RHETORICAL EMERGENCE AND THE ECONOMY: THE SANTA FE INSTITUTE ARTIFICIAL STOCK MARKET, COMPLEXITY ECONOMICS, AND THE RHETORICAL DIMENSIONS OF ECONOMIC ACTIVITY

by

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Abstract

Drawing on work in digital and algorithmic rhetoric, I analyze the organization of space and time in complexity models. I argue that the success of complexity economic models is a consequence of their ability to reflect the rhetorical situation of the marketplace: they represent time as a series of causal interactions and space as a consequence of coordinated interaction. Complexity economics investigates the inclination of markets to behave as complex systems: self-organizing, emergent, and non-linear. The 1999 Artificial Stock Market designed by Sante Fe Institute theorists Blake LeBaron, William Brian Arthur, and Richard Palmer is perhaps the fundamental expression of a complex marketplace. It was among the first models to accurately predict market downturns, a success that followed as a consequence of its construction. In ordinary market models, traders are driven by profit maximization and a simple recursive strategy: they remember their mistakes, and respond to analogous market situations with new information in a linear, causal process. In their model, LeBaron, Arthur, and Palmer created a series of overlapping causal processes in which the market could operate as a persuasive agent. The unique compositions of complex economies is rhetorical. Their complex causal processes reflect a discursive marketplace in which space and time to emerge as relational properties.

Preface

This thesis is original work by the author, B. Eldredge. All of the data were collected independently. No part of this thesis has been published before.

Due to publication restrictions, and the fact that I needed to move internationally in order to take up a working position, I have not had the time to obtain permission to republish the relevant tables from variations of the SFI ASM; I encourage my reader to follow the included citations in order to compare the relevant graphs with their analysis.

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Acknowledgements

I would like to extend my sincere thanks to my supervisor, Dr. Ian Hill. Dr. Hill's constant thoughtful interaction was vital to the development of this project, and his influence in and support of my ongoing project to apply rhetorical criticism to economics exceeds words.

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For my wife, Em.

CHAPTER 1: INTRODUCTION

THE SANTA FE INSTITUTE, COMPLEXITY, AND RHETORICAL ECONOMICS

"In a richer environment, there is no evidence of equilibrium. Instead we obtain what we call *economic life*; as described in the following observations, there is rich evolving behavior that becomes more complex over time." —Palmer, Arthur, Holland, LeBaron, Tayler, "Artificial economic life: a simple model of a stockmarket."

In 1989, physicist John Holland and economist William Brian Arthur collaborated in the construction of an artificial, algorithmically-driven stockmarket at the Santa Fe Institute for Research in the Science of Complexity in New Mexico. In so doing, Holland and Arthur sought to model nonequilibrium dynamics in financial markets. Their motivations were primarily antipodal. Earlier that year, economists Ramon Marimon and Thomas Sargent had argued that even semi-rational agents would discover the fundamental form of a neoclassical market, in which every agent's demand was exactly matched by a corresponding agent's supply—homogeneous rational expectations equilibrium. Marimon and Sargent had constructed an agent-based model to support of their claim. For Holland and Arthur, the idea that heterogenous agents would discover perfect equilibrium was mathematically intractable and theoretically problematic; while perfect equilibrium originates in a top-down theoretical economy, semi-rational agents create a market form in relationship with one another. As a matter of course, that market form is relationally-contingent. Holland and Arthur's agent-based model was a success. In the first place, their agent's did not discover homogeneous rational expectations equilibrium. But, beyond refuting Marimon and Sargent's hypothesis, the SFI ASM had additional value. As William Brian Arthur explains:

> "We programmed the initial version in Basic on Macintosh…Initially our effort was to get the system to work, to get our artificial investors to bid and offer on the basis of their current understandings of the market and to get the market to clear properly…when all this worked we saw little at first sight that was different from the standard economic outcome. But when looking more closely, we noticed the emergence of real market phenomena…Our market was showing real-world phenomena that standard economics with its insistence on identical agents using rational expectations could not show." ("Preface," *Complexity and the Economy*)

The surprise for the discipline, and for the model's creators, was that when it ran, the SFI ASM operated almost exactly like a real-world market.

The publication of the SFI ASM marked a watershed moment in economics. For the first time, economists could observe, computationally, nonequilibrium dynamics that could not be proven mathematically. In 2006, Eric Beinhocker argued that "The field of economics is going through its most profound change in over a hundred years" (*The Origin of Wealth: Evolution, Complexity and the Radical Remaking of Economics*, xi), while Richard Holt, J. Barkley Rosser, and David Colander declared that "The neoclassical era in economics has ended and has been replaced by the complexity era" ("The Complexity Era in Economics"). While this high level of enthusiasm did not last, as many complexity theorists returned to neoclassical models, it remains that the SFI ASM succeeded in replicating real-world market behavior. In so doing, the SFI ASM opened up new methodological avenues for economic research, demonstrating that algorithms, properly composed, could imitate human agents. Those methodologies, and their corollary theories, continue to shape contemporary economies, where algorithms, rather than human agents, determine asset prices.[1] The SFI ASM's significant success is a consequence of two primary advantages. The first advantage is computation. By constructing algorithms to model economic behavior, analysts can observe, inductively, market behaviors that would be impossible to determine otherwise. The second advantage is complexity. The SFI ASM is a complex system, where novel phenomena emerge from ongoing interaction. As such, it calls attention to the persuasive characteristics of an environment, whose emergent dimensions work to coordinate divergent agendas and heterogeneous agencies.

The SFI ASM is composed of interacting agents: they reason, remember, project, and revise. The agents of the SFI ASM are algorithms; even so, those algorithms operate in order to effect one another's behavior. They are, in a word, persuasive. In that regard, the algorithms of the SFI ASM are models of rhetorical actors. My argument in this paper consists of two elements. The first is that the SFI ASM succeeded in replicating real-world market behavior because it succeeded in replicating real-world rhetorical agents. The second is that complexity economics, as expressed by the SFI ASM, evidences the relational relativity of economic dimensions. Time and space emerge through exchange and reflect the efforts of agencies to produce an effect in contrasting agents.

In this project, my approach diverges somewhat from other work in the field. For example, Deirdre McCloskey, whose oeuvre represents the pioneering work of rhetorical economics, usually argues that economists *use* rhetoric, that economics is, in her term, "literary" (*The Rhetoric of Economics*, 20). Other work combining rhetoric and economics takes a similar approach.[2] The effect of this inclination is to suggest that economists only *use* rhetoric to shape their audiences understanding of the economy. While this methodology affords valuable insights into the persuasive dimension of economic scholarship, its emphasis on the economist as an individual rhetorical agent elides the relationship between agencies and environments.

My approach emphasizes the *emergent* quality of rhetoric, in which environments, interactive modalities, and distributed processes all contribute to the formation of a common world. In this approach, the human agent is de-centered, or is, rather, composed of multiple intersecting agencies. As a consequence, my approach is similar to a number of methodologies that view the individual human agent as a single node in a larger, distributed agency. It is similar to Bruno Latour's Actor Network Theory, insofar as ANT defines an object as a stable array or network of relationships. It is similar to Deleuze and Guattari's formulation of nomadology, insofar as nomadology emphasizes the ontological dimensions of movement. However, my approach has the most in common with a discursive interactionist view of rhetoric. As Stephen Yarbrough writes, discursive interactionism is:

> "the view that the meaning of an intentional event, such as an utterance, is the product neither of its coherence with an already existent linguistic or cultural system of conventions, nor of its correspondence to an already existent set of 'real' things, nor of its mere effects upon perceivers. Rather, the meaning of an intentional event is the relation between the effects the agent expects the event to produce and the effects it actually does produce, so that meaning continually emerges as the agents interact." ("On 'Getting It'," 2).

The advantage of a discursive interactionist framework is that it emphasizes the phenomena of emergence, in which dimensions occur in a system as the anticipated but ultimately novel consequences of interaction: space, time, and even agency emerge through exchange. In this analysis, I employ a simplified version of discursive interactionism to define rhetoric: rhetoric is the study of competitive co-creation, the convergence of dynamic agencies who interact in order to effect the development of a continually-emergent common world.

