### *Appendix A: Description of Job Search Agent-Based Model*

This appendix describes the Job Search model based on Smith et al. (2012), using the guidelines for building agent based models recommended in Rand and Rust (2011). We begin by briefly describing what ABM is, and providing some pointers to relevant literature in the field. We then defend why ABM is appropriate for the present application, and describe the model, as well as the two major variants (adaptive model and policy intervention model) discussed in the paper. Finally, we finish by discussing the verification and validation of the model.

**What is ABM?**

Agent-based modeling (ABM) is a method of creating a computational model where the basic ontological units of the model are agents. In other words, rather than modeling populations, stocks, or flows, we model, as closely as possible, every agent actually acting in the model. The central tenet of agent-based modeling is that many phenomena in the world, and especially complex systems (Mitchell, 2009), are well modeled through a set of rules and formalizations that describe: (1) the agents, (2) the environment, (3) agent-agent interactions, and (4) agent-environment interactions (Wilensky and Rand, 2015).

**Survey of ABM**

Agent-based modeling has been used in a wide variety of fields, and applied to a wide variety of problems and phenomena. A full survey is beyond the scope of this work, but in this section we will discuss a few important references, and what they contain.

For instance, there are a number of books that describe the basic premise of agent-based modeling, and how to create an agent-based model. One of the most hands-on textbooks on ABM is Wilensky and Rand (2015). This book uses NetLogo (Wilensky, 1999) to describe the power of ABM, its various uses, and even how to construct an agent-based model from the ground up. Other general discussion of ABM include: (1) Railsback and Grimm (2011), which takes a similar approach to Wilensky and Rand but focuses more on ecological models, similar to their previous book (Grimm and Railsback, 2005), (2) Miller and Page (2009) describe ABM within the greater context of complex adaptive systems, (3) Gilbert (2008) provides a quick introduction to the basic concepts and ideas of ABM, (4) Gilbert and Troitzsch (2005) discuss ABM among other methods of simulation for the social scientist, (5) Bonabeau (2002) made a good case for the use of ABM as the primary method for studying human systems, (6) Epstein and Axtell (1996) provided one of the earliest explorations of ABM, its power to explain complex phenomena, and is widely considered to be one of the foundational books in the field, and (7) Holland (1995) describes many of the conceptual motivations and benefits of ABM.

In addition to these general surveys and descriptions of ABM, there are several surveys that have been specific to ABM's application to business and management science. For instance, Rand and Rust (2010) provide an overview of the use and guidelines of ABM in the field of marketing, Davis, Eisenhardt and Bingham (2007) describe how to use ABM and other simulation methods to produce novel theory, North and Macal (2007) describe the use of agent-based modeling to solve practical business problems, LeBaron (2000) presents an early review of the use of ABM in computational finance, and Garcia (2005) provides a good survey of the use of ABM in innovation research. There have also been special issues on ABM in both the *Journal of Business Research* (Gilbert, Jager, Deffuant, & Adjali, 2007) and the *Journal of Product Innovation Management* (Garcia & Jager, 2011).

Besides these general survey pieces, there have been specific applications of agent-based modeling in organizational science (Cohen, March, & Olsen, 1972), supply-chain management (Walsh & Wellman, 2000), diffusion of innovations (Rahmandad & Sterman, 2004), firm positioning (Tay and Lusch, 2005), word of mouth (Goldenberg, Libai, & Muller, 2001), and relationship marketing (Watkins and Hill, 2009). As mentioned before, a full survey is beyond the scope of this paper, but there are many more applications that have been published within the business and management science literature.

In addition to these traditionally published references there are a number of websites that are useful when exploring and understanding ABM, including (1) openabm.org which is a website devoted to the use of ABM in the sciences and contains a large model library, (2) ccl.northwestern.edu/netlogo which is the website for the NetLogo programming language and also contains many models and extensive documentation, and (3) www.econ.iastate.edu/tesfatsi/ace.htm which is Leigh Tesfatsion's page documenting agent-based computational economics. This is just a small selection, since there are many other resources available online.

In the next few sections, we will discuss the role of ABM in the particular model that we explore in this paper. We will examine the appropriateness of ABM for the phenomenon at hand, how the model was constructed, the verification and validation of the model, provide a description of the model in pseudocode, and lay out all of the parameter settings of the model.

**Appropriateness of ABM**

Rand and Rust (2011) lay out six conditions for determining whether or not agent-based modeling are appropriate for a given problem. As they describe these are not requirements for ABM but rather the more of these conditions are met, the more useful ABM will be. The conditions are: (1) Medium Numbers, (2) Local and Potentially Complex Interactions, (3) Heterogeneity, (4) Rich Environments, (5) Temporal Aspects, and (6) Adaptive Agents (Rand and Rust 2011). We will discuss each of these aspects in turn.

1. *Medium Numbers* – The question here is whether the system is attempting to model a very small number of agents, or a really large number of agents. In this case, we are interested in investigating a medium number of agents since we are not interested in how one or two agents perform there job search, and we are not interested in billions of agents, but rather how individuals in a local job market go about their job search.
2. *Local and Potentially Complex Interactions* – Do the agents interact only among their local neighborhood and potentially maintain memories about those interactions? In the job search case both of these conditions are met. The model as proposed has the agents search only among their local neighborhoods; moreover, the agents maintain a history of these interactions, which they use to make decisions in the future. Any system that has notions of strong and weak communication ties will inevitably meet this criterion for ABM.
3. *Heterogeneity* – Are the agents different from each other in substantial ways? In the system we are examining, agents have several important sources of heterogeneity. The agents differ in both wealth and earning rate, but perhaps less obviously they differ in their exact location within the overall social network. This is an important source of heterogeneity, and, in fact, is one of the arguments as to why we see significant differences in wealth distributions.
4. *Rich Environments* – The environment of the job search process may not actually seem that rich, but in the context described within this model, the environment is defined by the social connections of the agent. As the social connections are quite varied between individuals, and because the network is defined not just by those connections, but by the agents at the other end of those links, the environment can be quite rich.
5. *Temporal Aspects* – Is the phenomenon of interest something that evolves over time or is it static? In this case we are interested in how individuals pursue jobs over time, so this requirement is clearly met.
6. *Adaptive Agents* – Do the agents change their actions based on previous experience? In one of the modifications of the model this is exactly the question that is pursued.

