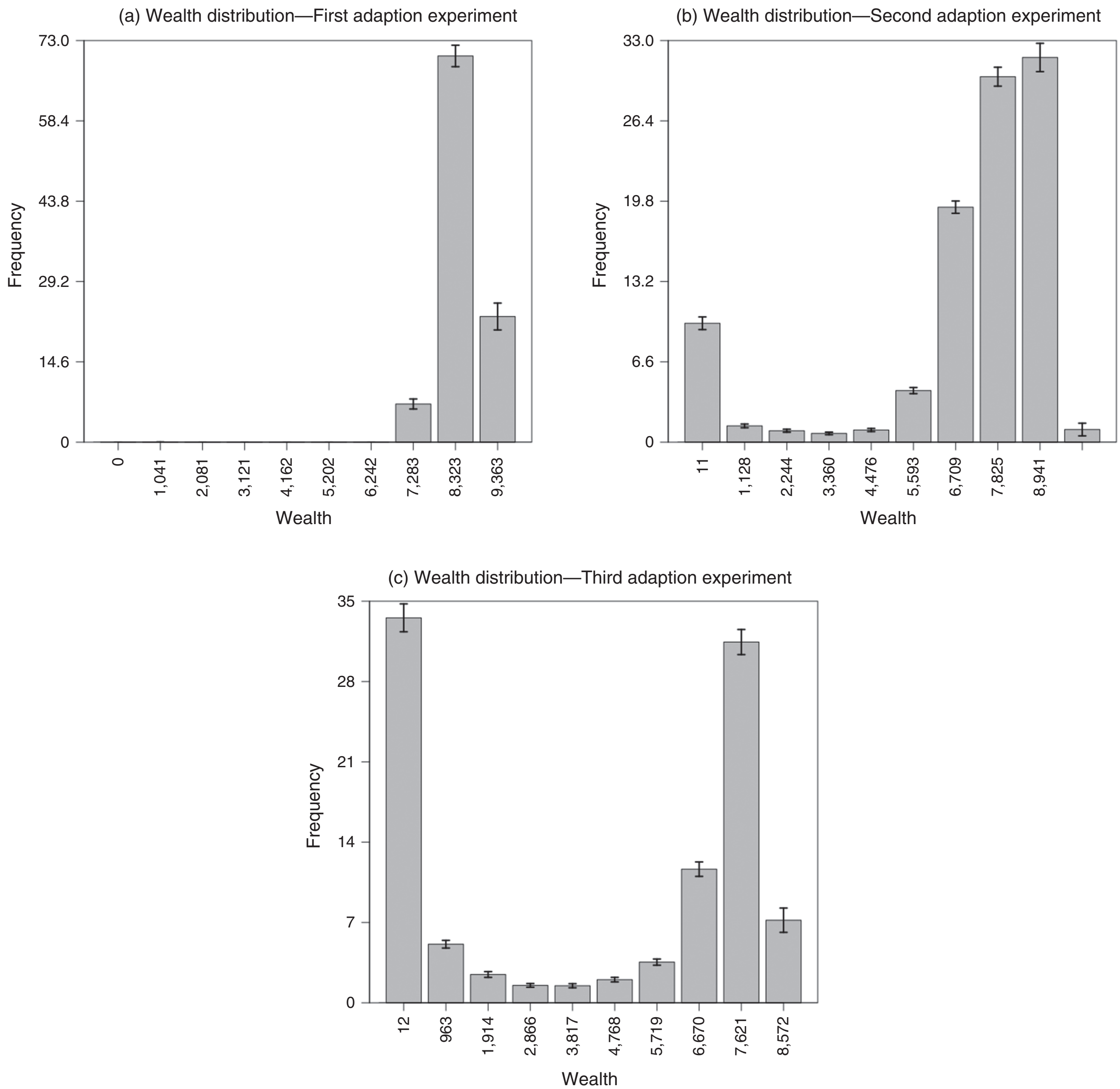
A natural question to emerge from the results of SMT is whether it is possible to change the behavior of low-status job seekers for the better. For example, might the "network winnowing" effect among low-status individuals be reversed by way of an intervention designed to educate people about the importance of weak ties in the job search process (for a real-world experiment on this very topic, see Burt and Ronchi 2007), or alternatively by having organizations encourage laid-off employees to network more broadly when seeking new employment?[18] How would such an intervention, if successful, affect patterns of social connectedness and distributions of wealth and employment?