In the remainder of this introduction, I outline the theoretical context of the SFI ASM. In the first section, I delineate the assumptions of neoclassical economics, and gesture towards some of neoclassical economic's limitations. In the second section, I introduce complexity theory and describe the import of complexity theory into economics. In the third section, I describe the development of the SFI ASM and call attention to differences between iterations of the model. In the fourth section, I briefly outline the chapters of this project.

1.1 NEOCLASSICAL ECONOMICS

Neoclassical economics describes an economic model rooted in the theory of rational expectations. The term was introduced by Thorstein Veblen in his article "The Preconceptions of Economic Science" where Veblen wrote "No attempt will here be made even to pass a verdict on the relative claims of the recognized two or three main 'schools' of theory, beyond the somewhat obvious finding that, for the purpose in hand, the so-called Austrian school is scarcely distinguishable from the neo-classical" (261). The term received rapid uptake on account of its flexibility: the assumptions that unify the neoclassical school do not begin with the nature of the economy, but with the composition of the economic actor. Importantly, the actor imagined by neoclassical theorists does not resemble an agent. It is instead a set of principles relating to rational activity: risk aversion, utility maximization, conditioned responses. Thus, while neoclassical economics shares definition of rational agent, it in fact originates in a highly-specific expression of rationality.

The theory of rational expectations is composed of three elements: human actors consider *all* relevant market data when making a trading decision, work to maximize their utility, and respond to repeated situations in the same way. Moreover, rational expectations theory assumes that all agents know all other agents share a rational form. As Palmer et al. explain, "All agents are assumed to know that all others are working with the same information on the same 'perfectly rational' basis. And they know that the others now this too, and that the others know that they know they know, and so on *ad infinitum"* ("Artificial economic life," 265). On account of this theoretical omniscience, an economy populated by perfectly rational actors always arrives at a self-consistent equilibrium. It is hardly surprising; there is nothing quite like understanding the whole universe to find one's place in it. Unfortunately, rational expectations are mathematically prohibitive, since the motivational complexity of even a single actor defies reduction.

The language of "rational" actors in rational expectations theory is misleading: "rationality" implies a cognitive process, the ability to reason. Unlike agents in complexity economics, rational expectations agents do not need to differentiate between viable alternatives. As Palmer, Arthur, Holland, and LeBaron explained, "One of the consequences of [rational expectations] is that almost everything is determined at time zero. The agents first work out how the future should be, and then the world just plays itself out" ("An Artificial Stock Market"). One consequence of rational expectations theory is that a rational expectations market is not like a real market. It does not unexpectedly crash. It certainly does not swing between the Bearish and Bullish moods that characterize real-world markets.

Neoclassical economics is also methodologically suspect, since the complex dynamics of markets are pared away, and the remaining element does not usually resemble a real-world economy. For example, in Robert Solow's foundational growth model, for which Solow won the Nobel Prize, economic growth is represented as a function of population and productivity, where population is a vector of movements between the city and the country, and productivity is a function of labor and employment ("A Contribution to the Theory of Economic Growth," 68). The problem with vectors is that they do not make choices; Solow does not allow people to live in the country in the summer and the city in the fall, or to have especially productive days, or to quit their job. The cumulative effect of constraining action through parameters is that a macro-model of a functioning economy is superimposed onto the motivations of its composite agents. This inclination is referred to as the fallacy of composition; it is evident when one agent's behavior is reflected in the macro-behavior of the economy.

Real-world economies, however, exhibit emergent behavior. As economists as diverse as Robert Lucas and Thomas Schelling have observed, the macrophenomena of economic trends are not usually indicative of or anticipated by the underlying microbehaviors. The distinctions between micromotivations and macro market behaviors eventually catalyzed the introduction of complexity theory into economics.

1.2. COMPLEXITY THEORY AND ECONOMICS

Complexity theory appeared in economics in 1986, when physicist John Holland suggested that an economy was an "Adaptive Nonlinear Network," a term that was later replaced by "Complex Adaptive System." Holland's insight rested on the concept of composition; if, as indeed seemed the case, the complex microbehaviors of underlying actors created novel macrophenomena, an economy was an emergent entity, and similar in concept to physical space, or a biological ecosystem, or an evolutionary process. Holland was not alone in making this claim: four years earlier, R. R. Nelson and S. G. Winter suggested that an economy reflected evolutionary dynamics (*An Evolutionary Theory of Economic Change*), while other economists had forwarded rough complex models for several decades (Marc Nerlove, "Adaptive Expectations and Cobweb Phenomena"), as well as complex game theoretical structures (*Theory of Games and Economic Behavior*).

Complexity theory describes the behavior of large-scale dynamical systems. A dynamical system is an entity whose composite elements are governed by stable principles. A complex system does not have an agreed-upon definition. However, like neoclassical models, complexity models are characterized by a common set of traits. Complex systems are nonlinear: their composite causal processes do not repeat continuously, but turn, and effect novel consequents. Complex systems are emergent: the multitudinous interactions of agents create large-scale structures that effect the consequent potentialities of the system. Complex systems are interdependant: their composite agents co-evolve. The actions of one agent both effect and are informed by the status of parallel figures.

Complexity economics's advantage is methodological; it works form the bottom up. Thus, an analyst can establish governing principles, such as the adaptive process of an agent, and then observe, computationally, long-run effects that are not evident mathematically. Unlike neoclassical models, in which every action is determined at time zero, complexity models allow for novel behavior. However, complexity economic's methodological advantage is also its problem. Since complexity begins at the bottom, with an adaptive actor, it does not offer governing theories. As a consequence, it is not easy to transform complexity economics's insights into economic policies. On account of this limitation, complexity economics declined in popularity in the early 2000's.

The Sante Fe Institute shut down its economics forum in in the early 2000s. The final economics publication produced by the Institute appeared in 2006, but reflected work discussed at a conference in 2001. The rationale for the SFI's termination of the economics forum is expressed in the volume's introduction. As Lawrence Blume and Steven Durlauf explain, "*The Economy as an Evolving Complex System I*, published in 1988, is largely speculative in that it describes the possibilities associated with the application of complex systems ideas to economics. *The Economy as an Evolving Complex System II*, published in 1997, presents some of the successes of the research program that was only dimly visible in 1987. The current volume, based on nearly 15 years of a functioning Economics Program, in turn reflects work in economics and complexity as a mature research program" (1). Evidently, while *The Economy as an Evolving Complex System III* represented the discipline's maturity, it also reflected its limitations. The editors, Lawrence Blume and Steven Durlauf, further write "this volume reflects some of the ways in which, at least informally, some of the early aspirations were not met. The models presented here do not represent any sort of rejection of neoclassical economics…the theory was able to absorb SFI-type advances without changing its fundamental nature" (1). By 2006, many scholars formerly affiliated with complexity economics had returned to neoclassical approaches. That they did so reflects the rising economics attitude of the time: psychological markets and econophysics, as well as big data analysis, represented the freshest aspirations for the field at the time. In brief, it seemed that other analytical avenues explained economic phenomena better than complexity economics. Complexity economics, it seemed, had seen its time.

It hasn't. William Brian Arthur returned to complex theories in 2013 ("Complexity Economics: A Different Framework for Economic Thought"). The economics forum of the Santa Fe Institute reappeared at the Intelligent Systems Lab in Bristol in 2010. After a hiatus in 2003, even William Brock and Cars Hommes, who worked on early alternatives to the SFI ASM, took on research projects in complexity economics in 2006, in their contribution to *Post-Walrasian Macroeconomics: Beyond the Dynamic Stochastic General Equilibrium*, which demonstrated that complexity economics could be adapted into financial regulation policies, including volume control, that were more effective than neoclassical alternatives (14).

In an interesting historical turn, complexity economics is on the rise again precisely because so much was unexplained in the field's early efforts. Why don't emergent behaviors ever alter the organizing properties of a system? How do individuals actually survive in perpetually-novel environments? Why do economic systems stabilize around particular constructs, such as value? The central question for complexity economics is increasingly clear: why does a system created by and contingent upon interaction actually converge to periodic stability, and how are heterogeneous agents able to coordinate action in a world where the very mechanisms of interaction are perpetually-novel? In this regard, the resurgence of complexity economics represents a special opportunity, where rhetoric, with its established insights into human interaction, represents a range of insights into interactive systems.