Clearly then ABM is an appropriate methodology for understanding the job search phenomenon at hand, and we can proceed to constructing the model.

## Model Construction

There are seven design choices to be considered when constructing an agent-based model (Rand and Rust 2011): (1) Scope of the Model, (2) Agents, (3) Properties, (4) Behaviors, (5) Environment, (6) Input and Output, and (7) Time Step. When well-specified these choices define the agent-based model to be constructed.

1. *Scope* – The scope of this model is a local job search market with all of the job seekers and potential job targets represented. We do not seek to replicate the whole US labor market or to study effects beyond simple hiring decisions and overall wealth accumulation.
2. *Agents* – There is essentially only one type of agent in the model. This agent is both a job seeker and a potential source of employment for other job seekers.
3. *Properties* – Agents in this model have three properties: (a) wealth, (b) earning-rate, and (c) social network. (a) Their wealth is monotonically increasing, and is initially set to draw from *N(100,50)* though if the value is less than 1 it is set to 1, since the assumption is that everyone has some minimal wealth. Agents never spend money so wealth always goes up. (b) The earning-rate of an agent is how much wealth they accumulate per turn. It is initially set to *N(10,1)*, but if the value is less than 1 initially it is set to 1 since the assumption is that all agents at the beginning of the model are gainfully employed. Their earning rate can change during the course of the model. (c) Finally, agents' social networks are the connections they have to other individuals. Initially, they are a part of a preferential attachment network, which has a scale-free degree distribution (Barabási and Albert 1999), but their network evolves over time. This network also has a strength associated with it, which individuals use to decide who their strongest connection in their local network is. The initial strength is set to 1 for all connections, including those that are created during the run of the model.

    *Adaptive Model* – In the adaptive model, the agents also have a (d) network-search-probability property which controls with what probability they search their local network. The initial value of this is controlled by a parameter that is experimented with in the paper. The value also changes over time as agents learn which method (high-status vs. low-status) of job search works better for them.
4. *Behaviors* – Agents in this model have essentially four behaviors: (a) earn wealth, (b) communicate, (c) become unemployed, and (d) find a new job. (a) All agents earn money every timestep, essentially an increment equal to their earning-rate is added to their wealth. (b) They then find a network neighbor to communicate with. They do this with a probability proportional to how often they have communicated with that neighbor in the past. Once this neighbor is found the strength associated with that connection is incremented by 1. (c) If an agent becomes unemployed then their earning-rate is set to 0. The percentage of agents who become unemployed each timestep is controlled by the unemployment-rate. The heart of the model is (d) which controls how an agent finds a new job. The first thing that is done is to see if the individual is a high-status individual or a low-status individual. An individual is high status if their wealth exceeds *wealth-threshold* standard deviations above the mean wealth; otherwise, the individual is low status. High status individuals find the individual among all of their friends and friends of friends who has the highest earning-rate and they approach them for a job. In the basic model they are given the job automatically, and they create a new social connection of strength 1 to this individual if they were not connected with them before. They then gain the earning rate of this individual. Low-status individuals contact the person who they have the strongest social connection to as measured by their frequency of communication (see behavior (b)). Since this individual has to be someone they already had a connection to they do not create new connections, but instead simply take on the earning-rate of this individual.

*Adaptive Model* – In the adaptive model, the behaviors differ though they are the same four behaviors. In particular the find a job behavior (d) changes. If a user has an earning-rate of 0 then they look for a job regardless of whether they became unemployed in this timestep or a previous timestep. They then generate a random number and compare that to their probability of using the high status search method. If the random number is less than this probability than they employ the high-status method, otherwise they use the low-status method. Once they have determined which method to use they then approach the target they have identified. They are given a job with a probability equal to the base-hiring probability in the first model described in the adaptive model section. If they are not given a job then they decrease their probability of using that same method again by an increment called the learning rate. In the second model, if the job seeker has less wealth than the job target and they are using the high-status method, then baseline probability is multiplied by ((1 – ((target-wealth - my-wealth) / (target-wealth)) ^ wealth-power). In other words, it is a function of the differences in wealth raised to the wealth-power exponent. In the results presented in the paper, wealth-power is set to 10. In all cases in the paper the low-status method remains the same, where the probability of being hired is simply the base-hiring probability. Finally, in the third model the initial probability of using the high status method is set to 0, and all agents start by using the low status method.

5. *Environment* – The main environment of the model is defined by the preferential attachment social network (Barabási and Albert 1999). There are a few other parameters that affect the overall behavior of the model, such as the number of agents, and the unemployment rate but those will be described in the next section.
6. *Input and Output* – In the basic model, there are four parameters that control the model, and the results are examined through one output variable. The four parameters are: (a) number of agents, (b) minimal degree, (c) unemployment rate, and (d) wealth threshold. The number of agents (a) simply controls how many agents are in the model. The minimal degree (b) is a controlling characteristic of the Barabási-Albert model and specifies what the minimal number of connections that any node has. The unemployment rate (c) controls what fraction of the population has their earning rate set to 0 each timestep. The wealth threshold (d) controls how many standard deviations above the mean wealth an individual has to be to be considered high-status. In all cases, the output of the model is the distribution of the wealth of all agents.

