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PSO

Politics, Economics, and Financial Markets

Welcome to the fourth issue of the *Journal of Policy and Complex Systems*. This issue focuses on politics, economics, and financial markets.

The issue begins with the paper by Zining Yang which "combines system dynamics and agent-based modeling with game theory to formalize a multilevel simulation framework to understand the relationship between politics, economics, and demographic changes over time." This work explains how microlevel human actions and interactions can drive macrolevel dynamics, while, at the same time, these macro structures provide "a political, social, and economic environment that constrains or incentivizes microlevel human behaviors."

Krejci, Domeich, and Stone explain how they simulated development of intermediated regional food supply networks that connect regional food producers and consumers. They demonstrate how "the intermediary, known as a regional food hub, serves as an aggregation point for products and information and may also act as a filter to ensure that the requirements of both producers and consumers are consistently met." The agent-based model was used to "test a variety of sourcing policies that could be implemented by the food hub manager to improve operations. Results indicate that policies that protect producers from competition may have negative consequences for consumer satisfaction."

Su and Hadzikadic continue their exploration of stock markets by evaluating the role of trust metrics and learning in simulations of behavior of human investors. "A trust metric is an indication of the degree to which one social actor trusts another, while aggressiveness in learning determines the degree to which one trader decides to mimic another. This paper introduces an agent-based model for finding the optimal level of aggressiveness in learning and the optimal degree of trust in order to optimize the stock trading returns."

Sakahira and Terano propose "an agent-based simulation (ABS) to generate anthropological and archaeological hypotheses." They focus on "the diffusion process of the agriculture and pottery in the Gusuku period (11th–14th centuries) in Okinawa, Japan." They propose plausible but falsifiable hypotheses: (1) agriculture spread rapidly among native people and was, in the early stages, performed mainly by native people; and (2) the immigrant-style pottery was mostly used by immigrants and was not widely diffused among native people." These hypotheses will be verified by the future discovery of anthropological and archaeological evidence.

Unlike the previous four papers that deal with concrete examples, Russ Abbott seeks to shine additional light on the concept of emergence, a critical issue for all complex systems, including the four described in the four papers above. "Since emergence typically involves an entity whose components are organized in

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specific ways, the glue that holds the components together and allows for that organization becomes fundamental to the system itself. Emergent phenomena built with self-management activities have more mass than their components considered separately." Abbott analogizes type creation in programming languages to these mechanisms. But he goes further by stating that "public policies famously have unintended consequences." He explains "why such phenomena—and in fact why reactions to many policy-based changes to our living and working environment—should be considered a form of emergence." Thus, this paper aims to enhance our understanding of the concept of complex systems.

Andrea Jones-Rooy concludes this issue by looking at another property of complex systems—adaptability—as "a central component of both individual and group success in a complex adaptive system, as well as a major part of policy design and implementation." Jones-Rooy posits that "adaptability is often narrowly conceived and applied post hoc. In addition, we lack a general framework for understanding the circumstances under which it is desirable *a priori*." She proposes "behavioral flexibility as a useful conceptualization, operationalization, and measure of adaptability." Jones-Rooy presents "an agent-based model that employs behavioral flexibility to evaluate the utility of adaptability to both individuals and groups in a turbulent environment."

Overall, this issue of the *Journal on Policy and Complex Systems* provides an interesting mix of theoretical and practical considerations of complex systems in the context of policy-relevant societal challenges.

Mirsad Hadžikadić, *Editor*

The Freedom of Constraint: A Multilevel Simulation Model of Politics, Fertility and Economic Development

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Abstract

Government policy choices impact economic, fertility, and political decisions across generations, which can dramatically affect a country's development path. Combining system dynamics and agent-based modeling with game theory approaches in a complex adaptive system, we formalize a multilevel simulation framework of the Politics of Fertility and Economic Development (POFED) to understand the relationship between political, economic, and demographic change over time. We first validate the original system dynamics model with the latest data and updated political capacity measurement. Then we fuse these endogenous attributes with noncooperative game theory in an agent-based framework to simulate the interactive political economic dynamics of individual intra-societal transactions. Finally, we connect the macro and micro levels by merging system dynamics and agent-based components. This work explains that a microlevel human agency can act, react, and interact, thus driving macrolevel dynamics, as well as how macro structures provide political, social, and economic environments that constrain or incentivize microlevel human behavior. The simulation result is compared against real-world data, suggesting policy implications for society to achieve development goals.

Keywords: *complex adaptive systems, economic development, political capacity, demographic change, agent-based model, system dynamics, game theory*

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1. Introduction

The paper explores both the micro and macro levels, as well as the linkage between the two, to answer the question of how political, economic, and demographic factors impact each other in a country's development process. Scholars in international political economy have done considerable research on two scenarios of development: one is a poverty trap with persistent economic stagnation and the other is industrialization and rising incomes. It is argued that political development, measured as political stability and political capacity, is sometimes identified as a cause of economic growth and fertility decision, but sometimes it is an effect of it (Chen & Feng, 1996; Feng, Kugler, & Zak, 2000). At the same time, economic development is sometimes modeled to have an impact on human capital and political development, but sometimes because of fertility decision and political institution (Chen & Feng, 1996, 2000; Feng et al., 2000; Feng, Kugler, Swaminathan, & Zak, 2008).

The development literature primarily uses country-year as the unit of analysis, using society-level variables, like GDP, GDP growth, fertility rate, and literacy rate among others. Each one of these indicators is the sum of millions of human choices, sampled at arbitrary annual frequencies from an imperfect data and population distribution. However, research in the micro level is sparse, and until now the linkage between macro constraints and microlevel choices has not been established for Politics of Fertility and Economic Development (POFED). As a result, this paper studies income level, fertility decision, and education at the micro level of human agency, to better understand how individuals behave under different environments. Additionally, we investigate individual's behavior feedback mechanism on macro-societal trends and conditions, and provide policy implications for societies to achieve development.

2. POFED Background

For many decades, a great number of scholars have been systematically exploring the relationship between demographic change, economic growth, and political institutions. There have been contradictory findings in studies of the political economy of growth, exploring the factors that lead to either steady growth or a poverty trap. These include political, demographic, social, and economic factors. Scholars argue that demographic change has a significant impact on economic growth, with fertility rate and human capital as the two most important attributes (Feng et al., 2000, 2008). For example, Barro (1991), Chen and Feng (2000), and Feng et al. (2008) found that the growth rate of real per capita GDP is positively related to initial human capital and low fertility rate. In the first POFED model, fertility is stated to connect politics to long-run economic performance,

with the implications of the model derived from rational decision-making by individuals (Feng et al., 2000).

At the same time, it is also argued that political stability and political capacity play a critical role in a country's growth path. At the macro level, political instability impacts government policy-making by pulling resources away from other programs; at the micro level, it impacts individual decisions by reducing the physical capital stock (Feng et al., 2000). Scholars also show that politically capable governments improve a variety of economic activities, such as attracting investment, enhancing trade and reducing inflation, and so on (Arbetman & Kugler, 1997). Feng et al. (2000) present a formal model that characterizes the two trajectories of development: a poverty trap with persistent economic stagnation, and industrialization and rising incomes, and establishes that the interaction between politics and economics determines which path a nation travels. In one of the latest POFED pieces of literature, Abdollahian, Kugler, Nicholson, and Oh (2010) have emphasized the dynamic interrelationships between income, fertility, human capital, political effectiveness, and social stability. They show that fertility rates depend on the income level, and that income depends on past income and political conditions. There is generational feedback on the creation of human capital, as increased education would increase political capacity and income. Political instability also has a temporal feedback and depends on political capacity. Similarly, political capacity depends on per capita income, fertility rate, and level of instability. Their system of equations describes how the five main components work at the society level, which can be empirically tested via two systems of equations: one at the aggregated individual level focusing on human capital, fertility, and income, and the other at the society level focusing on instability and political capacity.

3. Complex Adaptive Systems

One general critique of the formal or empirical macrolevel, structural analysis across most of social science is that aggregate structures often help explain or predict necessary, but not sufficient conditions of political, economic, and social phenomena. Many individual level explanations, spanning positive political theory, microeconomics, and game theoretic behavior might provide insights into human agency and thus offer the promise of theory sufficiency (Farmer & Foley, 2009).

However, recent advances in complex adaptive systems work (Abdollahian, Yang, Coan, & Yesilada, 2013; Abdollahian, Yang, & deWerk Neal, 2014; Abdollahian, Yang, deWerk Neal, & Kaplan, 2015; Holland, 1995) demonstrate how macro structures provide political, social, and economic environments that constrain or incentivize human behavior in which a human agency can act, react, and interact, thus changing macrolevel structures. Thus, both structural analysis

and human choice are still relevant, both theoretically and empirically, as the immolation of a Tunisian fruit seller set off a wave of Arab Spring revolutions across the Middle East in countries where the structural preconditions for domestic instability existed (Kugler et al., 2015).

The world is facing a wide range of complex and dynamic problems in the public and private arenas alike. System dynamics discipline is an approach to explain dynamic, long-term problems, including policy analysis and design. It applies to dynamic problems arising in complex social, managerial, economic, or ecological systems, or any dynamic systems characterized by interdependence, mutual interaction, information feedback, and circular causality. Since the turn of the twentieth century, social scientists have identified dynamic linkages between economic development, social change, and political development with popularized arguments for and against modernization (Huntington, 1996; Sachs, 2005). Revolutions, international terrorism with economic development (Barnett & Finnemore, 2004), instability via globalization (Rodrik, 1997), modernization's "clash of civilizations" (Huntington, 1997), the interlocks between politics and economics and the interdisciplinary human development perspective (Inglehart & Welzel, 2005) are some examples. Across all, positive feedback mechanisms shift seemingly stable system phenomena toward complexity and catastrophic, far-from-equilibria conditions (Arthur, 1994a, 1994b). Such events force our current scientific understanding to change perhaps radically, considering new possibilities and outcomes that integrate explanations across previously disparate fields.

Rooted in international political economy, POFED is a qualitative, trans-disciplinary approach to understanding development through the lens of interdependent economic, demographic, and political forces at multiple scales, from individuals to institutions and society as a whole. In this paper, we extend previous work by Abdollahian et al.'s (2010) systems dynamics representation of POFED at the society level toward integrated macro–micro scales in an agent-based framework. As macroscopic structures emerging from microscopic events lead to entrainment and modification of both, co-evolutionary processes are created over time. We posit a new approach where agency matters: individual game interactions, strategy decisions, and outcome histories determine an individual's experience. These microlevel decisions are constrained or incentivized by the changing macroeconomic, demographic pattern, social and political environment via POFED theory, conditions on individual attributes at any particular time. Emergent behavior results from individuals' current feasible choice set, conditioned upon macro environment. Conversely, progress on economic development, the level of political instability, and population structure emerge from individuals' behavior interactions.

In order to create a robust techno-social simulation (Vespignani, 2009) platform, we first instantiate a system of equations that capture the core logic of POFED macro-social theory. Following the Abdollahian et al. (2013, 2014, 2015) approach, we then empirically validated with updated real data with fertility,

income, and human capital from World Bank (2014), instability and political capacity from Fisunoglu (2014) and Kugler and Tammen (2012).

We then fuse POFED endogenous systems to agent attribute changes with a generalizable, noncooperative prisoner's dilemma game following Axelrod (1997a, 1997b, 1997c), Nowak and Sigmund (1993, 1998) to simulate intra-societal, spatial economic transactions. Understanding the interactive political effects of macro-socio dynamics and individual agency in intra-societal transactions is a key element of a complex adaptive systems approach. Finally, we explore the parameter space via simulation methods to identify paths and pitfalls toward economic, demographic, and political development, as well as societal interaction across different stages of development.

4. Empirical Estimation

This is the first time the full POFED model was tested in a system, following the previous work (Feng et al., 2000, 2008) that empirically tested different parts of the model separately. Previous research all focus on single equation and ignore simultaneous correlations between various equations' error terms, which results in inefficiency. More specifically, the classical linear regression model, general linear regression model, and seemingly unrelated regressions model make the assumption that the error term is uncorrelated with each explanatory variable, which doesn't seem to be the case in the POFED model. Following the system dynamics approach by Abdollahian and Kang (2008) and Abdollahian et al. (2013, 2014, 2015), I first use three-stage least-squares estimation to generate POFED coefficient estimates of the system to gain more efficiency by incorporating unobservable correlation across equations. Three-stage least-squares is a combination of multivariate regression and two-stage least-squares that permits correlations of the unobserved disturbances across several equations, as well as restrictions among coefficients of different equations, and improves upon the efficiency of equation-by-equation estimation by taking into account such correlations across equations.

$$\begin{cases} fertility_t = \beta_{10} + \beta_{11} fertility + \beta_{12} income_{t-1} + \varepsilon_1 ; \\ income_t = \beta_{20} + \beta_{21} income_{t-1} + \beta_{22} human\ capital_{t-1} + \beta_{23} instability_{t-1} + \beta_{24} political\ capacity_{t-1} + \varepsilon_2 ; \\ human\ capital_t = \beta_{30} + \beta_{31} human\ capital + \beta_{32} fertility_{t-1} + \varepsilon_3 ; \end{cases}$$

$$\begin{cases} instability_t = \beta_{40} + \beta_{41} instability_{t-1} + \beta_{42} political\ capacity_{t-1} + \beta_{43} \dfrac{political\ capacity_t}{political\ capacity_{t-1}} + \varepsilon_4 ; \\ political\ capacity_t = \beta_{50} + \beta_{51} political\ capacity_{t-1} + \beta_{52} \dfrac{income_{t-1}}{fertility_{t-1}} + \beta_{53} instability_{t-1} + \varepsilon_5 . \end{cases}$$

In our estimation, we use panel data that covers 171 countries in the period

between 1960 and 2010. Fertility is measured as a rate of population change in the absence of migration. Income is measured as GDP per capita, and then normalized using logarithmic function. Political instability captures the proportion of the physical capital stock destroyed in antigovernment uprising. These three variables are measured in the same way as the original model (Feng et al., 2000). Instead of the literacy rate, I use the gross secondary school enrollment ratio for all programs per thousand people to measure human capital, because the original measure lacks desired variation and is inappropriate for estimation. We also update the measure for political capacity. Instead of using relative political extraction alone, we incorporate both relative political extraction and relative political reach as indicators of political capacity, to provide more granular measures and policy levers of the government's input policy. Relative political extraction incorporates the actual total tax revenue of a country and compares it with predicted total tax revenue, while relative political reach gauges the capacity of governments to influence and mobilize populations under their control (Kugler & Tammen, 2012). The three-stage least-squares model is specified in above systems of equations, with one at the aggregated individual level focusing on human capital, fertility, and income, as those variables come from individual decisions and interactions, while the other at the society level focusing on instability and political capacity, as those two variables are better captured at the macro level instead of the micro level, though some explanatory variables are measured from the aggregation of individual variables. Besides supporting original POFED theory, this step is necessary because it provides empirically validated coefficients in the multilevel agent-based model.

5. Multilevel Simulation Model

We propose an agent-based model in a complex adaptive system framework that captures both macrolevel changes and microlevel behavior by incorporating a system dynamics component and a game theory component. Following the work by Abdollahian et al. (2013, 2014, 2015), this model has both the interactive effects and feedbacks between individual human agency as well as the macro constraints and opportunities that change over time for any given society. Individual decisions are affected by other individuals, social context, and system states. These elements have first- and second-order effects, given any particular system state or individual attributes.

Such an approach attempts to increase both theoretical and empirical verisimilitude for some key elements of complexity processes, emergence, connectivity, interdependence, and feedback found throughout several disciplines across all scales of development. There are three modules in the agent-based model: micro-agent process, macro-society process, and heterogeneous evolutionary game process. The accompanying pseudocode is shown below:

```
To micro agent process

  Ask agents update reproduction process

  Ask agents update three endogenous attributes

End


To macro society process

  Ask society attributes to be updated at aggregation level

  Ask society update five endogenous attributes

End


To evolutionary game process

  Ask random 50% of the agents be source and the rest be
target

  Ask source agents create links to target agents within
talkspan

  Ask links evaluate distance between y and S to calculate
probability of playing game

  If probability < 0.05 [ask link die]

  Ask source agents keep the out-link with highest probability
and kill other out-links

  Ask target agents keep the in-link with highest probability
and kill other in-links

  Randomly set game value

  Ask both ends of a link to calculate the distance between h
and probability of playing cooperate and defect

  Ask both ends to choose strategy

  Ask both ends calculate payoff from game value and strate-
gies of CC/CD/DC/DD

  Ask both ends to update y based on the payoff from the game

End
```

The design of the micro-agent process module incorporates system dynamics, which allows each individual agent to behave as a system. We maintain individual agent variable relationships and changes following the latest POFED literature (Abdollahian et al., 2010). These endogenously derived individual agent variables impact how economic transaction games occur, based on society variables either

increasing or decreasing individual wealth and ultimately societal productivity (Axelrod, 1997b). Thus, we create the population adjusting the mean and standard deviation of fertility, income, and human capital at the society level. Each individual agent carries all three variables that are randomized from the society's distribution. At the beginning of this process, agents are allowed to give birth to new agents based on their fertility variable. Here we use empirically validated parameter values from three-stage least-squares estimation as a good first approximation. This method has been widely used by many scholars recently (Abdollahian et al., 2013) to simulate the dynamic process at the individual level. In this module, feedback is used to model individual and social phenomena. The value of the system dynamic component is tied to the extent that constructs and parameters represent actual observed project states. As discussed in Madachy (2007), system dynamics models help facilitate human understanding and communication of the process, and are more accurate to model time-based relationships between factors and simulate a system continuously over time.

Similar to the micro-agent process, we also use the system dynamics technique in this macro-society process. Instead of taking each individual agent as a system, this module takes the entire society as the system, with political instability, political capacity, economic condition, human capital, and fertility rate as main attributes. This module is critical as it connects the micro-individual level and the macro-society level. A society's economic condition is aggregated from individual wealth by taking the mean. Human capital is aggregated from the individual level of education, and the fertility rate is also aggregated from the individual level in the same way. The feedback loop is completed in the way that initial individual variables are randomized from the society distribution, get updated in the micro-agent and evolutionary game processes, and then get aggregated at the society level and interact with other society variables, while society variables also impact the evolutionary game process. We also use empirically validated parameter values from three-stage least-squares estimation in the simulation. The updated instability is brought into the evolutionary game process to affect the probability that agents interact with each other. This feedback loop is helpful when we focus on how individual behavior changes the macro environment, and how the environment in turn impacts individual behavior.

Evolutionary game theory provides insights into understanding individual, repeated societal transactions in heterogeneous populations (Fudenberg & Maskin, 1986). Social co-evolutionary systems allow each individual to either influence or be influenced by all other individuals as well as macro society (Snijders, Steglich, & Schweinberger, 2007; Zheleva, Sharara, & Getoor, 2009), perhaps eventually becoming coupled and quasi-path interdependent. Therefore, after the micro-agent process and the macro-society process, we choose to focus on the noncooperative game in the macro-political stability environment. Prisoner's dilemma game is chosen because it allows agents to choose between maximizing

individual benefit and mutual benefit. In this model, variable talkspan defines spatial proximity interactions, ranging from 1 to 20, defining the grid size radius for the local neighborhood. To model communications and technology diffusion for frequency and social tie formation (McPherson, Smith-Lovin, & Cook, 2001), we have agent i evaluated the likelihood of conducting a simple socio-economic transaction with agent j based on the similarity of the income level $|y_i - y_j|$, stability of the environment, and physical distance talkspan. This also reflects recent work on the importance of both dynamic strategies and updating rules based on agent attributes affecting co-evolution (Abdollahian et al., 2014, 2015; Kauffman, 1993; Moyano & Sanchez, 2013). After each source agent calculates its probability of playing a game with all possible target agents, it chooses the target with the highest probability to be its partner. The target agent also repeats the same process symmetrically, and then chooses the A^{ij}, pairing the highest probability derived from its preference-proximity function as its partner.

Once agents decide to play, they choose strategies based on $|h_i\text{-}h_j|$. Siero and Doosje (1993) among others show that messages close to a receiver's position have little effect, while those far from a receiver's position are likely to be rejected. So when the difference of human capital is small, there is a high probability of playing cooperate, while a long distance results in a high probability of playing defect. The relative payoff for each agent is calculated based on simple prisoner's dilemma, noncooperative game theory (Dixit & Skeath, 2015; Nowak & Sigmund, 1993; Sigmund, 1993) where T > R > P > S, with T = 2, R = 1, P = 0 and S = –1. When both agents cooperate, they both gain TT; when one plays cooperate but the other plays defect, the cooperating one loses, while the defecting one gains ST; when both play defect, they don't gain anything from the transaction PP. The updated goes back to agent i endogenous POFED processing for $t + n$ calculations.

In the next step, we set up noncooperative A^{ij} games whose outcomes condition agent y^i values for the next iteration. Following Abdollahian et al. (2013, 2014, 2015), we specifically model socio-economic transaction games as producing either positive or negative values as we want to capture behavioral outcomes from games with both upside gains or downside losses.

Subsequently, A^{ij} games' V^{ij} outcomes condition agent values, modeling realized costs or benefits from any particular interaction. The updated $= + A^{ij}$ game payoff for each agent then gets added to the individual's variables for the next iteration. We then repeat individual endogenous processing, aggregated up to society as a whole and repeat the game processes for $t + n$ iterations, where n is the last iterate. In this module, A^i strategies are adaptive, which affect A^{ij} pairs locally within an approximate radius as first-order effects. Other agents, within the society but outside the talkspan radius, are impacted through cascading higher orders. Following Abdollahian et al. (2013), we explicitly model interactions (Kauffman, 1993) to capture co-evolutionary behavior in a simple, yet elegant manner. Memory and history matters, as the sum of all prior individual system

dynamics behavior and evolutionary through iterations contributes to each individual and societal current states.

As an initial effort at a scale-integrated framework, the design of three modules frees me to focus on the coupling of structure and agency before enriching subcomponent process detail. Thus, agents simultaneously co-evolve as strategy pair outcomes cooperation–cooperation, defection–cooperation, or defection–defection at t to increase y at $t + 1$, thus driving both positive and negative h, b, and y feedback process through $t + n$ iterations. These shape A^i variables allow adaptation to a changing environment by summing y_i, b_i, and h_i values. Feedback into subsequent A^{ij} game selection networks and strategy choice yields a complex adaptive system representation across multiple scales. The model is instantiated in NetLogo (Wilensky, 1999); Figure 1 shows the model interface.

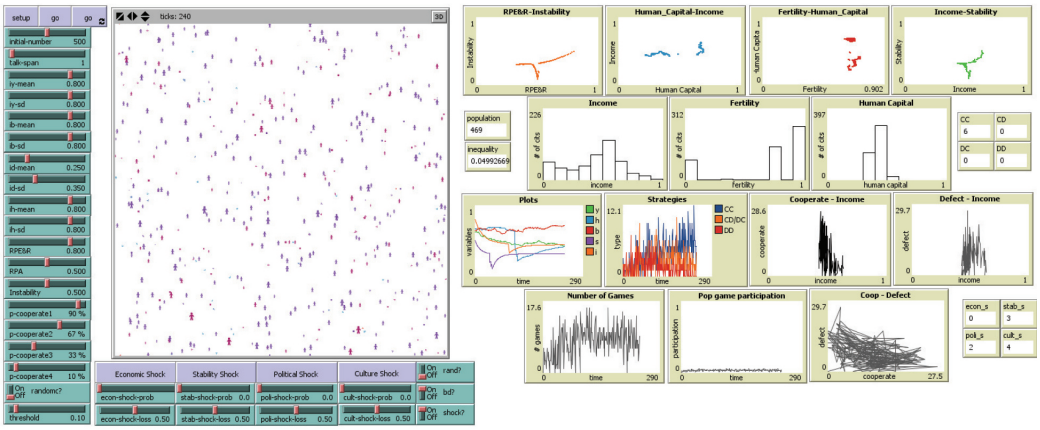

Figure 1. NetLogo Model Interface.

6. Results

In order to make generalizable inferences, we conducted a quasi-global sensitivity analysis on both input and initial condition parameters, for over 17,000 runs across 240 time steps. The detailed result is shown in Appendix A. With income as a dependent variable, we first run the baseline model from POFED theory with only macro-level variables. The result confirms POFED theory that instability negatively impacts the wealth level with technology having a positive influence. About 20% of the variance is explained by the aggregated fertility rate, human capital, political instability, political capacity, population, time, and technology. Then, we include microlevel variables that reflect the impact of evolutionary games. To start with, only the number of socio-economic transactions is added. With other variables having the same sign and level of significance, this new explanatory variable is positive and highly significant. Compared to the baseline model, this model contributes to explanatory power at a limited level by approximately 2.6%.

However, when using the number of cooperative strategies in the society as the new independent variable instead, the model fit dramatically increases to 54.3%, with the new variable being positive, significant, and with the strongest impact compared to other variables. Finally, when the number of defective strategies is also added, the adjusted R^2 increases to 55.3%. The last new variable is also significant and has strong negative impact on the level of income.

The sensitivity test first confirms the original POFED theory that the negative value of instability does significantly speed the pace of economic development, while technology has a positive impact, in increasing individual agents' ability to reach other like-minded agents spurs cooperation dramatically based on first-order local interactions. More importantly, individual decisions matter in society's development trajectory, as micro-level variables explain more variance than macrolevel variables only. In the process of individuals communicating and making deals with each other, more products and services become available while the cost of which goes down. This logic at the societal level is well discussed and empirically tested in the globalization literature: in the process of increased interconnections among countries, benefits are derived from the specialization of products and services, which outweighs the economic and social costs by achieving higher efficiency. Cooperation pays higher dividends, while defective strategies reduce social wealth. In other words, this model captures the micro-level behavior that can better explain macrolevel phenomena.

The sensitivity test results suggest that the agent-based model more effectively captures the relationship between economic, political, and demographic factors than traditional econometric models. Now, we explore the growth path for a few selected countries to understand each specific situation. During this process, we control initial populations' mean and standard deviation; density and social connectivity via talkspan to simulate any socio-economic conditions for a given society as well as political and economic patterns to simulate agent and system response to emergent behavior.

We chose to simulate the development path of China from 1960 to 1980. Figure 2 shows the comparison between real data and simulated data for four main variables: income, human capital, fertility, and political capacity. The blue line plots real-world data taken at the macro level, while the orange line shows simulated data that gets aggregated from micro-agent interactions.

The graph on the top-left corner shows the dynamic of economic growth. China had a weak economic foundation at the beginning of the 1960s, when industrial development was severely hampered by the Civil War coupled with the inflow of cheap substitutable foreign goods (Abdollahian et al., 2013; Yang & Abdollahian, 2014). Both actual and simulated lines on the graph show a decrease in economic growth in the early 1960s, indicating the drop in living standards. Although there is a slight difference between the simulated line and the actual line at levels, the trend in both lines is very consistent, showing a low growth rate

until the late 1970s, when Cultural Revolution (1966–76) ended. Only after Deng's Reform and Opening up Policy in 1978, China began to quickly develop its economy, open to foreign investment and global markets. On the top-right corner of the panel, we show actual and simulated paths of human capital dynamics from 1960 to 1980. Both lines have the same trend and the difference at levels is minimal, indicating the simulation matches reality very well. Due to the low level of economic development, there were very limited resources to be used for education in the early 1960s, so the overall level of human capital was relatively low. With great damage to higher education and enhancement to basic education, the impact of the Cultural Revolution on popular education varied among regions, and formal measurements of literacy did not resume until the 1980s. From the graph, we can see a slow increase in human capital during the two decades from the best data available, and the simulated trend coincides with it.

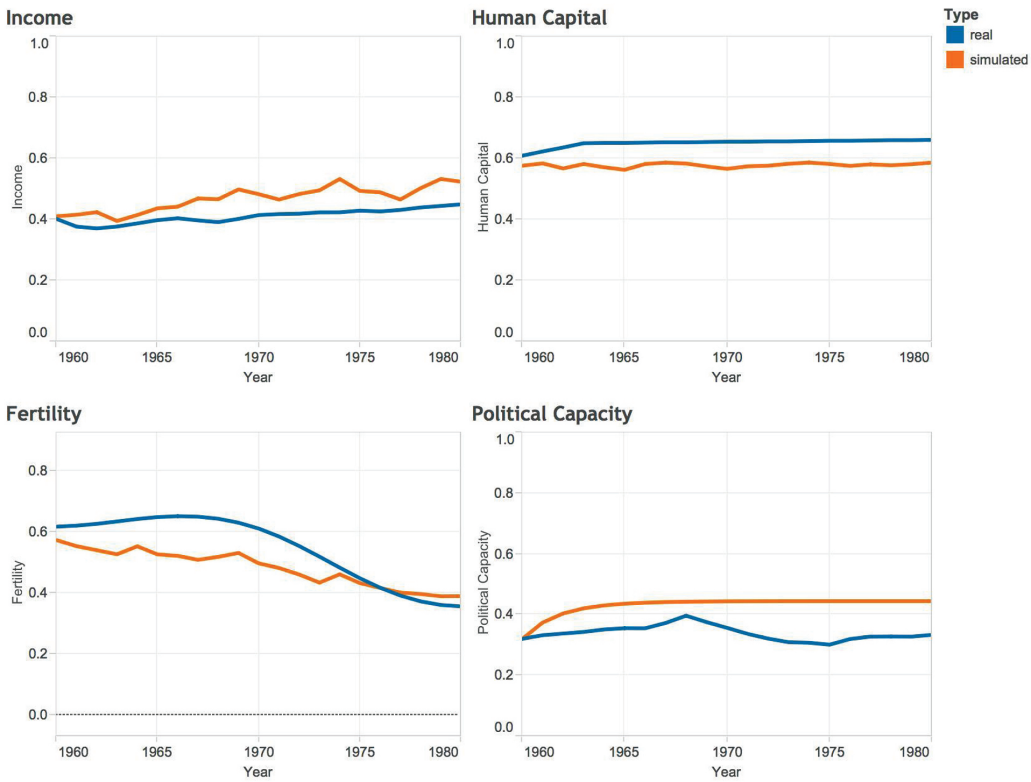

Figure 2. Real versus Simulated China Case.