1.3 DEVELOPMENTAL TRAJECTORIES FOR THE SFI ASM

The first version of the SFI ASM was operational at the end of 1989, although Palmer, Arthur, LeBaron, and Tayler did not publicize their results until 1994. The SFI ASM first appeared in *Physica D*, a journal that then focused on the biological sciences. It was titled "Artificial economic life: a simple model of a stockmarket." The initial publication of the SFI ASM represents an odd moment in the history of agent-based modeling, and indicates just how little understood the emergent science of algorithmic adaptation was at the time: no economic journal published the project for another three years.

The original collaborators contributed to two additional versions[3], one appearing in 1997, "Asset Pricing Under Endogenous Expectations in an Artificial Stock Market," and the other in 1999, "Time Series Properties of an Artificial Stock Market." Both were coded in Objective-C, and both employed a market clearing mechanism to stabilize economic activity at the end of each period. Still, the SFI ASM iterations are not identical. The most important transition came in 2000, when the SFI ASM was ported from the Objective-C to the Java programming language

The most important difference between Objective-C and Java is that in Objective-C, the programmer sends messages to bundles of code, rather than "calling," or specifying coded functions to execute tasks. The effect of this "messaging" is that the receiving bundle of code interprets the message when it arrives, which means that Objective-C only resolves its code when it is actually running. Moreover, the Objective-C version of the SFI ASM was constructed to run on the Next operating system, which was obsolete by the end of the 20th century. On account of this limitation, two scholars, Brandon Weber and Paul Johnson, exported the original version to Java between 1998 and 2000 ("What I Learned From the Artificial Stock Market," 3). There were two further reasons for this transition; first, by the middle of the 1990s, only Apple used Objective-C (a language they still use today), while Linux and Windows both used Java. Second, the Swarm toolkit, which still allows analysts to construct artificial markets from a range of pre-coded material, was developed on Java as well. Swarm is coded in Java because Java allows analysts to analyze individual functions without actually running the program. For this reason, Norman Ehrentreich's 2008 investigation of the SFI ASM employed the modified Java version.

In this analysis, I analyze the Java version of the SFI ASM as it appears in Norman Ehrentreich's book, *Agent-Based Modeling*. The decision is pragmatic: the Objective-C versions obscure the actual process of interaction. An analysts can guess how certain functions process data, but cannot outline the precise component of a function that creates particular behaviors. Moreover, the Swarm library, to which the Java version contributes and from which many real stock market instruments are constructed, is still an active project.[3] In other words, the Java version still informs the shape and behavior of real world stock markets. I do, however, prefer the 1997 version in one section, Chapter 3, Complex Spatiality. The Objective-C version produces real-time time series data which offer a visual expression of emergent spatial phenomena. In the Java version, those phenomena would appear as statistical values.

The SFI ASM remains the fundamental expression of an algorithmically-driven stock market. As such, it is still adapted into contemporary models. The ongoing application of the SFI ASM's underlying code and composite theory is extensive. Tobias Wittmann's extensive book, *Agent-Based Models of Energy Investment Decisions* adapts the SFI ASM to study consumption, Matthieu Cristelli's recent book *Complexity in Financial Markets Modeling Psychological Behavior in Agent-Based Models and Order Book Models* extends the insights of the first SFI ASM to study dynamical psychology, and Olivier Barreteau and Alexander Smaigl's tractatus, *Empirical Agent-Based Modelling - Challenges and Solutions Volume 1, The Characterisation and Parameterisation of Empirical Agent-Based Models*, foregrounds an overarching project to formalize the computational insights of the SFI ASM, to name but a few examples. The contemporary resurgence of the SFI ASM foregrounds the questions of algorithmic agency from which the model emerged, and represents a special opportunity for scholars from other disciplines to critique the form of the economic agent.

1.4 CHAPTERS

Chapter 2 contains the most general analysis. I first outline the architecture of the SFI ASM. Then, drawing on work in procedural rhetoric, I analyze the formulation of rationality represented in the model. In the model, the core of an operational rationality is an agent[4]. In turn, an agent is a discrete algorithm that can accumulate stocks and cash. In general, it is difficult to talk about algorithms without accidentally misrepresenting my argument. Two basic terms are available: algorithmic agents, and agents. I prefer the latter because, as I explore in Chapter 2, an algorithm is only one unit in the distributed cognitive process of the model. An agent calls attention to the fact that the trading element of each cognition is the site of agency: they are the location where the ability to act is expressed. I argue that the rationality represented in the SFI ASM's mathematics is only one element of an agent's cognition. I extend my analysis to outline the discrepancies between the rationality represented in the model's mathematics and the rationality anticipated by the model's creators, and explain that the discrepancies those are overcome in the model's implementation. The SFI ASM's implementation is a form of procedural rhetoric by which the actual process of implementation evidences the rational form outlined by the model's creators.

In Chapter 3, I explore time in the SFI ASM. I observe the foundational rhetorical division between *chronos* and *kairos* and argue that the SFI ASM succeeded in replicating real-world market behavior because it allowed its agents to operate at the intersection of temporal constructs. First, in the model, the serial progression of the marketplace is stabilized by *chronos*, progressive time or periodization. Intriguingly, the model suggests that different logics correspond to different lengths of time, and that *chronos* is therefore a component of logical accuracy. Second, the market's trade activity is a function of *kairos*, the opportune time. The SFI ASM calls attention to the ontological dimensions of *kairos*: different market forms can reconcile different degrees of difference in trader strategies.

In Chapter 4, I explore the spatial phenomena of the SFI ASM and argue than in complex systems space is a consequence of interaction; the kinds of spaces that appear are an indication of the interactive modalities available to agents. In order to clarify this point, I explore three distinct spatial phenomena in the SFI ASM: the formation of stable sub-strata in market activity, where some agents abstain from adaptation in order to remain in relationship with compatible traders, the cascades of knowledge across the market, where complex knowledge structures force the market to adapt, and the belief space each agent explores, where each agent's persuasive capacity is expressed as a spatiality.

I conclude by gesturing towards some of the implications of complexity economics for rhetorical inquiry, and argue that complexity economics's focus on system dynamics represents a generative extension for existent rhetorical formulations.

CHAPTER 2

PROCEDURAL RHETORIC AND ADAPTIVE RATIONALITY

"We see our stockmarket model, and others of its class, as a fertile testbed for exploring markets…We also expect to make public our software (which includes dynamical displays of market and agent behavior) within the next year, so that others can share in the endeavor."
—Palmer et al.

After its initial appearance in 1994, the SFI ASM's architecture was adopted into what Paul Johnson called a "cottage industry" ("What I learned from the Artificial Stock Market," 1) of agent-based complex models. As Norman Ehrentreich, referencing a small selection of corollary models, explains, "Joshi et al. slightly adapted the original Objective-C version to analyze wealth levels. Tay and Linn extended the original model by using fuzzy logic for expectation formation. Wilbert, who used his own Borland C++ implementation, tested the model with different modifications[…]Gulyás programmed a participatory market model in which real humans were placing market orders alongside the artificial agents" (93). The model's numerous variations gesture towards one of the key attributes of the SFI ASM's success: in order to understand the consequences of the model, an analyst first needs to construct and run their own iteration. In other words, the model is only apprehensible when it is implemented. When the SFI ASM is implemented, it shapes the analyst's understanding of an economy in such a way as to support, methodologically, the market dynamics described by the model's creators theoretically. In this regard, the SFI ASM represents a successful expression of procedural rhetoric.