We began to investigate these questions by running our initial model exactly as before, without the adaptation element explored in the last section, and then implementing, at a halfway point, an intervention designed to change the behavior of individuals pursuing the low-status search strategy. The most straightforward way to do this involved decreasing the wealth threshold that determines agents' search strategies. Recall that our initial wealth threshold was one standard deviation above the mean, which produced the starkly bimodal, left-skewed wealth distribution. If instead one decreases the wealth threshold by two standard deviations—i.e., individuals up to one standard deviation *below* the mean use the high-status search method—the low-status population begins to regain wealth and increase their social connectivity. As before, the exact parameters used to control this intervention are detailed in Table 1. Although the bimodal distribution of wealth does not go away under this specification—the wealthiest individuals are still earning at the rate they were before and no behavioral changes among low-status individuals will slow that down—low-status individuals are able to increase their earning rates and generate more wealth. Figure 9 highlights the results of the intervention visually, suggesting that while targeted education would do surprisingly little to affect wealth disparity, it may positively affect the overall wealth levels within the population at large. Naturally, an untested assumption of this model is that it is possible to educate people in such a way as to affect their network search behaviors. Beyond the limited existing empirical support for this idea (e.g., Burt and Ronchi 2007), we view this assumption as something that might be meaningfully explored back in the context of the experimental lab.

Discussion and Conclusion

Inference is best supported by an integration of multiple methods and multiple kinds of data (Paluck 2010). In this spirit, our aim in the present paper has been

Figure 8. Adaptive Agent Experiments

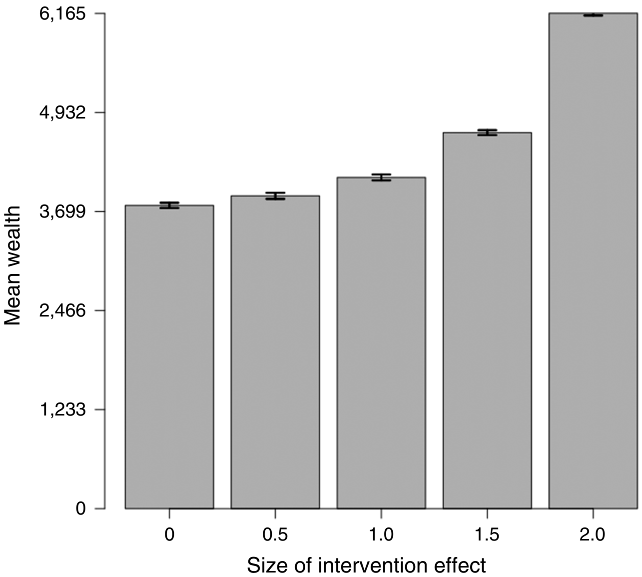


Notes. Wealth distribution averaged over 100 runs. (a) Initial experiment with basic adaptation, where agents start out using the high-status job search method, and everyone has a 50% chance of being hired. (b) Second experiment, where differences in wealth are taken into account when calculating probability of being hired. (c) Third experiment, where agents start out with the low-status job search method.

to convince readers that experimental research with human subjects and ABM have a lot to offer one another, and that merging these two approaches can generate unique insights into multilevel phenomena. Our brief descriptions of each method were meant to be just that, brief. Prior papers—indeed, entire textbooks—are more comprehensive in introducing and describing each method, its history, its epistemological orientation, and its technical and theoretical application (e.g., for ABM methods, in particular, see Miller and Page 2009, Rand and Rust 2011, Wilensky and Rand 2015, Railsback and Grimm 2011 for computational simulation; more generally, see Davis et al. 2007). Instead, our guiding motivation here has been to pique readers' interest in considering the advantages of combining experimental and computational research methods.