Turning to the second row of the graphs, the left one plots the actual and simulated paths of the fertility rate in China during the two decades. The blue line shows a small increase at the beginning, then a constant large decrease until 1980. The simulated orange line captures the general trend, but misses the detail during the mid-1960s. It is not surprising that the fertility rate starts at a relatively high level in 1960, and there were lags in demographic change. China's post-1949

leaders initially were intentionally disposed to view a large population as an asset, which had built a foundation for the large base, high growth demographic pattern. In 1972 and 1973, the party mobilized its resources for a nationwide birth control campaign. In the graph, it is where the line starts to drop at a high rate. The implementation of those policies resulted in a significant decrease in fertility in the 1970s and the rate starts to be stable toward the end of that decade, where in the graph the simulated trend almost overlaps with the actual trend.

The bottom-right graph shows the dynamics of political capacity during the two decades. The simulated data does not capture enough details of the reality, but the level is not off by much. Overall there was no improvement in government's capacity in terms of extracting physical capital resources and human resources. We see a small peak in the late 1960s, because the government mobilized a great number of populations at the middle stage of the Cultural Revolution. During the "Down to the Countryside Movement," young intellectuals living in cities were ordered to go to the countryside. In other words, recently graduated middle school students, most of whom were Red Guards, were mobilized from the cities to the countryside, where they would cause less social disruption.

The growth path of China from different perspectives shows the story of a slowly growing society. The low level of political capacity together with instability hinders the development of human capital. Although at a slow pace, the development of education system brings human capital to a higher level, which greatly helps the reduction of the fertility rate. Improved human capital and lower fertility enhance economic development of the society, and has a feedback to the improvement of the education system and government capacity. Behind macrolevel indicators is microlevel behavior. At the beginning of the simulation, individual interactions were limited with little incentive for cooperation due to political instability and low level of technology that suffered from economic stagnation. As wealth is slowly created in the society, individuals are incentivized to interact more in the slowly growing society. At the same time, cooperation starts to emerge due to increasing and converging education level. More cooperative socio-economic transactions accelerate growth, paving the way for economic openness and faster development. In this case, the simulation result matches reality at a reasonable level, proving the validity of the agent-based model.

7. Conclusion

Combining all system dynamics, agent-based modeling, and evolutionary game in a complex adaptive system, we formalize a multilevel simulation framework of POFED to understand the relationship between political, economic, and demographic change at both macro and micro levels. Results confirm the findings of the POFED model at the macro level that political, economic,

and social factors are interrelated. Advanced technology and compressing potential social space speed development processes. The sensitivity analysis provides more explanatory power to economic development. The number of individual interactions is critical to development. The more people interact with each other, the more value they can potentially create. However, besides the quantity of individual interactions, what matters most is the individual agent's strategic choice when they play socio-economic transaction games. Cooperation does pay higher social dividends on average. Individual's mutual cooperative behavior creates trust among each other, which enhances both political stability and economic growth. Defective strategy reduces social wealth, in addition to its negative impact to the level of trust in the society. Macrolevel variables also feed back to individual agents updating their attributes and change the pace and tempo of socio-economic transactions, which reinforce national development and economic growth. Incorporating the micro level with the macro level increases the model fit by doubling that of the baseline model in which only macro inputs are taken into account. The simulation result of China's development trajectory from 1960 to 1980 matches reality, further confirming that individual interactions are the driver for changes at the macro level, and the macro-environment shapes individual strategy choice. The result suggests that the improved education level impacts fertility decision and strategy choice, which results in change in individual wealth as well as aggregated wealth, thus enhancing technology development and individual interaction, providing more opportunity for value creation.

This multilevel simulation model creates a baseline for current policy efforts, showing when sustainable development and growth are likely to occur. The strength of the agent-based model is its ability of modeling interactions between individual agents and the environment, as well as emergent behavior and complexity of the entire system. A key benefit is to understand how macrostructural environments change and constrain or incent individuals' micro-level behaviors, and how micro interactions shape macro structures. Policy can then be tested compared to baseline outcomes, under normal and crisis scenarios, to assist in robust policy development.

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Appendix A

Sensitivity Test Result

	(0) Income	(1) Income	(2) Income	(3) Income
Fertility rate	0.0470***	0.1223***	0.1331***	0.0324***
	(0.0032)	(0.0024)	(0.0024)	(0.0031)
Human capital	–0.0460***	–0.0067	0.0044	–0.0915***
	(0.0072)	(0.0054)	(0.0054)	(0.0071)
Instability	–0.0304*	–0.2269***	–0.2491***	–0.0026
	(0.0126)	(0.0095)	(0.0094)	(0.0124)
Political capacity	0.0121	0.0036	–0.0057	0.0292**
	(0.0111)	(0.0084)	(0.0083)	(0.0109)
Cooperation		2.3920***	2.1699***	
		(0.0079)	(0.0089)	
Defection			–0.3522***	
			(0.0067)	
Game				0.7777***
				(0.0121)
Population	–0.0896***			–0.4343***
	(0.0053)			(0.0075)
Talkspan	0.2792***	0.1071***	0.2275***	–0.0087
	(0.0017)	(0.0014)	(0.0027)	(0.0048)
Time	–0.0165***	–0.0411***	–0.0408***	–0.0153***
	(0.0010)	(0.0008)	(0.0008)	(0.0010)
_cons	0.3430***	0.3306***	0.3280***	0.5365***
	(0.0083)	(0.0059)	(0.0058)	(0.0087)
N	121035	121035	121035	121035
Adjusted R^2	0.2002	0.5432	0.5533	0.2265

Standard errors in parentheses

*** $p < 0.001$", ** $p < 0.01$, * $p < 0.05$

Assessing Values-based Sourcing Strategies in Regional Food Supply Networks: An Agent-based Approach

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Abstract

The recent increase in demand for regionally produced food has resulted in a need for more efficient distribution methods. To connect regional food producers and consumers, intermediated regional food supply networks have developed. The intermediary, known as a regional food hub, serves as an aggregation point for products and information. It may also act as a filter to ensure that the requirements of both producers and consumers are consistently met. This paper describes an empirically based agent-based model of a regional food network in central Iowa that is intermediated by a food hub. The model was used to test a variety of sourcing policies that could be implemented by the food hub manager to improve operations. Results indicate that policies that protect producers from competition may have negative consequences for consumer satisfaction.

Keywords: *local food distribution, food hubs, empirical agent-based modeling, values-based organizations, socially responsible supply chain management, sustainability*

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Introduction

A supply chain's ability to effectively and efficiently convey and provide value to customers is critical to its success. However, traditional assumptions about consumers' values may no longer be valid. In particular, consumers are increasingly prioritizing environmental and social sustainability as non-negotiable criteria when making purchasing decisions. Many consumers no longer view "green" or socially responsible sourcing as a competitive advantage or a differentiating feature that they are willing to pay more for; it is expected. To meet these new customer expectations, many organizations have worked to adapt their existing practices and structure, often by mandating certifications (e.g., fair trade, organic, cruelty-free) throughout their supply chains. Some organizations have gone further and have incorporated new sustainability and values-focused components in their mission statements. For example, the "triple bottom line" emphasizes environmental and social sustainability, as well as traditional economic objectives (Elkington, 1998). However, current approaches to social responsibility are often fragmented and disconnected from organizations' primary business strategies, such that the greatest opportunities to benefit society may remain unrealized (Porter & Kramer, 2006).

As existing organizations grapple with these new requirements, new organizations have emerged that are leveraging consumers' changed preferences and turning this challenge into an opportunity. These types of organizations are known as values-based organizations (VBOs). Rather than viewing sustainability as a secondary consideration, these organizations are strategically focused on providing consumers with products and services that are socially and environmentally responsible. A key component of this strategy is offering transparency and traceability throughout the entire supply chain and communicating product and process characteristics to the end customers (Pullman & Dillard, 2010).

Food supply chains, which directly influence human health and well-being, have been the target of consumer demands for environmental and social responsibility and transparency. This has led to significant increases in demand for food that is produced regionally, that is, in the same geographic region in which the consumer is located. Consumers are increasingly choosing food that is produced locally and sustainably over food from the conventional food system. Their reasons vary widely, from saving money to wanting to ensure food nutrition, quality, freshness, and safety, to concerns over environmental implications, to concerns over the treatment of farm workers, to a desire to support the local economy, to having a connection with the person who produced their food (Bloom & Hinrichs, 2011. Interest in supporting local food systems is also rising among policymakers, who are incorporating local foods into programs designed to reduce food insecurity, support small farmers and rural economies, encourage more healthful eating habits, and foster closer connections between farmers and consumers (King et al., 2010).

Regional food hubs are an example of an emerging type of VBO that can facilitate the fulfillment of this increasing demand for local food. The United States Department of Agriculture (USDA) working definition of a food hub is "a centrally located facility with a business management structure facilitating the aggregation, storage, processing, distribution, and/or marketing of locally/regionally produced food products" (Barham, 2010). Food hubs act as intermediaries between small-scale food producers (e.g., farmers) and customers, providing connections and infrastructure in support of regional and local food systems. A primary objective for regional food hubs is to support local economies by providing market opportunities for small-scale producers and treating them as valued business partners, rather than interchangeable suppliers (Barham, Tropp, Enterline, Farbman, Fisk, & Kiraly, 2012). However, these producers must also possess attributes that are valued by the food hub's customers (e.g., reasonable prices, high quality). Thus, the food hub's process of determining which producers to work with should carefully balance these requirements. However, in practice, food hubs tend to follow ad hoc sourcing and supplier management methods, which can lead to suboptimal performance and often business failure.

This paper describes an agent-based model (ABM) that was developed using empirical data from a regional Iowa food system. The model was used to assess the value of having a food hub manager agent act as a centralized control for the system by exploring the impacts of different management strategies on the food hub's performance. In particular, the Iowa food hub manager would like to know what types of producer selection policies should be employed (if any). The manager's current policy is to allow any producer in Iowa who wishes to sell food through the food hub to do so. The manager then relies on consumers to determine whether a producer may continue to participate: if a producer's prices are too high, or if their products are of poor quality, or if there is insufficient demand for their product, they will make few sales. Such producers will typically either try to improve their offerings or they will cancel their membership. Thus, producer selection at the food hub is a decentralized process, in which the overall makeup of food hub's producers at any point in time is an emergent property resulting from competition among the producers.

However, the food hub manager suspects that if he intervenes via appropriate producer selection policies, he may be able to increase his consumers' satisfaction by only allowing in those producers that are most likely to meet their needs. The food hub manager may also be able to improve the well-being of his producers by preventing an oversupply of any given type of food, thereby keeping competition among producers reasonable and prices sufficiently high. The question addressed in this paper is: What producer selection policies should the manager implement to best support the food hub's objectives?

Background and Literature Review

In this section, sourcing strategies that are common to traditional organizations are described, and the strengths and weaknesses associated with these strategies are reviewed. This is followed by a description of the sourcing strategies that have been used by VBOs, as well as the unique challenges that VBOs face with respect to supplier selection.

Traditional Sourcing Strategies

Traditionally, supply chain management strategies have focused strictly on financial objectives, such as maximizing profit/market share or minimizing exposure to risk. With these objectives in mind, a supply chain manager must decide on an appropriate sourcing strategy, which includes the size of the organization's supply base, as well as the criteria by which suppliers are selected. The question of how many suppliers an organization should use and how business should be allocated to these suppliers is an ongoing topic of debate, and the answer depends on many factors. One strategy involves single sourcing, which is the process of selecting and using only one source of supply for all inputs of a particular type. By contrast, with a dual or multiple sourcing strategy, two or more suppliers are used as sources of the same commodity. Determining which of these sourcing alternatives is best involves difficult tradeoffs and requires a careful multi-objective analysis of the buying organization's preferences, with respect to short- and long-term costs and risk management, and an assessment of the industry environment in which the organization operates. Although much of the supply chain management literature treats these sourcing strategies as mutually exclusive, in reality, this is not necessarily true. In fact, Gadde and Snehota (2000) argue that a balanced combination of single and multiple sourcing is often a practical strategy.

Traditionally, multiple sourcing has been used in supply chain management as a means of encouraging competition among multiple suppliers, wherein a buyer plays suppliers against one another to obtain the best terms, including price, delivery, and quality (Treleven & Schweikhart, 1988). This competition increases a buyer's negotiating power through the perceived threat of giving its business to another supplier (Ramsay & Wilson, 1990). Also, supplier power over a buyer is weakened when the buyer splits its total requirements among multiple sources (Newman, 1989). Li and Debo (2009) provide several examples of organizations that follow this strategy for sourcing components, including Apple and Microsoft, in order to maintain power over suppliers and keep prices low.

Multiple sourcing also allows a buyer to spread risk across several suppliers. Supply chain risks can be classified as either operational risks, which are inherent to the supply chain and its participants (e.g., insufficient supplier capacity, quality

problems, suppliers reneging on contracts), or disruption risks, which are related to natural and man-made disasters, including earthquakes, hurricanes, fires, and terrorist attacks (Tang, 2006). By having multiple redundant suppliers, organizations can reduce their exposure to both operational and disruption risks, since it is unlikely that all suppliers would be disrupted simultaneously (Chopra & Sodhi, 2004). Because of this, multiple sourcing is one of the most commonly employed supply chain risk mitigation strategies (Hallikas & Lintukangas, 2016).

However, there are disadvantages associated with multiple sourcing. Because multiple sourcing typically involves short-term contracts and frequent rebidding, managing a large number of suppliers increases a buyer's transaction and supply handling costs (Dyer, Cho, & Chu, 1998). Multiple sourcing may also increase supply chain costs by preventing suppliers from achieving economies of scale (Hahn, Kim, & Kim, 1986). Treleven (1987) argues that multiple sourcing can reduce overall quality as a consequence of the increased variation in incoming quality among suppliers.

In response to these concerns, organizations have increasingly adopted single sourcing as a strategy for some or all of their purchased inputs. Single sourcing strategies strive for the development of partnerships between buyers and suppliers, with an aim to increase cooperation and achieve shared benefits (Burke, Carrillo, & Vakharia, 2007). In these arrangements, buyers and suppliers have jointly aligned goals to accomplish mutually beneficial ends, resulting in collaborative relationships that yield greater benefits than the "transaction-based" relationships that characterize multiple sourcing. Such relationships rely on the development of trust between the buyer and supplier, the willingness to coordinate activities and share information, and the ability to convey a sense of commitment to the relationship (Mohr & Spekman, 1994). Single sourcing can yield higher quality and lower total supply chain costs, but only if the supplier is very carefully selected, ideally through a rigorous certification process (Larson & Kulchitsky, 1998). In particular, concentrating purchase volumes with a single supplier can reduce logistics costs, which is important when suppliers are geographically distant from the buyer (Bozarth, Handfield, & Das, 1998). Additionally, reducing the supplier base tends to substantially reduce the volume of communication that is required for supply chain coordination (Dumond & Newman, 1990).

However, when an organization reduces its supplier base, it relies on fewer suppliers for critical materials, and this increased dependency increases the risk of a supply interruption (Cousins, 1999; Smeltzer & Siferd, 1998). Also, the amount of trust that is required to support a strong strategic relationship with a supplier is significant, and true long-term strategic alliances between buyers and suppliers are uncommon in practice (McCutcheon & Stuart, 2000).

Once an organization has decided whether or not to have redundancies in its supply base, a method of evaluating and selecting candidate suppliers is needed. Because there are almost always multiple critically important criteria that

managers must consider in the supplier selection decision (e.g., price, quality, flexibility), and no single sourcing option will always perform best with respect to all criteria, it is not possible for a buyer to simply rank different options using a single attribute (Elmaghraby, 2000). As a result, a wide variety of decision-making methodologies have been applied to the problem of supplier selection, including multicriteria decision analysis (MCDA) methods and mathematical programming models. For comprehensive reviews of these methods, see de Boer, Labro, and Morlacchi (2001) and Ho, Xu, and Dey (2010).

VBO Sourcing Strategies

Sourcing strategies and decisions for VBOs are not entirely different from those of traditional organizations. To remain financially viable, VBOs must consider economic objectives and risks when designing their supply chains. However, the emphasis that traditional organizations place on these factors is typically inappropriate for VBOs, which tend to focus on elements that impact nature and society (Shrivastava, 1995). The relative importance of these objectives may differ among different organizations. For some VBOs, the social/environmental sustainability imperative outweighs or eclipses the profit motive, whereas in other organizations, financial considerations are the main driver of decision-making. For example, Koch and Hamm (2015) interviewed the managers of 11 Midwestern food hubs to assess the degree to which they focus on increasing access to underserved consumers. They found that, while the managers were interested in increasing food accessibility, in all cases, their main objective was to run a viable business, with access as a secondary priority.

The debate over single and multiple sourcing strategies is not widely discussed in the literature on VBOs. However, there is a clear emphasis on the importance of viewing suppliers as collaborative strategic partners, rather than the more traditional view in which they are leveraged through power imbalances. Stevenson and Pirog (2008) described the concept of a values-based supply chain (VBSC) framework, in which the objective of supporting the well-being of all participants is incorporated into traditional supply chain management strategies. VBOs and VBSCs are typically characterized as "flat" (i.e., nonhierarchical) organizations whose participants work collectively to achieve a common aim, and they tend to allocate decision-making power to individuals and local communities (Pullman & Dillard, 2010). This focus on long-term and egalitarian supply chain relationships suggests that VBOs might prefer single sourcing over multiple sourcing. However, when buyers specifically target sustainable and/or local suppliers as part of their social mission, working with multiple small-scale suppliers may be necessary to satisfy demand (Feenstra, Allen, Hardesty, Ohmart, & Perez, 2011). A VBO may also use multiple sourcing as a strategy by which it can provide financial support to

as many suppliers as possible. For a regional food hub, having a large and diverse set of suppliers is recommended to hedge against the many disruptive risks (e.g., weather, pests) that are inherent to food production (Moragham & Vanderbergh-Wertz, 2014).

Because of their emphasis on transparency and traceability, VBOs should be especially rigorous in evaluating and selecting suppliers—they must ensure that suppliers' practices are consistent with the values of the VBO and its customers. Methods for including environmental criteria in supplier selection decision are well established (Handfield, Walton, Sroufe, & Melnyk, 2002; Humphreys, Wong, & Chan, 2003). However, incorporating social concerns into sourcing decisions has proven challenging, and there is little existing research that investigates how consumer values can be translated into principles and rules to guide sourcing decisions (Zorzini, Hendry, Huq, & Stevenson, 2015). A case study by Pullman and Dillard (2010) provides one example, in which a natural beef producers' cooperative has developed specific values-based requirements for membership in the cooperative, including a codified set of sustainable land and water management principles, a detailed list of mandatory production standards (e.g., prohibitions on hormone/antibiotic usage), quality and capacity criteria, and connection to the land (i.e., ownership and plans for future ranch management). Trust, egalitarian values, and freely shared information and ideas characterize the cooperative's supply system.

For VBOs and VBSCs, a natural tension often exists between the often opposing objectives of profitability and social/environmental responsibility. Organizations that do not go far enough to meet consumers' values-based requirements may be in danger of accusations of "green-washing" and lose legitimacy, whereas those that focus on social and environmental aspects at the expense of financial sustainability will struggle to remain viable (Walker & Wan, 2012). Thus, maintaining an appropriate balance is challenging but critical to a VBO's organizational success. Accomplishing this requires that organizations have a clear understanding of their customers' values and provide products and services that are aligned with these values.

Empirical Data Elicitation and Analysis of a Regional Food Hub Regional Food Supply Chain

The food hub described in this paper is a VBO that operates as an online grocery store, using its website to broker sales between small-scale Iowa food producers and the food hub's consumer members. The food hub operates a small warehouse to facilitate sorting, short-term storage, and distribution, but it does not actually take ownership of any inventory, and there is no comingling of different producers' products—every item that passes through the food hub is

source-identified via producer labels. The only absolute requirement for a producer to become a member of the food hub cooperative is that its operations must be located within the state of Iowa.

Upon joining the food hub, each new producer member develops a descriptive profile that he/she uploads to the food hub's website. These producer profiles are visible to consumer members and are intended to help inform their decisions regarding from which producers to purchase. The food hub manager gives new producers suggestions about the types of information that are appropriate for their profiles, but these are merely guidelines, and there is no formal certification required. At a minimum, most producers provide the following information: farm/production facility location, types of products offered, and production practices used (e.g., certified organic, chemical-free, free-range, grass-fed). Many producers also include photos of their farms and their families, as well as links to their websites, and they may volunteer additional information, including the histories of their farms and statements about their values and personal beliefs with respect to sustainability and food production. In this way, the profiles give consumers a sense of connection with the producers, although they may never actually meet. An effective profile can make a producer more competitive and increase his/her sales to consumers. None of the information in the profiles is formally verified by the food hub's manager; the system relies on consumer trust.

At the beginning of each biweekly distribution cycle, each participating producer uploads information about his/her current product offerings (i.e., product types/descriptions, prices, and available quantities) onto the food hub's website. This information is made available to the consumer members, who select and order items from the producers whose products and profiles best meet their own personal preferences. The producers then package and label these items and deliver them to the food hub's central distribution center, where products are sorted for transport to various secondary distribution sites throughout central Iowa. Consumers then travel to the site nearest to them to pick up their orders.

To remain economically viable, the food hub charges its members a fee for this service. However, supporting small-scale Iowa producers is also a critical component of the hub's mission. Therefore, the food hub manager encourages small producers to participate, although this increases the number of transactions the hub must broker. The manager is also mindful of the number of producers in each product category, with an aim toward avoiding too much competition and unsustainable prices. The food hub also tries to promote greater consumer access to regional food by seeking to provide a range of price points. There are often tradeoffs between supporting producer and consumer members, which can be challenging for the food hub to successfully manage.

This regional food system is a complex sociotechnical system, composed of multiple autonomous and interacting actors. The individual decisions and adaptations of the consumers, producers, and the food hub manager yield complex

and unpredictable system-level behavior and outcomes (e.g., food hub success/failure) that cannot be predicted by examining the motivations and behaviors of the individual participants (Meter, 2006; Pathak, Day, Nair, Sawaya, & Kristal, 2007). Agent-based modeling (ABM) is a tool that is well-suited to capturing the complexity of such supply networks (Choi, Dooley, & Rungtusanatham, 2001). For example, Krejci and Beamon (2015) developed a theoretical ABM to study the impact of farmer coordination on the development of regional food system structures and social sustainability outcomes. To gain an increased understanding of the preferences, drivers, attributes, and behaviors of food hub participants, as well as the factors that encourage/discourage consumers and producers to participate in the system over time, Krejci, Stone, Dorneich, and Gilbert (2016) developed an ABM of a regional food system in Iowa using NetLogo (v. 5.0.2). The model was based on empirically derived inputs, which enabled a more realistic representation of the system and its constituent actors. This empirical ABM provides the basis for the study presented in this paper, in which the food hub manager's sourcing strategy is investigated.

To collect the data for this study, a structured interview with consumer and producer members of an Iowa food hub was conducted to provide a scientific profile of both groups. These profiles would then be used to help identify critical variables and ultimately provide more accurate information to be used in modeling consumer and producer behavior. The interviews were conducted onsite at the food hub's distribution center in Des Moines, Iowa. Interviewees first signed IRB-approved consent forms and then began a structured interview with a researcher for a period of 1 hour. Interviewers followed a strict interaction protocol so as to avoid influencing participants' responses. After completing all of the interview questions, participants were given the opportunity to ask questions of the researchers. Upon completion of the interviews, survey questions were transcribed into a spreadsheet and then categorized.

Data Analysis

In total, 33 individuals participated in the interview process (22 consumers and 11 producers). The typical consumer was 48.5 years of age (range 28–78), had a median household income of $100,000 (range $40,000–$300,000), and lived 6.5 miles (SD = 3.2) from the food hub (or associated distribution center). They tended to be very comfortable with technology and were typically the primary shoppers for their family, which averaged 2.5 (SD = 1) individuals. Consumers were also likely to have a college education. The typical producer was 49.1 years of age (range 28–67), had a median household income of $78,000 (range $13,000–$175,000), and lived 39.8 miles (SD = 22.7) from the food hub. Producers were very comfortable with technology, had a family which averaged 3.4 individuals

(SD = 1), and were nearly half as likely as consumers to have a college education. Consumers were largely motivated to interact with the food hub for health, environmental, and sustainability issues, whereas producers were somewhat motivated by similar issues but much more so by classical economic motivators related to profit and entity survival. Nearly all of the consumers interviewed (19 of 22) reported that the producers' online profiles were important to their purchasing decisions, and they rated their level of trust in the information provided as very high, with a mean of 4.7 on a Likert rating scale of 1–5 (SD = 0.5). As a typical example, one consumer participant, when asked whether or not she trusted the information in the producers' profiles, commented that she had "no reason not to."

For each of 14 different values (price, convenience of food preparation, nutrition, freshness, familiarity, novelty, convenience, variety, supporting of local economy, relationship with producers, communicate with vendors, food production practices, food safety, and treatment of animals), consumers responded on a 5-point Likert scale to describe the level of importance of each of the values in determining their participation with the food hub. The average Likert value for each of the 14 values was scaled from 0 to 1, where 1 indicates a strong preference for the given value, and 0 indicates very little interest in that particular value (see Table 1.)

Table 1. Consumer agent persona preference values for food hub and producer parameters

Value / Persona	Variety	Buy Convenience	Price	Preparation Convenience	Nutrition	Freshness	Familiarity	Novelty	Distance	Relationship	Reliability	Production	Safety	Treatment Of Animals
Locavore	0.700	0.700	0.633	0.367	0.917	1.0	0.650	0.467	1.0	0.717	0.817	0.950	0.983	0.917
Pragmatist	0.720	0.680	0.560	0.640	0.840	0.880	0.480	0.560	.720	0.480	0.560	0.720	1.0	0.800
Frugalist	0.200	0.600	1.0	0.600	1.0	0.800	0.800	0.400	1.0	0.600	0.800	0.800	0.600	0.400
Idealist	1.0	0.860	0.700	0.750	1.0	1.0	0.650	0.850	1.0	0.950	0.950	1.0	1.0	1.0

The participants' responses to these questions were statistically analyzed (using a hierarchical cluster analysis) to enable the categorization of consumers into different personas (Everitt, Landau, Leese, & Stahl, 2011). This method for interviewee selection and persona development has been widely used (Adler, 2005; Aquino & Filgueiras, 2005). The output of this analysis resulted in the development of four distinct personas: Locavores, Pragmatists, Frugalists, and Idealists (Krejci et al., 2016). The Locavore is a consumer who feels strongly about supporting the local economy and obtaining the freshest foods possible. The Pragmatist is a consumer who values food safety, freshness, and nutritional content, but tends to take a moderate view on other attributes associated with food purchase. The Frugalist is a highly price-conscious consumer, and the Idealist represents a consumer who feels strongly about all sustainable values and is motivated by serving

those values. For an in-depth analysis of the interview findings and the personas developed from them see Krejci et al. (2016).

Modeling Methodology

In this section, the agents that inhabit the empirically based ABM of the central Iowa regional food system (producers, consumers, food hub manager) are described, and an overview of the model and its constituent submodels is provided.

Agents

The consumer agents in the model are described by three parameters: their persona, their demand category, and their food familiarity level. Based on the results of the interviews with food hub consumer members, the probability of the generation of a consumer agent having a given persona in the model was 54%, 23%, 5%, and 18% for being Locavores, Pragmatists, Frugalists, and Idealists, respectively. Each consumer agent is assigned a demand category, which describes its level of demand (low, medium, or high) for each of six product categories in each distribution cycle. The probability that the model generates a consumer agent in any given demand category was determined via food hub historical data, which indicated that many (47%) of its participating consumer members were relatively low-volume customers. Each consumer is also assigned to categories that represent its likelihood of being familiar with a food or finding a food to be "novel" in a given interaction with a producer: 50% of consumers will find 5% of food interactions to yield foods that are unfamiliar/particularly novel to them, and the other 50% will encounter unfamiliar/novel foods in 10% of their interactions. For consumers who prefer familiar foods, the encounters with unfamiliar food will reduce their overall appraisal of the producer who provides it. In contrast, for consumers who prefer novel foods, this type of encounter will increase its rating of a producer.

Consumer agents are also characterized by a utility value, which is a measure of the consumer's satisfaction at any point in time. The higher a consumer's overall utility value is, the more likely he/she is to engage in commerce with the food hub in a given cycle, which influences his membership status. Utility values are scaled from 0 to 1, with 0 being the least preferred value and 1 the most preferred. The direction of preference for these utility distributions tends to be intuitive; for example, consumers prefer low prices and highly nutritious/fresh/safe food.

Producer agents are characterized by 11 parameters, each of which governs how the agent is evaluated by consumers and/or how it makes its decisions. Table

2 lists these parameters, the possible values that they can take on, the associated probability of each value being assigned to a given agent, and the source of information/data that provides the basis for the probability distribution. The values that are assigned to a producer for each of these parameters represent innate characteristics that are fixed throughout the duration of the simulation run.