*Adaptive Model* – The adaptive model adds three new parameters to the model: (e) the baseline hiring probability, (f) the wealth power exponent, (g) the initial network search probability, and (h) the learning rate. In the base model all individuals are given jobs from the targets that they approach, in the adaptive model they are only given jobs with a probability equal to the baseline hiring probability (e) times ((1 – ((target-wealth - my-wealth) / (target-wealth)) ^ wealth-power), where target-wealth is the person they are approaching's wealth, my-wealth is the current agent's wealth, and wealth-power (f) is an exponent controlling the effect of wealth. In the first runs of this model wealth-power is set to 0 essentially meaning everyone is hired based solely on the baseline hiring probability (e). In later runs, this is increased. The initial network search (g) probability controls whether they start by using the low status search method or the high status search method or some combination thereof. A value of 1.0 means they only use the high-status method, and a value of 0.0 means they only use the low-status method, and values in between specify the probability with which they use each. Finally, the learning rate (h) controls how big an effect each job rejection has on the individuals. When an individual approaches someone using either the high-status or low-status method if they are not given a job then they decrease the probability of using that method (and increase the probability of using the other method) by this rate. This is set to 0.01 in all experiments in this paper.

*Intervention Model* – The policy intervention model extends the base model and adds two additional parameters: (i) intervention time, and (j) intervention effect. The intervention time (i) specificies at what time in the model the intervention takes effect. Prior to this time the model is exactly the same as the basic model. After this time, the wealth threshold (d) is modified by subtracting the intervention effect (j). This has the effect of having more individuals pursue the high status method of job search.

7. *Time Step* – Almost all agent-based models have two different phases, an initialization phase and an iterative phase. In the initialization phase of this model, the agents are created and they are given their initial properties (earning rate, wealth, etc.). They are also embedded in their social network. In the iterative step, the first thing that happens is that all agents accumulate wealth according to their earning rate. Then they communicate with one other agent according to the description in (4b). After this a certain percentage of the agents become unemployed, and those agents that are unemployed seek new jobs. After this all statistics are recorded. This time step is the same for all three versions of the model though the behaviors change as described above.

**Verification of the Model**

Verification means making sure that the implemented model corresponds to the conceptual model as described. Rand and Rust (2011) describe three standards for verification of the model: (1) documentation, (2) programmatic testing, and (3) test cases and scenarios.

1. *Documentation* –The model was well documented both within the code and within lab notes. This documentation and the code will eventually be published on openabm.org a repository that maintains such information. This appendix serves as another source of documentation.
2. *Programmatic testing* – The model was developed using a combination of unit testing and code walkthroughs. In the unit testing, as each additional level of complexity was added to the model, the model was tested to see if the previous results of the model could still be created. In addition, the code was explained by one of the co-authors (Rand) to the other co-author (Smith) and this provided a code walkthrough.
3. *Test Cases* – Corner cases and sampled cases were examined to see if the model was creating any aberrant behavior.

**Validation of the Model**

Validation means comparing the implemented model to the real world in some meaningful way. Rand and Rust (2011) describe four standards for validating a model: (1) Micro-face validation, (2) Macro-face validation, (3) Empirical Input validation, and (4) Empirical Output Validation. Most of the validation of this model is documented in the main body of the text of the paper. Micro-face validation (1) involves determining that the agents at the micro-level on face behave the way real agents do. One of the benefits of basing this model directly on lab experiments is that we have valid evidence from the experiments that back up the way that agents behave in this model. Macro-face validation (2) involves determining whether the processes at the macro-level seem to reflect real-world macro-processes, given that the model exhibits standard patterns of employment and unemployment it seems to reflect macro-patterns on face. Empirical input validation and empirical output validation relate to comparing the model's input and outputs to real data. As described in the main text of the paper, in some cases input validation is impossible because we simply do not know the value of the input, and hence we conduct a sensitivity analysis of the input parameter space. Finally, with respect to empirical output validation, we have shown in this model that the output patterns, such as a bimodal wealth distribution, seem to reflect real-world wealth patterns.

**Pseudo-code of Models**

In this section we will describe each of the model variants using pseudo-code, which is a natural language version of the code used to create the models. The full code of the model as well as documentation will be available from OpenABM.org upon publication of this paper.

*Base Model*

```
to setup
	create num-nodes agents
		wealth = Normal(100,50)
		if wealth < 1 then wealth = 1
		earning-rate = Normal(10,1)
		if earning-rate < 1 then earning-rate = 1
	create-social-network(minimal degree = k)
		for all links
			strength = 1
end

to go
	for all agents
		wealth = wealth + earning-rate
		target-link = find-communication-target(strength)
		strength of target-link = strength of target-link + 1
	unemployed = random set of unemployment-rate * count agents
	for all unemployed
		earning-rate = 0
	for all unemployed
		if wealth < mean of wealth + wealth-threshold * sd of wealth [
			target = max earning-rate of friends of friends and friends
			create-link-with target
			earning-rate = earning-rate of target
		]
		else [
			target = max communication of friends
			earning-rate = earning-rate of target
		]
end
```

*Adaptive Model*

```
to setup
	create num-nodes agents
		wealth = Normal(100,50)
		if wealth < 1 then wealth = 1
		earning-rate = Normal(10,1)
		if earning-rate < 1 then earning-rate = 1
		prob-search-network = initial-network-search
	create-social-network(minimal degree = k)
		for all links
			strength = 1
end
```

```
to go
	for all agents
		wealth = wealth + earning-rate
		target-link = find-communication-target(strength)
		strength of target-link = strength of target-link + 1
	unemployed = random set of unemployment-rate * count agents
	for all unemployed
		earning-rate = 0
	for all agents with earning-rate = 0
		if random 1.0 < prob-search-network [
			target = max earning-rate of friends of friends and friends
			if (wealth > wealth of target) or (random 1.0 < baseline-prob-hire * ((1 - ((wealth
	of target - wealth) / wealth of target)) ^ strength-power))
			 [
				create-link-with target
				earning-rate = earning-rate of target
			]
			else [
			 prob-search-network = prob-search-network – learning-rate
			]
		]
		else [
			target = max communication of friends
			if wealth > wealth of target or random 1.0 < baseline-prob-hire
			[
				earning-rate = earning-rate of target
			]
			else [
			 prob-search-network = prob-search-network + learning-rate
			]
		]
end
```