Procedural rhetoric represents an effort to critique the persuasive dimension of processes. It was developed by Ian Bogost; according to Bogost, procedural rhetoric is "the art of persuasion through rule-based representation and interaction" (Bogost, *Persuasive Games*, ix). As such, procedural rhetoric reflects a series of theoretical principles that delineate the persuasive elements of organized interaction, or procedures—in the case of financial markets, the persuasive dimension of organized economic activity. In his work, Bogost focuses primarily on computational structures "because computers function procedurally" and are therefore "particularly adept at representing real or imagined systems…that operate according to a set of processes" (5). While Bogost does not extend his analysis to analyze mathematics, it remains that mathematics parameterize causal relationships. In so doing, they model interactive procedures, and are structured to reflect particular interactive modalities. Moreover, as Brian Rotman argues, the performance of mathematics creates a *type* of performing self. In so doing, mathematics constrain accepted forms of knowledge, and accepted forms of rationality (*Mathematics as Sign*, 13). Mathematics, according to Rotman, are an *act*. This is especially the case in the SFI ASM, where mathematics constitute the raw material of the model. They are performed when they are assembled. Even so, the mathematics of the SFI ASM are expressed in code. So constituted, they work at the intersection of two distinct procedures: formal mathematics, which create a performing subject, and computational semantics, which direct that subject through a mediating structure.

Intriguingly, the theoretical assumptions which are evidenced in the model's semantics do no always align with the assumptions reflected in its mathematics. In other words, it is not uncommon for the act of assembly, in code, to contradict the interactive modalities represented by the mathematics of the model. In the SFI ASM, this is especially visible in regards to two theoretical constructs: learning, and rationality.

In the first place, Palmer et al. argue that in the SFI ASM, agents evolve to a periodic rationality (266), and, implicitly, that evolution is a progressive adaptive modality. This is not quite the case in the model's structure. Instead, the mathematics of the model indicate that the agent's are already-rational and adapt their condition bits to drive the market towards stability. Even so, this theoretical contrast does not receive very much attention from the criticism surrounding the model. Part of the reason for this disciplinary oversight is the fact that the nature an agent's learning is confused by the implementation of the SFI ASM. When an analyst actually interacts with the SFI ASM, that analyst must themselves go through an adaptive process in order to direct the artificial market towards real market behavior, therefore substantiating the model's claims concerning learning and progressive evolution.

In the second, insofar as the SFI ASM forwards a challenge to neoclassical models, it forwards an alternative figuration of the rational actor. In review of their model, Palmer et al. describe rationality as a characteristic of interaction, interchangeable with intelligence[5]. The form of rationality inherent in the model's structure contrasts somewhat with this definition. In the SFI ASM, an agent only constitutes one part of a market cognition: the former refers to an operational trading node, while the later describes the total thinking processes surrounding one such node. This cognitive model, a form of embodied cognition, is elided by the procedural rhetoric of the SFI ASM. When an analyst implements the model, they interact with a form of Objective-C code language. Objective-C code establishes a series of metaphors in which an agent's rationality corresponds to the stable structures within which action takes place. In contrast, an agent's intelligence corresponds to the activity itself. As a consequence, Objective-C effectively creates an artificial separation between an agent's rationality and an agent's knowledge, and thus confuses the relationship between an agent's knowledge structure and the kinds of information that can emerge through that structure.

In this chapter, I compare the mathematics of the SFI ASM with its code in order to describe the persuasive element of market processes. I argue that the form of learning and the form of cognition represented in the market's theory contrast, often intentionally, with the form of learning and the form of rationality latent in the model's structure. By obscuring the actual character of the model's rationality, the model's creators obscure the determinate dynamics of that market. This is because the form of learning and the form of rationality represented by a market together constrain the behavior of that market: they restrict what counts as information and as efficacious behavior. In so doing, the form of learning and the form of rationality represented in a market determine the distribution of goods and values in an economy.

In the first section, I outline the structure of the SFI ASM. This both clarifies the vocabulary of the model and speeds subsequent analysis. In the second section, I analyze the model's figuration of learning and delineate how the model's procedural rhetoric obscures that figuration. In the third section, I analyze the model's representation of rationality and contrast that representation with the representation forwarded by the model's procedural dimension. In the fourth and final section, I extend the model's insights concerning cognition to a real-world example—oil futures markets—in order to explain how a market's cognitive mode constrains the form of that market in the world.

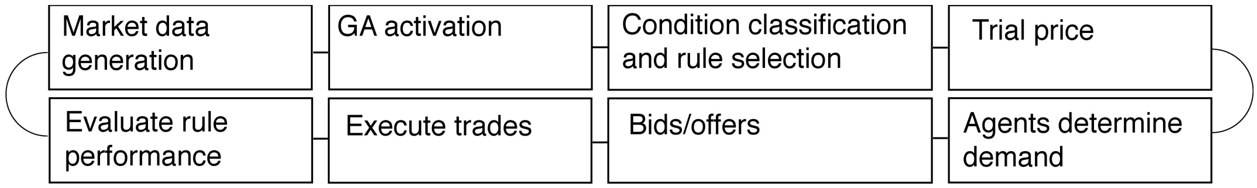
2.1 THE STRUCTURE OF THE SFI ASM

When an analyst began their investigation of the SFI ASM, they received a series of coded functions which were then assembled into the operational structure of the model. By and large, those functions constituted the interactive modalities of the agents, but they also included the rules that created a basis for activity.

In the SFI ASM, an algorithmic agent must choose between two available forms of market capital: a risky stock, which pays a stochastic dividend, and a liquid asset, cash. The stochastic dividend is determined in each period by a mean-reverting process that converges towards its basic value, if it is allowed to do so, over time. Each agent starts with one unit of stock and 20,000 units of cash. In terms of the model, an agent is a discrete trading node driven by a profit maximization strategy. An agent is further characterized by its risk aversion; like most human traders, it would like to get rich quickly but would rather stay comfortable in the long run.

At the beginning of every period, the agents receive market data and select an appropriate condition/action rule. They then determine a trial demand, which they submit to a market professional—a special set of functions—who generates a trial price. With that trial price, the agents determine their optimal demand and submit that demand back to the market professional. The professional then generates a clearing price, and if it satisfies the agents, trade activity occurs. At the end of each period, the agents evaluate the performance of their applied rule rule. At the start of some periods, determined by an established interval, the agents activate a Genetic Algorithm (GA) to create new trading rules. In general, the market activity of the SFI ASM is a circular process of the following form:

Figure 2.1



The data, which the agents receive at the beginning of each period, is constructed to reflect real-world market data: it describes the percent above or below its fundamental value at which a stock is trading and the long-term trend in dividend prices. Each of those states appears as a bit in a bit string, of a determined length. Each bit is either a 1 or a 0 or a #. In the early versions of the SFI ASM, the bit strings contained ten bits. The later versions contained sixty four. Those market condition bit strings are compared with an agent's condition-forecast rules, a version of a classifier system.

A classifier system is an expert system, which is, in turn, a term derived from the science of artificial intelligence: it describes a set of causal logics motivated by discrete outcomes and revised through recursive analysis. An expert system matches states of the world with conditional responses and then evaluates the effectiveness of that pairing relative to particular goals. In the case of the SFI ASM, the classifier system is responsible for generating price and divided forecasts, and takes the following form:

$$\text{rule}_{i,j} = \{(\text{condition part}); (\text{predictor}); \text{fitness, forecast accuracy}\}$$

In this, the (condition part) element is an individual rule. It is expressed as an if-then syllogism, and takes the form of the descriptor bit string: 0,1,1,#,0. The agents compare their bit strings with real market states. When a market condition is met, the related element in a given bit string is set to 1; if not, it is set as a 0; if a particular rule ignores particular market data, the place is filled with a #. For any given market condition, it is possible that multiple bit strings, otherwise described as rules, will become active, and the algorithmic agents differentiate between possible rules according to their fitness, the number of non-# bits represented in the rule, and by their forecast accuracy, which is a weighted punitive mechanism applied after each period. Once the agent converges to an active rule, that agent produces a forecast of stock and dividend prices based on its intrinsic causal consequent, and then uses that forecast to determine its optimum stock holding, relative to its constant risk aversion. The difference between an agent's optimum stock holding and its actual stock holding is its demand, which in turn becomes an action—buying or selling—at the end of each period.