Table 2. The 11 parameters/values that characterize producer agents

Producer Parameter	Possible Values	Probability	Distribution Basis
Maximum Production Capacity	50 units/cycle	0.50	System Data
	100 units/cycle	0.25	
	150 units/cycle	0.25	
Remaining Inventory Threshold	70%	0.33	Assumption
	80%	0.33	
	90%	0.33	
Price	Low	Varies based on food category	System Data
	Medium		
	High		
Ease of Food Preparation	Low	0.25 or 0.50: based on food category	Assumption
	Medium		
	High		
Food Nutritional Content	Low	0.25 or 0.50: based on food category	Assumption
	Medium		
	High		
Food Freshness Issues	1% chance	0.75	Assumption
	5% chance	0.25	
Distance From Food Hub	≤ 20 miles	0.70	System Data
	20–40 miles	0.19	
	> 40 miles	0.11	
Reliability Issues	1% chance	0.90	Assumption
	5% chance	0.10	
Production Practices	Insufficient information	Varies based on input data	System Data
	Conventional		
	Chemical-free		
	Certified organic		
Food Safety Issues	0.1% chance	0.75	Assumption
	0.5% chance	0.25	
Treatment of Animals	No certification	Varies based on input data	System Data
	certified humane		

The model also contains a single food hub manager agent that assesses relative supply and demand levels at the end of each distribution cycle. The manager

agent then uses this information to determine whether or not to allow new producer agents to become members of the hub.

Model Overview

The producer and consumer agents trade six different categories of food, using the food hub as an intermediary. Each producer agent produces and sells one of the six product categories to consumers through the food hub. The categories and percentage of producers supplying them were: meat (25%), dairy (5%), eggs (9%), fresh produce (36%), ingredients (3%), and processed convenience foods (22%). Each time the model generates a producer agent, there is a fixed probability that the agent will be assigned to particular category (e.g., there is a 25% chance that it will be a meat producer), based on historical data from a real-life food hub. It is assumed that a producer agent may only provide items in a single category, which is typically true in the real regional food system (Krejci et al., 2016).

Each simulated time step represents a distribution cycle by the food hub, which occurs approximately every two weeks throughout the year, for a total of 22 cycles per year. Producers and consumers can be in one of three different membership states with respect to the food hub: nonmember, member, or canceled member. Agent interactions are confined to producer–consumer transactions. It is assumed that consumers do not interact with one another directly, and neither do producers.

The model consists of five major submodels: initialization, consumer purchase decisions, consumer evaluation and status update, producer evaluation and status update, and food hub membership update. The initialization submodel is only run once, at the start of each simulation run. The other four submodels are executed sequentially in every time step.

Initialization. In each simulation run, the model is initialized with 30 producer agents, each of which is randomly assigned parameter values based on the probabilities determined from the interview data, system data, and assumptions. Different random number streams and seeds are used for each run, such that the outputs of each run are statistically independent. Each producer is initialized with 100% of its yield available for sale through the food hub. Fifty consumer agents are created, each of which is randomly assigned a demand category (i.e., low, medium, high), a food familiarity category, and a persona. Each consumer's producer rating matrix is initialized with producer attribute values for each of the producer agents in the model. A consumer's overall utility is initialized to 1.00 (the maximum value), and food hub membership status for all consumers and producers is set to "member."

Consumer purchase decisions. Each consumer who is currently a food hub

member checks its overall utility value: if the value is greater than 0.70, then the consumer decides to participate in purchasing; if the value is less than 0.70, the probability that the consumer decides to participate corresponds to its utility value. If the consumer decides to purchase from the food hub, it is assumed that he/she will try to fill as much as his/her demand as possible via the food hub. Consumers who have decided to participate are selected in random order to make their purchases from participating producers. Each consumer first assesses his/her demand in each product category. Then, he/she seeks out producers that have inventory available in each product category. As a consumer successfully purchases items from producers in each cycle, the consumer's demand for that item is reduced. It is assumed that demand that goes unfilled by the food hub will be filled by other exogenous sources (i.e., there is no demand backlog from one time-step to the next). After a consumer completes a transaction with a producer, he/she will update the parameter values in his/her producer ratings vector for that producer. If the consumer is unable to find any producers with inventory in a product category, his/her overall utility will be reduced by 0.05, and he/she will move on to the next category. If the consumer finds a producer(s) with inventory, but this inventory is insufficient to completely fill his/her demand, then his/her utility will be reduced by 0.01. If the consumer's demand is completely satisfied, his/her utility will increase by 0.01.

The consumer will then assess each of the available producers with respect to its values, using the producer's ratings vectors. Then the consumer ranks each of these producers by the total value he/she gives. He/she then selects the producer with the highest rank and purchases either enough of the producer's inventory to fill his/her demand or all of the producer's inventory (whichever is larger). If the consumer has any unfilled demand, he/she will move on to the next ranked producer and will purchase as much as available/needed from that producer, and so on. After each interaction with a producer, the consumer will update his/her producer ratings vector for that producer. The consumer will continue this process for each of the remaining five product categories.

Consumer evaluation and status update. After all consumer agents are finished purchasing food, each consumer will evaluate his/her overall utility with the food hub, which is based on his/her previous transactions. If a consumer's overall utility falls below a threshold value of 0.10 (out of 1.00), or if the consumer observes that he/she has participated with the food hub fewer than four times out of the previous 11 distribution cycles, he/she will change his/her membership status to "canceled member" and will no longer participate in transactions with the food hub.

Producer evaluation and status update. A producer makes one key decision in each distribution cycle: what percentage of its production capacity to sell to consumers via the food hub. Throughout the simulation, the percentage of production capacity that a producer allocates to the food hub (rather than to other

market channels, such as farmers' markets) may vary over time, according to how well the producer's products have sold through the food hub in previous distribution cycles. This update defines the producer's degree of participation with the food hub and depends on the producer's upper threshold for unsold inventory ratios. The unsold inventory ratio is simply the amount of inventory (in food units) that a producer has left at the end of a cycle, divided by the total number of units that he/she offered to consumers through the food hub at the beginning of the cycle. If this ratio is equal to zero (i.e., he/she sold the entire available inventory), then in the next cycle, the producer will increase his/her offerings by 10% (up to its capacity). If this ratio is greater than the producer's upper threshold for unsold inventory, he/she will calculate a weighted average of the ratio of number of items sold to capacity, over the three most recent cycles and will change the percentage of capacity that he/she offers through the food hub in the next time step to that average value. If the ratio is greater than zero but less than the upper threshold value, the number of units that the producer offers through the food hub in the next time step will remain unchanged. It is assumed that if a producer's participation drops to less than 10% of his/her capacity at any point in time, that producer will no longer participate with the food hub for the duration of the simulation run (i.e., its status will become "canceled member").

Food hub membership update. At the end of each distribution cycle, new producer and consumer agents are generated, and they are randomly assigned parameter values based on probabilities that were determined from the empirical food hub data. It is assumed that new consumer agents are created at a constant rate of two consumers per cycle. A new producer agent is created in every other cycle, on average. These rates approximate the actual rates at which new producer and consumer members joined the real-life food hub, based on food hub historical data.

Producer Selection Policies: Experimental Method

To assess the value of implementing various different producer selection policies, the food hub manager agent may choose to intervene during the "Food Hub Membership Update" submodel execution. To execute a given selection policy, when a producer agent is created and attempts to join the food hub, the manager will determine the producer's attributes, assess how well these attributes fit the needs of the food hub and its consumers, and based on this assessment, decide whether or not to allow the producer to join the food hub.

Five different producer selection policies were tested to assess the impact of having the food hub manager intervene in the selection of producers:

1. *No centralized management of supplier selection*: This policy represents the status quo—any producers who wish to join the food hub are allowed to join.

2. *Balance supply and demand*: Following this policy, when a producer attempts to join the food hub, the manager will assess total system supply and demand levels from the previous distribution cycle for the candidate producer's product type. If the supply of that food type in the previous cycle is less than 120% of the demand (allowing for future growth), then the manager will allow the producer to join; otherwise, the producer is removed from the system.
3. *Account for producer size*: The manager evaluates a producer in terms of system supply and demand (as in Policy 2) but makes exceptions for small-sized producers. That is, if a small dairy producer requests membership, even if the food hub's supply of dairy items from other producers is already much greater than existing demand, the manager will make an exception to the policy and will allow that producer to join. This policy reflects the food hub's socially responsible imperative to support small-scale regional producers.
4. *Account for producer price level*: This policy is similar to Policy 3, but here the manager will make an exception for producers who are at a low price level; that is, such producers will be allowed to join even if the supply–demand ratio of their food type is greater than 120%. This policy does not reflect current practices at the Iowa food hub but serves as a "what-if" scenario to determine what would happen to the system if the food hub decided to place a greater emphasis on improving access for low-income consumers.
5. *Account for producer size and price*: This policy combines Policies 2, 3, and 4, such that the manager's selection policy is very generous—producer membership is only restricted if the candidate producer is medium/large size and/or medium/high price, and the supply for that producer's product type is greater than 120% of demand.

The model was run for 1000 replications for each of the five policies. The length of each model run was 110 time steps (i.e., distribution cycles), which represents five years of system operation at 22 distribution cycles per year. The food hub manager has two primary objectives: maximizing food hub revenues while providing support and economic opportunities for regional producers. To reflect this, the following output metrics were captured at the end of each replication:

- Total volume of food units traded through the food hub
- Total number of consumer and producer agents participating
- Average "age" (i.e., length of participation) of participating producer and consumer agents
- Number of small-, medium-, and large-sized participating producer agents
- Number of low-, medium-, and high-priced participating producer agents

Results

All quantitative metrics were analyzed with analysis of variance (ANOVA) tests. The results are reported as significant for a significance level alpha <0.05. Post-hoc Tukey's test with adjusted *p*-values was used to test for a significant difference in the means for pairwise comparison, for which no *a priori* hypotheses had been developed. Additionally, Cohen's *d* was calculated to check the effect size to provide a standard measure to express the differences in means between two groups in standard deviation units. The Cohen's *d* results are reported as small effects for $0.20 < d < 0.50$, medium effects for $0.50 < d < 0.80$, and large effects for $d > 0.80$. Pairwise differences in means will only be discussed if the effect size was greater than 0.20.

Volume of Food Units Traded

illustrates the means and standard deviations of the volume of food units traded. The volume of food units traded was significant (F (4,4995) = 10.17, $p < 0.001$) across the five different policies. In the figure, means that do not share a letter are significantly different, as calculated by post-hoc analysis. There was a small ($d = 0.24$) difference between Policy 1 (No Management) and Policy 2 (Supply & Demand). There was also a small ($d = -0.22$) difference between Policy 2 and Policy 5 (Size & Price).

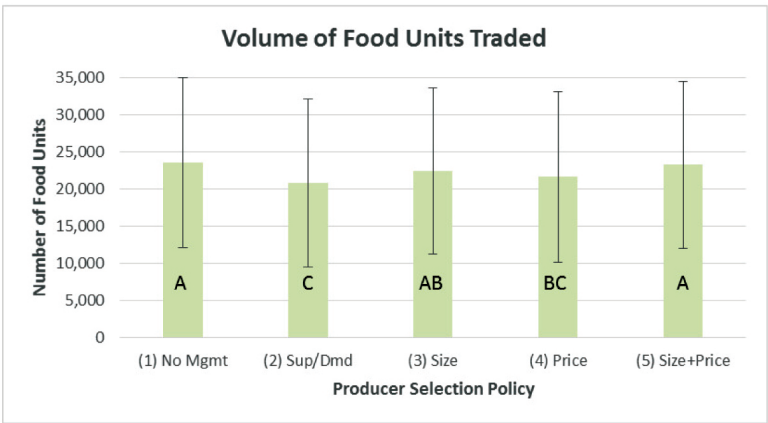

Figure 1. The volume of food traded under each policy option. The bars represent standard deviation. Means that do not share a letter are significantly different.

Number of Participating Consumers

Figure 2. Number of consumers participating under each policy option. The bars represent standard deviation. Means that do not share a letter are significantly different. illustrates the means and standard deviations of the number of consumers participating under each policy option. The number of consumers was significant (F (4,4995) = 9.52, $p < 0.001$) across the five different policies. In the figure, means that do not share a letter are significantly different, as calculated by post-hoc analysis. There was a small ($d = 0.23$) difference between Policy 1 (No Management) and Policy 2 (Supply & Demand). There was also a small ($d = -0.22$) difference between Policy 2 and Policy 5 (Size & Price).

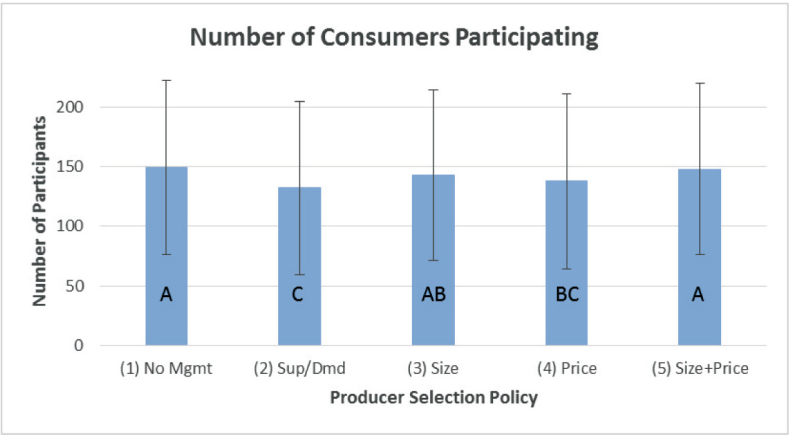

Figure 2. Number of consumers participating under each policy option. The bars represent standard deviation. Means that do not share a letter are significantly different.

Number of Participating Producers

Figure 3 illustrates the means and standard deviations of the number of producers participating under each policy option. The number of producers was significant (F (4,4995) =9.52, $p < 0.001$) across the five different policies. In the figure, means that do not share a letter are significantly different, as calculated by post-hoc analysis. There was a medium ($d = 0.52$) difference between Policy 1 (No Management) and Policy 2 (Supply & Demand), and a small ($d = 0.37$) difference between Policy 1 and Policy 4 (Price). There was a small ($d = -0.36$) difference between Policy 2 and Policy 3 (Size), and a small ($d = -0.45$) difference between the Policy 2 and Policy 5 (Size & Price). Likewise, there was a small ($d = -0.21$) difference between Policies 3 and 4. Finally, there was a small ($d = -0.30$) difference between Policies 4 and 5.

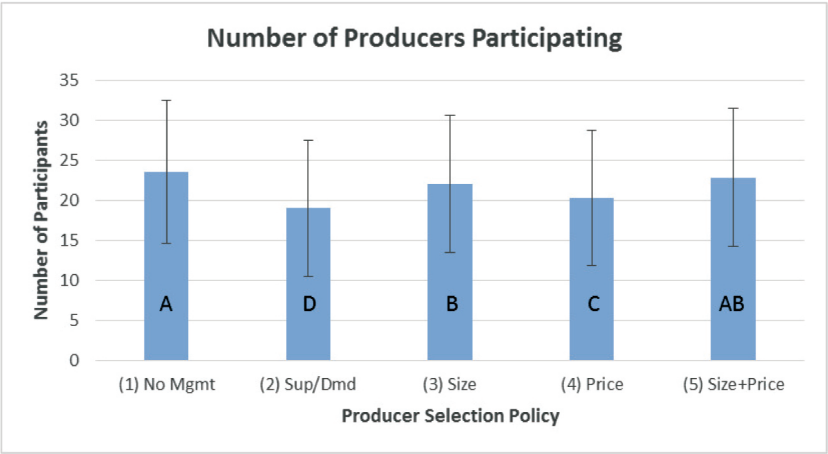

Figure 3. Number of producers participating under each policy option. The bars represent standard deviation. Means that do not share a letter are significantly different.

Average Age of Consumers

Figure 4 illustrates the means and standard deviations of the age of consumers participating (blue bars) under each policy option. The average consumer age was significant (F (4,4995) =6.07, $p < 0.001$) across the five different policies. In the figure, means that do not share a (upper case) letter are significantly different, as calculated by post-hoc analysis. None of the pairwise differences reached the small effect size threshold.

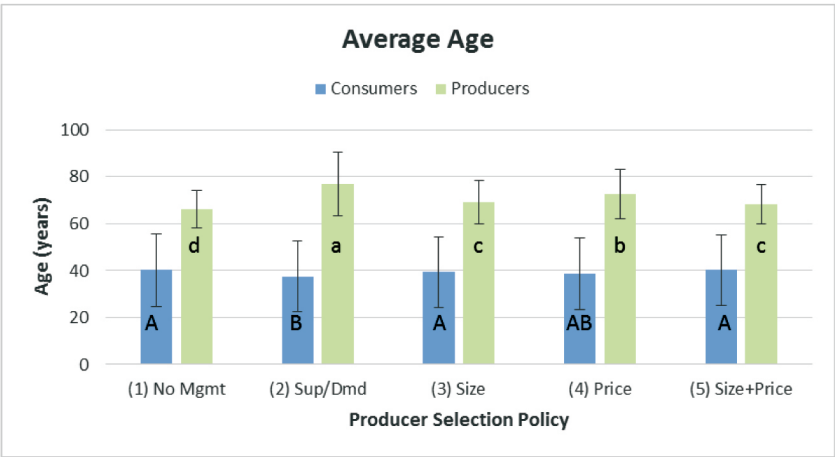

Figure 4. Average age of consumers and producers under each policy option. The bars represent standard deviation. Means that do not share a letter are significantly different.

Average Age of Producers

Figure 4 illustrates the means and standard deviations of the age of producers (green bars) participating under each policy option. The average producer age was significant (F (4,4995) =179, $p < 0.001$) across the five different policies. In the figure, means that do not share a (lower case) letter are significantly different, as calculated by post-hoc analysis. There was a large ($d = 1.07$) difference between Policy 1 (No Management) and Policy 2 (Supply & Demand), and a medium ($d = 0.73$) difference between Policy 1 and Policy 4 (Price). There was a medium ($d = 0.70$) difference between Policy 2 and Policy 3 (Size), and a medium ($d = -0.79$) difference between Policy 2 and Policy 5 (Size & Price). All other pairwise combinations showed a small effect size ($0.20 < d < 0.50$), except for the negligible effect size between Policies 3 and 5.

Average Producer Size

Figure 5 illustrates the means for the number of participating producers by size: small producers (blue), medium producers (green), and large producers (red), under each policy option.

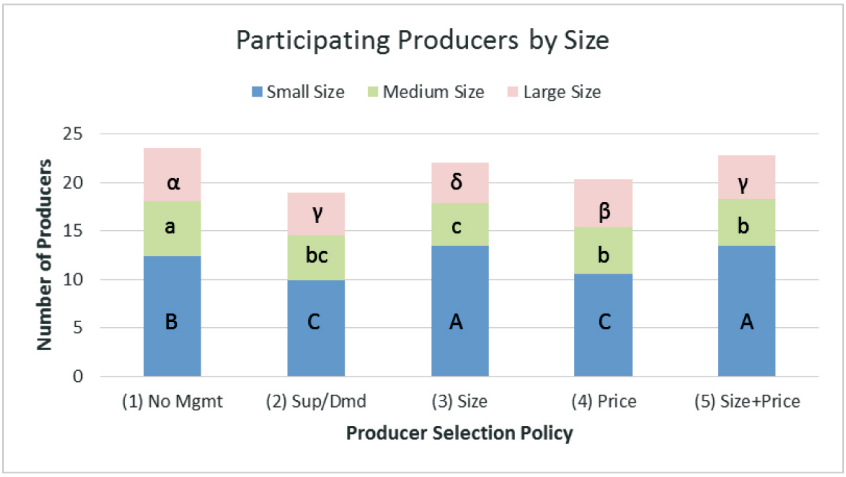

Figure 5. Average size category of producers under each policy option. Means from each producer size category that do not share a letter are significantly different.

Small producers. The number of small producers (blue bars in Figure 5) was significant (F (4,4995) = 86.3, $p < 0.001$) across the five different policies. In the figure, means that do not share a (upper case) letter are significantly different, as calculated by post-hoc analysis. There were small difference between the following pairs of means: between Policy 1 (No Management) and Policy 2 (Supply & Demand) ($d = 0.44$), and between Policy 1 and Policy 4 (Price) ($d = 0.33$). There

was a medium difference between the following pairs of means: between Policy 2 and Policy 3 (Size) ($d = -0.64$), between Policy 2 and Policy 5 (Size & Price) ($d = -0.63$), between Policy 3 and Policy 4 ($d = 0.53$), and between Policy 4 and Policy 5 ($d = -0.52$).

Medium producers. The number of medium-sized producers (green bars in Figure 5) was significant (F (4,4995) =35.3, $p < 0.001$) across the five different policies. In the figure, means that do not share a (lower case) letter are significantly different, as calculated by post-hoc analysis. Policy 1 (No Management) showed a small difference between every other policy: Policy 2 ($d = 0.41$), Policy 3 ($d = 0.48$), Policy 4 ($d = 0.30$), and Policy 5 ($d = 0.31$).

Large producers. The number of large producers (red bars in Figure 5) was significant (F (4,4995) =39.1, $p < 0.001$) across the five different policies. In the figure, means that do not share a (Greek) letter are significantly different, as calculated by post-hoc analysis. Policy 1 (No Management) showed a difference between every other policy: Policy 2 ($d = 0.39$, small), Policy 3 ($d = 0.52$, medium), Policy 4 ($d = 0.21$, small), and Policy 5 ($d = 0.35$, small). Additionally, there was a small ($d = -0.29$) difference between Policies 3 (Size) and 4 (Price).

Average Producer Price

Figure 6 illustrates the means for the number of participating producers by price: low price (blue), medium price (green), and high price (red), under each policy option.

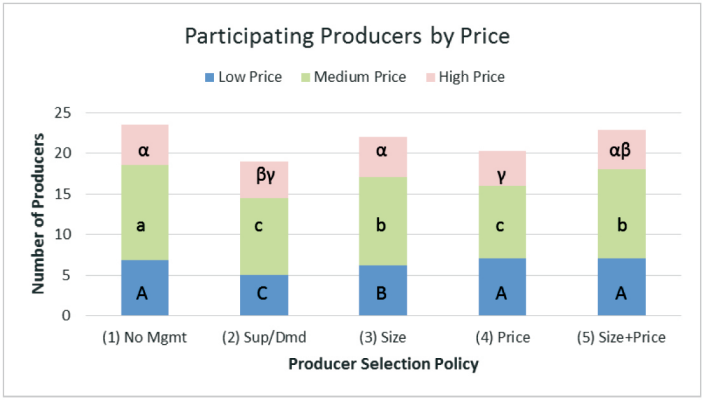

Figure 6. Average price category of producers under each policy option. Means from each producer size category that do not share a letter are significantly different.

Low price. The number of low-price producers (blue bars in Figure 6) was significant (F (4,4995) =104.5, $p < 0.001$) across the five different policies. In the figure, means that do not share a (uppercase) letter are significantly different, as calculated by post-hoc analysis. There were small differences between the following

pairs of means: between Policy 1 (No Management) and Policy 3 (Size) ($d = 0.24$), between Policy 2 (Supply & Demand) and Policy 3 ($d = -0.30$), between Policy 3 and Policy 4 (Price) ($d = -0.31$), and between Policy 3 and Policy 5 (Size & Price) ($d = -0.34$). There was a medium difference between the following pairs of means: between Policies 1 and 2 ($d = 0.69$), between Policies 2 and 4 ($d = -0.76$), and between Policies 2 and 5 ($d = -0.79$).

Medium price. The number of medium-price producers (green bars in Figure 6) was significant (F (4,4995) = 57.8, $p < 0.001$) across the five different policies. In the figure, means that do not share a (lowercase) letter are significantly different, as calculated by post-hoc analysis. There were small differences between the following pairs of means: between Policy 1 (No Management) and Policy 2 (Supply & Demand) ($d = 0.46$), between Policy 2 and Policy 3 (Size) ($d = -0.30$), between Policy 2 and Policy 5 (Size & Price) ($d = -0.29$), between Policy 3 and Policy 4 (Price) ($d = 0.43$), and between Policies 4 and 5 ($d = -0.42$). There was a medium ($d = 0.59$) difference between Policies 1 and 4.

High price. The number of high-price producers (red bars in Figure 6) was significant (F (4,4995) = 9.41, $p < 0.001$) across the five different policies. In the figure, means that do not share a (Greek) letter are significantly different, as calculated by post-hoc analysis. There was a small ($d = 0.21$) difference between Policy 1 (No Management) and Policy 4 (Price). There was also a small ($d = 0.22$) difference between Policy 3 (Size) and Policy 4.

Discussion

Of all five sourcing policies, Policy 2 (the unmodified supply–demand selection policy) is the strictest. However, Policy 4 (Price) is effectively nearly as strict as Policy 2, since relatively few low-price producers attempt to participate in the food hub (a reflection of real-life producer behavior), and therefore an exception for these producers does not relax the supply–demand ratio constraint very much. By contrast, Policies 1, 3, and 5 represent less interference by the food hub manager. Based on the results of the ANOVA tests, all of the system performance metrics of interest were significantly influenced by the food hub manager's choice of supplier selection policy. However, the effect sizes varied considerably for different pairwise comparisons of policies on each metric, which tended to reflect the difference between less restrictive approaches (as with Policies 1, 3, and 5) and strategies that were more selective (i.e., Policies 2 and 4).

Under Policy 2 (Supply & Demand), both the mean number of food units traded through the food hub and the number of participating consumers are shown to be significantly less than the mean values under Policies 1 and 5 (No Management and Size & Price, respectively). These results suggests that, in terms of sales, the best option for the food hub may be to continue allowing any producer

who wishes to join to become a member (i.e., maintain the status quo). If the food hub manager wants to implement a sourcing policy, he/she should consider relaxing restrictions for small-sized and low-price producers. Either of these strategies (Policy 1 or Policy 5) appears likely to support consumer satisfaction and continued participation.

On average, Policy 2 (Supply & Demand) yielded significantly fewer participating producers and a significantly greater average producer age than Policies 1, 3, and 5 (No Management, Size, and Size & Price). These three policies also resulted in a higher concentration of small-sized and low-price producers (a result that is preferred by consumers) than Policy 2. Interestingly, there is no significant difference between Policy 1 and Policy 4 (the supply–demand selection policy in which exceptions are made for low-price producers) with respect to the mean number of low-price producers. This suggests that consumers' preferences for low prices can help to maintain a pool of competitive low-price producers without the need for food hub manager intervention.

These results indicate that in deciding which of these five supplier selection policies to implement, the food hub manager must make a tradeoff between protecting producers and meeting the needs of the consumers. By following "protectionist" Policy 2, the food hub manager's loyalty to currently participating producers protects them from healthy competition and reduces the ability for consumer preferences (i.e., for lower prices and smaller producers) to be fully expressed. The food hub manager must determine whether it is in the food hub's best interest to fully support a smaller group of producers, or partially support many producers and allow for some competition among them. Additionally, though the modifications to Policy 2 to encourage small-sized/low-price producers yield statistically significant reductions in average producer size (with Policies 3, 4, and 5) and price (with Policy 3) when compared to the status quo, the food hub manager should carefully assess whether the effort involved in implementing these policies would be truly worthwhile in the long run, and whether the chosen policy would be perceived by the producers and consumers in the community as being socially responsible and equitable.

Conclusion

For VBOs like regional food hubs, developing a suitable sourcing strategy can be a challenging task. Food hubs are in a unique position of having to balance the social and economic concerns of both food producers and consumers. For a food hub manager, an appropriate policy for determining which producers should be allowed to participate in the system may not always be clear. Because regional food systems tend to be collaborative and community-based networks, maintaining traditional "arm's length" or adversarial relationships with

producers can be difficult (and likely undesirable) for a manager. However, the manager should be cautious about allowing relationships with producers to dictate the food hub's sourcing policy at the expense of consumer satisfaction.

This paper described an empirically based ABM of a regional food system in central Iowa, in which the success of the entire system (including the producers, consumers, and the food hub) relies on the achievement of potentially conflicting social and economic objectives and the careful balance of meeting both producer and consumer requirements. The experiments described in this paper show how ABM can be used to capture the effects of different sourcing policies on regional food hub consumer and producer participation. The results of these experiments suggest that centralized control via management policies can lead to desired outcomes, but such policies can also have unintended (and sometimes undesirable) consequences for system behavior.

In future work, it will be interesting to observe the effects of different sourcing policies on the evolution of the system's consumer persona distribution. For example, if the food hub manager implements a policy that strongly supports the inclusion of low-cost producers, will the price-conscious Frugalist persona become dominant? Would this strategy drive other personas away from the food hub? How would this impact the food hub financially? Is this beneficial for individual producers and consumers, and for the regional food system as a whole? The ABM can be used to answer these questions.

The ABM will also be further developed to allow for social interactions and information sharing among the consumer agents, and to assess the impact of these interactions on food system metrics. These interactions may be personal; for example, the consumer agents could discuss their experiences with one another when they pick up their orders from the food hub. Alternatively, the interactions could occur via the food hub's website, through a system of producer ratings. The implications of allowing and/or encouraging communication between consumers would be useful for the food hub manager to understand. ABM is a particularly useful tool for studying the effects of these types of complex interactions on system behavior over time.

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Enhancing Stock Investment Returns with Learning Aggressiveness and Trust Metrics

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Abstract:
Trust metrics and learning can be extremely useful in enhancing the overall investment returns. A trust metric is an indication of the degree to which one social actor trusts another, while aggressiveness in learning determines the degree to which one trader decides to mimic another. This paper introduces an agent-based model for finding the optimal level of aggressiveness in learning and the optimal degree of trust in order to optimize the stock-trading returns. The system has been evaluated in the context of the Bank of America stock and S&P 500 performance in the period of 1987–2014. The model significantly outperformed the buy-and-hold strategy on both S&P 500 and the Bank of America stock. In addition, the model can provide relevant information to policy maker regarding interest rate setting and expected investor behaviors.

Keywords: *complex adaptive systems, investment, trust metrics, learning aggressiveness*

1. Introduction

Finding best stock investment strategies requires not only rational trading rules practices but also the faith that market information is reliable. A trust metric is an indication of the degree to which one social actor trusts another. It is hard to pick the right timing for stock selection or to take the correct position in the stock market, because stock intrinsic values are affected by both endogenous and exogenous phenomena. Some investors actually make profit by taking advantage of the asymmetric property of information, which is what happens when one party in a transaction has better information than the other party does. However, actions taken based on asymmetric information are reflected in the

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trading volume and the transaction price of the stock. As a result, a trust metric may alleviate the impact of asymmetry in information by simply following market's trends. Investors who adjust their trading rules to accommodate the current market trends can outperform the average investor and maximize their profits.