*Policy Intervention Model*

```
to setup
	create num-nodes agents
		wealth = Normal(100,50)
		if wealth < 1 then wealth = 1
		earning-rate = Normal(10,1)
		if earning-rate < 1 then earning-rate = 1
	create-social-network(minimal degree = k)
		for all links
			strength = 1
end

to go
	for all agents
		wealth = wealth + earning-rate
		target-link = find-communication-target(strength)
```

```
                    strength of target-link = strength of target-link + 1
          unemployed = random set of unemployment-rate * count agents
          for all unemployed
                    earning-rate = 0
          for all unemployed
                    if timestep > intervention-time [
                     mod-wealth-threshold = wealth-threshold + intervention-effect
                    ]
                    if wealth < mean of wealth + mod-wealth-threshold * sd of wealth [
                              target = max earning-rate of friends of friends and friends
                              create-link-with target
                              earning-rate = earning-rate of target
                    ]
                    else [
                              target = max communication of friends
                              earning-rate = earning-rate of target
                    ]
end
```

**Parameters of Main Paper**
In this section we will detail the exact parameters used to create each of the sections in the main paper.

*Fixed Parameters for All Model Versions*

| *Parameter* | *Value* |
|---|---|
| Initial Wealth | Normal Distribution μ=100, σ=50 (≥1) |
| Initial Earning Rate | Normal Distribution μ=10, σ=1 (≥1) |
| Number of Agents | 100 |
| Length of Run | 750 Timesteps |

*Macro Exploration: Figures 3 and 4*

| *Parameter* | *Value* |
|---|---|
| Wealth Threshold | 1 (2 for part of Figure 4) |
| Unemployment Rate | 0.1 |
| Minimum Degree (k) | 2 |
| Number of Replications | 100 |

*Sensitivity Analysis: Figures 5, 6, and 7*

| *Parameter* | *Value* |
|---|---|
| Wealth Threshold | 1, 2, 3, 4, 5 |
| Unemployment Rate | 0.1, 0.2, 0.3, 0.4, 0.5 |
| Minimum Degree (k) | 1, 2, 3, 4, 5 |
| Number of Replications | 20 |

*Theory Development: Figures 8abc*

Figure 8a

| *Parameter* | *Value* |
|---|---|

| | |
|---|---|
| Unemployment Rate | 0.1 |
| Minimum Degree (k) | 2 |
| Initial Network Search Probability | 1.0 |
| Learning Rate | 0.01 |
| Baseline Hiring Probability | 0.5 |
| Wealth Power | 0 |
| Number of Replications | 100 |

Figure 8b

| *Parameter* | *Value* |
|---|---|
| Unemployment Rate | 0.1 |
| Minimum Degree (k) | 2 |
| Initial Network Search Probability | 1.0 |
| Learning Rate | 0.01 |
| Baseline Hiring Probability | 0.5 |
| Wealth Power | 10 |
| Number of Replications | 100 |

Figure 8c

| *Parameter* | *Value* |
|---|---|
| Unemployment Rate | 0.1 |
| Minimum Degree (k) | 2 |
| Initial Network Search Probability | 0.0 |
| Learning Rate | 0.01 |
| Baseline Hiring Probability | 0.5 |
| Wealth Power | 10 |
| Number of Replications | 100 |

*Intervention Testing: Figure 9*

| *Parameter* | *Value* |
|---|---|
| Wealth Threshold | 1 |
| Unemployment Rate | 0.1 |
| Minimum Degree (k) | 2 |
| Intervention Time | 375 |
| Intervention Effect | 0, 0.5, 1.0, 1.5, 2 |
| Number of Replications | 100 |

**References**


Barabási, A. L., & Albert, R. 1999. Emergence of scaling in random networks. *Science, 286*(5439), 509-512.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*,*99*(suppl 3), 7280-7287.

Cohen, M. D., March, J. G., & Olsen, J. P. (1972). A garbage can model of organizational choice. *Administrative science quarterly*, 1-25.

Davis, J. P., Eisenhardt, K. M., & Bingham, C. B. (2007). Developing theory through simulation methods. *Academy of Management Review*, *32*(2), 480-499.

Epstein, J. M., & Axtell, R. (1996). *Growing artificial societies: social science from the bottom up*. Brookings Institution Press.

Garcia, R. (2005). Uses of agent-based modeling in innovation/new product development research. *Journal of Product Innovation Management*, *22*(5), 380-398.

Garcia, R., & Jager, W. (2011). From the Special Issue Editors: Agent-Based Modeling of Innovation Diffusion. *Journal of Product Innovation Management*,*28*(2), 148-151.

Gilbert, G. N. (2008). *Agent-based models* (No. 153). Sage.

Gilbert, N., & Troitzsch, K. (2005). *Simulation for the social scientist*. McGraw-Hill Education (UK).

Gilbert, N., Jager, W., Deffuant, G., & Adjali, I. (2007). Complexities in markets: Introduction to the special issue. *Journal of Business Research*, *60*(8), 813-815.

Goldenberg, J., Libai, B., & Muller, E. (2001). Talk of the network: A complex systems look at the underlying process of word-of-mouth. *Marketing letters*,*12*(3), 211-223.

Holland, J. H. (1995). *Hidden order: How adaptation builds complexity*. Basic Books.

LeBaron, B. (2000). Agent-based computational finance: Suggested readings and early research. *Journal of Economic Dynamics and Control*, *24*(5), 679-702.

Miller, J. H., & Page, S. E. (2009). *Complex adaptive systems: an introduction to computational models of social life: an introduction to computational models of social life*. Princeton university press.