In order to evaluate their rules, the agents are equipped with two learning mechanisms: recursive evaluation and evolution. The first, recursive evaluation, is comparatively fast. At the end of each period, the agents compare their rule's forecast with real data to evaluate its accuracy, and then reconstruct their internal rule hierarchy in order to develop successful strategies. The hierarchy of rules together constitutes an agent's knowledge structure. It is worth noting that a knowledge structure includes both the order of the rules and the distance between them, expressed as variations of accuracy. Thus, agents with a similar pattern of rules might differ significantly in operation if they employed those rules in different market periods, and thus attributed varying levels of success to them. In addition to recursive evaluation, agents employ a Genetic Algorithm. The GA is coded to correct an obvious limitation: with a limited set of rules, the agents could not condition upon every possible market configuration, unless they could develop new rules.

A GA is an adaptive mechanism; it is, in the model's terms, "evolutionary." The application of language from the biological sciences is intentional; algorithmic learning is modeled to reflect ecological development, rather than neurological development. That selection is largely pragmatic. As David Goldberg and John Holland explain, "Of the two natural archetypes of learning available to us—the brain and evolution—why have genetic algorithm researchers knowingly adopted the wrong metaphor? One reason is expedience. The process of natural evolution and natural genetics have been illuminated by a century of enormous progress in biology and molecular biology. In contrast, the brain, though yielding some of its secrets, remains largely an opaque gray box" ("Genetic Algorithms and Machine Learning," 98) Of course, the application of evolutionary frameworks to learning processes introduces a number of questions: are a person's adaptive processes themselves environmentally contingent? Or, more to the point, what counts as an environmental component? Fortunately, in the SFI ASM, these questions are less relevant. The genetic algorithm only interacts with rule accuracy values, and not with the agent's environment, the market.

The Genetic Algorithm's operation is comparatively simple: every so often, agents combine two of their most successful rules, with each parental bit having the same probability of appearing in the child condition. The GA also employs a mutation operator, in order to generate condition bits not present in the parent conditions, and so expand, rather than constrain, an agent's rule set. When the mutation operator is activated, each bit in the string is subject to semi-random variation according to predetermined probabilities. As Ehrentreich later demonstrated, the mutation operator in fact represents an internal path dependency: it is biased towards technical trading bits and drives the agents towards complexity (109). Ehrentreich's discovery is increased in significance by the fact Palmer et al. did not notice this bias for twenty years. Palmer et al.'s oversight indicates the theoretical assumptions with which the team operated.

2.2 LEARNING IN AN INTERACTIVE MARKET

In the SFI ASM, Palmer et al. conceived of their learners as "inductively rational" (266). Moreover, as Blake LeBaron later clarified, the SFI ASM co-creators imagined a system where they could "let evolution do most of the work" (Building the Santa Fe Artificial Stock Market," 3). In brief, the model's co-creators forwarded a formulation of learning through adaptation: by revising an endowed rule set, the algorithmic agent's would develop a mind, or a rationality, that was conditionally fit in a dynamic system. Learning thus represented the formation of operational intelligence.

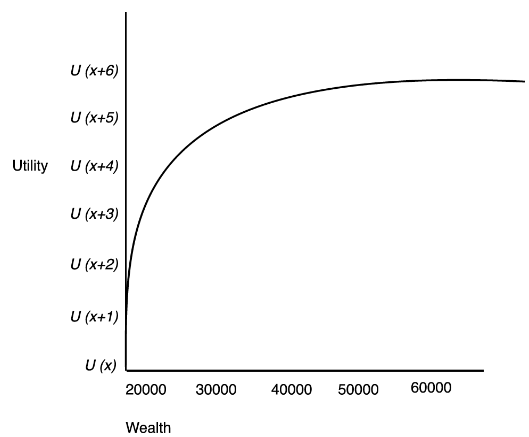
The mathematics of the model do not reflect this conception, and instead represent a system where agents are already-endowed with rationality; learning represents the negotiation of a common form of exchange. In order to clarify this point, some definition is helpful. As John Henry Holland explain in his onerous book, *Adaptation In Natural and Artificial Systems: An Introductory Analysis With Applications to Biology, Control, and Artificial Intelligence*, learning is comprised of two distinct bodies: the learner, and the environment (20). The learner is composed of a goal, an interactive modality, and a process of revision. The environment is the set of conditions with which the learner is confronted.

In the SFI ASM, the agent's goal is represented by their utility maximization function: they want to get rich. However, the significance of an agent's wealth is relativized by their constant absolute risk aversion (CARA). They want, more than anything, to avoid becoming poor. The CARA equation evidences the already-apparent intelligence of the agents. It looks like this:

Eq. 1

$$U(W_{i,t+1}) = -e^{-\lambda W_{i,t+1}}$$

In this equation, *U* relativizes the utility, or usefulness, of wealth. Wealth is represented by *W*. It is the total value an agent expects in period *t+1*, and combines their calculations for future stock dividends with their liquid cash. The equation for risk, $-e^{-\lambda}{}_{W_{i,t+1}}$, is isoelastic. On a graph, it looks like this:



The above illustration indicates that at a certain point, the risk associated with wealth (the *X* axis) increases more rapidly than the benefit of that wealth (the *Y* axis). The revelatory element of the risk equation is that it is predicated upon a series of rational axioms developed by John von Neumann and Oskar Morenstern. In simple terms, the mathematics here are only true if certain attributes are already evident in the agents; those attributes concern rationality. Von Neumann and Morenstern’s axioms describe four behaviors: agents can decide between alternatives, agents will decide consistently, agents will order potential actions in a single hierarchy regardless of the order in which those actions arise, and agents can conceive of combined actions that relativize their decisions (*Theory of Games and Economic Behavior*, 8-19, 617-631).

The point, for this analysis, is that on account of the CARA function, the agents are endowed with a form of rationality, built upon axioms not present in the model itself. The agents are already-intelligent. The question thus remains what the process of recursive evaluation represents. An analysis of the mathematics reveals that each agent's revision resembles negotiation more than progressive development. The equation takes the following form:

Eq. 2

$$\nu_{t,i,j}^2 = \left(1 - \frac{1}{\theta}\right)\nu_{t-1,i,j}^2 + \frac{1}{\theta}\Big[(p_t + d_t) - [a_{t,i,j}(p_{t-1} + d_{t-1}) + b_{t,i,j}]\Big]^2$$

Nothing is surprising here: agents calculate their forecasting errors by comparing the realization of prices and dividends [$(p_{t-1}+d_{t-1})$, (where $a_{t,i,j}$ and $b_{t,i,j}$ are the real-valued elements, the predictor bit of the chosen rule *j*)] with their expectations [(p_t+d_t)]. They then square the difference to correct for broad disprepencies, and combine previous and current errors along a graduated scale [$(v^2_{t-1,i,j}+1/\theta)$], where $v^2_{t-1,i,j}$ represents errors from the previous period. In so doing, they value current market formations over past iterations. That correction is important for a simple reason: agents operate in the present. Since the difference between the errors is relativized by a time interval, θ, that interval is the most significant parameter. The agents express forecasting errors as a value: ($v^2_{t,i,j}$).

Perhaps the most interesting element in the model's structure is the fact that the forecast accuracy of a rule, ($v^2_{t,i,j}$) is used also used as the measure of variance, ($\sigma^2_{t,(p+d)}$), or the measure of market stability. The variance value is employed in the following period to determine an agent's optimal stock holding. As agent's optimal stock holding determines that agent's demand:

Eq. 3

$$\widehat{x_{i,t}} = \frac{E_{i,t}[p_{t+1} + d_{t+1}] - p_t(1+r)}{\lambda\sigma^2_{t,p+d}}$$

In which the amount of stock an agent will hold is equal to its expectations of future prices and dividends [($E_{i,t}[p_{t+1}+d_{t+1}]$)], minus how much stock is going to cost in the next period [$p_t(1+r)$], divided by their constant risk aversion (λ), times the measure of observed variance of a stock's price and dividend ($\sigma^2_{t,(p+d)}$), which is also their rule's forecast accuracy. If it sounds circular, it is: an agent's experience of the accuracy of its rule is equivalent to their experience of a market's stability. The same equation (Eq. 2) is used to determine the two values.