Although trust plays an important role in stock markets, learning is also an inseparable part of stock trading. It is an act of acquiring new or modifying existing knowledge, behaviors, or skills. Learning builds upon the previous knowledge over time. Similar to trust metrics, learning investment strategies involves mimicking the behavior of top market performers, copying their philosophy of stock trading. However, unlike trust metrics, learning is a continuous process. Investors are constantly aware of the latest market changes, and they possibly benefit from the current state of the market (Linn & Tay, 2007). A learning curve captures the progress of learning over time. It is a graphical representation of the increase of learning with experience. The slope of learning reflects how aggressive (eager, motivated, or capable) the learner is in attempting to become a better performer over time. A typical learning curve is shown in Figure 1. A more aggressive learner tends to copy more from the market best performers, and consequently has a much steeper learning slope. Less aggressive learners, however, tend to use best performers' behavior only as a minor correction to update their own trading rules.

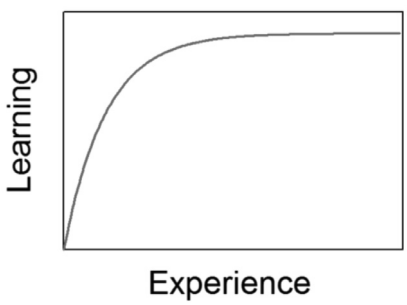

Figure 1. Learning curve.

Computers and sophisticated analytical techniques have offered an automated extraction of trading strategies, (Teixeira & de Oliveira, 2010), although with limited success. In the past decade, complex adaptive systems (CAS)-inspired methods, primarily using agent-based modeling (ABM) techniques, have made advances in simulating traders' behaviors and capturing the intricacies of stock trading (Kodia, Said, & Ghedira, 2010). This paper introduces an agent-based model for searching for the optimal balance between the level of trust and learning aggressiveness. The model is a derivative of the multisectors-trading model introduced by Su and Hadzikadic (2014). The system has been evaluated in the context of a financial services company stock performance in the period of 1987–2014. The model significantly outperformed the buy-and-hold strategy on both S&P 500 and the bank's stock.

In addition, since interest rates impact agents' cumulative return overtime in the model, the model could be used to inform policy makers on the setting of the interest rate in the context of anticipated investor reactions. This is due to the fact that the government's open-market operations induce liquidity effects that leads to interest rate behaviors (Lucas, 1990), and market liquidity also affects the trading activities (Chordia, Roll, & Subrahmanyam, 2001).

2. Background

Investment strategies are usually classified as either passive or active portfolio management strategies (Barnes, 2003). Passive portfolio management only involves limited buying and selling. Passive investors anticipate the appreciation of their capital in the long term, and there is only limited engagement involved in their portfolio maintenance. In contrast, active portfolio management strategies can bring investors extra profits because they can benefit from short runs, but it requires their active engagement with the stock market. Thus, active engagement covers a wider range and frequency of stock price movement. Active equity portfolio management requires periodic forecasting of economic conditions, as well as portfolio rebalancing based on the forecasted conditions (Grinold & Kahn, 1999). A degree of trust in the rationale for market movements and trends impacts the stock-trading activities and investors' risk control strategies (Asgharian, Liu, & Lundtofte, 2014). Risk control methods make it possible for a dynamic portfolio management strategy to outperform the market (Browne, 2000). A simple momentum and relative strength strategy has been outperforming the buy-and-hold strategy by 70% since the 1920s (Faber, 2010). Performance can be improved by considering simple trends before taking positions. Overall, learning from past performance and from actions of others makes investors become better through their accumulated expertise (Seru, Shumway, & Stoffman, 2010). This is, in turn, reflected in their actions in the market place. Clearly, this constant dynamic interplay between investors' changing strategies and hard-to-predict market movements makes the problem of understanding the market place and anticipating its behavior extremely challenging.

However, the automated methods described above simply provide a retroactive, aggregated model of the stock market. They don't take into consideration interactions between/among agents, as they learn from each other and change their behavior and strategies accordingly. These interactions, in fact, can better inform investors about changing market conditions due to changed investment strategies. This clearly affects the performance of anyone's investment portfolio.

The CAS methodology offers a natural framework for augmenting portfolio management strategies with simulation of individual agent interactions in the market place and their financial surroundings. A further advantage of CAS stems

from its ability to (a) evaluate many different rules and parameters at the individual level, (b) test different trust thresholds among agents, and (c) adjust learning aggressiveness, thus enabling the system designer and the end users to uncover agent interactions that actually improve portfolio performance.

3. Complex Adaptive System in Investment Management

Since CAS simulations have the capability to capture the essence of distribution, self-organization, and nonlinear social and natural phenomena, characterized by feedback loops and emergent properties, they offer an innovative way of modeling inherently complex systems such as a stock market. Interaction patterns and emergent regularities are important features in the financial markets (Cappiello, Engle, & Sheppard, 2006). It is natural to utilize ABM techniques to model financial markets as a dynamic system of interacting agents. There already have been successful implementations of ABM models in many theaters of human endeavor, including economics, government, military, sociology, healthcare, architecture, city planning, policy, and biology (Hadzikadic, Carmichael, & Curtin, 2010; Johnson, Hadzikadic, & Whitmeyer, 2013). In financial market simulations, a large number of agents engage repeatedly in local interactions, giving rise to global markets (Bonabeau, 2002; Darley & Outkin, 2007; Roberto, Cincotti, Focardi, & Marchesi, 2001). The dynamics can be readily captured by a well-designed and CAS-enabled ABM simulation. ABM models can be augmented with learning, as demonstrated by Farmer's agent-based investment model (Farmer, 2001) that yields powerful insights about market behaviors. Also, ABM models combined with artificial intelligence-based reinforcement learning provide a plausible way of stock modeling (Ramanauskas, 2008).

In this paper, we describe an ABM system that seeks a balanced level of trust and learning aggressiveness for individual agents, based on a single stock-trading model presented by Su and Hadzikadic (2015). This model issues a stock-trading signal (buy, sell, or hold) for a stock (Bank of America, BAC, in our example) on a daily basis. Agents trade the BAC stock based on the publicly available, adjusted, daily data from January 2, 1987 to December 31, 2014.

4. A CAS Stock-Trading Model

We built a stock-trading model using the concept of CAS that issues a stock-trading signal at the end of each trading day. Agents use the current closing price of BAC to determine the next trading action, which includes buy, sell, and hold options. The closing price is adjusted to eliminate the effect of stock dividends. Interest is distributed based on the agent's cash on hand

on a daily basis, and the rate values come from the Federal Reserve Web site. In addition, the transaction cost is set to be $10 for each transaction. As a result, agents cannot capture the niche profit with high volume of buying and selling in slight price change situations. At the same time, transaction costs provide agents with a stable trading environment.

4.1 Agents

The world of stock trading in this ABM simulation is built from a collection of agents. In order to reduce the complexity of the problem and to minimize the size of the exploration space of the model as much as possible, we decided to investigate agents on the individual level only. Although one of the major participants in the financial markets is a group known as institutional investors, our intent was to find the optimal balance between learning aggressiveness and trust metrics for individual agents only. The concept of individual investors refers to common investors in the stock market.

Agents are initialized with a pre-specified amount of money and with randomized initial trading strategies. Once they start trading, their available capital, trading strategies, and market momentum influence and trigger transactions. The momentum in the market adjusts agents' decision rules temporarily, and the individual trust metrics decides the degree of change. Agents also have the opportunity to learn the best trading strategies from the best performers within their radius during the open learning period. The speed of learning is controlled by their aggressiveness value. On the basis of Su and Hadzikadic (2014, 2015), Table 1 describes the trading rules assigned to individual agents.

Table 1. *Trading Rules Assigned to Individual Agents*

Buy threshold	Minimum price change required for taking a long position
Buy period	Time window agents observe before evaluating the buy threshold
Sell threshold	Minimum price change required for taking a short position
Sell period	Time window agents observe before evaluating the sell threshold
Aggressiveness	Degree in learning while copying the trading styles from top performers
Self-confidence	Degree of trust in the trading rules born with agents

4.2 Trading Rules

The following formulas describe agents' basic decision rules in detail (Su & Hadzikadic, 2014, 2015).

Buy rule:
- Price change > Buy threshold * (1 – (1 – self-confidence) * *momentum of buying*) in past *Z* days
- Agents will take long positions

For example, if the values of *buy threshold*, *buy period*, *self-confidence*, and *market momentum* for a particular agent are 0.2, 40, 0.9, and 0.7, respectively, then the buying rule for this agent is:

If the stock price goes up 0.2 * (1 – (1 – 0.9) * 0.7) * 100% = 18.6 % in the past 40 trading days,

then, the agent takes a long position.

Sell rule:
- Price change < Sell threshold * (1 – (1 – self-confidence) * *momentum of selling*) in past *Z* days
- Agents will take short positions

Similarly, if the values of *sell threshold*, *sell period*, *self-confidence*, and *market momentum* are 0.1, 10, 0.2, and, 0.3 respectively, then the selling rule for this agent is:

If the stock price goes up less than 0.1 * (1 – (1 – 0.2) * 0.3) * 100% = 7.6% in the last 10 trading days,

then, the agent takes a short position.

Agents have two sets of trading rules. One is for the bull market, and the other is for the bear market. Agents identify current market status based on the recession indicator provided by the National Bureau of Economic Research (NBER). Agents switch trading rule sets once they have the latest knowledge of the market status change. Since the financial markets are not perfectly correlated with recessions, it usually takes about 250 trading days for a recession to start impacting the stock market. The recession signals from NBER are delayed for a year.

In addition, agents are permitted to sell short the stock at any time. This decision makes it possible for agents to capture profits in market downturns, as well as to hedge the potential risk with making erroneous decisions. An agent can sell short any amount of stock up to their available cash amount. In financial terms, a long position indicates the purchase of a security such as stocks, commodity, or currency, with the expectation that the value of these assets will rise in value over

time. A short position denotes the opposite scenario. Short selling indicates the sale of a security that is not currently owned by the seller. However, in order to close the position in the future, agents will have to buy the same amount of securities to cover their short selling positions.

4.3 Market Momentum

Market momentum phenomenon can be summarized as:

Momentum ranges in [0, 1]
- Count how many people intend to buy/sell
- If no one is *buying/selling*, *momentum of buying/selling* will be 0
- If everyone is *buying/selling*, *momentum* of *buying/selling* will be 1

Despite the claims of equilibrium economists, rationality is not present in every transaction. Although stock market participants believe that they are rational in their decisions on stock purchasing, panics and frenzies also drive many market trends. Investors' greedy and panic-prone behaviors amplify regular ups and downs of the market, thus building up a bubble that inevitably ends up in a market crash. Some of the most famous examples include the tulip craze, the South Sea bubble, and the great depression. Also, the recent market trends in the Shanghai Composite Index, as shown in Fig. 2, validate this phenomenon as well.

Figure 2. Shanghai Composite Index (Source: Yahoo Finance).

Clearly, market momentum is an important factor that affects agents' decision-making rules. Otherwise, there would be no bubbles and the price moves will be closer to our expectations. Heterogeneous agent models show that most of the behavioral models with bounded rational agents using differing strategies may not be perfect, but they perform reasonably well (Hommes, 2006). With the adaptive trading strategies, agents are able to seek more trading opportunities and boost their profits.

Inclusion of market momentum in the stock-trading model potentially increases the return of investors since it allows agents to adjust their trading rules temporarily according to the latest market changes (in anticipation of other traders' behavior). In the stock-trading model, momentum was generated and updated by the overall buy/sell intentions of agents, thus creating a bid-ask spread for the stock they are trading. Bid-ask spreads are determined by the difference between the prices quoted for an immediate sale and for an immediate purchase. As a result, the bidding price increases if there are more buyers than sellers. Likewise, the stock price will decrease if there is a greater quantity of sellers.

4.4 Degree of Trust

The degree of trust in our model is denoted with the variable called *self-confidence*, which is created to control the degree of trust in the market momentum. The self-confidence only adjusts agents' trading rule temporary. If agents have a strong belief in the validity of their trading rules, then their self-confidences is high. As a result, their trading rules will be less impacted by the trading environment around them, due to the fact that they prefer to continue with their own trading strategies.

All agents have access to both the latest and historical market information, which is the basis for all the agents' trading decisions. Market momentum can also simulate the bandwagon effect in economics. The bandwagon effect means that an individual does something primarily because other individuals are doing it, regardless of his or her own beliefs. This effect is especially present in the bull market with the bubble-style growth of assets. As a result, agents' buy thresholds will increase rapidly if there are a lot of other agents who intend to buy, and sell thresholds will decrease quickly if many agents intend to sell. Because the self-confidence ranges from 0 to 1, agents with the self-confidence of 1 will only follow their own trading rules, while the ones with the self-confidence of 0 will completely override their own believes with the market trend. But these extreme scenarios are rare in the simulation. Just like Guiso noticed (Guiso, 2008), in this simulation, the degree of trust affects the stock-trading participation rate, which impacts the market momentum in return.

Self-confidence captures agents' degree of trust toward other agents'

expectation of future market moves. Self-confidence is assigned randomly in the simulation setup stage, and changes based on the agent's learning aggressiveness during the simulation. This mechanism makes it possible for agents to explore the best degree of confidence in their decision rule sets. At the same time, best performers' self-confidence values will be tracked and available to all agents in the learning stage of the simulation.

4.5 Learning and Interaction

In agent-based models, agents interact with each other. Learning is one of such interactions. In our model, learning offers agents the opportunity to check and compare their decision rules with those of the best performers, thus making it possible for them to refine their rules and secure more profits in the future similar market trends (Cui, Wang, Ye, & Yan, 2012).

Unlike the degree of trust, which only changes the agents' decision rule temporarily based on the latest market trends, learning has a permanent impact on agents' trading strategies. The learning mechanism makes it possible to investigate alternative strategies that have not yet been discovered in the market (Outkin, 2012). In this implementation, to preserve computational time and to maximally alleviate the constraints of the limits of available computing power, a radius is introduced in the simulation. Agents can only see other agents within their own radius while moving around, which helps with avoiding the homogenization of agents. Agents have the opportunity to learn from the best performers within their radius, thus within their neighborhood, which helps with improving the learning efficiency as well. With the ability to learn and to decide how much they want to learn from their neighbors (i.e., how close they want to get to their neighbor's value on a particular variable), the size of the exploration space of optimal decision rules is reduced from the size of trillions of combinations into a much smaller one.

The variable *aggressiveness* defines the extent of neighborhood best performers' behavioral structure the agent wants to adopt. It ranges from 100% to nothing, with most cases being somewhere in the middle. Prior to the learning phase, agents' original decision rules will be given sufficient time to evaluate their performance. The learning process starts only after this evaluation period.

4.6 Search Space and Mutation

Given the number of variables in the model used in this research, the size of the search space of all possible combinations is in trillions of space states. In order to run a simulation with a much small search space and to still make sure that the simulation can theoretically explore all possible states, a

mutation mechanism is introduced in the model. With mutation and a sufficiently long simulation time, it is possible to use a small quantity of agents to simulate agents with a sufficient number of possible combinations of parameters. With this in mind, in this model, agent parameters are initialized within a small range of all possible values, while a small portion of agents are initialized within a larger range. Mutation also exists in the hatch-and-die portion of the NetLogo simulation, ensuring that descendants have the opportunity to explore a larger space as well. Finally, Monte Carlo simulation is used to get the best simulation results with a minimal round of simulations.

4. 7 Genetic Algorithm

The concept of "Survival of the fittest," proposed by Darwin, can also be applied to the financial markets. According to the theory of evolution, descendants are born with behaviors that are likely better adapted to the changes in the environment they are being born into. With the benefits of the hatch-and-die mechanism in Netlogo, model designers can implement natural selection into the agent "births," agent interactions, and agent behaviors. The best agents can have descendants that have similar trading rules, while the worst performers can be ruled out of the system (in this case, when they have used up all their capital). When agents get eliminated from the model, newly randomized agents with initial capital agents replace them to keep the number of agents constant, thus ensuring an active trading environment. The implemented genetic algorithm ensures that the total number of active agents in the simulation remains at the same level. The results of agents of different age are evaluated at the same time. Agents simply follow and learn from the richest agents within their radius.

4.8 Benchmark Agents

There are two additional agents generated in the model with the purpose of helping the end user evaluate the model performance over time. These agents use the buy-and-hold strategy for BAC and S&P 500, respectively. In other words, these agents buy a certain amount of BAC and S&P 500 stock shares in the beginning of the simulation. They hold onto those shares until the end of the simulation. Their cumulative returns are treated as the benchmarks for evaluating the performance of other agents in the same period.

4.9 Global Trading Environment

The CAS stock-trading model is a two-dimensional square world with both *X*- and *Y*-axes ranging from –10 to +10. A variable called *radius* is used to define the maximal view range for an agent (a neighborhood). In order to make sure that every agent has the same opportunity to discover and learn from other agents, the radius is the same for all agents. Also, agents know their location and the identity of agents within their radius.

5. Implementation

The stock-trading CAS model used in this project is implemented using the Netlogo 5.1.0 integrated programmable modeling environment (Wilensky, 1999). Netlogo offers a user-defined grid and the possibility of defining agents, commonly called turtles.

In the stock-trading model, variables are created to capture many of the properties investors evaluate in the real world. Also, each variable has a different value range and the increment step size, thus pushing the overall exploration space to the size of trillions. Theoretically, a simulation of this complexity is doable but it requires a & tremendous computational power. For most computing platforms it may take decades before we are able to obtain final results of running a model that uses trillions of agents. Therefore, the agent number was set to 1,000 as a trade-off between the available computing speed and the minimum size of the exploration space. Table 2 shows the settings for the parameters used in the stock-trading model. All transaction decision rules are randomized within the [-0.4,0.4] range for required returns, and within [0,100] range for the trading periods. Aggressiveness is randomized from 0.0001 to 0.1, with step size of 0.0001. Self-confidence is randomized from 0 to 1, with the step of 0.01. The small range used in the simulation is chosen with the purpose of decreasing the search space and increasing the coverage for each run. Because mutation is enabled in the simulation, the mutated agents are initialized with a full search range. The initial capital allocated to agents is $50,000, and the transaction cost is fixed at $10 per transaction. The mutation rate is fixed at 0.1, which allows 10% of all agents to get buy/sell threshold and buy/sell period generated in the whole range [-1,1] and [1,1,000], respectively.

The price of the BAC stock used in the simulation is adjusted for the effect of dividends. The interest is distributed at the end of each tick, based on the amount of cash held on hand by each agent. As a result, investors have to decide between two goods, BAC shares and money with a fixed interest rate.

Table 2. *Parameter Ranges*

Nonmutation	Buy threshold	[–0.4, 0.4] with step size 0.2
	Buy period	[0, 100] with step size 20
	Sell threshold	[–0.4, 0.4] with step size 0.2
	Sell period	[0, 100] with step size 20
Mutation	Buy threshold	[–1, 1] with step size 0.2
	Buy period	[0, 1,000] with step size 20
	Sell threshold	[–1, 1] with step size 0.2
	Sell period	[0, 1,000] with step size 20
Mutation rate		0.1
Self-confidence		[0,1] with step size 0.01
Aggressiveness		[0.0001, 0.1] with step size 0.0001
Initial capital		$50,000
Transaction cost		$10

Learning from other agents is disabled in the first 1,000 days. This will allow agents sufficient time to evaluate the profitability and durability of their randomly initialized trading strategies. Afterward, agents learn until the end of the simulation. In this way, agents have enough time to optimize their strategies in different phases of the market, which has different volatilities at different times, that is, financial crises, bull markets, and bubble development periods.

6. Results

Two underlying assets, S&P 500 Index and BAC, with the buy-and-hold strategy were used as the benchmark for evaluating the performance of this stock-trading model. The timeframe of the simulation starts at 2 January, 1987 and ends at 31 December, 2014. In this period, the S&P 500 Index increased from $246.45 to $2059.9, and BAC increased from $2.37 to $17.89. With the buy-and-hold strategy, the return for both benchmarks is 735.82% and 664.53%, respectively. Figure 3 shows the cumulative return of different agents in one of the simulations.

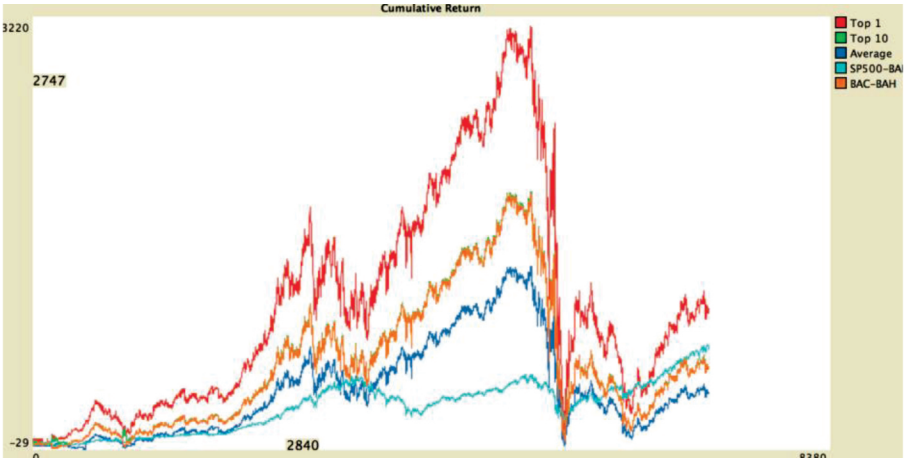

Figure 3. Simulation results.

The best performer achieved 1277.43%, which is 1.74 times higher than the S&P 500 benchmark. In the same period, the top 10% best performer had an average return of 682.35%, which is only slightly better than the benchmark of BAC. The main reason behind the result is that S&P 500 is a weighted index across all industries. If one industry has a crisis and it suffers a tremendous downturn, then the upward trend in other industries can compensate for the downturn, at least to some extent. As a result, the change in the index is not as dramatic as it can be in an individual stock. That is why the index created several historical highs recently. However, there is a different story with BAC. Since the root of the last financial crisis was in the banking industry, BAC is still around 60% below its historic high, which was $54.87 per share recorded on 30 September, 2006. Table 3 shows the summary of the results.

Table 3. Simulation results.

Best performer	Cumulative Return	1277.43%
	Self-confidence	0.45
	Aggressiveness	0.94
Top 10% performers	Cumulative return	682.35%
	Self-confidence	0.51
	Aggressiveness	0.95
Benchmark Agent 1	S&P500	735.82%
	Buy-and-hold	
Benchmark Agent 2	BAC Buy-and-hold	664.53%

Based on the simulation results, the optimal levels of self-confidence and aggressiveness are 0.45 and 0.94, respectively. These values indicate that investors should use (assign weight) 45% of their lifelong accumulated decision-making wisdom and use 55% of the information received form the latest market changes when making decisions on stock market investments in order to maximize their performance in the stock market at that time. The degree of aggressiveness is optimized at 0.94, which is very close to the initial upper bound for the variable. This high value indicates that agents should learn as much as possible from the strategy sets of the local best performers. Because the effect of learning is permanent, agents with a faster learning speed are able to mimic all the best rules in a much shorter time.

Since the market in our simulation was mainly a bull market, the bull market-trading rule set is more representative in the simulation. However, in simulations with a longer time horizon, the bear market-trading rule set actually evolves overtime, and it emerges as one of the major components in the final trading rule set.

The best decision rule set is described as follows:

- If the stock price goes down 31% in last 71 trading days, take a long position.
- If the stock price goes up less than 14% in last 13 trading days, take a short position.

However, these rules are adjusted according to the degree of trust in the latest market momentum, which is generated on a daily basis. The above rule, after being modified according to the market momentum information, was updated to assume its final form as follows (this rule was actually used by an agent on December 31, 2014):

- If the stock price goes down 20.7% in last 71 trading days, take a long position.
- If the stock price goes up less than 12.46% in last 13 trading days, take a short position.

The rationale for the best performer's decision rules basically states that an investor should track the past performance of a particular stock for a long time, and then make a decision whether to get in the market or not. As for the exit strategy, if the trend of the stock does not follows the investor's expectations, then the investor should clear all positions immediately.

7. Discussions, Conclusion, and Future Work

This agent-based model allows investors to see the behind-the-scene actions of agents, as well as to make long-range forecasts of the anticipated behavior of agents. The CAS stock-trading model provides a higher return on

investment when it takes into consideration optimized levels of learning aggressiveness and trust, as compared to the benchmarks of S&P 500 and BAC in the same timeframe.

The top agents in our simulations have a very aggressive learning style. They learn very fast once they have access to the best performers. With a high speed of learning, they are able to get trading rules that work best in the current market environment. Also, these agents believe in following market trends. They tend to react to the latest market changes more aggressively than other agents. Once they realize that their strategies are not maximally profitable in the market place, they immediately lower their trading thresholds for taking or clearing positions. This trading style makes it possible for these agents to prevent further loss when they make incorrect decisions.

Since in this simulation investors have to decide between BAC shares and money with a fixed interest rate, policy makers could try to test various options using this model to see the market reactions to differing scenarios. With varying interest settings, agents may exhibit preferences toward the stock or money. Rationality also plays an important role in the stock price determination, because rationality is affected by the supply and demand of the stocks. Irrational markets occasionally display bubble phenomena. The interest rate setting may be able to control the formation of bubbles and indeed ensure that economy is healthy.

In the future, we will use multiple underlying assets, selected from different sectors of the S&P 500, in order to test the performance of this model and evaluate different market reactions to the change in interest rates. Policy makers may then use this model to test the impact of different interest rate settings under various market conditions, in order to confirm or disprove the desired changes in the financial markets. When used in this way, the model may be able to work as a new tool for policy makers, and help them improve the effectiveness of their recommended policies.

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Generating Anthropological and Archeological Hypotheses in Okinawa through Agent-Based Simulation

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Abstract

This paper proposes an agent-based simulation (ABS) technique applied to generating anthropological and archeological hypotheses. The basic idea is to develop a method to search for valid parameter sets of ABSs through intensive simulation experiments. In this case study, we focus upon the diffusion process of the agriculture and pottery in the Gusuku period (eleventh–fourteenth centuries) in Okinawa, Japan. Following our intensive simulation results, we propose plausible but falsifiable hypotheses: (1) agriculture spread rapidly among native people and was, in the early stages, performed mainly by native people; and (2) the immigrant-style pottery was mostly used by immigrants and was not widely diffused among native people. These hypotheses should be verified by the new discovery of anthropological and archeological evidence. Therefore, these ABSs will contribute to the literature in the fields of anthropology and archeology in Japan.

Keywords: *anthropology, archeology, hypothesis generation*

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1. Introduction

Anthropology and archeology are disciplines where human history is reconstructed by research into materials such as animal and plant residues, and the remains of human bones, artifacts (e.g., stone tools and pottery), and architecture. Recently, many excavations have been performed and much anthropological and archeological evidence has been accumulated. Therefore, several cross-sectional situations at times and places in the past have been revealed by research into anthropological and archeological evidence. However, if any changes occurred between cross-sectional situations, researchers need to generate hypotheses for these changes.

To generate hypotheses in conventional anthropology and archeology, researchers have used the few materials available. Subsequently, they verify their hypotheses by investigating other evidence. However, missing materials and researchers' limitations can make it difficult to generate hypotheses. Even when hypotheses can be generated, these are often simple and of limited number.

We are developing novel techniques to generate systematically plausible and falsifiable hypotheses through agent-based simulations (ABSs). So far, we have applied these techniques to ancient Japanese history; in particular, the native Jomon people played a formative role in the establishment of agrarian culture on the Japanese mainland (Sakahira & Terano, 2014a, 2014b). In this paper, we will apply the same method to another Japanese case. Using a generative approach ABSs explain emergent phenomena (Epstein, 2007), therefore, they enable us to generate more numerous and complex assumptions than those generated by conventional methods. Additionally, these hypotheses enable us to narrow the ways of interpreting other currently undiscovered evidence.

In our previous papers (Sakahira & Terano, 2014a, 2014b), we discussed the problem of population dynamics after the introduction of agriculture on the Japanese mainland. The hypotheses were generated by ABSs. In the Japanese anthropological and archeological problem of whether the native Jomon people or Chinese–Korean immigrants played a formative role in the establishment of agrarian culture during the Yayoi period (300 BC–250 AD), which has long been a source of controversy (Fujio, 1999), we generated a new hypothesis that native Jomon people played a formative role in the establishment of agrarian culture by ABSs.

For most anthropological and archeological studies in Japan, the required data, especially paleoenvironmental records, are not widely available However, even if there are less data available, ABSs are able to compensate for this paucity of data. Referring to the conclusions of our previous papers, we will execute the same arguments in a different context in Japanese history.

In this paper, we deal with the case of the contact between hunter–gatherers and agrarian cultures in the Okinawa Islands of the southern Japanese archipelago.

It is thought that agriculture was introduced to the Okinawa Islands from the ninth to the tenth century, before the start of the Gusuku period in the eleventh century (Takamiya, 2002).

This hypothesis is supported by the discovery of grains excavated from ninth century ruins. The sudden onset of agriculture is assumed to be because of the immigration of agricultural peoples.