Mitchell, M. (2009). *Complexity: A guided tour*. Oxford University Press.

North, M. J., & Macal, C. M. (2007). *Managing business complexity: discovering strategic solutions with agent-based modeling and simulation*. Oxford University Press.

Grimm, V., & Railsback, S. F. (2005). Individual-based Modeling and Ecology:(Princeton Series in Theoretical and Computational Biology).

Rahmandad, H., & Sterman, J. (2008). Heterogeneity and network structure in the dynamics of diffusion: Comparing agent-based and differential equation models. *Management Science*, *54*(5), 998-1014.

Railsback, S. F., & Grimm, V. (2011). *Agent-based and individual-based modeling: a practical introduction*. Princeton university press.

Rand, W., & Rust, R. T. 2011. Agent-based modeling in marketing: Guidelines for rigor. *International Journal of Research in Marketing*, *28*(3), 181-193.

Smith, E. B., T. Menon, and L. Thompson. 2012. "Status Differences in the Cognitive Activation of Social Networks." *Organization Science* 23(1).

Tay, N. S., & Lusch, R. F. (2005). A preliminary test of Hunt's General Theory of Competition: using artificial adaptive agents to study complex and ill-defined environments. *Journal of Business Research*, *58*(9), 1155-1168.

Walsh, W. E., & Wellman, M. P. (2000). Modeling supply chain formation in multiagent systems. In *Agent mediated electronic commerce II* (pp. 94-101). Springer Berlin Heidelberg.

Watkins, A., & Hill, R. P. (2009). A simulation of business-to-business decision making in a relationship marketing context. *Industrial Marketing Management*,*38*(8), 994-1005.

Wilensky, U. (1999). NetLogo, http://ccl.northwestern.edu/netlogo.

Wilensky, U., & Rand, W. (2015). *An Introduction to Agent-Based Modeling: Modeling Natural, Social, and Engineered Complex Systems with NetLogo*. MIT Press.

*Appendix B: Modified Assumptions*

In this appendix we report the results of four additional robustness checks. The goal of the paper is to illustrate the advantages of combining ABM and lab experiments. To that extent, we include these additional examples not as evidence that our model perfectly matches the experiment on which it was based, but rather to illustrate the flexibility of the ABM framework in adapting to different research goals.

At the request of three anonymous reviewers, the four aspects of the ABM model we examine further in this appendix relate to the scope of agents' network search as well as the nature of what constitutes "weak" ties, and the probability of being hired. First, we modified the original model, so that high-status agents can only search their direct friendship connections, not the friends-of-friends connections that they could search in the original implementation of our model. Second, we ran a set of experiments where we reduced the baseline hiring probability for all experiments to 5%. In both of these cases, we recreated the data underlying Figures 3, 5, 6, 7, 8, and 9 in the paper. Third, in the original model if an individual approached someone for a job they would create a friendship tie with the person even if they did not receive a job from the individual. We wanted to see what would happen if we violated this assumption, so we created a version where a friendship tie was only created if the person received the job. Fourth, one of the reviewers asked if our results would apply to a real network rather than a synthetic network that we used in the original paper. So we ran the model on two large real-world networks

In all cases, the results were qualitatively similar to our original model. Below we offer additional details on each modification and result.

*Modifying Network Search*

In the presentation in the paper, high-status agents search not only their direct friends for a new job, but also their friends-of-friends. As we acknowledge in the paper, the friend-of-friend search approach may represent a deviation from the experimental findings in the paper by Smith, Menon, and Thompson (2011). Accordingly, we modified our initial model by constraining high-status agents to activate only their direct connections when searching for a job. We then correlated the underlying histogram data from the original Figure 3, with the histogram data from the modified model. The Pearson correlation was 0.99. Figure B-1a/b illustrates this correlation visually by including the initial Figure 3 from the main paper side-by-side with the results from the modified model.

We did the same thing for each of the additional figures in the main paper. For Figure 5, the results are qualitatively similar to the original paper for unemployment rates below 0.3, but above that level we see a dip in the resulting Gini coefficient. From looking at the model results, this difference occurs because when high-status agents can only search immediate neighbors, and the unemployment rate is very high, these agents cannot find jobs for some time, and so their wealth decreases as they remain unemployed.

For Figure 6, the results are again qualitatively similar to the results presented in the main paper. Under the modified ABM, there does appear to be a slight decrease in the Gini coefficient as $k$ increases, but this difference is not significant. Moreover, the Gini coefficient under the modified model starts (at $k = 1$) slightly higher than the original results (~0.55 vs. ~0.5), which seems to indicate that as the average degree size grows the two results converge. This is likely due to the fact that inequality stabilizes once the neighborhood agents are able to search reach a certain size threshold.

For Figure 7, the results are qualitatively similar to the original paper with some minor differences.

For Figure 8a, the results are qualitatively similar to the original paper with some minor differences.

For Figure 8b and 8c, the wealth distribution appears to be more unequal under the modified ABM. The results again show a clear bimodal distribution, but the wealth is even more concentrated among a fewer number of agents. This may be because one way to think of this assumption change is that it makes the high-status search method less successful on average so more agents choose to use the low-status search method, and, thus more agents wind up acquiring less wealth.

For Figure 9, the results were qualitatively similar to the results in the paper, though quantitatively different.

The exact datasets and figures for this variation are available from the authors on request.