This equivalence implies two contradictory formulations of learning. The first is that the market is perfectly stable: if that were the case, an agent would be right to equate its experience of variance with the accuracy of its own knowledge, and adapt its knowledge to progress towards precision. The second is that an agent's knowledge is perfectly stable: all observed variance is then market misbehavior, and so an agent can update its rules to move the market towards stability. The latter is reflected in the model's structure, evidenced both by the substitution of agent's accuracy for a market's stability, which prevails across the architecture of the model, and by the pre-established rationality with which agents enter the market. Interestingly, in models populated by heterogeneous agents, this formulation, where agent's drive the market towards stability, is very difficult to avoid. Blume and Easley's 1992 adaptive market is perhaps the only contemporaneous model that allows *agents* to adapt; Blume and Easley accomplished this feat by modeling the macro-behavior of wealth share ("Evolution and Market Behavior," 12). The amount an agent owned changed the manner in which that agent weighted its demand, and so the agent's rational process was itself flexible. Nevertheless, Palmer et al. argue that the SFI ASM also model demonstrates the efficacy of evolutionary adaptation. The chief vehicle for this argument is found in the model's procedure.

In the procedural rhetoric of the model, there are two elements that support evolutionary adaptation as a learning mechanism. The first is the separation of an agent's learning from an agent's knowledge structure in the model's code. The second is the adaptation required of the analysts themselves.

After the demise of the Next operating system, Paul E Johnson ported the SFI ASM to the Swarm library; in so doing, Johnson clarified some of the persuasive dimensions of the SFI ASM's early code. Johnson writes, "A glance through the sfsm code reveals that, although it is written in Objective-C, it is in fact ordinary C that is doing most of the work…The importance of the distinction is in the extent to which an *object-oriented* framework is used. The sfsm is object-oriented to the extent that the significant actors in the model are housed in separate files and when the simulation runs, objects built from those classes are instantiated" ("What I learned from the Artificial Stock Market," 2, emphasis in original). As Johnson further explains, the sfsm code operates by "separating the functionality of the components into clearly demarcated containers." Otherwise put, the mathematical components of the model appear as coded objects; an object is a set of functions and the data to which those functions correspond. In this framework, there is no difference between those objects that house an agent's learning structure and those that house the market's data dynamics, such as its price mechanism. Moreover, an agent's learning structure and an agent's bit structure, or rule set, are housed in separate objects. As a consequence, when an analyst actually implements the components of the SFI ASM, they are forced to treat an agent's learning function as an organizing dynamic of the model, rather than as an element of an agent itself. One of the consequences of this division is that that dynamic rule structure, or bit structure, seems unilaterally to constitute the agents. The agents therefore appear to be adaptive intelligences, rather than static intelligences that drive the market to stability with intelligent instruments.

The act of formal assembly reflects what Ian Bogost calls an "operational logic" (13), an organizing trope of a procedure. Bogost writes, "Operational logics for opening and saving files are also reasonable candidates [for procedural tropes]; these tropes encapsulate lower-level logics for getting handles to file streams and reading or writing byte data. We might call [these] *input/output (IO) logics*" (14). In other words, the process of arranging and opening coded objects structures the significance of code. In the SFI ASM, an agent's learning functions are not associated, operationally, with an agent's bit structure; an agents' learning functions are therefore separated from an agent's actual learning by the procedural tropes of the model.

Because an agent's learning functions are housed in their own objects, they are not easy to adjust. There are two variables that are. The first is θ, the period of an agent's reflection. The second is the amount of time an analyst runs the model before collecting data. As LeBaron et al. allow in their 1999 paper, "To generate time series experiments, the market was run for 250,000 time periods to allow sufficient learning, and for early transients to die out. Then time series were recorded for the next 10,000 periods" (1499-1500). Significantly, an analyst working with the SFI ASM tries different θ values and allows for different lengths of market activity in order to learn the lengths of time within which agents reflect market behavior. This often takes several tries. As Arthur et al. write, "We now run two sets of fundamental experiments[…]In the slow-learning-rate experiments…the predictors' accuracy-updating parameter θ is set to 1/150. In the medium-exploration-rate experiments…the predictors' accuracy updating parameter θ is set to 1/75[…]In the medium-exploration-rate experiments, we find that the market enters a complex regime" (28). When an analyst updates θ values in an attempt to reflect real-market behavior, the analyst performs an adaptive evolutionary learning procedure. The learning of the analyst is itself a significant determinant in whether or not the model will reflect real-world action.

Thus, while LeBaron et al. describe their learners as "inductively rational," the learners are not really inductive. As Daniel Schwartz and Taylor Martin explain in their work on adaptation, in an inductive framework "people do not have stable, mature ideas, but…are operating in well-structured and stable environments" (119). In the SFI ASM, the environment is not stable. The agents are. They enter the model with a pre-established rationality. As a consequence, the SFI ASM reflects a learning procedure where stable agent's co-create a stable market in order to model the cognitive form of exchange. That procedure in turn reflects a form of interaction evident in cognitively distributed systems: the market is both medium of exchange and medium of cognition.

2.3 RATIONALITY AND DISTRIBUTED COGNITION IN THE SFI ASM

In the field of algorithmic intelligence and machine learning, it is common to describe cognition as a "black box," an essentially impenetrable set of functions. In an algorithmic economy, this is especially the case, since it is difficult to delineate those processes that are constitutive of market reason. As an algorithmically-driven market, SFI ASM represents an attempt to clarify the position, and character, of market cognition. Like the agent's learning, the agent's cognition emerges when the model is implemented. And, as with the agent's learning, the implementation of the SFI ASM constrains the way in which an analyst can conceive of a market cognition.

In discussion of their model, Palmer et al. repeatedly assume that agents develop some bounded form of rationality, but is unclear what they mean by “rationality.” The problem is twofold. First, Palmer et al. draw upon economic conventions and refer to agent “intelligence” “rich psychology” and bit “technicality,” further confusing the location, and character, of an agent’s reason. In general, Palmer et al. frequently substitute qualities of action for a cognitive facility. Second, Palmer et al. do not make clear distinctions between a structure organizing knowledge, and an application of a structure to particular problems. The most clear expression of cognition is that expressed in the 1999 paper, where Arthur et al. describe the emergence of “several new analytic approaches to heterogeneity…[that] view the market as made up of populations of different strategy types, usually including technical, fundamental, and rational traders.” From Arthur et al.’s explanation, it is clear that the they understood rationality to be a performative characteristic. So understood, rationality is a modality in which an agent acts in a way that is compatible with its goals. If this were the case, an agent’s profit maximization function and its recursive evaluation equation would together describe the agent’s rationality. In the model itself, this is not quite the case. An agent’s rationality is only one element in an agent’s cognition, which is itself the main determinant of the action that emerges in a marketplace.

It is perhaps obvious that an algorithm itself, which is coextensive with an agent, represents the core of an agent’s cognition, but the question remains what, exactly, constitutes an algorithm in the SFI ASM. It is common to conceive of an algorithm as a problem-solving set of instructions, but that definition is incomplete. In the SFI ASM, each algorithm contains four discrete mathematical entities, the components of its problem-solving instructions: a risk aversion function, a demand function, a utility maximization equation, and a recursive evaluation equation. Each algorithm also contains a classifier system and the condition-action rule set itself. When analyzing an economic algorithm, it is not uncommon to stop there, and describe an algorithm as the set of functions that characterize its action (Arthur et al., 24). However, the materialization of each agent's action in the marketplace is expressed through pre-coded functions that perform a great deal of the knowledge work of the algorithms.

As Johnson explains, the SFI ASM's coded functions include "the behavior of stock investors (most importantly, the bitstring forecasting agent: bfagent), the dividend generator (dividend), a specialist who manages the market (speclist), a world object that collects data and makes it available to agents when asked (world), and various other classes that orchestrate the interaction of these classes" (3). The combined productive work of the various functions of the SFI ASM together compose the cognitive work of the algorithms. This is somewhat visible when Arthur et. al argue that "[The agents] not only update linear prediction models, they must also make some selection as to what information is relevant for their forecasts." In this regard, the algorithms the SFI ASM, and perhaps algorithms generally, are an embedded, environmental intelligence. Their cognition includes the total knowledge processes of a structure. The SFI ASM is thus in fact an example of a distributed, or an embodied, cognition.