There were large differences before and after the start of the Gusuku period. First, there was a population explosion: there are seven times more ruins in the Gusuku period than in the Shell midden period, an antecedent of the Gusuku period (Takamiya, 2005). It is thought that the population increased during the Gusuku period because of the start of agriculture. Second, there were large differences in anthropological morphology. The bones of the people before the Gusuku period indicate that they had low and small faces (Asato & Doi, 2011; Doi, 1998; Doi, Hirata, Zukeran, & Sensui, 1997), while the bones of the people in the Gusuku period show that they were heavyset and tall, with dolichocephaly (long narrow head). It is assumed that this change also follows the population replacement by the immigrants bringing agriculture from the Japanese mainland. Third, in evidence of immigrants bringing agriculture from the Japanese mainland, there is a study of ancient mitochondrial DNA (mtDNA) from the people of the Gusuku period (Shinoda, Kakuda, & Doi, 2013). The mtDNA haplogroup D4, which has high frequency on the Japanese mainland, also has high frequency in the people of the Gusuku period. Fourth, there were large differences in the style of pottery. In the Gusuku period, while the pottery of the distribution products—which is influenced by the pottery style of the Japanese mainland—was widely propagated, the style of pottery made in the settlement varied from the conventional native style to a different style, which is an imitation of the distribution products (Miyagi, 2011).

However, the process of these changes following the introduction of agriculture is unknown. Therefore, we apply ABSs to the hypothetical processes of the anthropological and archeological change following the introduction of agriculture. Similar to our previous study (Sakahira & Terano, 2014b), the ABSs in this paper deal with the diffusion process of the trait gene, mtDNA, and the vertical transmission of pottery styles under agricultural diffusion. In this study, we also add the horizontal transmission of pottery styles to the previous simulation model.

2. Description of the Simulation Model based on ODD Protocol

Our simulation model follows the Overview, Design concepts, and Details (ODD) protocol (Grimm et al., 2006; Grimm et al., 2010). This protocol is intended to address the criticism that agent-based models lack reproducibility. Furthermore, it aims to improve the integrity and standardization of the model description.

2.1 Agent and State Variable

The agent in our model was defined as an ancient person with the following variables.

Identity (ID) Number and Spatial Placement: The following information was assigned to an agent: an ID number and a coordinate position [X: 50 cells, Y: 50 cells] within a two-dimensional space. This space represented the main island of Okinawa. Within our simulation model, the simulation space represented a very abstract space. This meant that the space was not directly related to real geographical space, because we mainly focused on discussing the relative diffusion of trait genes, mtDNA, and pottery style and agriculture. Considering the gene flow and pottery style relative to the speed of agricultural diffusion, the abstract space was sufficient for considering the issues at hand. The size of the space within our simulation was defined by the speed of diffusion of agriculture as described below.

Sex: The agent was male or female.

Life Expectancy and Age: Upon creation (birth), an agent was given an individual life expectancy based on the mortality table. If the age of the agent exceeded the life expectancy, the agent was removed (died). Supposing that the mortality table has not changed from ancient times up until the modern period, we created this by reflecting an infant mortality rate of 20% up to recent years on that of people of the Jomon period (Nagaoka, Sawada, & Hirata, 2008). *Food Production System*: The food production system variables were hunting and gathering or agriculture. This system changed from hunting and gathering to agriculture through the diffusion of agriculture based on the assumption that the difficulty of food obtained by hunting and gathering in the late Shell midden period, an antecedent of the Gusuku period, introduced an opportunity for this conversion process (Takamiya, 2002). However, we assumed that the opposite condition did not hold, because there is no evidence of the diffusion of hunting and gathering during this period.

Marriage Institution: The marriage institution variable for the male agent was monogamous or polygamous. To date, the type of marriage institutions that prevailed during the Shell midden period and the Gusuku period have not been ascertained. However, in the Yayoi period (300 BC–250 AD) of the Japanese mainland, it has been assumed that polygamous marriage occurred based on descriptions of this type of marriage contained in "*Gishi-Wazin-Den*," an ancient Chinese text on the Yayoi period customs. According to this text, some men of high status had four or five wives, and there were even some men of normal

status who had two or three wives. Therefore, together with other references, it is assumed that polygamous marriage has been widely diffused in the Japanese mainland from the Yayoi period up until the early modern period. Additionally, we postulated that sustaining more than one wife—polygamous marriage—requires a surplus of food. Therefore, in our simulation model, if the male agent included both of the following variables: polygamous and a high-yielding food production system, namely agriculture, then the agent was assumed to be married to three female agents. A new agent (child) inherited the father agent's marriage institution.

Trait Genes: Trait genes determine trait characteristics. Originally, it was thought that trait characteristics are determined through the involvement of many genes in a complex manner. However, to simplify this for the simulation, it is assumed to be composed of a major pair of alleles: the native-type gene (N) and the immigrant-type gene (M). When a new agent (child) is created (born), the agent inherits either of the father agent's and either of the mother agent's alleles, that is, the agent's combination of alleles is NN, MM, or NM. In accordance with these combinations, each agent is classified as one with native or immigrant traits. Specifically, a NN agent comprises traits of the native people, a MM agent comprises immigrant traits, and a NM agent displays mixed traits (mixed people) and comprises immigrant traits, because the individuals were determined to be immigrants based on the assumption that a person with even a small amount of immigrant traits is an immigrant.

MtDNA Haplogroup: The mtDNA haplogroup variable for an agent was haplogroup D4, haplogroup M7a, or other. The mtDNA, which is the cell organelle DNA of mitochondria, is inherited maternally and relatively easy to extract from human bone remains. Therefore, mtDNA analysis is a useful way of investigating the origin of the maternal line of ancient peoples. In the frequency of the mtDNA haplogroup of people of the Gusuku period, the frequency of M7a, considered as native type, was 28.6%. In contrast, the frequency of D4, with high frequency in the Japanese mainland, was 35.7% (Shinoda, Kakuda, & Doi, 2013). In our simulation model, when a new agent (child) was created (born), the agent inherited the mother agent's mtDNA haplogroup as described ahead.

Pottery Style: The pottery style variable was either the native style or the immigrant style. In our simulation model, for the sake of convenience, we restricted the pottery style to either the native or immigrant styles. The argument made by Tsude (1982) that women produced pottery during the Yayoi period is supported by an extensive ethnographic literature

(Murdok & Provost, 1973). Therefore, within the field of Japanese archeology, it has generally been held that it was women who produced pottery during ancient times. Therefore, in our simulation model, the inheritance of pottery is assumed to be maternal. Additionally, because the pottery style had rapidly become varied, we must consider that the diffusion pattern of pottery styles contains not only the vertical transmission, but also the horizontal transmission. Therefore, as will be described later, we also simulate the horizontal transmission in addition to the vertical transmission. The horizontal transmission also shows reversibility, that is, there are changes not only from the native style to the immigrant style, but also from the immigrant style to the native style.

2.2 Process Overview and Scheduling

Our simulation model proceeded according to annual time steps; the annual time step was a year. Each year, the four submodels of each agent were executed in turn as follows: diffusion of the agriculture rule, diffusion of the pottery style rule, marriage rule, and moving rule. Additionally, agents were processed in a random order during each year.

2.3 Design Concepts

Our simulation model corresponded to 7 out of the 11 design concepts contained in the ODD protocol (Table 1). The model was simple, and we considered that the description of the model and design concepts was sufficient to indicate reproducibility.

Table 1: Design concepts

Number	Design concepts	Elements
1	Basic principles	Trait gene, mitochondrial DNA (mtDNA) haplogroup, and pottery style were diffused under the increased population based on the food production system by the diffusion of agriculture
		・For the diffusion of agriculture and pottery styles, we apply the SI (susceptible-infected) model
		・For the increase of people, we apply Malthus' theory
		・For the inheritance of the trait gene, we apply Mendel's laws

2	Emergence	The population explosion, the demographic transition, the replacement of pottery styles, and the high-frequency mtDNA haplogroup D4
3	Adaptation	・If an agent is near another agent with agricultural culture, it introduces an agricultural culture at a given rate
		・If an agent is near another agent with another style of pottery, it introduces another pottery style at a given rate
4	Sensing	・Recognizing whether an agent is near another agent with agriculture
		・Recognizing whether an agent is near another agent with the another pottery style
		・Recognizing whether a male agent is near the female agent
5	Stochasticity	・Life expectancy
		・Spatial placement at the start of the simulation
		・Allocation of mtDNA haplogroup at the start of the simulation
		・Introduction of agriculture
		・Introduction of pottery style
		・Selection of female agent for marriage
		・Sex of child agent
		・Combination of trait genes
		・Movement in random direction
6	Collectives	The number of agents created is determined by the number of hunter–gatherer or agricultural agents
7	Observation	・Total number of agents
		・Proportion of people with immigrant traits
		・Frequency of mtDNA haplogroup D4
		・Proportion of the immigrant-style pottery
		・Compositional proportion of each descendant of agricultural culture holders
		・Compositional proportion of each descendant of the immigrant-style pottery holders

2.4 Submodels

Diffusion of the Agriculture Rule: The diffusion of agriculture occurred through neighboring agents and inheritance from a father agent. In our simulation model, we assumed that these very simple patterns of cultural transmission followed the conventional susceptible–infectious (SI) model of infectious diseases.

In the diffusion from a neighboring agent, if the agent's food production system was hunting and gathering, while that of all the other neighboring agents was agriculture within a given cell radius (the extent of diffusion occurring within a cell range was: one cell [narrow], three cells [moderate], and five cells [wide]), the agent's food production system would then be transformed into agriculture. This transformation was based on a given probability (introduction rate: difficult 0.1%, middle 0.5%, and easy 1.0%). Conversely, in the inheritance from a father agent, and according to the marriage rule described ahead, when a new agent (child) was created (born), the agent inherited the food production system from their father agent.

Diffusion of the Pottery Style: The diffusion of pottery style occurred through the vertical transmission from a mother agent and the horizontal transmission from a neighboring agent. In the vertical transmission, as mentioned above, the argument made by Tsude (1982) that women produced pottery during the Yayoi period is supported by an extensive ethnographic literature (Murdok & Provost, 1973). Therefore, within the field of Japanese archeology, it has generally been held that women produced pottery during ancient times. Therefore, in our simulation model, the vertical transmission is the inheritance from a mother agent. In the horizontal transmission, this is reversible, that is, there are changes not only from the native style to the immigrant style, but also from the immigrant style to the native style. Specifically, the agent's pottery style would change to another pottery style used by a different agent within a given cell radius (the extent of diffusion occurring within a cell range was: one cell [narrow], three cells [moderate], and five cells [wide]). This transformation was also based on a given probability (introduction rate: impossible 0%, difficult 0.1%, middle 0.5%, and easy 1.0%).

In summary, we simulate two pottery-style diffusion patterns: (1) maternal vertical transmission pattern and (2) vertical and horizontal transmission pattern.

Marriage Rule: A new agent (child) was created (born) by the marriage of a male and a female agent. The male agent was married to a female agent selected randomly from all of the female agents within three surrounding cells. Furthermore, a new agent was created according to the population growth rate of the mother agent's food production system and at the same spatial placement as that of the mother agent. The sex of the new agent was allocated according to a 50% probability of being male, along with a life expectancy and age of 0. For the trait gene, as previously explained, the new agent inherited either of the father agent's alleles and either of the mother agent's alleles. Additionally, the new agent inherited the food production system and the marriage institution from their father agent, and the pottery style and mtDNA haplogroup from their mother agent. Moreover, as mentioned above, the male agent could be simultaneously married to three female agents only when associated with both the polygamous and agriculture variables.

Moving Rule: Within each step, an agent moved one cell in random directions within the simulated space.

2.5 Initialization

Time Span of the Simulation: The time span of our simulation was 400 years (400 steps), extending from the beginning era to the final era of Gusuku period.

Population Growth Rate based on the Food Production System: The population growth rate of agriculturalists was higher than that of hunters and gatherers. As mentioned above, there are seven times more ruins in the Gusuku period than in the Shell midden period, an antecedent of the Gusuku period (Takamiya, 2002), that is, it is thought that the population also increased in the Gusuku period at the same rate of increase. Considering these evidences, working backward from a sevenfold increase in the population over 400 years, we assumed that the increase in the agricultural population was 0.6% per year. Conversely, considering that the growth rate of the agriculturalist population had not increased during the Shell midden period, we assumed that the growth rate of the hunter–gatherer population was 0.0% per year.

Speed of the Diffusion of Agriculture: The speed of diffusion of agriculture in our simulation model comprised the range of cells associated

with the diffusion and introduction rate. The range of diffusion cells corresponded to the distance within which cultural exchange would occur while they were in contact with each other. As mentioned above, we assumed there were three possible degrees: narrow (one cell), moderate (three cells), and wide (five cells). The introduction rate corresponded to the difficulty associated with the introduction of agriculture. Here, we assumed three degrees: difficult (0.1%), medium (0.5%), and easy (1%). The level of difficulty did not relate to agricultural techniques, but rather to the adequacy of the environment and culture required for the acceptance of the new agricultural practice. These values were set assuming that even when the range of cells was narrow and the introduction rate was difficult, ~400 years were required for the majority of agents to have agriculture.

Pattern of the Diffusion of Pottery Styles: To show the pattern of the diffusion of pottery styles, as mentioned above, we simulated two patterns as follows in each simulation case.

- First pattern (vertical transmission): The pottery style is only inherited from a mother agent.
- Second pattern (vertical and horizontal reversible transmission): The diffusion of pottery styles occurred through neighboring agents and inheritance from a mother agent. Additionally, in the horizontal transmission, this is reversible, that is, there are changes not only from the native style to the immigrant style, but also from the immigrant style to the native style.

Speed of the Diffusion of Pottery Styles: Like the speed of agriculture, the speed of diffusion of pottery styles in our simulation model comprised the range of cells associated with the diffusion and introduction rates. The range of diffusion cells corresponded to the distance within which pottery style exchange would occur while agents were in contact with each other. We assumed there were three possible degrees: narrow (one cell), moderate (three cells), and wide (five cells). The introduction rate corresponded to the difficulty associated with the introduction of a pottery style. Here, we assumed four degrees: impossible (0%), difficult (0.1%), medium (0.5%), and easy (1%).

State Variables of the Initial Native People and Immigrants: The simulation run commenced with the initial native people and immigrants whose state variables are described ahead.

Initial native people.

- Number of agents: 1800
- Sex proportion: male and female 50% each
- Trait gene: NN
- Spatial placement: uniformly and randomly placed
- Food production system: hunting and gathering
- Marriage institution: monogamous
- Pottery style: native style
- MtDNA haplogroup: In total, 0.0% had haplogroup D4, 47% had haplogroup M7a, and 53% had another haplogroup. With reference to Shinoda and Doi (2008), Shinoda, Kakuda, and Doi (2012), and Shinoda, Kakuda, and Doi (2013), we calculated the frequencies except for the haplogroup D4, which was derived from the Japanese mainland.

Initial immigrants.

- Number of agents: 200
- Sex proportion: male and female 50% each
- Trait gene: MM
- Spatial placement: placed in the center of the upper side of the simulated space [X: 25, Y: 50]
- Food production system: agriculture
- Marriage institution: monogamous or polygamous in each simulation case
- Pottery style: immigrant style
- MtDNA haplogroup: With reference to Sakahira (2007), the frequency of mtDNA of medieval people on the Japanese mainland, 53.0% had haplogroup D4, 7% had haplogroup M7a, and 40% had another haplogroup.

2.6 Number of Simulation Cases and the Evaluation Index

There were a total of 180 simulation cases—that is, cases combining each of the above-mentioned parameters. In each simulation run, the number of agents might increase from 200 to 20,000. This means that each run takes very long computation time. Thus, although the numbers of runs are not enough,

all cases were run only 10 times. The random seed value of these 10 runs was the same across cases. The improvement of computational efficiency will be one of our future issues.

The main evaluation index in our simulation results was the total number of agents, the proportion of people with immigrant traits, the frequency of mtDNA haplogroup D4, and the proportion of the immigrant-style pottery across all agents 400 years later.

For the total number of agents, we investigated how much the population increased among cases. For the proportion of people with immigrant traits, 80% was considered a measure of demographic transition. For the frequency of mtDNA haplogroup D4, with reference to Shinoda, Kakuda, and Doi (2013), the value of 35% is regarded as the results along the anthropological facts. For cases that met these requirements, we depicted a time series of the compositional proportion of each descendant of the agriculture holders to investigate who had performed agriculture.

Additionally, to discuss the pottery-style diffusion patterns, among cases of only vertical transmission and cases of vertical and horizontal transmission, we investigated how much the proportion of immigrant-style pottery is high. Furthermore, in cases in which the proportion of immigrant-style pottery was more than ~80%, we investigate how to diffuse the immigrant-style pottery by depicting a time series of the compositional proportion of each descendant of the immigrant-style pottery holders.

3. Results and Discussion

3.1 Difference in the Total Number of Agents Depending on the Speed of Agricultural Diffusion

The total number of agents varied depending on the speed of diffusion of agriculture. Cases in which the speed of agricultural diffusion is rapid (e.g., a wide [five cells] range of diffusion cells and an easy introduction rate [1%]) had a larger total number of agents than cases in which the speed of agricultural diffusion is slow (e.g., a narrow [one cell] range of diffusion cells and a difficult introduction rate [0.1%]) (Figure 1). Considering these, we generated a hypothesis that the reason for population explosion in the Gusuku period is that agriculture had been diffused quickly and widely. The results coincide with our intuitions; however, the interpretations of the results should be further investigated, whether they are a possible simulation artifact or it is a natural outcome.

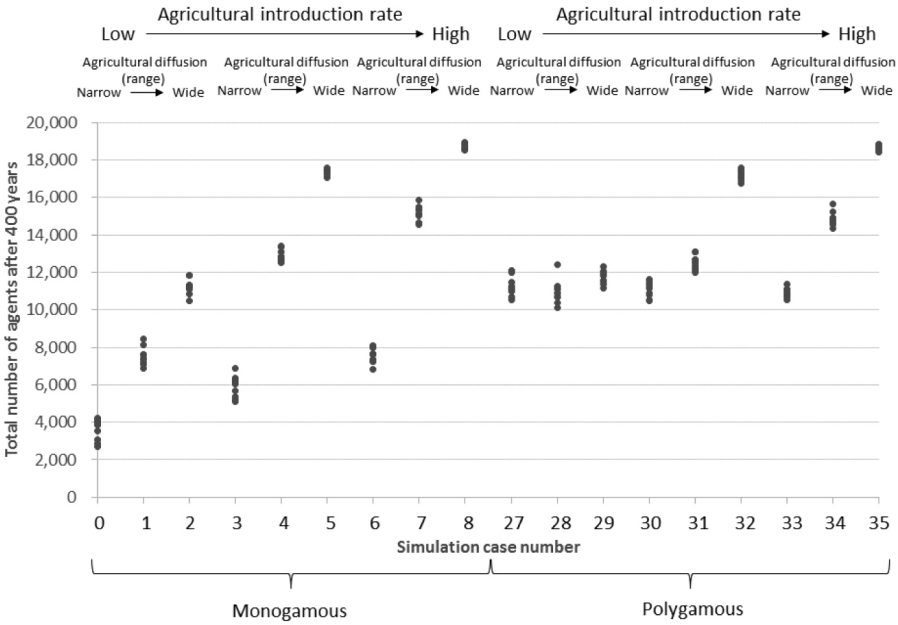

Figure 1. Difference in the total number of agents depending on the speed of agricultural diffusion.

3.2 Difference in the Proportion of People with Immigrant Traits and the Frequency of mtDNA Haplogroup D4 Depending on the Marriage Institution and the Speed of Agricultural Diffusion

Cases of Monogamous Marriage: In the proportion of people with immigrant traits and the frequency of mtDNA haplogroup D4 400 years later, all cases of monogamous marriage did not reach 80% of the proportion of people with immigrant traits, which is a measure of demographic transition and 35% of the frequency of mtDNA haplogroup D4 (Figure 2). In general, cases in which the speed of the diffusion of agriculture was slow (e.g., a narrow [one cell] range of diffusion cells and a difficult introduction rate [0.1%]) indicated a higher proportion of people with immigrant traits and a higher frequency of mtDNA haplogroup D4. Conversely, cases in which the speed of the diffusion of agriculture was rapid (e.g., a wide [five cells] range of diffusion cells and an easy introduction rate [1%]) indicated a lower proportion of people with immigrant traits and a lower frequency of mtDNA haplogroup D4. Demographic transition did not occur because once agriculture had diffused among native people at an early stage, their population increased at a high rate of agricultural population growth.

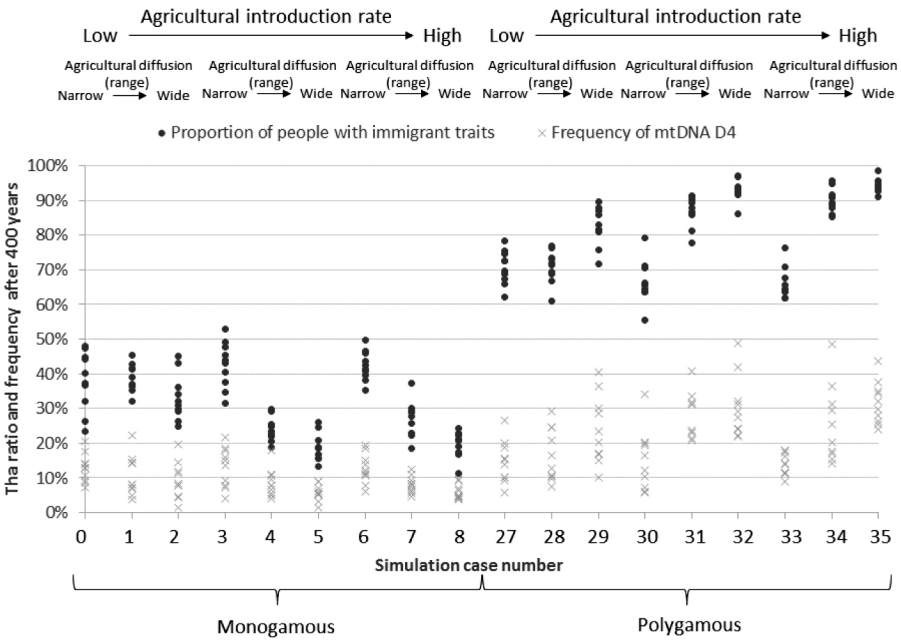

Figure 2. Difference in the proportion of people with immigrant traits and the frequency of mtDNA haplogroup D4 depending on the marriage institution and the speed of agricultural diffusion.

Cases of Polygamous Marriage: The proportion of people with immigrant traits and the frequency of mtDNA haplogroup D4 after 400 years varied depending on the speed of the diffusion of agriculture (Figure 2). In cases of polygamous marriage, some cases of slow-speed diffusion of agriculture did not achieve a population of 80% with immigrant traits and 35% with mtDNA haplogroup D4 after 400 years. By contrast, some cases demonstrating a significant speed of agriculture diffusion demonstrated a population of 80% with immigrant traits and 35% with mtDNA haplogroup D4 after 400 years. These results demonstrate that in cases in which polygamous marriage was combined with the diffusion of agriculture, demographic transition was facilitated by the wider diffusion of agriculture. This could be attributed to a time lag between the diffusion of agriculture and polygamous marriage, which influenced the increasing populations of native people and immigrants. Specifically, the density distribution of immigrants meant that the number of immigrants increased during the earliest stage. However, polygamous marriage and mtDNA haplogroup D4 remained within immigrants because these traits were inherited from parent agents. Consequently, the neighboring native people came to possess agriculture by diffusion. Furthermore, in a situation in which immigrant neighbors engaged in

agriculture displayed a higher population growth rate, the immigrant trait gene type and mtDNA haplogroup D4 were diffused through polygamous marriage. That is, for wider diffusion of the immigrant trait gene type and mtDNA haplogroup D4 to occur, it was necessary for immigrant neighbors to demonstrate use of agriculture and a higher population growth rate. Although whether there is a polygyny marriage has been unknown in Gusuku period, our simulation results suggest the possibility of the existence of a marriage institution in which people with immigrant trait genes and mtDNA haplogroup D4 can be distributed preferentially.

To discuss the diffusion process of agriculture in the Gusuku period, we investigated who had performed agriculture. The compositional proportion of descendants of those practicing agriculture showed a slight degree of mixing of native and immigrant descendants but that immigrant descendants constituted the majority at the early stage in cases that entailed slow diffusion of the agriculture (Simulation case number 29, Run 7) (Figure 3). Both descendants thus came to account for most of those who engaged in agriculture as a result of marriage. These results suggest, as our first hypothesis, that agriculture was performed mainly by immigrants in the Gusuku period. In contrast, for cases demonstrating significant and rapid diffusion of agriculture, at the earliest stage, only the descendants of immigrants were the holders of agriculture. However, shortly thereafter, native descendants constituted the majority (Simulation case number 35, Run 9) (Figure 4). Consequently, both descendant groups became the majority group through marriage. These results indicate that it is probable that even if agriculture was widely diffused among the native people, demographic transition could occur. These results suggest, as our second hypothesis, that agriculture was introduced to and performed mainly by native people in the Gusuku period. Both these hypotheses are probable. However, as described previously, considering that the reason for population explosion in the Gusuku period is the rapid and wide diffusion of agriculture, the latter hypothesis that the speed of agricultural diffusion was rapid and agriculture was performed mainly by native people is more probable.

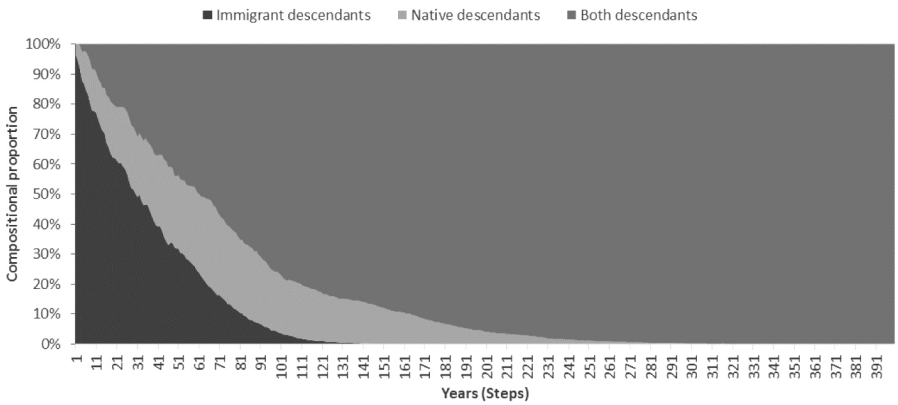

Figure 3. Compositional proportion of each descendant with agricultural holders in cases that the diffusion speed of agriculture was slow (Simulation case number 29, Run 7).

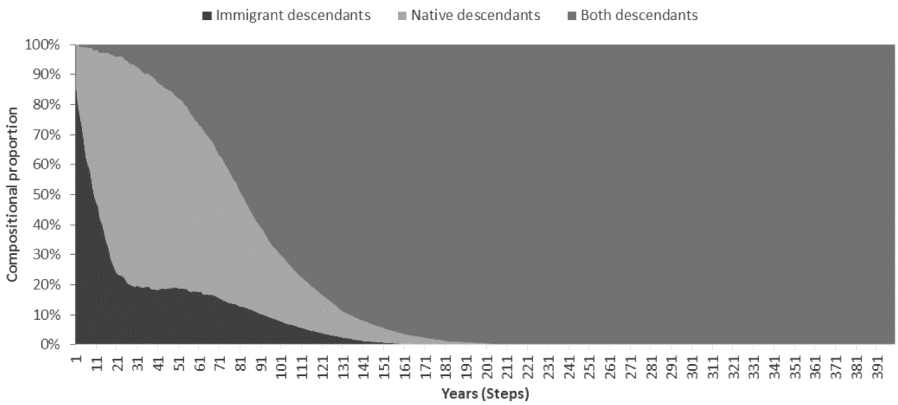

Figure 4. Compositional proportion of each descendant with agricultural holders in cases that the diffusion speed of agriculture was rapid (Simulation case number 35, Run 9).

In summary, our simulation generated new hypotheses about the processes of population explosion and agricultural diffusion. These are as follows: (1) agriculture was introduced by immigrants and diffused widely and quickly among native people; (2) rapid diffusion of agriculture among the native people created the population explosion in the Gusuku period; and (3) during the population explosion, demographic transition occurred by through the marriage institution (e.g., polygamous marriage) to distribute the immigrant trait gene and mtDNA haplogroup D4 preferentially.

3.3 Diffusion of Pottery Styles

Vertical Transmission of Pottery Styles: In cases of polygamous marriages, even in only the vertical transmission of pottery styles, the proportion of immigrant-style pottery in the cases of rapid diffusion of agriculture (e.g., a wide [five cells] range of diffusion cells and an easy introduction rate [1%]) is higher than that in the cases of slow diffusion of agriculture (e.g., a narrow [one cell] range of diffusion cells and a difficult introduction rate [0.1%]) (Figure 5). The reason is assumed to be that after the female immigrant population increased by polygamous marriage within immigrants in the earliest period, during the population explosion by diffusion of agriculture among native people, the immigrant-style pottery was widely diffused though marriage with many female immigrants. These results support the hypothesis that the speed of agricultural diffusion was rapid and agriculture was performed mainly by native people. The process of pottery diffusion in this case is that immigrant-style pottery had been held mostly by immigrants and had not been diffused among native people because of vertical transmission without horizontal transmission.