*Reduced Probability of Being Hired*

In the main paper, we initially set the probability of being hired to 100%, subsequently reduced it to 50% (Figure 8), and finally set it to be contingent on the wealth differences of the hirer and job seeker (Figure 8, last panel). We decided to explore what if the probability per interaction of being hired was even lower, so we set it to 5%. This is an extraordinarily low value, since when the model runs in many time steps more people lose there jobs than are hired.. As a result in many of our additional runs the entire population winds up being unemployed before the end of the run. Nonetheless, we ran the model with these inputs and, as in the case of the modification above, correlated the resulting histogram data from the original Figure 3, with the histogram data from the new results. The Pearson correlation was 0.56. Figure B-2a/b shows Figure 3 from the original paper side-by-side with the new results. The main difference between the two figures is that though there is still an extreme inequality, there are very few wealthy agents in the modified ABM. The reason for this is that with a baseline hiring probability of 0.05, many of the agents in the model remain unemployed for long periods of time, failing to accumulate wealth. The result is that of lower Gini coefficient values for most of the figures discussed below, but only because there is a higher proportion of poor agents. This aside, the majority of the qualitative patterns revealed in the main paper remain. Because reducing the baseline hiring rate also has the effect of slowing wealth accumulation in the model, it should be the case that if one were to run the model for a longer period of time, the results may converge to those of the original model.

Figure 5 is qualitatively similar to the original results, but increasing the unemployment rate has even less of an effect on the results in a world in which agents rarely get rehired.

Figure 6 is qualitatively similar to the original results.

Figure 7 is qualitatively similar to the original results. However, the wealth threshold has even less effect on inequality.

For Figure 8a, 8b and 8c, the results are similar to the original model results in many ways, but the bi-model distribution is less pronounced. This may be because when agents face a lower probability of being hired, the difference between high-status and low-status agents is less pronounced early on.

For Figure 9, we do see a difference between the original model and the new results. It appears that interventions have little effect on the mean amount of wealth in a world where agents are mostly unemployed.

Once again, the exact datasets and figures for this modification are available from the authors on request.

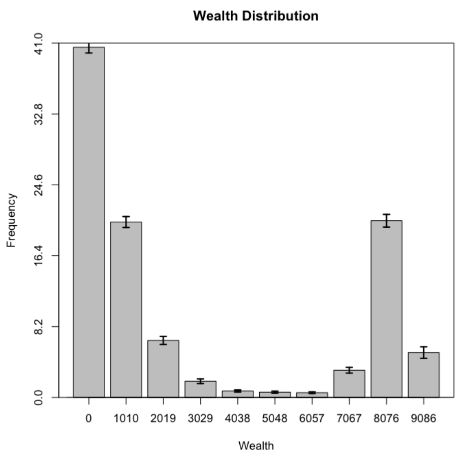



Figure B-1a: New Data.

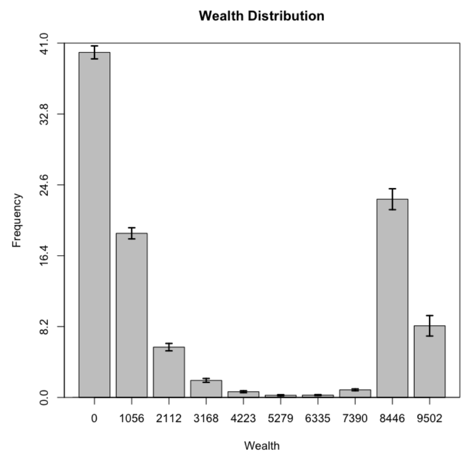



Figure B-1b: Original Data.

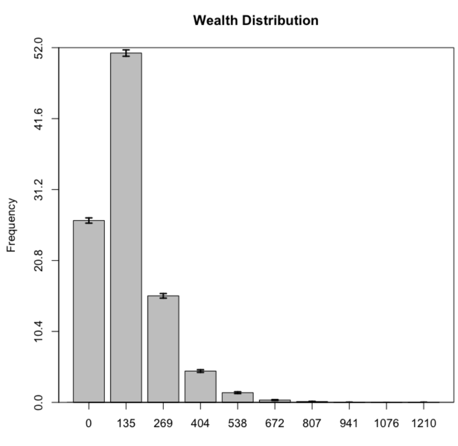



Figure B-2a: New Data.

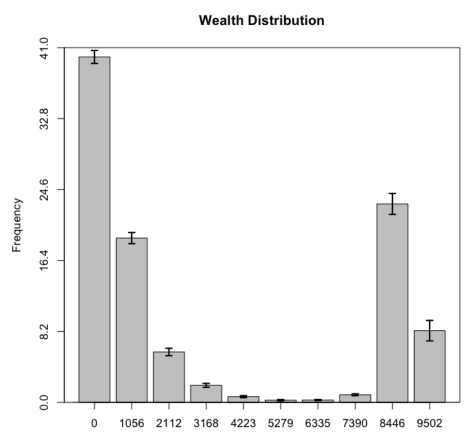
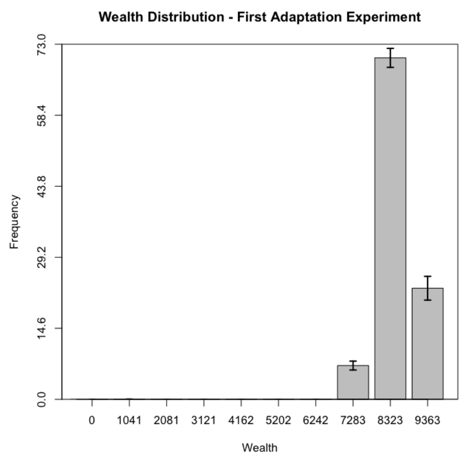



Figure B-2b: Original Data.