The chief advantage of a distributed cognitive framework is that it formalizes the cognitive modes of dynamical systems. As Pierre Poirier and Guillame Chicoisne explain, "One truly has a distributed cognitive system when one has a system where a new cognitive property *emerges* from the interaction between the system's components, which may themselves be cognitive systems" ("A framework for thinking about distributed cognition," 28, emphasis in original). This formulation emphasizes the cognitive work already evident in a model's architecture, but relativizes that work through the interaction of agents.

The latter is especially significant, because it often confuses the situation of an agent's rationality. In the SFI ASM, the data generation functions create information. In so doing, they define what counts as information. The significance of that information, in terms of its causal dimension, emerges in interaction. David Lane and Robert Maxfield describe this phenomenon as "attributions of functionality" (182): the response of a group will determine how an agent conceives of each element of information. Thus, the kinds of knowledge that can emerge are contingent upon the kinds of interaction that take place. The relativization of information in interaction foregrounds the social constructivist dimension of market cognition. As a consequence, some theorists have described algorithmic rationality as an exclusively relative rationality, since it deals with effective behavior in particular settings, that algorithmic rationality is, in short, "performance" rationality (De Jong, "Learning with Genetic Algorithms," 123). This is not actually the case. The model itself represents the totality of each agent's cognitive processes. The market, where information is relativized through exchange, represents a common causal structure developed to facilitate exchange. The functionality of this structure is clarified by theoretical work from the field of embedded cognition.

In an embedded cognitive framework, agents structure their environment to reflect the epistemic conditions of particular problems. To use a prosaic example, a man who puts his car keys in his shoe offloads the work of memory onto his environment; he builds a structure in which the epistemic connections between dressing and driving in a morning routine are reflected in the material unification of two objects. In the SFI ASM, the agents restructure the environment to reflect the cognitive work of exchange. The market's form thus reflects the epistemically-relative act of economics activity. As David Kirsh argues, this environmental manipulation is a vital component of coordination, as an environment can instruct divergent agencies in the common form of interaction ("Distributed cognition: A methodological note," 66). So understood, the market is itself a cognitive coordinating mechanism whose constructed causal dimension saves the agents from having to calculate a novel course of action in every period. As Andy Clark otherwise argues, agents "will neither store nor process information in costly ways when they can use the structure of the environment and their operations upon it as a convenient stand-in for the information-processing operations concerned" (*Being There: Putting Brain, Body, and World Together Again*, 64). The market is thus the entity through which the agents coordinate the logics of exchange.

A close reading of the model's structure reveals that the rationality it reflects diverges somewhat from the rationality Palmer et al. describe in the model's surrounding theory. As with the distinctions in the agent's learning, it is intriguing that few, if any, economists were perturbed by the distinctions between the agent's theoretical rationality and the agent's observed rationality. As with the agent's learning, this is in part explained by the procedural rhetoric which evidences Palmer et al.'s formulation of rationality.

The theoretical rationality foregrounded by Palmer et al. (that of rationality as an operational modality) is evident in the process by which the market becomes visible. In the Objective-C versions of the SFI ASM, an analyst could only "see" market activity through coded memory allocations. Those memory functions are C structs. Johnson explains "A C struct is used to contain the information about a 'thing,' and one piece of information in the struct is a pointer to the next 'thing' in the collection. As long as one has access to one struct, then on can always find the next one" (10). In this code structure, the behavior of the agents is collected in to memory functions. In order to view the change in a value over time, such as trade volume, an analyst moves through the C structs and determines which elements will be assembled into market visualizations, such as functions or graphs.

In the SFI ASM code, the C structs represent what Bogost calls *interface logics* (14), the artifacts that allow an analyst to interact with computational structures. As Bogost further argues, interface logics form the basis of persuasive expression (14); interface logics establish implicit relationships. In the case of the SFI ASM code, the C structs establish implicit connections between bits of data, such as one period's price and the next period's price, but obscure other relationships. For example, in moving through C structs, the analyst moves through an ostensibly stable environment. The code behind the structs contains the model's implicit properties, its organizing dimensions. Significantly, the code behind the C structs reflects dynamic decisions, functions, and equations. However, by foregrounding a series of operational metaphors, the Objective-C code brings the analyst into alignment with the theory behind the model.

Since an analyst can only move *across* the equations that constitute an algorithm's cognition, such as a moving-average function or a trial price generator, the process of investigation itself constructs a contrast between the stable architecture of an agent's properties and the dynamic behavior of an agent's knowledge bits, which condition to particular forms of intelligence. The process of implementing the SFI ASM establishes a spatial metaphor in which the cognitive functions of the agents stand as the properties organizing activity, like physical laws, while the bits operate as the active, decisive material. Given this procedural limitation, it is hardly surprising that even Palmer et al. frequently equate bit technicality with agent rationality.

2.4 PROCEDURAL RHETORIC AND FINANCIAL MARKETS

The cognitive mode evidenced by formal structure of the SFI ASM differs significantly from the model of periodic, operational rationality forwarded by Palmer et al. and supported in the model's procedural rhetoric. In the SFI ASM, the entire market is a model of cognition, even though much of that cognitive work is obscured in the market's representation. Even so, Palmer et al.'s formal construction of a model as a distributed cognitive entity is immensely significant: different forms of cognition constrain the kinds of action that are possible in a system. As a consequence, much of the rhetoric of economics, insofar as financial markets are concerned, is found in the assembly of the whole cognitive apparatus.

In his work on algorithmic rhetoric, Chris Ingraham identifies a similar persuasive dimension. Ingraham writes, "In a more complex sense, then, algorithms are best understood as rhetorical if we consider that their outcomes are not empirically inevitable but rather the product of a particular set of parameters designed strategically to lead toward a particular kind of result. In other words, algorithms implicitly make a rhetorical argument for what factors matter in order to persuade their 'audience' that their resultant outcome is the best, truest, and most important" ("Towards and Algorithmic Rhetoric," 63). As Ingraham argues, algorithms reflect problem-solving systems that support particular ends. Similarly, cognitive modes constrain reasonable behavior in order to emphasize actions that are advantageous to particular parties. The ability of cognitive modes and algorithmic intelligences to constrain action is usually seen retroactively, as values or commodities pool in particular sectors. Nevertheless, the tendency of values and commodities to circulate in particular environments is in part a consequence of the cognitive models interpreting their activity. Oil prices, which rarely reflects the underlying economies in which oil is distributed, furnishes an excellent example of the cognitive procedurality's ability to shape space.

Unlike gasoline or other oil-derived commodities, oil prices are not determined by supply and demand. Oil is instead traded on futures markets. In a futures market, buyers and sellers trade contracts that allow the signing party to buy a commodity at a set rate at a future date. Large oil-based industries usually purchase the largest amount of oil futures in order to stabilize their production costs.

How, exactly, is the price set? The process is described as "price discovery." It is a process in which the current prices of underlying commodities, such as gasoline, are extrapolated based on large-scale market factors, such as national stability, international trade agreements, and even global weather. The algorithms that discover prices are ponderous, but, share a genetic algorithm and operate in an artificial marketplace that is very similar to the SFI ASM (Wang, An, Zia, Liu, Sun, Huan, "Generating Moving Average Trading Rules on the Oil Futures Market with Genetic Algorithms"). For the sake of this analysis, it is enough to focus on one dimension: national stability.

Oil futures are determined in part by the anticipated stability of governments. A government's stability is a function of its size, itself composed of income tax structures and governmental expenditures (Gali, "Government size and macroeconomic stability," 117). As in the SFI ASM, the information composing national stability contains a great deal of cognitive work. Specifically, the information representative of governmental tax structures privileges some governmental forms over others. As James Hamilton argues, oil moves within financial frameworks determined by particular theories of national development ("Understanding Crude Oil Prices," 180). In general, participatory democracies will have larger, distributed tax structures than oligarchical government forms, and thus, larger stability values in oil futures markets. In other words, in the rationality of futures markets, some governments will always count as more stable than others. As a consequence, low oil prices tend to pool under particular governmental regimes, even more so than in particular geographies. In 2008, when the United States's financial structure was considerably unstable, American companies still paid less than global averages, in part because its national apparatus corresponded to stability in the cognitive framework of oil futures.