Our example model, built first from the empirical results in SMT, should not be read or interpreted as an attempt to show that ABM would have made the original experiment itself any better, although that certainly

Figure 9. Policy Intervention Effects on Mean Wealth



Note. Average of 100 runs with an intervention at the middle time point.

may have been the case. Moreover, we noted a handful of ways that our model differed from SMT, including that our model investigates networking behaviors whereas SMT focus on networking cognition, and it remains to be seen if "cognitive network activation" in fact affects "network mobilization" in the real world. Rather, our intention is to illustrate how using ABM alongside an experiment can provide different and/or additional insights and guide the construction of follow-up experiments to aid researchers' understanding of a given mechanism of interest.

Regarding our specific example, we can imagine several additional considerations and parameters worthy of exploration that could be used to enhance the predictive validity of the model and derive new hypotheses for further exploration in the lab, or field. For example, a more thorough model might include the important distinction between "active" and "dormant" network ties (Levin et al. 2011, Walter et al. 2015), or imbue agents with additional psychological orientations such as openness, extroversion, or trustworthiness. Similarly, one might vary job-seeking strategies as a function of the length of an agent's unemployment (cf. Pescosolido 1992) or overlay various organizational constraints that prior research has shown to affect people's networking patterns (Srivastava 2015).[19] Jackson (1988) found that people change over time in the kind of support—instrumental versus expressive—they seek following job loss. In a similar vein, recent research by Sharone (2007) indicates that long-term unemployment induces different emotional responses between "blue collar" and "white collar" workers, with the latter group being particularly likely to exhibit feelings of relative deprivation. As papers such as these constitute a mere fraction of the empirical research examining the human dynamics of job search, ABM offers a method for bringing together multiple parallel observations into a single framework. Accordingly, we view ABM as useful not only for exploring the validity, mechanisms, and macro-level implications of single micro-level preferences, decision-making patterns, or behaviors, but also as a tool for combining multiple findings into more comprehensive systems of action.

Relatedly, it should be possible to return to the human subjects lab and/or conduct field research to test and validate insights gleaned from simulation. To this end, Castella et al. (2005) have even called for the use of "participatory simulations"—which we take to represent an exciting combination of field experimentation and computer simulation—where humans play the role of the agents and their behavior is calibrated against that of their simulated analogues. In the context of the model presented in this paper, various interventions such as educating people about the role of networks in job search could be explored in either a simulated or real job loss environment where researchers can subsequently assess individuals' likelihoods of approaching others for help.

For the many potential benefits of combining experimental research with ABM, it is also important to recognize inherent limitations, scope conditions, and difficulties of this suggested merging of methods. To start, many of the outcomes, or dependent variables, associated with lab experiments are preferences, emotions, and behavioral intentions. When ABM researchers use these outcomes to assign behavioral rules to the agents in their simulations, they do so by turning behavioral intentions into behavioral facts, as we have admittedly done in the example presented here. The importance of this point should not be overlooked as numerous factors—many of which are controlled away by conducting their research in the controlled environment of the lab—can affect the relationship between preferences and/or intentions, and behaviors. Even if ABM can partially compensate for the less-than-perfect relationship between preference and behavior by affixing probabilities to various decisions (as some of our later models have done), researchers should be explicit about such decisions.

Second, while ABM does indeed offer a unique ability to "scale up" experimental research results by way of simulating observed behaviors on an aggregate scale, many kinds of research questions may not be well suited for ABM. ABM will offer little, for instance, in cases where an aggregate outcome constitutes nothing more than the linear scaling of underlying behaviors. For example, if the goal of an experiment were to understand how stress affects a manager's ability to make optimal decisions, using ABM may prove unhelpful, unless perhaps the intention is to simulate how those decisions might affect others. Instead, ABM will be most useful for experiments involving interactions, whether real or implied, and multilevel phenomena—such as the emergence of trust within an organization as a result of individuals beliefs and subsequent experiences in successive dyadic encounters (see Hedström and Bearman 2009 for a relevant discussion distinguishing between "methodological individualism" and "structural individualism"). In our third and final appendix, Online Appendix C, we highlight several topic areas that we believe to be most amenable to combining human-subjects experiments and ABM.