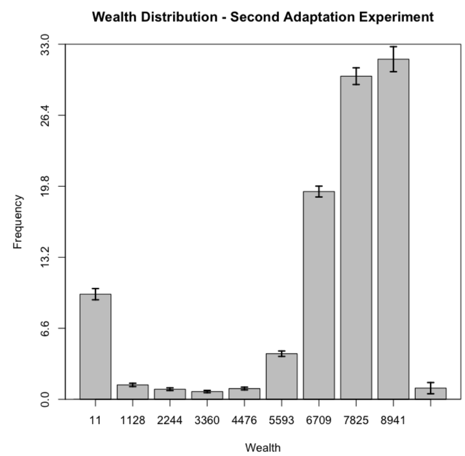
*Severing tie if job not received*

In our original conceptual model if someone approached someone else for a job and was not hired they still kept the new social tie. The idea being that they still now knew this person and could ask them for a job again in the future. We decided to see if altering this assumption affected the results. So we went back and changed the assumption. In the graphs below (Figure B-3 and Figure B-4) the original results are presented first, and the new model that cuts any ties that do not result in a job below. It can be observed that the graphs are very similar. The only large qualitative difference is in the third graph, where there the number of wealthy people is far less than the original graph. This clearly occurs because the robustness check results in far fewer links than the original model, which means that the possibility of the average individual being connected to someone with a high paying job goes down. If anything this further confirms our supposition that the differences in these job search methods can potentially cause large levels of income inequality.

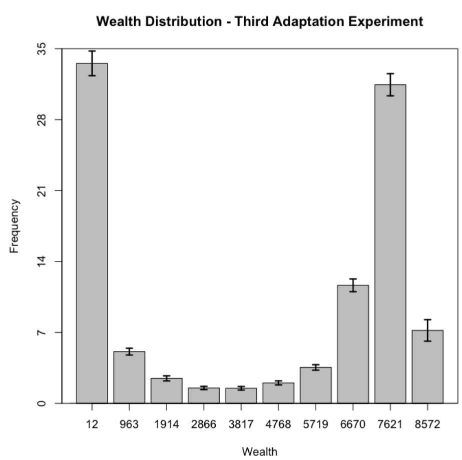
Figure B-3: Original Figure 8.




(a)

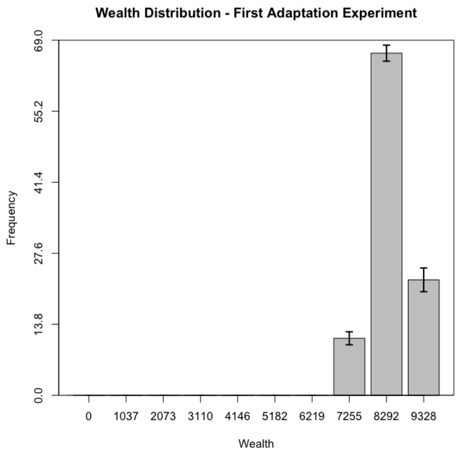



(b)

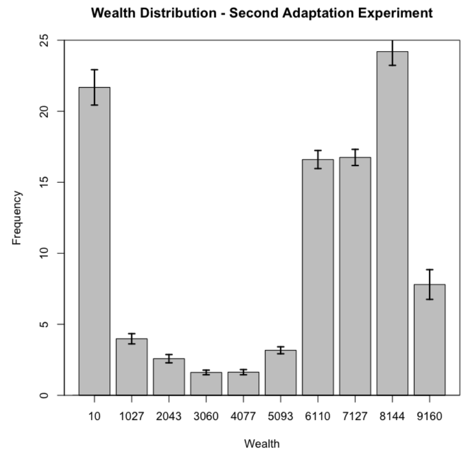



(c)

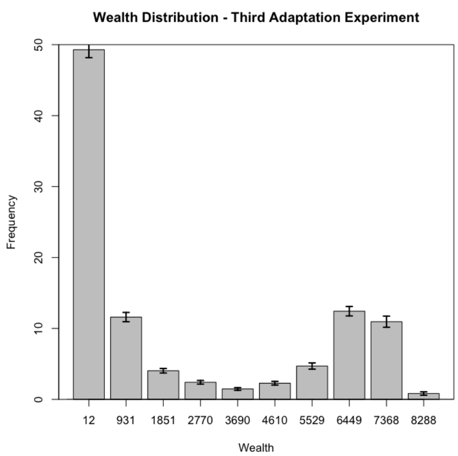
Figure B-4: Robustness check of Figure 8 where ties are not formed if the job searcher is not hired.




(a)




(b)




(c)

*Real-World Social Networks*

Our choice of a preferential attachment network for the degree distribution in the original model in the paper was based on empirical research that shows that real-world social networks do have scale-free distributions similar to the preferential attachment network. In fact, if anything real-world social networks are even more skewed than the baseline preferential attachment network, hence why we test for higher levels of skew. However, to explore the robustness of our results we decided to test our results with alternative network structures. In particular, we used (1) a real-world social media network of friendships, and (2) a network drawn from an alumni contact network at a Midwestern university. We did have to make one additional change to the model since these networks have about 10 times the number of nodes as our original model, we had to run them 10 times as long. We also ran these models for a fewer number of repetitions (10 repetitions) to decrease the computational cost. After running, however, in both cases our results are qualitatively similar to the results that we observed with the synthetic network. We present the original Figure 3 (the first wealth distribution graph) below (a), along with the same Figure on a Twitter (b) network and on an alumni network (c). As can be observed, the real world networks also result in strong bimodal distributions. The one notable difference is that the real world networks result in more wealthy individuals; though the variance is still high around the mean at the point we stopped the runs to analyze the data. The higher number of wealthy individuals may be due to the fact that the processes do not scale linearly with the size of the network, i.e., it may take longer than ten times the number of nodes to observe the same decrease in the number of wealthy individuals. As mentioned, it may also be that the number of wealthy individuals would decrease with more repetitions of the model.  The results are consistent with our description of the findings in this paper, and so we feel confident in leaving the paper as is, but the results are also interestingly enough that we have modified this paper to describe this investigation as something for future work, and we thank the reviewer for this very interesting comment.