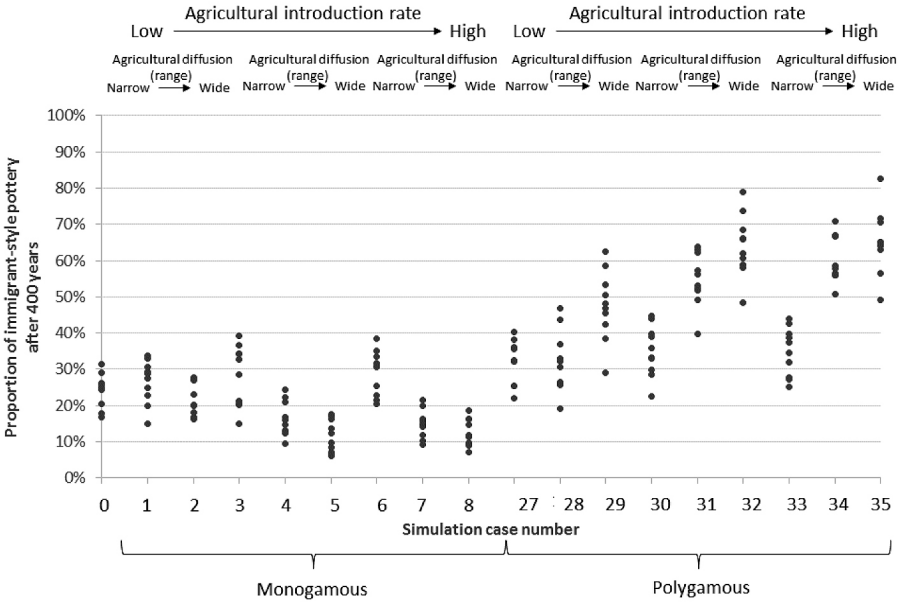

Figure 5. Difference in the proportion of immigrant-style pottery depending on the speed of agricultural diffusion in the vertical transmission of pottery styles.

Vertical and Horizontal Transmission of Pottery Styles: In the case of polygamous marriage and slow speed of diffusion of pottery styles, the high diffusion proportion of immigrant-style pottery holders was shown

because the effect of vertical transmission of pottery style is stronger than that of horizontal transmission (Figure 6, Simulation case number 194). The reason is the same as previous. Moreover, the proportion of immigrant-style pottery after 400 years varied depending on the speed of the diffusion of agriculture. The proportion of immigrant-style pottery holders in the cases of rapid diffusion of agriculture is higher than that in the cases of slow diffusion of agriculture (Figure 6). These results are same as those of only the vertical transmission of pottery styles. Therefore, the difference between the vertical transmission of pottery and the vertical and horizontal seem not to be necessary important in our model.

However, in cases of the rapid diffusion of pottery styles, because of the reversibility of changes in pottery styles, there are some runs in which the immigrant-style pottery disappeared by stochasticity. Concretely, in cases of the rapid diffusion of agriculture and pottery styles, there are some runs in which the immigrant-style pottery was dominant and there are some runs in which the immigrant-style pottery disappeared. That is, in cases of the rapid diffusion of agriculture and pottery styles, the dominance of immigrant-style pottery had been by chance unlike the dominance of agriculture. Investigating the process of pottery-style diffusion in these cases, there is only a slight difference between slow pottery diffusion (Figure 7) and rapid pottery diffusion (Figure 8) in the proportion of native descendants with immigrant-style pottery holders. That is, in both cases, within the immigrant-style pottery holder group, native descendants were small.

In summary, our simulation generated new hypotheses of the diffusion process of pottery styles. These are as follows: (1) the high proportion of immigrant-style pottery holders needs polygamous marriage and rapid speed of agricultural diffusion. The result that the high proportion of immigrant-style pottery holders need rapid agricultural diffusion supports the assumption that the change of pottery styles is indivisible with agriculture (Shinzato, 2002); and (2) in such conditions, immigrant-style pottery had been held mostly by immigrants and had not been widely diffused among native people.

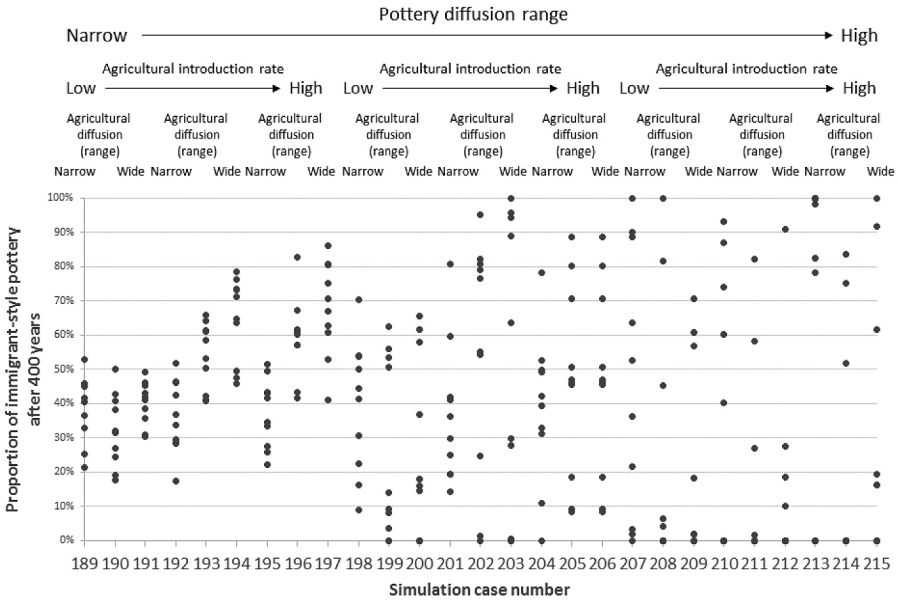

Figure 6. Difference in the proportion of immigrant-style pottery holders depending on the speed of agricultural diffusion and pottery-style diffusion in the vertical and horizontal transmission of pottery styles in cases of polygamous marriage.

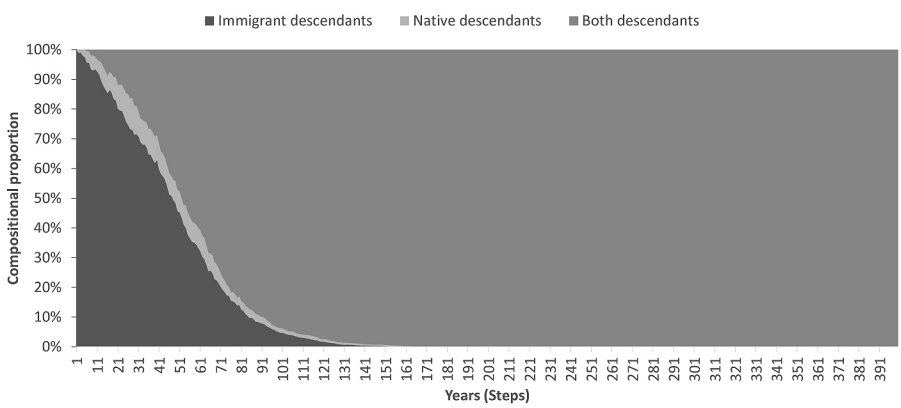

Figure 7. Compositional proportion of each descendant within the immigrant-style pottery holder group in cases of rapid diffusion of agriculture and slow diffusion of pottery styles (Simulation case number 194, Run 9).

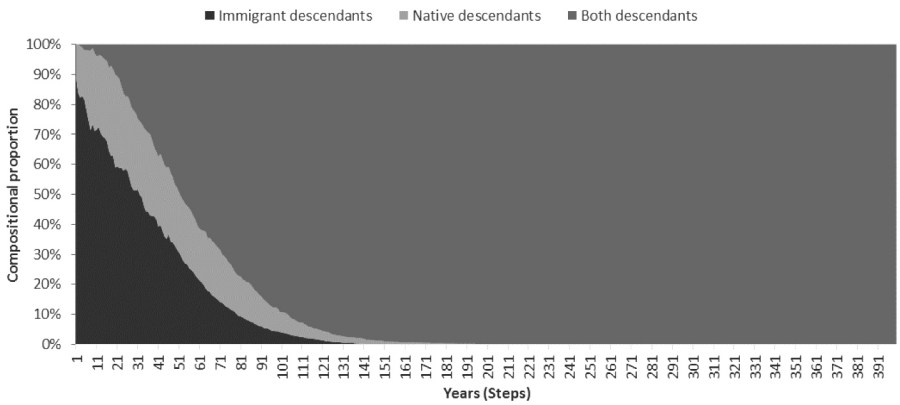

Figure 8. Compositional proportion of each descendant within the immigrant-style pottery holder group in cases of rapid diffusion of agriculture and pottery styles (Simulation case number 215, Run 7).

4. Conclusion

In this paper, we generated new hypotheses about the process of population explosion, agricultural diffusion, and pottery-style diffusion. Although these hypotheses are only hypotheses based on simulation results, they have falsifiability. Specifically, for the process of population explosion and agricultural diffusion, the hypothesis that, during polygamous marriage, agriculture spread rapidly among native people and was, in the early stages, performed mainly by native people could be verified by the discovery of human bone remains of peoples with native traits, along with artifacts verifying the existence of agriculture before and after the start of the Gusuku period. Additionally, for the pottery-style diffusion process, the hypothesis that during polygamous marriage, the high proportion of immigrant-style pottery holders need rapid agricultural diffusion and that the immigrant-style pottery had been held mostly by immigrants and had not been widely diffused among native people would be disproved by the discovery of the bone remains of peoples with native traits, along with immigrant-style pottery before and after the start of the Gusuku period.

Within Japanese anthropology and archeology, it is difficult to apply the ABSs developed in the famous pioneering studies on factors relating to the residential transition of the Anasazi tribe (Dean et al., 2000). As mentioned previously, that is because the required data, especially paleo-environmental records, are not widely available. However, in hypothesis generation such as in this study, the hypotheses based on simulation results with falsifiability would be able to facilitate the new discovery of anthropological and archeological evidence. This study reinforced our assertion that even if there are less data available, ABSs are able to

compensate for this paucity of data and generate hypotheses [2]. The technical limitations of our simulation model is that we only run the limited number of simulations and that we fail to explore the very large parameter space, because of our computational abilities. Mathematical analyses of our simulation model, such as nonlinear dynamics, may provide us with the further insights on the history simulation studies. These are our future problems.

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The End of (Traditional) Emergence: Introducing Reactive Emergence

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Abstract

Emergence is not a mystery; it is the realization of properties that do not derive (directly) from the properties of the realization's constituents. A concrete canoe floats in water, a property that derives primarily from how its components are arranged, not primarily from the components themselves. Since emergence typically involves an entity whose components are organized in specific ways, the means that hold the components together and allow for that organization become fundamental. Negative interaction energy (from fundamental physics) holds static structures together. Emergent phenomena built with negative interactive energy have less mass than their components considered separately. I call the creation and persistence of such structures general evolution. When added to negative interaction energy, self-management (i.e., autopoietic) activities (as in biological organisms) hold dynamic structures together. Emergent phenomena built with self-management activities have more mass than their components considered separately. I analogize type creation in programming languages to these mechanisms.

Since the preceding clarifies most (traditional) emergence issues, labeling phenomena emergent adds little additional value. Given its baggage and minimal utility, we might be better off abandoning the term. Then what is reactive emergence? Public policies famously have unintended consequences. I explain why such phenomena—and in fact why reactions to many policy-based changes to our living and working environment—should be considered a form of emergence.

Keywords: *emergence, energy accumulation and release, implementation, interaction energy, reactive emergence, realization, specification, type creation, unintended consequences*

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1. The Continuing Mystery of Emergence[1]

Since Aristotle noted, "The whole is more than the sum of its parts" (Aristotle, 1989, Meta 10f-1045a) emergence has seemed like a free lunch: you put a bunch of things together and something new (and surprising, interesting, and useful) may pop out.

Emergence is one of a web of ideas associated with what has come to be known as complex systems. According to Google's *Ngram* website,[2] usage of the terms *complex system* and *emergence* peaked just before the turn of the century.[3] At about the same time, philosophers like Jerry Fodor and philosophically minded computer scientists like Cosma Shalizi described emergence in quasi-mysterious—and even explicitly mysterious—terms.

Molto Mysterioso. Damn near everything we know about the world suggests that unimaginably complicated to-ings and fro-ings ... at the extreme micro-level manage somehow to converge on stable macro-level properties. The "somehow" really is entirely mysterious. How can macro-level stabilities supervene on a buzzing, blooming confusion of micro-level interactions? ... Why is there anything except physics? Well, I admit that I do not know why. I do not even know how to think about why. I expect to figure out why there is anything except physics the day before I figure out why there is anything at all (Fodor 1997).[4]

Someplace where quantum field theory meets general relativity and atoms and void merge into one another, we may take to be given—as an empirical fact, not susceptible to any meaningful explanation—the rules of the game. But the rest of the observable, exploitable order in the universe—benzene molecules, $PV = nRT$, snowflakes, cyclonic storms, kittens, cats, young love, middle-aged remorse, financial euphoria accompanied with acute gullibility, prevaricating candidates for public office, tapeworms, jet-lag, and unfolding cherry blossoms—where do all these regularities come from? They are connected to the fundamental physics somehow, just like pawn formations and end games are connected to the rules of chess, but how do you get from one to the other? Call this emergence if you like—it is a fine-sounding word, and brings to mind southwestern creation myths in an oddly apt way. However, doing so just marks a mystery, without explaining anything (Shalizi,1998).

A decade later, emergence had sunk from mystery to muddle. The following is from the 'Introduction' to Bedau and Humphreys (2008).

1 The first three sections of this paper talk about emergence as traditionally understood. For simplicity, I use the term *emergence* rather than *traditional emergence*.

2 See http://bit.ly/1IHWZal.

3 By 2008, the last year for which data is available, usage had declined by about 1/3.

4 Fodor did not use the term *emergence*, but the phenomena he describes are associated with it.

- When we finally understand what emergence truly is [we will know] whether there are any genuine examples of emergence.
- How should emergence be defined? ... Irreducibility, unpredictability, conceptual novelty, ontological novelty, supervenience?
- In what ways are emergent phenomena autonomous from their emergent bases, irreducible to their bases, inexplicable from them, unpredictable from them, supervenient on them, multiply realizable in them?
- Does emergence necessarily involve novel causal powers, especially powers that produce "downward causation?"
- Emergence ... is simultaneously palpable and confusing.
- The very idea of emergence seems opaque, and perhaps even incoherent.

Philosophical uncertainly about emergence can be tracked by how philosophers have thought about Gresham's law[5] over the past four decades. Fodor (1974) pointed to Gresham's law to illustrate the autonomy of the special sciences. A third of a century later, Loewer (2008) and then Papineau (2009) argued that Gresham's law is not emergent. Half a decade after that, Pigliucci (2013) claimed that Gresham's law is *prima facie* evidence for *ontological* emergence. Two years later, O'Connor and Wong (2015)[6] said that Gresham's law is a form of *epistemological* emergence. In short, philosophers have long been—and remain—divided about emergence.

2. Demystifying Emergence

2.1 Nonreductive Physicalism

Loewer (2009) established a solid foundation for discussions of emergence.[7]

According to Non-Reductive Physicalism Light (NRPL), the special sciences contain vocabulary/concepts that are conceptually independent of the concepts/vocabulary of physics ... A biologist may have evidence that a biological

5 Gresham's law asserts that if two mintings of a coin have the same face value but different intrinsic values (because of the metals of which they are made differ) those with the greater intrinsic value will be hoarded while those with the lesser intrinsic value will circulate. In slogan form: bad money drives out good.

6 O'Connor and Wong's "Emergent Properties" in the *Stanford Encyclopedia of Philosophy* might be considered the definitive survey of *emergence*. O'Connor and Wong define *emergence* as follows. "Emergent entities (properties or substances) 'arise' out of more fundamental entities and yet are 'novel' or 'irreducible' with respect to them." They note that "each of the quoted terms is slippery in its own right" and that different ways of understanding them "yield varied notions of emergence."

7 Like Fodor, Loewer did not use the term *emergence*, but his point is the same.

generalization is lawful (think of the Mendelian laws) without having any idea how this regularity is rendered lawful or implemented by fundamental laws of physics, even though the former is grounded in the latter. NRPL holds that the nomological structure of the world is completely specifiable by fundamental physics. The special sciences (simply) characterize aspects of (that) structure ... that are ... amenable to scientific investigation in languages other than ... physics.

As far as it goes, I think NRPL is right: properties at levels more complex than elementary particles may be characterized independently of the properties of their constituents. In explaining how this can happen, I frequently refer to the following examples.

- Make a triangle. Use any rigid materials you want. The sum of the interior angles will be 180°. Yet that sum has nothing to do with the materials of which the triangle is made. Philosophical functionalism was built on similar observations.
- A heart acts as a pump. Even though a heart has pump functionality, that functionality is not characterized in terms of the properties of a heart's construction materials. A heart has pump functionality because (among other reasons) it is arranged as multiple *containers* with *valves* and *squeezable walls*. These properties have no more to do with the properties of the materials out of which a heart is realized than the property of being a triangle has anything to do with the materials one might use to make one. Structure and organization add new and independent properties.
- A concrete canoe floats in water, sinking until the water it displaces outweighs it. Water is displaced because the canoe's bowl-like shape excludes water. The canoe's shape is a property of the canoe as a whole, not of its component materials. As a solid block—or chopped into fragments—the same concrete sinks.

2.2 How a Whole is More than the Sum of Its Parts

There is an important difference between implementing or realizing a property and defining a property in terms of other properties. One implements a triangle, a heart, or a concrete canoe by putting various materials together. One uses those materials because they have certain properties—including being able to be put together in certain ways, and in the case of the canoe and heart being impermeable to water/blood. In that sense, the implemented property depends on properties of the implementing materials.

Nevertheless, the implemented property itself can be independent of the particular implementing material. Any suitable materials will do. This is like saying that a melody, which is notes arranged in a certain way, could not

exist without—and is therefore dependent on—the notes of which it is composed. However, the arrangement of the notes is an independent property. In this sense, the whole is more than the sum of its parts. When I talk about a property being independent of the properties of its constituents I am referring to properties that depend on and are brought about by the organization of the constituents.

2.3 What is Emergence?

Why do the interior angles of a triangle sum to 180°? The answer, of course, is that this property follows from the axioms of Euclidian geometry. If a physical implementation is true to its abstract specification,[8] its interior angles sum to 180°. I suggest it is fruitful to see emergence in terms of specifications and implementations and, as we will see, in terms of scientific models and realizations.

Turner (2014) defines a specification as "correctness criteria" and an implementation as "a realization[9] of a specification." He also distinguishes between two kinds of abstract descriptions: a specification and a scientific model.

In computer science, the specification determines the correctness of an implementation. In science, things are reversed. [The physical object determines the correctness of the scientific model.] ... When things go wrong, the blame is laid with the implementation in computer science and with the model in science.

When a property description (a model or a specification) matches the embodiment (e.g., a heart or a program), we say (a) the model correctly captures the heart's behavior, but (b) the program correctly implements the specification. The (concrete) realization and the (abstract) specification are the givens; the (abstract) model and the (concrete) implementation are derived from them.[10]

We can characterize emergence in these terms.

- Naturally occurring emergence occurs when nature happens to realize properties that are independent of the properties of the elements that play a role in the realization. We recognize the emergence of this sort by developing a model of the emergent properties. The model may be scientific,

8 Steven Weinberg suggested the triangle example in Carroll (2012). His point was that the implementation details are crucial and that they depend on the laws of physics.

9 A word about the terms *implementation* and *realization*. In the functionalist and computer science literature (including Turner) *implementation* and *realization* are often used (interchangeably) to refer to a generally physical—software being the exception—embodiment of something that satisfies a specification. An often-implicit difference between *implementation* and *realization* is that to implement tends to suggest intentionality whereas to realize does not. System developers (deliberately) implement a given specification. Nature realizes some (apparent) functionality, but with no intentionality implied.

10 On the other hand, once some functionality becomes important to survival, evolution tends to produce better and better realizations of that functionality. See Denny and McFadzean (2011).

quasi-scientific, or even just intuitive. A heart's pumping functionality is emergent in this sense.

- Fabricated emergence occurs when an entity implements a specification.

In both cases, the realized/implemented properties are characterized independently of the properties of the materials of the constituents.

3. How Emergence Happens

Emergence has traditionally been applied to entities and properties (O'Connor & Wong, 2015). In general, structure and organization provide the keys to new entities and properties.

3.1 Negative Interaction Energy

We know that a hydrogen atom consists of a proton and an electron. Why do they stay together as an entity? The answer has to do with what physicists call interaction energy (Strassler, 2012).

Interaction energy, which is born from interactions among fields and particles, can be positive or negative. Positive/negative interaction energy corresponds to what one may intuitively think of as a force pushing things apart or pulling things together. The repulsive/attractive force between two objects with the same/different electric charge is understood in terms of positive/negative interaction energy—similarly for gravity. The attractive force between two objects with mass is a consequence of negative interactive energy. As Strassler (2012) says,

The possibility that interaction energy can be negative is the single most important fact that allows for ... structure in the universe, from atomic nuclei to human bodies to galaxies.

How does this relate to the hydrogen atom? When the magnitude of the negative interaction energy between a proton and an electron reaches a high enough level, the two become a hydrogen atom.[11] The mass of a hydrogen atom is the sum of the masses of its proton and electron *plus* the mass equivalent to the interaction energy. Since the interaction energy is negative, the mass of a hydrogen atom is strictly less than the sum of the masses of a proton and an electron considered separately. Separating a hydrogen atom into its constituents, proton and electron, requires the addition of enough mass (in the form of energy) to make up for the negative interactive energy.

This framework explains, for example, how two hydrogen atoms and an oxygen atom release energy when they come together to create a water molecule. The released energy matches the negative interaction energy that remains after the

11 One must also be concerned about kinetic energy and interaction energy from another source.

water molecule is formed. The resulting entity exists in what is sometimes called an energy well.

Other static entities include those joined together by the electromagnetic forces that make nails, screws, glue, and simple friction work as binding mechanisms. The resulting entities have less mass than their constituents considered separately.

3.2 General Evolution and the Less-mass Criterion for Emergence

Negative interactive energy and the compound materials it produces give rise to what might be considered a more general form of evolution. In general, *evolution* compounds are created as combinations of existing entities. These creative activities occur both in the interior of stars and more both in the interior of stars and in more prosaically in environments like the earth. Some of those compounds have enough negative interactive energy to persist over extended periods.

The stable properties that Fodor marveled at result from this sort of evolutionary process. They are properties of compound objects held together by negative interaction energy. Because these objects persist over extended periods, they interact with each other as objects. Fodor's "to-ings and fro-ings of bits and pieces at the extreme micro-level" become irrelevant. Negative interaction energy overcomes the to-ings and fro-ings and ensures that the larger entities retain their identities and properties.

This picture suggests an alternative criterion for some forms of emergence: any phenomenon that persists[12] because of negative interaction energy. Such phenomena will have less mass than the sum of the mass of their constituents considered separately. This approach eliminates the need to talk about properties and their independence as a way to establish emergence. Abbott (2010b) called this *static emergence*.

Consider hemoglobin. A hemoglobin molecule consists of four iron atoms plus thousands of atoms of carbon, hydrogen, nitrogen, oxygen, and sulfur. Its physical and electrical structure is such that it binds oxygen molecules in the chemical environment of the lungs and releases them in the chemical environment of cells. Its oxygen binding and releasing behavior is a consequence of its structure and does not depend solely on—nor can it be either characterized in terms of— properties of its constituents, individually or aggregated. Important as these oxygen-delivery properties are, hemoglobin is emergent because it has less mass than the sum of the mass of its constituents.

12 I realize that *persists* does not provide a sharp criterion.

3.3 Autopoiesis and the More-mass Criterion for Emergence

How do biological organisms hold together? The static structure and organization of a biological organism is held together by negative interaction energy—along with some additional topological constraints. However, static structure does not explain how living organisms work. As Schrödinger (1944) famously pointed out, any physics-based "lawfulness and orderliness (of biological organisms) is made inoperative by heat motion."

To defend against the disorder resulting from ongoing internal motion, biological organisms continually rebuild and repair themselves. In a review of autopoiesis,[13] Luisi (2003) argues that all biological organisms have "a semipermeable chemical boundary (within which they are) capable of self-maintenance by a process of self-generation." The term *autopoiesis* may be understood to refer to all such self-management activities, including the acquisition of energy (and other resources) and the avoidance of hazards.

Social systems—such as families, packs, tribes, colonies, social clubs, societies, corporations, countries, and so on—also hold together through autopoiesis. Flocking, in which birds create flocks as each bird positions itself with respect to its neighbors, serves as a standard example. When applied to social systems *autopoiesis* may be understood as self-management within a self-created boundary (Luisi, 2014). The boundary may be created simply through the ability to distinguish members from nonmembers.

Abbott (2010b) used the term *dynamic emergence* for systems that hold themselves together through self-management. Because the (kinetic) energy of this ongoing activity is equivalent to a certain amount of mass, autopoietic entities have more mass than the mass of their immediate constituents considered separately.[14]

3.4 Symbolic Entities

There is a third class of emergent entities. These include symbolic entities. Examples include files, records, programs, software objects, etc.[15] These are held together neither by interaction energy nor by self-management; yet they do not disintegrate. They persist because there is no deterioration within their symbolic environments. The work to keep symbolic structures intact is done

13 The term *autopoiesis* is sometimes dismissed as vacuous, trivial, overly complex, self-referential, circular, or intentionally mysterious. The original and fundamental idea is that of a system that has the capacity to repair itself. All living systems are autopoietic, but autopoiesis is not sufficient for life. See Razeto-Barry (2012) for a review of the term's history.

14 This perspective suggests identifying the extra mass as a soul.

15 I am referring to the symbolic aspects of these entities only. Any physical implementation is vulnerable to the same hazards as any other physical phenomenon.

by computer hardware. Of course, computer hardware is subject to deterioration. However, the energy used to maintain it does not depend on the symbolic entities within (Abbott, 2010a). Symbolic entities live in a charmed world of immortal symbols—you cannot break a bit—and pure structure.

The same reasoning holds for mental symbolic constructions. A melody is held together by its composer (if any), its performers (if any), and its listeners (if any). Its integrity is no more dependent on the physical medium on which it is recorded than the integrity of a computer program depends on its recording medium. In both cases, some recording mechanism is required—even if it is the ability of human minds to remember—but its record does not define the entity as an object.

Symbolic entities rely on symbol processing systems like computers or human (or animal) minds. They cannot exist on their own. Abbott (2010b) called them *subsidized.*

3.5 Type Creation Mechanisms

Software has been the source of extraordinarily creativity. This section explores parallels between mechanisms that programming languages make available for building new entities and the mechanisms discussed above.

Modern programming languages categorize values as types. In a statically typed programming language, the only way to create a new value is with a constructor, which produces a value of a known type. As a result, it is not possible to have a value without a type or a value whose type is not known. Every value is of a known type.

One might think of nature in terms of a similar regime. A simple example would declare *AtomicElement* as a type with subtypes *hydrogen*, *helium*, *etc. AtomicElement* might have a so-called factory method that takes objects of the (subatomic) types *proton*, *neutron*, and *electron* and produces an *Atomic Element*. The constructor is parameterized and may produce a different subtype of *Atomic Element* depending on how many subatomic particles of each subatomic type of are provided. Besides building elements from subatomic particles, one would also have constructors that took objects of various element types and produced objects of other element types as in fusion or fission. Chemistry might be characterized similarly: an H_2O constructor takes two *hydrogen* instances and an *oxygen* instance and produces an H_2O instance.

In software development, the primary reason to create a new type is to allow for objects that have properties that differ from those of other types. Each type illustrates emergence in the sense of having new properties. In software, properties are not expressed as predicates. Instead, each type includes functions. A type's collection of functions implicitly defines the properties of the type.

Software systems may have hundreds of types. A primary activity of modern software development is the definition of new types. Although everyone in any creative discipline produces some emergent phenomena, software developers create emergence as their primary product.

When seen in this light, nature too has the means for similar creativity. In software, creativity is intentional; in nature, it is a matter of random combinations that either persists or does not. The underlying process seems similar: create something new by putting existing things together, add some functions, and see what you have. Open-ended type creation mechanisms in both nature and software enable extraordinary creativity.

3.6 Energy-independent Binding Mechanisms

This section examines two other binding mechanisms.

Topological Constraints

Consider two interlocked rings. They are bound together into an entity. Yet no inter-ring forces bind one ring to the other. One can make chains of such rings as in a necklace. A chain-link fence uses the same principle. A fascinating case involves Borromean rings. "The three rings taken together are inseparable, but remove any one ring and the other two fall apart" (Cromwell, Beltrami, & Rampichini, 1998). In chemistry, such structures are called mechanically interlinked molecular assembly (MIMAs) (van Dongen, et al., 2013). Such structures are bound together topologically and without energetics. Other examples of topological (or at least structural) binding include key rings, ball joints, hook and eye latches, etc.

Gravity-assisted Binding

The earth's gravity provides the bulk of the negative interaction energy in constructs such as a traditional arch or a fastener-free bridge. Friction that involves electromagnetic negative interaction energy plays a role, but gravity's negative interaction energy provides the primary binding mechanism. What is distinctive is that the gravity is attraction to the earth, which is not part of the arch itself. This is similar to symbolic entities that rely on external forces to keep them together.

3.7 Is there Anything Except Physics?

Fodor asked, "Why is there anything except physics?" My answer: there is nothing but physics—unless you consider chemistry, biology, etc. as separate. What do I mean by that? The fundamental (and only) forces in the universe are the forces of physics. Nevertheless, as our examples show, there is more to the world than the forces of physics.

Physics explains how things can come together to create compound entities. It provides the binding mechanisms for building less mass—that is, static—emergent phenomena. This mechanism, along with (a) the relative densities of materials found on earth and (b) the history of the solar system, has produced a planet that consists of an inner core, an outer core, a molten mantle, and a crust, which includes tectonic plates, which float on the mantle. As the tectonic plates move, they store energy as stress, which is released in earthquakes. Geysers and volcanoes also release geologically stored energy. Once we know that our planet is organized this way, it makes sense to study its properties—for example, how tectonic plates move and what happens when they bump into each other. Considering all the phenomena in the universe, this is a very specialized study—and one that is not conducted at the level of elementary particles. Although we call this study *geology*, it is really a specialized area of physics.

We tend to think of physics as the study of processes that move toward equilibrium—with a concomitant increase in entropy. However, the processes we find most interesting are those that accumulate, store, and later release energy. (Entropy increases even when energy is being stored.) These processes tend to be more dramatic or more useful (to us)—often both. As just noted, geology provides many examples.