Third, it is important for researchers combining experimental and ABM research to be explicit about what aspects of the experimental research they are interested in exploring further. The goal of supplementing experimental research with ABM need not be only to generalize effects from the lab to the real world, or a simulated version of the real world. As the latter models from our example illustrate, ABM can also be used to compare two or more different mechanisms and explore learning and adaptive behavior in ways that are sometimes difficult to do in the lab. Further, ABM may also be used to generalize the theoretical conclusions of lab research—even if those conclusions have few direct empirical analogues (Mook 1983)—by investigating the conditions necessary for a given preference or behavior to emerge and matter.

Fourth and finally, integrating experimental research with ABM involves addressing and overcoming significant technical barriers. Because of the nonoverlapping technical demands of laboratory and simulation research, it is unlikely that many experimentalists will read this paper and immediately be able to apply our suggestions to their own work. The same is likely to hold true for computational researchers. Accordingly, the most successful integration of these methods is likely to emerge from active collaboration across the methodological divide. If the present paper helps to accelerate that sort of collaboration, then we view it as a success.

To move toward this goal of greater collaboration, we conclude with several recommendations. First, we urge ABM researchers to make a habit of looking to experimental research and social and organizational psychology especially for guidance in selecting parameters and devising the decision rules that make up their models. Second, experimental researchers should be more receptive to questions regarding the long-run implications of their findings. Third, in addition to replicating findings and running field experiments, we urge experimental researchers to look to computational modeling and simulation as additional means for assessing the validity of their research findings and theoretical claims. Given the "replication crisis" affecting social psychology (see Finkel et al. 2015), we see no better time for this integration of multiple methods. Fourth and finally, as instructors, we should consider introducing experimental and computational methods together, as opposed to the more common pattern of offering "micro methods" and "macro methods" separately.

Acknowledgments

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Endnotes

[1] In fact, Schelling's model indicates a critical value at around 35%–50%: in this range, because of what Schelling calls "tipping," the amount of segregation grows rapidly as a function of the preference for racial homophily (Schelling 1971).

[2] During the course of the preparation of this paper, one of the authors had a chance to interview Schelling, shortly before he passed away, who acknowledged that the inspiration for his agent rules came from his own casual observations about the world about him.

[3] Admittedly, psychologists seldom speak of "long-run" and "equilibria" effects (see Murnighan and Roth 2006) in the same way, or with the same regard as economists or sociologists.

[4] As it is primarily our intention here to point out the promising integration of experimental and ABM methods, we point the interested reader to other, far more comprehensive histories and technical descriptions of experimental methods (e.g., Mook 1983, Davis and Holt 1993, Roth 1995, Roth and Murnighan 1978).

[5] Indeed, we encourage all readers unfamiliar with Mook's article, whether psychologists or otherwise, to acquaint themselves with Mook's perspective on experimental psychology. That researchers are increasingly employing multiples methods to explore social and organizational phenomenon is exciting from a scientific standpoint but also lends to inevitable mismatches between author and reader, or author and reviewer. Misunderstandings rooted in methodological differences stand in the way of effective, multimethod research. For nonpsychologists, especially, Mook's article sheds important light on the mindset and orientation of the experimental researcher, notably explaining that, "Rather than making predictions about the real world from the laboratory, we may test predictions that specify what ought to happen in the lab. We may regard even 'artificial' findings as interesting because they show what can occur, even if it rarely does" (Mook 1983, p. 379).

[6] Agent-based models have been created with agents that are cells, projects, animals, countries, and a host of other entities.