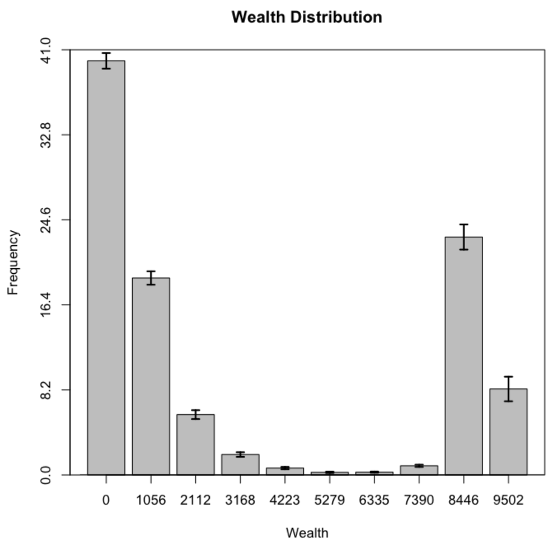



*Figure B-5a: Original from Paper.*

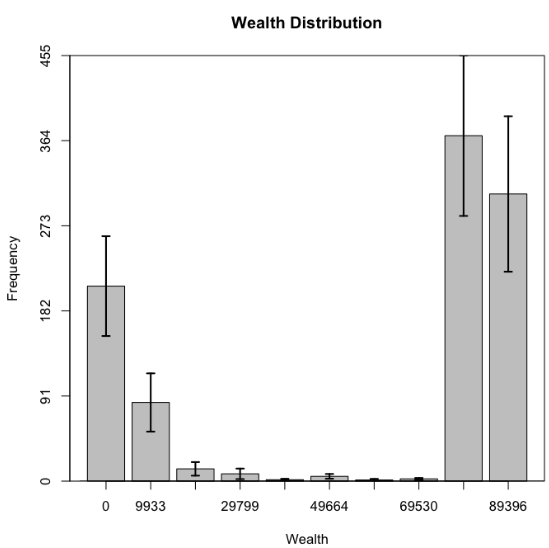



*Figure B-5b: Twitter Network.*

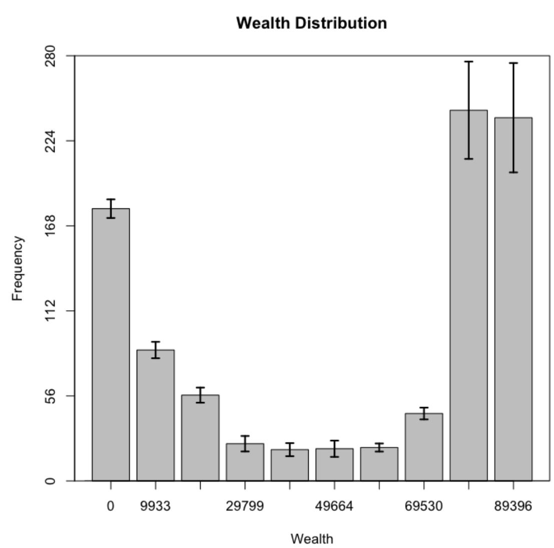



*Figure B-5c: Alumni Network.*

*Appendix C*

**Table C.1 Topic Areas for Combining Experiments and ABM**

| **Selected Important Conditions for ABM** | | **Example "Micro" Topic Areas in Organizational Behavior*** | **Example** |
|---|---|---|---|
| **Local and Potentially Complex Interactions:** | Do the agents interact only among their local neighborhood and potentially maintain memories about those interactions? | Intergroup contact, conflict, and cooperation; Small groups and social networks; Goal contagion; Emotional Contagion | Experimental research (e.g., Aarts et al 2004, Barsade 2002) has shown that factors such as goals and emotions may diffuse differently than other kinds of information. ABM may be used to explore goal or emotional contagion findings from the experimental lab in simulated organizational/network environments. |
| **Heterogeneity among Agents and Environment:** | Are the agents different from each other in substantial ways? | Culture; Power, Status, and Social Influence | Heterogeneous agents in an ABM could use decision-making rules according to observed demographic variation in holistic versus individualistic thinking (e.g., Nisbett et al 2001), simulating various forms of multi- versus mono-cultural teams tasked with solving problems requiring varying amounts of interdependence. |
| **Temporality:** | Is the phenomenon of interest something that evolves over time or is it static? | Attitudes and persuasion; Identity formation; Spreading of norms; Enculturation processes | Experimental research has proposed that the "self" is the "me" at the center of experience, and that "selves incorporate the patterning of their various environments" (Markus and Kitayama 2010: 420). ABM could be used to explore the implications of such a view on group formation and various equilibria outcomes over time. |
| **Adaptivity:** | Do the agents change their actions based on previous experience? | Formation of hierarchy; Ethics; Mate choice | Employees who perceive their creativity to be rare are more unethical in their behaviors (Vincent and Kouchaki 2015). Use ABM to model how different organizational/network forms affect the amount of rarity one perceives of their own creativity, holding constant the number of creative people in the organization. Predict what organizational and/or network forms, at the collective level, are most likely to be associated with unethical behavior. Triangulate with empirical data. |

* Our intention is neither to be exhaustive, nor to imply that some topics do not fulfill more than one important condition

**References**

Aarts, H., P. M. Gollwitzer, and R. R. Hassin. (2004). Goal Contagion: Perceiving is for pursuing. *Journal of Personality and Social Psychology, 87(1)*, 23-37.

Barsade, S. G. (2002). The ripple effect: emotional contagion and its influence on group behavior. *Administrative Science Quarterly, 47*, 644-675.

Markus, H. R., and S. Kitayama. (2010). Cultures and Selves: A Cycle of Mutual Constitution. *Perspectives on Psychological Science, 5(4),* 420–430.

Nisbett, R.E., K. Peng, I. Choi, A. Norenzayan. (2001). Culture and systems of thought: holistic versus analytic cognition. *Psychological Review 108(2)*, 291-310.

Vincent, L. and M. Kouchaki. (2015). Creative, rare, entitled, and dishonest: How commonality of creativity in one's group decreases an individualâ€™s entitlement and dishonesty. *Academy of Management Journal* 59(4), 1451-1473.