On a much grander scale, gravity compresses mass into black holes, which release energy as Hawking radiation. More relevant to us, gravity compresses space gas and dust into stars, which release energy in nuclear reactions. That nuclear energy becomes available on earth as solar radiation (sunlight), one of whose clients is our weather system. Evaporation moves water from the surface of the earth to high in the atmosphere—thereby creating significant stored energy. When released, the result includes rivers, which among other things carve canyons in stone. This system is also essential for moving massive amounts of water from one place on earth to another.

When we turn to life, adenosine triphosphate (ATP) often called the energy currency of life, stores chemical energy. It provides energy for the self-management processes that keep living things alive. Living things also store energy as glycogen, fat, and maple syrup.

These mechanisms are also based on physics. Does it matter whether we call them physics or use names that are more specialized?

4. Reactive Emergence

The preceding all involved direct effects. Indirect effects are often more important. Consider one of the simplest indirect effects: turning on a light by flipping a switch. The act of flipping a switch does *not* supply energy to the light source. All it does is enable a flow of electric current, which provides the energy that produces the light.

Should the light going on be considered an emergent phenomenon? It does not satisfy the traditional definition of emergence: something "arising" from elements that are more fundamental. It is more a matter of redirecting—or in this case unblocking—an existing energy flow to produce a new effect. If we were not so familiar with this phenomenon, it would be quite surprising. Flip a switch, say, on a wall and light appears somewhere else in the room. Amazing! Surprises like that are considered one of the hallmarks of emergence.

However, considering all redirections of energy as emergent is probably more than we want. Otherwise all computation becomes emergent. After all, the heart of a computer is the transistor, and the job of the transistor is to act as a switch, that is, to redirect energy flows.

When energy flows are redirected in the course of a computation, the redirection is both direct and intentional. Flipping a light switch also qualifies as direct and intentional redirections of an energy flow. What we want are cases in which energy flows are redirected in some sense intrinsically rather than directly.

Consider Gresham's law again. Gresham's law involves an indirect redirection of energy flows. The introduction of coins with the same face value but less intrinsic value than existing coins leads to the hoarding of coins with more intrinsic value and wider use of the new coins. Is this an emergent phenomenon? It does not "arise" from elements that are more fundamental. It is not emergent in the traditional sense.[16] Yet like the light going on, Gresham's law reflects a redirection of energy flows—the act of withdrawing certain coins from circulation. As such, it is reasonable to consider it an emergent phenomenon.

Since such phenomena frequently involve agents that behave differently because of a change to the environment, it makes sense to refer to it as *reactive emergence*. Thus, reactive emergence involves two elements: a change to the environment and an intrinsic (often agent-mediated) redirection of an energy flow. Some examples may help clarify the nature of this class of phenomena.

- A recent Supreme Court decision upheld the University of Texas approach to admitting students through both a "top percentage" plan and additional "holistic" considerations. In his majority opinion, Justice Anthony M. Kennedy (2016) quoted Justice Ruth Bader Ginsberg's minority opinion in an earlier hearing to describe the unintended effect of the rule that

16 Since it does not originate from more fundamental elements, it is not clear why Papineau (2009), Pigliucci (2013), and O'Connor and Wong (2015) considered it even a candidate for emergence.

admits into the University of Texas system the top few percent of students from each high school.

Percentage plans "encourage parents to keep their children in low performing segregated schools, and discourage students from taking challenging classes that might lower their grade point averages."

This unintended consequence qualifies as reactive emergence: establishing the percentage plan serves as the change to the environment; the decisions (a) by parents to keep their children in low-performing schools and (b) by students to avoid challenging courses are the agent-mediated redirected energy flows. Most unintended consequences qualify as reactive emergence.

- Braess's paradox[17] describes situations in which the addition of a new road to an existing network results in additional rather than reduced congestion. The new road is the change to the environment; the choice by drivers to use the new road—and thus unintentionally and paradoxically to create additional congestion—is the agent-mediated energy flow.
- The evolution of antimicrobial-resistant "superbugs" qualifies as reactive emergence. The widespread use of antibiotics constitutes the change to the environment. The spread of genes capable of resisting those antibiotics qualifies as an intrinsic redirection of energy flows. The redirection is intrinsic because it depends on the survival or nonsurvival of bacteria bearing the resistant genes. It is not directed by the antibiotics.
- The redirection of a river by digging a new channel and blocking the old one is *not* reactive emergence, even though the new channel and the blocking of the old one are changes to the environment and the river's new path is a redirection of energy flows. It fails to be reactive in that the redirection of the river is neither agent mediated nor intrinsic—the river is not an agent and did not change its own path. However, once a river has been rechanneled, the changes in the surrounding flora and fauna constitute reactive emergence.
- My favorite—and probably apocryphal—story concerns a country infested with snakes. The interior minister offered a bounty for each dead snake. The enterprising citizens established snake farms.

17 See Section 8.1 of Easley and Kleinberg (2010).

5. Summary and Conclusions

Do we need emergence? One might reasonably conclude that emergence in the traditional sense is not a very useful concept.

5.1 Physical Emergence

In most cases, (traditional) emergence involves a difference in mass—either more or less—between a phenomenon and its constituents. Understood this way, emergence is purely physical. That seems to me the simplest and best way to think about it.

5.2 Conceptual Emergence

The distinction between the conceptual emergence and the physical emergence plays a central role in how the term *emergence* has traditionally been used. Properties that are said to be emergent are necessarily conceptual—since by definition properties are conceptual. The implementation/realization of properties is almost always physical.[18] Linking conceptual properties to their physical implementation or realization requires a mind. This is not to say that were it not for our making that link the implementations or realizations would not have (or would not approximate) the properties attributed to them. Hearts pump blood whether or not we think of hearts as pumps.

The point, though, is that characterizing emergence as the creation of new properties is more a matter of describing how we think—by mapping between conceptual properties and physical realizations—than a matter of characterizing nature. Emergence in this sense becomes mysterious when we attempt to understand it as describing how nature works.

To the extent, we want to continue to think of emergence in terms of properties, I recommend that we think about it as a relationship between specifications and implementations or between models and realizations. Perhaps more important is, we must remain vigilant about the distinction between the conceptual emergence (i.e., specifications and scientific models) and the physical emergence (i.e., implementations and material reality).

5.3 Symbolic Emergence

Symbolic emergence depends on the existence of a symbol-processing system.

18 Software and mathematical model theory are notable exceptions.

5.4 Reactive Emergence

We may rescue the term *emergence* for situations in which a change to an environment leads entities in that environment to change how they act or interact. The new actions or relationships may be considered reactive emergence.

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Thresholds of Behavioral Flexibility in Turbulent Environments for Individual and Group Success

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Abstract

Adaptability is a central component of both individual and group success in a complex adaptive system, as well as a major part of policy design and implementation. Yet adaptability is often narrowly conceived and applied post hoc. In addition, we lack a general framework for understanding the circumstances under which it is desirable a priori. I propose behavioral flexibility as a useful conceptualization, operationalization, and measure of adaptability. I present an agent-based model that employs behavioral flexibility to evaluate the utility of adaptability to both individuals and groups in a turbulent environment. I find (1) there are thresholds of behavioral flexibility and environmental turbulence above and below which flexibility is undesirable at the individual level; (2) individual flexibility can contribute to group outcomes of, surprisingly, increased inequality and lost diversity; (3) very high levels of environmental turbulence can overshadow any benefit to flexibility, suggesting, counterintuitively, that the best strategy in a highly variable environment may be to stay constant; and (4) if everyone in a system is flexible, the benefits of adaptability for any one agent decrease. A final contribution is I am able to generate disadvantages to flexibility without relying on explicit costs to change, as is done in much of the literature on adaptability.

> *In war as in life, it is often necessary when some cherished scheme has failed, to take up the best alternative open, and if so, it is folly not to work for it with all your might.*
>
> Sir Winston Churchill (1948)

> *Never give in, never give in, never, never, never, never—in nothing, great or small, large or petty —never give in except to convictions of honour and good sense.*
>
> Sir Winston Churchill (1941)

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Stay or Switch?

Most of us, in most aspects of life, at some point face the question of whether we should make the most of our current situation or try something else. Whether it is a question of love, career, or the place we call home, we are always making a choice over whether to *stay* with the current situation or *switch* to (potentially) greener pastures.

The exceptions are in the extremes. If you are with the love of your life or your job is everything you have ever wanted, you should probably stay. If you're in a relationship with someone you hate, or your job is the worst thing that's happened to you, you should probably go.[1] However, the vast majority of us, the majority of the time, are somewhere in the middle on any number of dimensions. Things are good, but they could be better. To make them better, should I do more of whatever I am doing, or change goals altogether? If things are not great, should I switch to something else? Or do I do as well as I can in the current circumstances?

In the policy world, this question applies most obviously to situations where a policy is not yielding the desired outcome: should we *stay* and increase our efforts with the current policy, or are our goals misguided, and we should *switch* to another policy altogether? For example, a major debate in foreign aid is when aid does not achieve the outcomes we desire, is it because we are not doing enough, or because we are channeling our resources in the wrong direction?

One way to think of this is as nested questions. Suppose I want to combat malaria. Breman et al. (2006) divide extrinsic malaria factors into three categories: control and prevention; social, behavioral, economic, and political; and environmental (Breman et al. 2006). A first question I might ask is how to allocate resources over solutions within one of these categories.

For example, within control and prevention I might decide whether to focus on drugs or insecticide-treated nets (ITNs). If after a period I conclude drugs are not yielding desired outcomes, I face a choice between providing even more drugs or switching to nets. Alternatively, I could select some threshold: if malaria diagnoses reach a given rate, I switch to the other strategy. As the environment becomes more variable, perhaps due to unrelated human or mosquito population trends, should I even become open to changing strategies more, either by adjusting the *threshold* above which I switch, or increasing the *probability* with which I switch, or both?

The same dilemma applies one level up. If I am unhappy with outcomes after another period of switching between nets and drugs, I could then expand my

1 You are welcome for this free, outstanding life advice.

search outward and decide whether to stay in the realm of Control and Prevention or to switch to, say, Environmental. Again, I would evaluate how my strategy worked and again be faced with the question of whether to stay or switch.

This dilemma then applies yet another level up, should I be focusing on extrinsic or intrinsic factors? I could go further: Should I even be focusing directly on malaria at all? Maybe if what I am after is saving human lives, I should be focusing on education or anti-corruption. On the other hand, is it maybe all pointless and I should just go buy a boat?

To make matters even more complex, the landscape in which we are injecting these policies is also typically turbulent: a strategy that worked great in the last period may not be effective in the next. In this case, should we ride out the turbulence and stick with the tried-and-true strategy or adapt to changing circumstances?

Of course, policymakers have many resources at their disposal to answer many of these questions—they know whether drugs are having an effect compared to nets, and whether it paid more to focus on the environment than on social behavior. We have, in many cases, a great deal of data to shed real empirical light on the value of these policies. However, what we never know is the counterfactual—what if we had switched? Moreover, we do not know how much better we could be doing. And most importantly, we don't know if, when the environment changes, we should change with it, how poorly things should be going before we do, and how ready we should be to change things once we hit that threshold.

Overall, this paper is about the question of when you should stay or when you should do something else. In the words of Winston Churchill, when should you "never, never, never ... give in" and when should you, also in the words of Winston Churchill, when things have failed "take up the next available option?"

More specifically, the paper attempts to address the question of whether there are principles by which we, in any environment, could identify conditions under which we should stay or go, taking into account exogenous and endogenous environmental turbulence, as well as group level outcomes. To do this, I share a simple spatial agent-based model to explore a handful of parameters surrounding the question of whether to stay or switch when a strategy stops working.

Most specifically, the model allows for the running of histories where adaptive agents can choose to maximize utility using a given strategy, or switching to another *type* of agent that is rewarded for different behavior altogether. The core parameters in the model map to those surrounding any such decision in our personal lives and in policy: the turbulence of the environment, the behaviors of other actors in the system, and our own tolerance for what counts as failure: how bad should things be before we change?

This structure allows us to ask and answer questions about the relationship between environment and flexibility in terms of individual utility: For example, how turbulent should the environment be before I change strategies? What is the

best utility "threshold" below which I should change strategies? An exciting part of this paper is that it also allows us to evaluate group outcomes of individual flexibility: If everyone changes strategies all the time, is that good for the group? What about when the environment is highly variable? What about when it is not highly variable?

The paper is also one in a series of papers on the topic of adaptability—what does it mean to be adaptive in a complex system? Does it mean to change behavior? To change goals? To be able to change or willing to change, or both? Does it imply optimization or matching? Alternatively, just flexibility? The paper is certainly not the first to take on such topics, but a discussion of adaptability is requisite for any inquiry into whether and to what extent adaptability serves an individual or the group in a complex system. This has direct application to policy choices: Policies are implemented into complex social, biological, and ecological environments that are turbulent and in which others implement other policies. As circumstances change, even the best policies may stop working. How flexible should we design policies to be?

This question is deeper than simply making choices over uncertainty. It is about fundamentally changing *type*—which means changing preferences. It is deeper than the question of, if I am trying to maximize *A* should I be doing more of action *X* or action *Y*? Rather, the question in this paper is, right now I am trying to maximize *A*, but should I instead be maximizing *B*?

To give an example, if a person is in an unhappy marriage, this model is about whether a person should be married or not—as opposed to the "within type" choice over whether a person should have more date nights or seek couples' counseling. Or in the world of higher education, this model is not about trying to answer the question of whether we might make college more affordable by reducing tuition or providing more scholarships, but instead is about questions like who should universities be targeting? On the other hand, should all students go to college? From the student's perspective, this might take the form of shifting the choice from, "what college should I go to?" to "Am I the type of person to go to college?" It's about the decision to switch from one decision tree to another altogether, which is effectively about changing the payoffs to your choices, which is about changing preferences.

In addition to being about whether one's preferences are the "right" ones for a particular circumstance, the paper is also fundamentally about the question of satisficing. A central component of the paper is *thresholds*. It is one thing to conclude that one is willing to change type given the realization that the current behavior is not working. How poorly do things need to be going before one switches?[2]

I do not pretend that the agent-based model I present in this paper has the

2 For a definitely not scientific article on this topic that is wildly depressing and highly controversial—but does a great job of underscoring the fundamental logic described here—see Gottlieb (2008).

answers to all of these questions. Rather, the model allows us to examine several parameters that surround this kind of indecision regardless of whether you are working in social, biological, or ecological systems. It offers a simulated thought experiment that will ideally provide a baseline for further work that applies the model to more specific questions of matters as far ranging—and important—as global and national policy and how we live our lives.

The model also offers several innovations over previous models of adaptability. It is able to demonstrate costs to flexibility without requiring flexibility itself to be costly. It also focuses on a deeper kind of adaptability than just the ability of switching to another action. Rather, it allows agents to change types, or preference, in light of changing circumstances. Finally, it evaluates the benefits of individual flexibility not just in terms of utility to the agent, but also to utility of the group as a whole. A shortcoming of much policy research is that it assumes policies are injected into systems in isolation. Insofar as an analysis might consider flexibility when it comes to policy design, it likely is forced to assume away any context for the policy that might complicate the analysis. Here, we consider the effects of flexible policies both on their own merit; as well, as how entire populations of flexible policies might perform and affect the groups they are designed to serve.

In the next two sections, I first unpack the concept of adaptability, and then I discuss my approach to it in this paper—within the broad landscape of adaptability—of *behavioral flexibility*. Any discussion of adaptability could fill books upon books (and indeed have). This is meant to be an orientation to the vast ways we might think about this elusive, yet centrally important, concept in social, natural, and even artificial life (Clark, 1996; Simon, 1996).

Adaptability

Adaptability means many things to many people. Fundamentally, it is about the question of changing something—be it genotype, behavior, or beliefs—in response to some kind of change in the social or natural environment in which one finds oneself. Adaptability can be both conscious and unconscious or, relatedly, purposive or reflexive. Individual actors, simple groups, and complex organizations can all be adaptive. Finally, while we often think of adaptive changes as inherently successful—that is, it is not *adaptive* unless the change makes one better off in a new environment—they need not be. The term *maladaptive* is sometimes used in these cases where the change is inappropriate or insufficient to the circumstances they are intended to match.

This final distinction is important. The connotation of adaptive as a positive term is problematic, as we cannot know whether the change made by an actor is one that will work—improve the actor's utility over not making that change—until after the fact. We are thus reduced only to evaluating the adaptiveness of a

change with hindsight, and we can never know the counterfactual on any "adaptive" change. What might have seemed to be a good choice to make in the present and given the information at that time may turn out not to be. Looking back, all we can conclude as observers is that the change led to a bad outcome. We cannot know anything about whether it was still better than the status quo, or whether a different change would have led to better outcomes. Does that make the change—or the actor making that change—not adaptive?

The question we are really asking when we inquire about adaptability is the following: under what conditions is it optimal to change behavior in response to environmental change, and when is it better to maintain consistent behavior? The emphasis here is on the utility to a future self of changing behavior (henceforth also a proxy for beliefs and genotype) in the present.

In this lens, whether you consider biological systems, social systems, or ecosystems, the idea of adaptability itself must take into account not just the conditions under which one should change behavior, but also must evaluate the actual *ability* of an actor to change behavior. A firm that is seeing lower profits may adjust its marketing strategy, a lonely individual may switch to online dating, and a cougar may hunt in new territory (wink).

These changes may be good (or not), but we can only evaluate adaptability according to the circumstances when they make the change in the first place, as well as whether the actors themselves are actually capable of making that change.

This emphasis on *conditions for change* and *ability to change* relieve us of a number of complicated issues that arise when thinking about adaptability. For example, adaptability could also look like an actor adopting one flexible behavior that does well under a wide variety of changing circumstances. Alternatively, an agent could look adaptive through random drift. On the other hand, that agent could for whatever reasons simply already have a behavior that happens to work. We might wrongly conclude this last actor is adaptive, when really they are more appropriately described as exhibiting *resilience*: the ability to withstand hardship without changing at all. Finally, a related concept is robustness, which we usually take to mean something to the effect of the ability to be constant amidst turbulence but also adapt when needed (Bednar, 2008).

A few simple examples clarify the distinction between behavioral flexibility and other kinds of adaptability discussed here. Behavioral flexibility can look adaptive, but it need not be.

a) *Pushing or waiting:* In China, one gets through a line faster if one pushes one's way through. In the United States, this will get you kicked out of the store. The decision of an agent to change from crowding to waiting is one that is behavioral flexibility, but is also adaptive if one moves from China to the United States. That same change is not "adaptive" if one goes the other way.

b) *City or suburb*: A person who loves the city might be willing to pay more and more to stay there. However, at a certain point the city may become so expensive, or crowded, that he deems it too costly to stay. Thus, the actor might change types to one who prefers to live somewhere more rural. The actor will now maximize over a different set of constraints.

c) *Specialist or generalist*: In a spatial representation of areas of expertise, a person might choose to specialize in one particular subject, field, or line of work, or they might become a person who spreads across many interests. As the labor market changes, one strategy may be more advantageous. Behavioral flexibility is about when you should make that switch and how willing you should be to do it.

d) *Diversify or concentrate*: The same tension is at work in investment in the stock market: do you pick a stock that you expect will do great or minimize risk by spreading your resources across a variety of options? Adaptability might refer to this diversification, but behavioral flexibility is specifically about altering your goals if what you have been doing is not working.

e) *Cluster or spread resources*: To make populations better off, does it make sense to put resources we value (like teachers and doctors) all in one place, or to spread them out across a state or country? Adaptability could refer to a number of different configurations, while behavioral flexibility refers to switching between spreading or clustering strategies.

f) *Stay in a career or change*: Suppose you are in an industry that looks like it is shrinking. Is it better to become the best version of a person in that field, or to switch before it becomes too difficult to change later? Either choice could look "adaptive" in retrospect if it turned out to be the "right" one.

g) *Stay in a market or change*: Building from the career choice in (f), suppose you run a firm in an industry that is shrinking. Do you try to hold fast and be the best firm in that industry—perhaps counting on continuing to offer the best version of the product in this field? Alternatively, do you re-orient your business to a new goal altogether? One example of this is the field of print journalism, where many papers faced the challenge of: Do I make a much better newspaper, or do I change my mission or product?

There is no shortage of ways to conceptualize and measure adaptability. To summarize the above, much of the varieties of adaptability can be distilled down into three broad categories. They are not fully comprehensive, but are representative of the broad classes of types of ways individuals or groups might be adaptive.

1. Having many actions at one's disposal to achieve a goal (Figure 1).
2. Having the ability to switch between actions to achieve a goal (Figure 2).
3. Having the ability to switch goals, which might mean switching actions, but could also mean changing the payoffs for a particular action (Figure 3).

These three types of adaptability are illustrated in Figures 1–3.

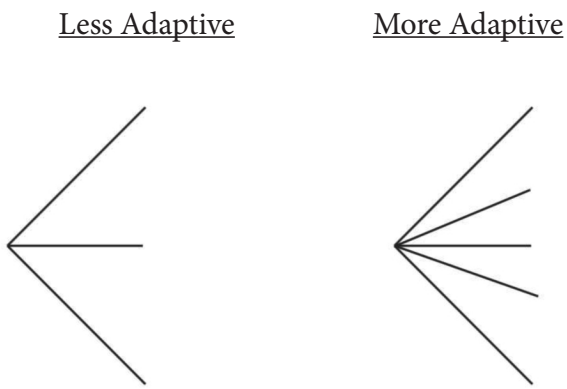


Figure 1. Adaptability as many actions.

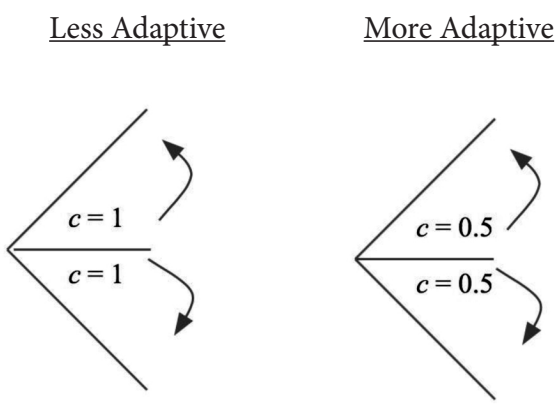


Figure 2. Adaptability as low cost to switching between actions.

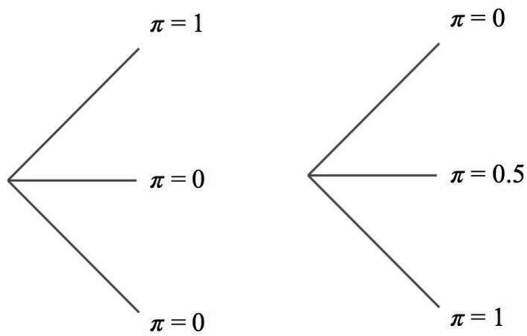


Figure 3. Adaptability as changing payoffs (π) to actions (behavioral flexibility).

Finally, there are two other considerations to adaptability. The first is *environmental turbulence*. As the environment in which we are embedded when we make these changes itself changes, the idea of what it means to adapt becomes even muddier. If the environment is turbulent, is it best to hunker down and stick with the policies—whether personal or governmental—that we know have worked in the past? They are tried-and-true, after all. On the other hand, is it time to try something new? How do we know? Note that environmental turbulence can refer both to exogenous and endogenous changes in the environment, for example, if other actors in a system are changing.

The second is *group outcomes* of individual adaptive behavior. If everyone around you is changing, is it ever beneficial to hold fast to what you have been doing? Alternatively, if other actors in your system—firms, individuals, and legislators—are all switching types, should you, too? Moreover, what is the result of all of this not just on your individual welfare, but also on group welfare?

In this paper, I will strictly consider adaptability as changing goals, or what I will henceforth refer to as behavioral flexibility. Within behavioral flexibility, I will consider both the *probability* of change and the *threshold* for change—how bad do things have to get before you change? The agent-based model I present in this paper not only allows agents to explore different flexibility probabilities and thresholds, but it also situates agents in an environment, which allows for the examination of the relationship of flexibility with endogenous and exogenous environmental turbulence and both individual and group outcomes.

In the next section, I briefly review samples of literature on behavioral flexibility from biology, ecology, and the social sciences, especially organizational science. I then present the model, analysis, results, and a concluding discussion.

Behavioral Flexibility versus Consistency

Behavioral flexibility, defined simply as the ability of an actor to change strategies, is generally a useful characteristic of actors in biological, ecological, and social systems. As discussed, flexibility is "adaptability" when we consider it in light of environmental changes, including exogenous ones and those brought about because of the behavioral changes of other actors in a system. Flexibility refers strictly to the change itself stripped of the context of the exogenous and endogenous environment. Finally, flexibility refers both to having more actions/strategies to switch to and the cost of switching.

To give just a very cursory overview of several vast literatures, work in biology has shown that there are species that are able to perform diverse sets of behavior outperform species with only one strategy. This has been demonstrated in the domains of the search both for mates and for food (Bijlsma, Bundgaard, & Boerema, 2000; Lande & Shannon, 1996; Rossmanith, Grimm, Blaum, & Jeltsch, 2006). Behavioral flexibility does not just arise in a vacuum: researchers have also found that the heterogeneity of species' habitats correlates with positively with more diversity in populations. Just to give a few examples: this has been observed in crickets, butterflies, fruit flies, among others (Ehrlich & Murphy, 1987; Kindvall, 1996; Piha, Luoto, Piha, & Merila, 2006; Weiss et al., 1988).

One of the most prominent works on the subject of flexibility and adaptability in social systems is James March's 1991 paper, "Exploration and Exploitation in Organizational Learning." March (1991) shows that some balance between exploration (trying new behaviors or looking for new solutions) and exploitation (imitating existing strategies) is important for the success of firms. This is because exploration is risky. It does not always yield improved performance—in fact, explorers may fail miserably. However, some exploration is desirable because it could lead to the discovery of improved strategies. Exploitation is less risky, but comes at the cost of never discovering a better strategy or adapting to changed circumstances.

This tradeoff holds for individuals and firms, as well as systems themselves. Thought leaders in institutional analysis (Hayek, 1945; North, 2005) also emphasize that while institutional stability is desirable, there is no guarantee that a particular institution will produce growth over time (North, 2005, p. 363); thus, institutions ought also to be capable of and act on some degree of flexibility in order to be successful in the dynamic environments—social and external—in which they operate. It is thus not controversial to argue that firms, governments, universities, and other organizations would all do well to undertake measures to be institutionally flexible and encourage flexible behavior by agents within the organization.

Nevertheless, when should they be flexible, and how flexible should they be? Should they be flexible only in the face of environmental change? Should they be as flexible as the environment is variable or turbulent? If the diversity of strategies

exhibited by a species is in some way correlated—presumably meaningfully—with the turbulence of their environment, this suggests that being more flexible than one needs to be may be unnecessary. However, what if a previously static environment suddenly becomes turbulent? Institutions are not species—we can deliberately engineer them in a way that a species, whose behavioral diversity may rely on the much slower and more reactive process of evolution, cannot. On the other hand, an institution or actor who is both capable of and willing to change strategies cannot do so without making tradeoffs, including trading off with the opportunity cost of not choosing the right strategy, with the risk of not getting "better" at any particular strategy, or of actually just incurring the cost of changing strategy.

It is generally this third tradeoff—the costliness of change—that is the reason stability might be valued in biological and social systems. Regardless of whether a new strategy would be superior, it costs time and resources for both a firm and an individual to develop with and implement a new strategy for responding to new market circumstances. The literature on heuristics also supports this idea—learning a new behavior requires not just learning something new, but also unlearning what might now be an automated response. With respect to the flexibility of species, the same tradeoff holds—whether it is through behavioral modification or genetic mutation—change is both risky and costly. Not all mutations are beneficial: mutation may make it worse off, not better. Moreover, one may never be able to get back to where one started.

This overview suggests that when it comes to the relationship between actor flexibility (strategic/behavioral or characteristic/genetic) and the environment, they should match. In constant environments, actors should be less flexible. Flexibility is costly, and if they are doing well *enough* (more on this in a moment), then there is no need to incur the cost or risk of change. If the environment is turbulent, however, then actors should have some flexibility in their strategies, or the species should be capable of changing over time. The environment itself includes the physical, exogenously given characteristics, and the flexibility of other actors (predators, firms, single men, or women) in that system. In order to understand the fate of a particular individual in an environment, these endogenous factors are at least as important as the exogenous ones.

Below I present an agent-based model that evaluates this relationship between actor (agent) flexibility and environmental dynamics. I consider both exogenous (modeled as topological) environmental turbulence and environmental dynamics that arise because of the changing behavior of other agents in the system. In the model, two types of agents attempt to spread themselves according to contrary agendas across a lattice. In the control case, the environment—the lattice—is constant, and agents are restricted to remaining whatever type they are initially assigned. In subsequent trials I allow the environment to change, then I allow the actors to change types, and then I allow both the environment and actor types to change. At the center of the model is a threshold: actors change types not just with

some probability, but also depending on their tolerance for poor performance. The model allows us not only to examine the effects of rates of behavioral flexibility, but it also allows us to explore how bad actors should allow circumstances to become before changing strategies.

My core result is that under some conditions behavioral flexibility can lead to suboptimality at the group level, even in dynamic environments. In addition, flexibility can be suboptimal in an indirect way in the form of lower diversity and greater inequality, again at the group level. The model only has two types, so diversity is the ratio of one type to another, where a 50/50 system is the most diverse and a 99/1 is the least. Equality is measured in terms of the proportion of utility held by each type. A smaller result in some cases is that the group with the higher utility does not necessarily have the most members.

A second result focuses on the role of the environment. The influence of a turbulent environment works in two directions. First, no amount of flexibility can help agents overcome environmental disadvantage in simply some situations. Second, even in situations where the physical environment should point to a clear advantage for one type of agent, the present of the second group can significantly detail the first's success—even if in the early rounds the first group was the more successful of the two. In this model, we can also observe evidence of some disadvantages from early success. If such derailing takes place after enough members of the first group have reached a particular satisfying threshold, they will not change strategies even if there are additional gains to doing so.