[7] While our focus in this paper is on combining ABM and lab experiments, we should note that ABM, by itself, has a rich history in management and social science, dating back to the early work of Cohen, March, and Olson's garbage can model (1972) and Axelrod's work on evolution of cooperation (1984). More recently, Messick and Liebrand (1995) and Nowak et al. (1990) both used individual-level computer models to explore social relationships, while Brehmer and Dörner (1993) and Lewandowsky (1993) explore the use of computer simulation to understand psychological phenomena. In many of these cases, the term "agent-based modeling" was not yet in common use, and so the more general term "computer simulation" was used instead, even though we would consider several of these to be classic examples of agent-based models. Coen and Maritan (2011), Davis et al. (2007), Burton and Obel (2011), and Colyvas and Maroulis (2015) each constitute modern examples of using agent-based modeling to better understand organizational behavior.

[8]This benefit also poses some risk that is worth highlighting. As Levitt and List (2008) argue, the proliferation of different and often contradictory explanations derived from lab research means "the empirical researcher has virtually unlimited freedom to explain any observed behavior ex post facto" (p. 909). We share this concern as it relates to the integration of lab research and ABM. It is perfectly plausible that lab-generated data can provide ABM researchers with *too many* degrees of freedom. To combat this possibility, we believe that the most successful combinations of ABM and lab experiments will involve active collaboration among researchers from both methodological traditions.

[9]It is important to note that the findings in SMT, which relate to people's cognitive "activation" of network contacts, may not apply to real-world job search or network "mobilization." At minimum, this observation represents an important scope condition of the example we develop. Because our model involves agents interacting with others in their networks, our example represents a test and extension of both the results *and* speculations in SMT—specifically, that cognitive network activation affects network mobilization.

[10]Once again, we acknowledge that our focus on *actual* job loss differs from SMT's focus on the *threat* of job loss. Furthermore, whereas the prior paper is concerned with the cognitive activation of networks, we model patterns of network mobilization (see Jackson 1988, Smith 2005). Like SMT, we believe that the process of network mobilization likely depends, at least in part, on which contacts first come to mind. Nevertheless, it is important to point out that for our example model here, we assume a perfect association between the contacts that come to mind following job loss and the contacts to whom one might turn in reality. If one were to develop this example model more fully, it would be possible to vary the association between network activation and network mobilization.

[11]Here, too, our model differs slightly from the findings in SMT as we constrain agents pursuing the network-widening strategy to mobilize a structurally "weak" tie, here meaning a friend of a friend. In an additional set of models not reported here, we further constrain actors pursuing this strategy to get a job from a preexisting tie. The main results are qualitatively similar under this alternative specification and in some cases are stronger, since activating only direct ties results in wealth being contained to a smaller social circle.

[12]A time step in this model is purely theoretical since it is constructed as an exploratory model, but it might be considered to be roughly one month.

[13]Taking on the earning rate of the person hiring you is surely an oversimplification that a researcher might choose to alter in a more complete model.

[14]This value was chosen to be at the higher end of typical unemployment rates. A higher value means that the results appear quicker, but the value can be lowered without producing qualitative changes in the long-run model results.

[15]In supplemental analyses, we replicated our model using initial network structures that mimicked the degree distribution and connectivity of two real-world social networks—first a sample of Twitter users and then a university alumni contact network. Results from these analyses were substantively identical to those we report here.

[16]The Gini coefficient is a measure of dispersion of a distribution commonly used to measure income inequality when it is applied to a distribution of income or wealth. A Gini coefficient of zero represents perfect equality, where all individuals receive the same income. A Gini coefficient of 1 represents maximum inequality, where one individual receive all income or holds all wealth.

[17]A common criticism of both analytical and simulation modeling is that the results of such models are somehow "engineered." To mitigate this concern, we also encourage researchers to program learning, adaptive agents to better understand the behavior of dynamic, complex social environments. We illustrate how the same results can be obtained through an adaptive mechanism.

[18]Both of these "interventions" are purely hypothetical. We raise them here only insofar as they are useful for our methodological purposes. As do the authors of that paper, we acknowledge that weak ties may be less useful for low-status individuals than for high-status ones (see also Yakubovich 2005, Smith 2005).

[19]We thank an anonymous reviewer for pointing out these possible additions to our example model.

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