Finally, this model contributes to the exploration versus exploitation literature in that it is able to generalize suboptimality in flexibility without relying on costs to explore or change directly. Risks are still embedded in the model, as the agents do not know when they are switching behaviors, what the best behavior actually is, but the actual act of changing bears no cost in the model. Much of the literature on cognition, bounded rationality, and decision making under uncertainty turns on the understanding that it is difficult for individuals to change their behavior (and this is even more difficult for groups). This model is able to produce suboptimal outcomes from changing behavior without this stipulation.

Next, I explain the model in detail. I then present evidence for the results I have described. I conclude with a discussion and comments on future research.

The Model

The model is simple. It offers the advantage of generalizability, as it is readily applicable to a range of social and ecological systems. Of course this comes with the tradeoff that the model on its own cannot offer predictive insights to any specific system, but the simplicity of the model also means the addition of more context-specific variables should not be difficult. Another advantage of

modeling simplicity is that it allows us to isolate the effects of the changing parameters on the model. Even the simplest agent-based models can yield complex results; adding complexity early on can muddle the insights from this, which is effectively a computational thought experiment.

The model consists of 100 agents of two types, *clustering,* and *spreading*, distributed across a nonwrapping lattice. Each agent's goal is to allocate itself across the lattice in a way that maximizes its own individual utility. Utility is given by type and distribution of agents. Clustering types earn a higher payoff the more agents are near it. Spreading types earn higher utility the fewer neighbors they have. At each time step an agent can choose to move to another square in the lattice, stay in that square, or change type. As the model proceeds, the environment, modeled as the size of the lattice the agent considers (the *neighborhood*, described below), can change. A tension emerges as each agent, not knowing how the environment will look in the future, needs to decide whether to keep optimizing over its current strategy or change type to one that earns utility with a different strategy.

Thus, the key moving parts of the model are the agent types, environmental turbulence (changing neighborhood size), number of neighbors, and the decision by each agent to move, stay, or switch types.

Core Parameters

Environment

In its initial state, the environment is a 5×5 nonwrapping lattice. It has two key features. First, the lattice is nonwrapping in order to approximate most instances of spatial reality. Because agents are concerned with how many neighbors they have, and in most real life populations neighborhoods really do have borders, outskirts, and dead ends, having edges and corners affects agent utility. We will see in the results that the existence of corners affects outcomes in ways that a toroidal lattice would not allow.

Second, the density of the lattice presented in the results is 100 agents over 25 units of space, or 4 agents per unit, or cell. The model is robust to most variations in density apart from very high and low ones. This is because, as we will see below, a very dense environment will favor the agents that prefer to cluster, while very low density will mean agents who prefer to spread to do best. In these cases, the agents of each type clearly win, and the model quickly settles to all clustering or spreading agents. The interesting results, as is true in many agent-based models and complex systems, are in the in-between (Miller & Page, 2007).

Agents

Agents are assigned one of two possible types, clustering or spreading. An agent is a clustering type with probability (p). An agent's type dictates how an agent's utility is calculated at a given timestep. Clustering agents earn higher utility (K_C) the more other agents are in its neighborhood (defined below). Spreading agents earn higher utility (K_S) the fewer agents are in its neighborhood. Over a 100-agent lattice, utility for each type is

$$K_S = n/100$$

$$K_C = (1 - n)/100$$

where n is the number of agents in each agent's neighborhood at that time step. Individual utility is evaluated at each time step of the model, with the maximum score any agent can earn being 1. Group utility (K_G) is measured by averaging across all agents of each type at each time step, then evaluating them cumulatively over 50 time steps, which constitutes one run. The maximum K_G that can be earned by a group over a run is 50 (a score of $K_G = 1$ over 50 time steps).

Action

Action in the model proceeds as follows. At each time step, every agent has the opportunity to move to a neighboring cell if it will increase its utility. There can be more than one agent per cell—in principle; all 100 agents could end up in one cell. The two types move simultaneously around the lattice to reflect uncertainty in real life decisions—we know the current state of affairs (at best), but we do not know what the other actors around us will do, even if we know their type and number of neighbors—or even if they engage in signaling.

Higher computational complexity could allow for more sophisticated agents that can also consider their neighbors and calculate what they are likely to do given their type and situation. There are two reasons why I do not include this here. First, as we will see ahead, interesting results emerge from this simpler version, so I begin there and leave more strategic play for future work. Second, while agents may be able to calculate the moves of other agents based on their current type and number of neighbors, each agent also holds private information about its own vision and willingness to change types (modeled as probability), which will render agents' calculations likely incorrect. Again, I leave this added complexity, as well as complexity that include signaling, for future work.

In real life, of course, we also rarely know beyond a guess what our neighbors will choose to do in the future. In the model, the present moment captures this to some extent—if a cell is very full at present, it is more likely to have agents

during the next time step than one that is empty, but occasional big swings are also likely if the model proceeds in a path where many spreading agents suddenly find themselves in the same place. This kind of tipping behavior is observable in other simple models like this, including Schelling's famous model of segregation (Schelling, 1978).

The construction of the model also suggests the proportions of one type over another will affect outcomes in important ways. If clustering agents are a minority, their utility will be limited to however many other clustering agents there are, plus perhaps the occasional unfortunate spreading agent who is trapped near them. If clustering agents were a majority, it would benefit them, and if we allow types swapping, we should expect all agents to become clustering types.

On the other hand, if spreading agents are a minority, at first it may seem that would benefit them, but this would actually mean there are more clustering agents instead, which, depending on the distribution over the lattice and the size of the neighborhood, may impose an upper bound on how spread out they can become. In addition, the more successful spreading is, the more agents will switch to spreading, which again poses a downward pressure on the utility of being a spreading agent. Ironically, spreading agents potentially make themselves worse off as they become more successful. Spreading agents can expect high utility only under certain larger neighborhood configurations.

We have now arrived at the two complexities at the heart of this model, and which will drive our most interesting results: environmental turbulence and agent adaptability.

Environmental Turbulence and Behavioral Flexibility

Environmental Turbulence

We first make the environment dynamic. Recall that agents are on a 5×5 lattice. To simulate a heterogeneous environment, I allow the *vision* (v) of agents to vary over three possible values: 0, 1, and 2. When $v = 0$, agents can only see as far as the cell that they occupy. At $v = 1$, agents can see their own cell and one cell further in every direction for 9 cells total. At $v = 2$, agents can see one cell further than even that in every direction. Given the nontoroidal lattice, at $v = 2$ agents in the middle of the 5×5 lattice can see all 25 cells, while those elsewhere see fewer depending on their location. This is illustrated in Figure 4.

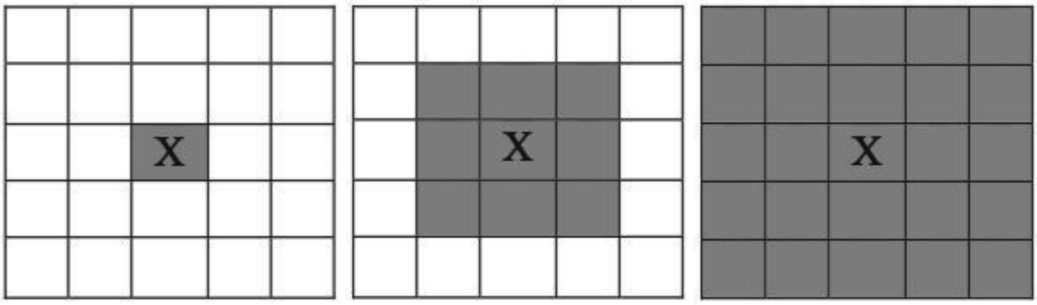


Figure 4. Vision/neighborhood size of agents depicted by the shaded area; from left to right: $v = 0$, $v = 1$, $v = 2$.

The vision of agents is a proxy for neighborhood or vicinity. As vision increases the size of the lattice that is considered an agent's neighborhood increases. Recall from above that the number of agents within a neighborhood is how an agent's utility is calculated. This means K_C increases with v, while K_S increases as v decreases. A simple run of 30 time steps of the model with all type C agents randomly distributed over the lattice and then another run of all S randomly distributed confirms this. The average cumulative score for clustering agents is 50 (perfect) when $v = 2$ and 47 for spreading agents when $v = 0$. (It is not 50 because when $v = 0$ agents are restricted in their movement, so the model is sensitive to initial conditions).

To further illustrate, consider the lattices in Figure 5, where v = 0 on the left and v = 2 on the right.

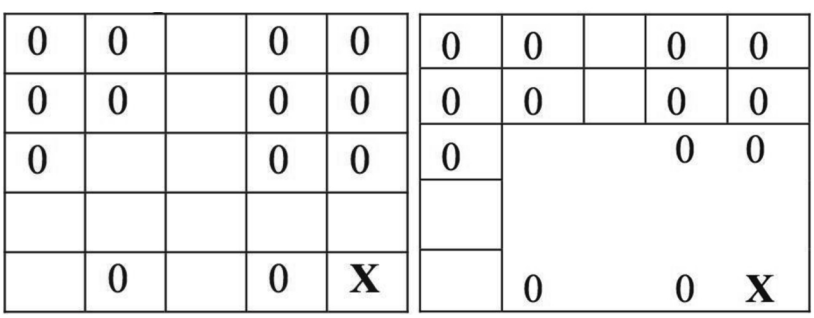


Figure 5. Calculating utility depending on vision/neighborhood size.

If agent X is a spreading agent, then $K_X = 1$ when $v = 0$ because it is the only agent in its relevant neighborhood. However, when $v = 2$ this same agent earns $K_X = 0.97$, because now there are three other agents in this spreading agent's neighborhood.

To create environmental turbulence, let vision change with some probability (q). At $q = 1$ vision changes at each time step (most turbulent) and at $q = 0$ vision never changes (completely static). In the simplest version of the model, all agents have the same vision.

Behavioral Flexibility

The final major dynamic in this model is agent adaptability. One way to express this is to allow agents to change type between clustering and spreading. As we just saw above, if $v = 2$ and $q = 0$ then it is best to be a clustering agent. Allowing agents to change from spreading type to clustering type means that they can capitalize on—adapt to—this environmental condition and earn much higher utility than if they had to remain spreading types. The probability of changing type (r) can range from $r = 1$, where agents always change type when a utility threshold is not met (maximum flexibility), to $r = 0$, where agents never change type regardless of how poorly they are performing in a given environment (minimum flexibility).

One last variable that we can modify is the *threshold* (θ) below which agents are triggered to potentially change strategy (depending on r). Lower thresholds correspond with quicker satisfying. Recall that a perfect score for any agent over 50 runs is 50. If $\theta = 1$ this means that very early on we should expect to see agents stopping changing strategies. Even if later on the environment changes such that it would be advantageous to change strategies, these agents will not change. While this may seem like a disadvantage, as a preview of the results, and an illustration of the counterintuitive outcomes of even such simple agent-based models, we will see that extremely high thresholds are surprisingly actually associated with lower group utility.

A Single Time Step

To summarize, the events that take place during a single time step of the model are as follows.

1. Agent X is located somewhere on the lattice. The location is randomly assigned. The probability the agent is a clustering agent is given by (p). v is randomly assigned to either 0, 1, or 2. θ between 0 and 1 is randomly assigned, as is the probability r.
2. Agent X calculates the number of relevant neighbors, given by vision.
3. The agent will then choose to **move** or **stay**:
    a. If Agent X is a clustering type, it will move to a neighboring cell if the number of the agents (n) in the neighboring cell exceeds the number in Agent X's current cell. If there are more than one neighboring cells with more agents, Agent X will **move** to the cell with the highest number. If there are no neighboring cells with n greater than the agent's current cell, Agent X will **stay** in its current cell.

b. If Agent X is a spreading type, the same process holds, except Agent X evaluates cells with respect to which has the lowest n.

4. Once Agent X has chosen to move or stay, Agent X then considers it utility K_X. If $K_X < \theta$ then Agent X **switches**, that is, changes type with some probability r, where in a purely nonflexible case $r = 0$.
5. The current time step concludes.

At the conclusion of the time step, a new one begins with Agent X again considering all current relevant neighbors. If Agent X changed types in the previous time step, Agent X now plays this new time step as this new type. If we allow some probability q for environmental turbulence, v may take on a new value. Moreover, the neighbors may have changed locations and types—though only types affect utility calculations in given round.

One run of the model is 50 time steps. For nearly all runs in the analysis that follows, 50 was more than enough to reach convergence to a fixed ratio of types in each population as well as to establish a clear type winner (the type with the highest group utility K_U for that particular run). For the few cases where even after 50 time steps there was not clear convergence, this lack of convergence was only with respect to group utility outcomes. That is, it was not necessarily clear by 50 time steps which type would emerge with the highest K_G. However, for all runs the long-run distribution of types converged within the first 10–20 time steps. This will be clear in the graphs discussed in the "Results" section.

The parameters of the model are summarized in Table 1.

Table 1. Parameters of the model

Symbol	Parameter	Details
C	Clustering type	Clustering agent
S	Spreading type	Spreading agent
p	Type probability	Probability agent is Type C
K_C	Clustering utility	$(1 - n)/100$
K_S	Spreading utility	$n/100$
n	Number of neighbors	Number of agents in a neighborhood
v	Vision	How far agents can see; 0, 1, or 2
q	Environmental turbulence	Probability vision changes
r	Behavioral flexibility	Probability agent changes type
θ	Threshold	Threshold below which p activated

Results

There are three central results. First, flexibility can lead to suboptimality, directly and indirectly. Second, environmental turbulence affects utility both in terms of the environment itself and the social environment. Third, there are disadvantages to flexibility that do not rely on costs to changing behavior.

First, I present results from the base cases of the model.

Results from Base Cases

I first present outcomes of the model in an unchanging environment. Recall that v can take on values 0, 1, and 2. Table 2 shows the average outcomes over 30 runs for each vision environment when there are an equal number of clustering and spreading types (p) and no agents can change their type (r).

Table 2. Average aggregate K per type in three diverse constant environments

	$v = 0$	$v = 1$	$v = 2$
Average K_C	2.2	27.8	50.0
Average K_S	47.9	42.7	20.1

We see that the game asymmetrically favors spreaders—you do not do nearly as horribly at the different visions. We will consider this when evaluating comparative utilities across groups in future analyses.

Table 3 presents average aggregate outcomes over 30 runs with varying environmental turbulence. Specifically, I vary the probability q that the agents' vision will change at any time step. As above, there are initially 50 spreading and 50 clustering agents with probability of changing types (r.

Table 3. Average aggregate K per type in changing environments

	$q = 1$	$q = 0.9$	$q = 0.5$	$q = 0.1$
Average K_C	33.0	31.6	34.2	31.3
Average K_S	36.6	37.4	34.8	35.9

For the final base case, we consider how each type performs in a homogeneous society: how well do clustering agents perform in the absence of spreading, and vice versa? Table 4 presents the average K per type over 30 runs when only one type is present. Both q and $r = 0$.

Table 4. Average aggregate K per type in three homogeneous constant environments

	$v = 0$	$v = 1$	$v = 2$
Average K_C	2.1	49.6	50.0
Average K_S	47.9	44.5	37.5

Result 1: Flexibility Threshold Effects

It is not surprising that flexibility is not always useful, but it is not obvious when it is and is not. The results of this model demonstrate two specific reasons why flexibility may not always be good, and it points to two circumstances under which this is so. The first reason flexibility may not always be useful has to do directly with utility, and the second reason is indirect—it can lead to other outcomes in a system that may undesirable, including inequality and loss of diversity.

In terms of the direct effects of flexibility on utility, we consider the role of the flexibility threshold (θ). It turns out that at high levels of (θ) combined with r >0.5, long periods of switching between types means that agents do not stay at a particular type long enough to earn points. That is, it takes a few periods of clustering agents attempting to cluster before they get close enough to one another to really earn high scores (generally in the 0.8–1 range per time step). Similarly, spreading type agents also need a few time steps to move around before they have spread themselves out to a point where their utility could grow over time. In other words, if the agents are too "picky" and they switch back and forth all the time, the entire period during which they are switching they aren't earning as many points as they might if they would just pick one type and stay there. What's more, since these agents have high thresholds, it takes them that many more time steps of switching in order to reach those high thresholds, after which they finally converge on a consistent distribution of types.

With respect to indirect effects, flexibility can mean that agents switch type frequently early on in a run, and then are locked into a certain ratio of types once the satisfying threshold θ is triggered. Interestingly, this is robust to any threshold. The agents which do well early on, and thus trigger their "stay at this type" threshold earlier than other agents end up losing out tremendously if the system ends up being one that favors agents of one type over another. This is a kind of unexpected first succeeder disadvantage and has some real world examples in industries where being the pioneer is not necessarily the most advantageous position in the end (e.g., social media examples where Friendster and MySpace were successful early on but then could not adapt when Facebook joined the mix later). In addition, the lower the threshold, the more agents there are who can capitalize on this new "knowledge" of which strategy is best, which exacerbates inequality in number,

and success, over each type. We will see far more of the successful type of agent than the less successful, which usually just makes the successful types even more successful. This is particularly startling if the system began slightly biased in favor of the type that ends up losing. The lack of diversity appears here, too, for in these cases we see an average of 91% of agents taking on the dominant type, leaving only 9% stuck in the minority with no way out given the constraints of the model.

The key to all of these results is the threshold (given we know p, q, r, and v). A higher threshold means you keep switching until you hit a high enough score. The higher θ is, the more the agent is an optimizer. The lower θ, the more the agent is a satisficer.

Result 2: Exogenous and Endogenous Environmental Turbulence

The second major result is that the environmental affects outcomes in two ways: physical and social. The first is with respect to the physical landscape, or topology, itself. As mentioned in the model description, when $v = 2$ there is little hope for any spreading agent to receive high K_S regardless of where on the lattice it moves. Even if we allow these unfortunate spreading agents to change types through increasing r or increasing θ, it turns out that unless $\theta = 0$ and $r = 1$, there will always be a not insignificant period during which agents who started out as spreading agents earn low K_S that they never regain compared to their peers.

The additional way that environment affects outcomes is social: unsurprisingly, how well one type performs in the model depends on what the other type is doing. This effect exhibits sensitivity to initial conditions. Often if clustering and spreading agents are earning similar utility scores for the first few runs, all it takes is a slight lead for one type before the system suddenly turns to favor that type.

Agent-based modeling offers the advantage of being able to observe processes unfold in real time, which can help enlighten the causal principles behind the outcomes we observe. In this case, it turns out that if spreading agents end up going to cells on some turns that earn them enough points to pass a threshold (and this result is robust to the range of θ levels), there will be more spreading types in the next turn, as some clustering agents will switch to spreading. This, in turn, means that on the next time step, spreading agents will do even better, as there will be more of them spreading out rather than clustering. Moreover, for the same reason, clustering agents will do even worse, as there will now be even fewer agents with which to cluster.

Note that half the time the reverse holds: if clustering agents get even a slight advantage on one turn—for whatever reason—the population quickly veers toward favoring clusterers, regardless of the topological environment.

In this way, we have created a kind of endogenous turbulence.

Result 3: Costs to Flexibility

The third result is more of a comment or innovation.

The final major result is that there are disadvantages to flexibility that do not rely on costs to changing behavior—which is typically modeled as a costly act. It is costly in the exploration versus exploitation literature, for one, and many other places (Jones-Rooy, n.d.; March, 1991). During early stages of model building, I intended to add a "cost to change types" variable in order to generate limitations on benefits from flexibility. Surprisingly, I discovered I did not need to add this effect in order to see negative effects of flexibility in the agents. As discussed above, flexibility frequently undermines agents despite our initial intuition that flexibility should imply adaptability, and thus success.

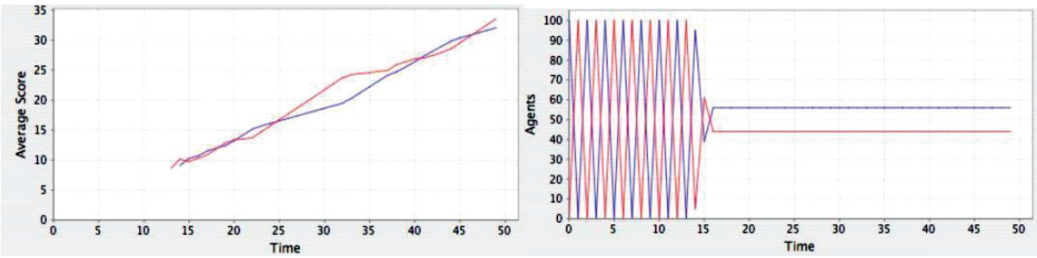
To make sure, I ran the model with an added constant cost to changing types. I discovered at it actually slightly improved outcomes at both the group and individual level, as it meant agents flipped back and forth between unsatisfactory strategies less. The result was not particularly strong, but it suggests a direction for further research that would include cost as a function of the magnitude of the change, or costs that vary over time—perhaps as agents switch types more they get better at it and thus it is less costly.

Examples of Runs

An advantage of agent-based modeling is that it can illustrate process as well as outcome. In this section, we examine some of the above-mentioned concepts—diversity and inequality—in terms of how they came about over time in the model. In all cases, I have selected just one or two examples of a run that are representative of most outcomes. If there are major outliers, I will say so.

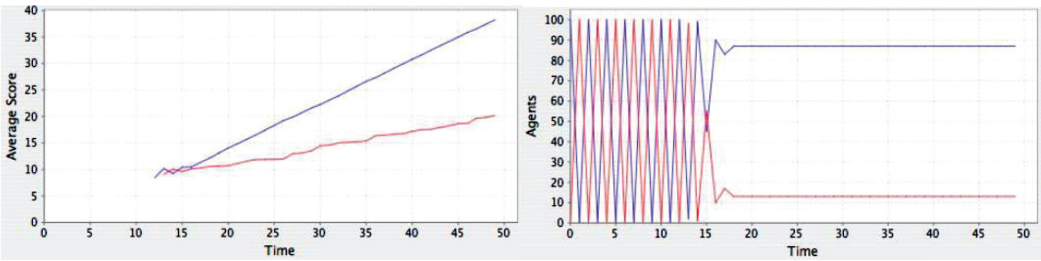
Figures 6 and 7 show equality and inequality in two sample runs, respectively. Notice that in the unequal case, the two strategies begin at the same utility, but just slightly more Type S starts to tip it, until there are a lot more Type S, and Type C is permanently lower simply because they do not have the numbers required to increase their utility.

Both cases begin with probability of changing type = 1 and probability of changing vision = 1, and they begin with equal number Type C (red) and Type S (blue).



(a) Average utility score (b) Number of agents

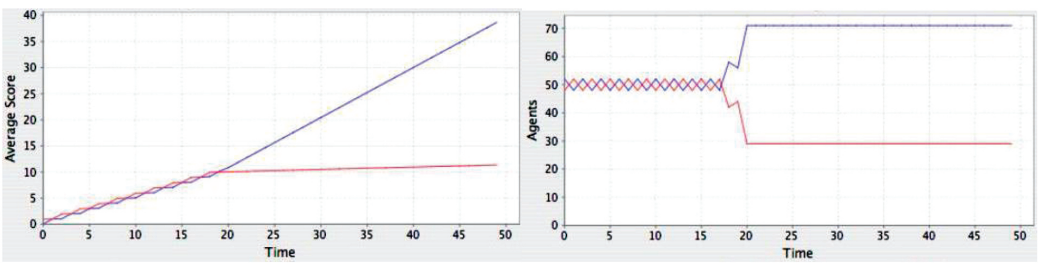
Figure 6. Equality.



(a) Average utility score (b) Number of agents

Figure 7. Inequality.

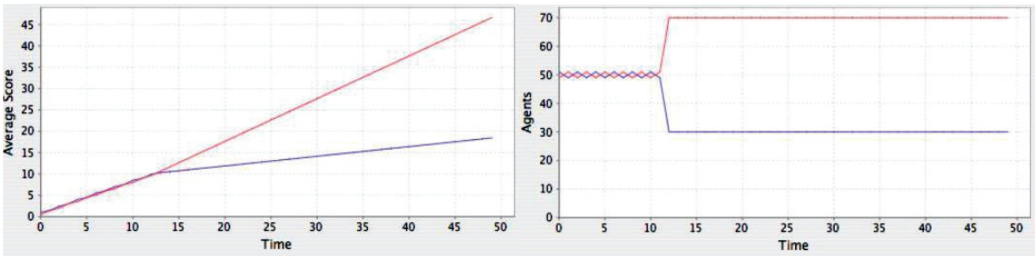
Figure 8 presents another graph showing the influence of just one or two time steps. This case begins with 50 Type S and 50 Type C. The probability to change type and the probability to change vision both = 1.



(a) Average utility score (b) Number of agents

Figure 8. Tipping effect.

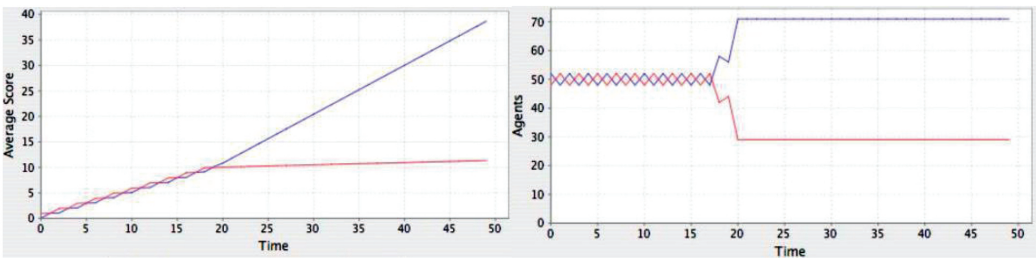
Figures 9 and 10 show the process and outcomes when vision is fixed at 2 and 0, respectively. In Figure 9, the clustering types clearly outperform the spreading types. Here the probability of changing types is 1, but some clustering agents and some spreading agents are stuck on the "losing" team because their thresholds were met before the utility scores diverged.



(a) Average utility score (b) Number of agents

Figure 9. Getting stuck when $v = 2$.

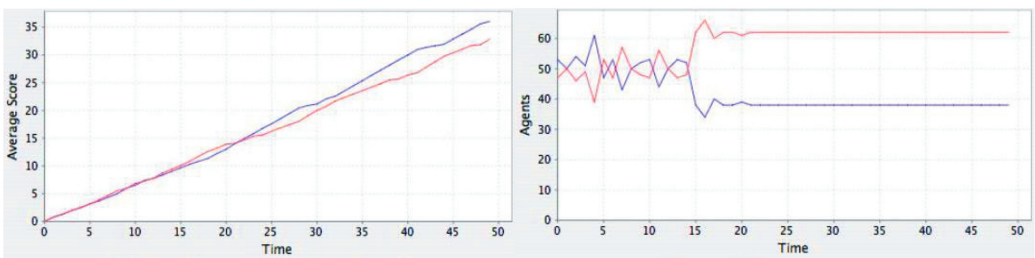
In Figure 10, the spreading agents clearly outperform the clustering agents. Again probability of changing types = 1, but the threshold effect keeps some agents from switching to the better performing type, which reduces overall group utility.



(a) Average utility score (b) Number of agents

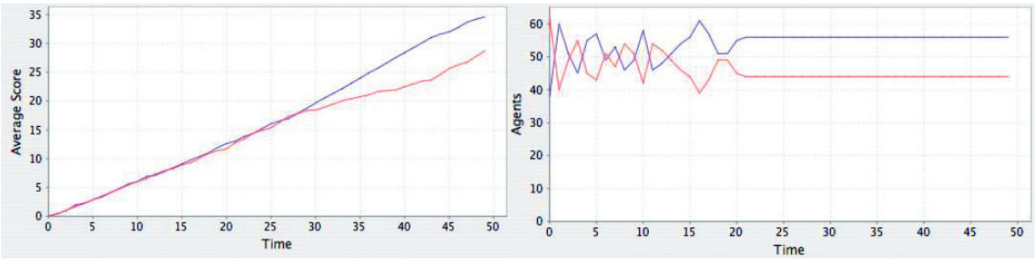
Figure 10. Getting stuck when $v = 0$.

Finally, we are able to observe the process by which decreasing flexibility can lead to greater equality. Figures 11 and 12 show the results of two representative runs when the probability of vision change = 1 but the probability of changing type only = .5. Both begin with 100% type C.



(a) Average utility score (b) Number of agents

Figure 11. Equality from lower flexibility ($v = 0$, $r = .5$).



(a) Average utility score (b) Number of agents

Figure 12. Equality from lower flexibility ($v = 1$, $r = .5$).

Conclusion

This model provides some preliminary insights into points after which behavioral flexibility can be disadvantageous, even in a dynamic environment. It is important to note that these results are for inherently competitive systems. Non-zero-sum situations may have different dynamics altogether.

That said, the results presented here from a competitive system are of course not to suggest that flexibility is bad. Indeed, if spreading agents were stuck in an environment with $v = 2$ and did not have the ability to change, then we would see consistently low scores with no way to improve. In addition, the observation that flexibility is more beneficial in a stable environment is intriguing and requires further exploration.

Future work should apply these insights to real world cases where we see groups stuck in suboptimal situations due to precisely the dynamics described here. Additional work should determine what adjustments would be required to tip or nudge the group out of these spirals of suboptimality, which can include everything from low payoffs to lost diversity to increased inequality. In addition, behavioral flexibility is but one way of thinking about adaptability. It is important to rigorously examine other kinds of adaptability as well as it applies to our ability to succeed as individuals and groups—especially when it comes to the implementation of important policies in an ever-turbulent and complex social and natural world.

Finally, we return to the opening Churchill quotes about not giving up. His words warn the listener to give in never except to convictions of "honor and good sense." This paper has attempted to provide some insight into what that good sense might be.

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