In economies increasingly driven by algorithms, procedural rhetoric represents a valuable avenue of investigation; algorithmic economies affirm particular forms of rationality, and those rationalities in turn shape economies in order to benefit particular parties. In these models, as in the SFI ASM, the actual act of understanding is a procedural persuasive process. The procedure through which an algorithmic model is implemented and analyzed actively affirms the theories of rationality and cognition which are the main determinant of its results.

CHAPTER 3

COMPLEX TEMPORALITY: KAIROS AND CHRONOS IN ECONOMIC MARKETS

"The use of multi-agent models for financial market is driven by a series of empirical puzzles which are still hard to explain using traditional representative agent structures. Among the puzzles are issues of time series predictability." —Blake LeBaron

In a system, time is usually a given vector, working together with space to adumbrate both the situation and the dynamics of that system. In conventional science, time is designated as the direction of entropy, but it is there the difficulty begins. Complex systems exhibit *negentropic* behavior. Rather than developing towards dissolution, they converge to order over time, and so seem to be composed of multiple contrasting and interdependant temporalities. The SFI ASM is no exception, but is complicated still further by the mathematics of the model. Mathematics are not temporal in their formal design. Rather, they are designed to seem a-temporal. As with a logical instrument, once the parameters of an equation are established, any evident element in a mathematical process immediately implies its corollary parts. As Brian Rotman notes, "For most mathematicians…mathematics is a Platonic science, the study of timeless entities, pure forms that are somehow or other simply 'out there'" (*Ad Infinitum*, 5). This evident objectivity of mathematical operation represents its own debate; summarizing Rotman, Mitchell Reyes argues that mathematics are performed through a temporally-contingent self ("Stranger Relations," 476), while theorists as diverse as George Lakoff and Rafael Núñez, Giovanna Cifoletti, or Alain Badiou situate mathematical axioms in the transient idea, the rhetorical form, or wherever Badiou actually locates them. It is beyond the scope of this project to incorporate or otherwise resolve these debates; it is enough to assume that since algorithmic agents operate through constrained cognitive structures, they do not operate in time exactly as human traders do. This peculiar temporal restriction is generative: the SFI ASM is organized by several temporal parameters, or at least several parameters constructed to reflect temporalities. Reflecting on their model, LeBaron et al. write that the "crucial parameter for controlling the behavior of the market is the frequency of learning" (1499). In his analysis, Ehrentreich determined that the "the parameter θ determines the size of the time window that agents take into account when estimating a rule's accuracy…the value of θ is a crucial design question since it strongly affects the speed of accuracy adjustment and learning in an artificial stock market" (98). The recursive process of learning, the serial organization of market activity, and the dynamic character of the market in relationship to those processes all reflect particular temporalities. As an assemblage of computational mechanisms, the temporality of the SFI ASM is a logical temporality. It moves forward when its composite agents achieve sufficient logical equivalence. It stabilizes when the causal dimension of a logical proposition corresponds to particular intervals of market activity. In this chapter, I analyze temporal formulation in the SFI ASM through the lens of chronos and kairos. I argue that market chronos calls attention to the temporally-contingent dimensions of logic, and that market kairos emphasizes the ontological dimension of the "right time."

While the temporality of the SFI ASM is peculiar, it is neither unprecedented nor unanticipated. As a discipline, rhetoric maintains a perennial fascination with discrete temporal situations. Its vocabulary alone is rife with technical temporalities; there is "chronographia (detailed description of recurring times), hysteron proteron (disordering time), procatalepsis (anticipating future arguments or events), enallage (manipulating grammatical structure to influence semantic interpretation), and ampliato (related to epitheton, giving a name to someone or thing prior to its having been given that name)" (Kelly, Autry, Mehlenbacher, "Considering Chronos and Kairos in Digital Media Rhetorics," 230). Even so, in most cases, rhetoricians analyze time by employing a canonical pair. That pair consists of *chronos*, and *kairos*.

In the first section, I introduce chronos as it is understood in rhetorical scholarship. I then outline the elements of the SFI ASM that reflect chronos and explore their implications for economic time. In the second section, I introduce kairos, and connect kairos to a market's intrinsic ability to reconcile divergent logics and motivate action. In the third section, I extrapolate some of the insights offered by chronos and kairos in order to expose the deficiencies of the regnant forms of economic inquiry, specifically, econophysics.

3.1 CHRONOS IN THE SFI ASM

Chronos is deceptively pedestrian. Chronos has come to signify the interval, the period, or serial order, and is usually regarded as the unimaginative and pedantic prerequisite for kairos. It is progressive, and it is cumulative: minute stacked on minute in so many centuries. The history of the concept is less static. As Hans Rämö has pointed out, "chronos, as a denomination for time, probably traces its origin to the Indo-European base **gher*—to seize, take, hold, close, envelop—from which: **ghr-on-os*, and the following Greek, *chronos*" ("An Aristotelian Human Time-Space Manifold," 311). Thus, before Aristotle codified time into the serial order of before-during-after, chronos was likely associated with an action, a purposive serialization whose constructed character has been somewhat obscured in the intervening millennia.

And yet, even Aristotle's dominant figuration is hardly stable. John E. Smith suggests that since chronos refers to the universal, it is in fact rather more theoretical than kairos ("Time and

Qualitative Time," 8). Moreover, as serial order, chronos "constitutes the continuity of becoming, which in turn leads to a definite outcome" (8). Even in a chronological figuration, the serial element of persistence is coextensive with an environment's motive element. It is a description of a *process* of development, and so, while bounded, its character remains indeterminate.

As a theoretical construct, chronos is useful as an instrument of association. It allows nonsimiliar processes to converge into the shared logic of progression. As Marshal McLuhan argues, chronos is chiefly used as a mechanism for "accelerating the pace of human association" (*Understanding Media: The Extensions of Man*, 209). In the SFI ASM, chronos allows Palmer et al. to circumscribe the agent's otherwise circular rationality. The model is divided into periods. A period describes a linear organization of actions. Beyond this progressive organization, chronos is hardly stable, even in the model.

In his reconstruction of the SFI ASM, which featured a truly random mutation operator, Ehrentreich revealed that the algorithmic agents could develop a stable market form with any level of intelligence (*Agent-based Modeling*, 116). Put another way, the agents could employ a trading rule of any specificity and eventually reflect real world market action, given enough time. It is not surprising, perhaps, that a stable market appeared more slowly when the agents used less specific rules. But even so, the prevailing emergence of stable market forms suggests that the logical modality of each trader is temporally, rather than objectively, constrained. Any causal logic, given enough time, could be true. Thus, the static appearance of chronos is complicated by its dynamic behavior. Aware of this, Smith outlined an operational bridge between chronos and kairos in the process of maturation. Smith writes: "The aging of wine"—which itself reflects an evolutionary process of development—"furnishes an excellent example of an organic process in which time takes on a qualitative character…virtually any wine, once it has been constituted, can be consumed while it is 'young' but there is, for great wines, a time of maturity—this may involve decades—when the development reaches its peak. It is at *this* time that the wine will be at its best" (9). In its movement as process, chronos contains an ineluctably relative character: appropriate amounts of time relating to conditional operations and identities.

In an agent's recursive rule evaluation, the most important element is chronological. It is the interval, θ, which an agent considers when evaluating the accuracy of a rule (for the function, see Chapter 1). Arthur et al. observed that with an overly-constrained period of reflection, anything under 100 periods, an agent would not discriminate between random fluctuation and periodic market trends, and so market activity would be prone to "noise," or nonconvergent behavior. Moreover, the necessary length of θ is dependent upon the problem to be solved. To discern long-term variance, a long period of reflection is paramount. However, if θ were too long, the agents could neither detect short-term trends nor employ highly specific technical strategies whose condition bits correspond to specialized market forms. In the market, particular intervals correspond to particular problems. This further suggests that particular lengths of time correspond to particular logical modalities, a finding affirmed by Shareen Joshi and Mark Bedau's work on generic behavior in the SFI ASM. The length of θ determines what kinds of interaction will constitute knowledge ("An Explanation of Generic Behavior in an Evolving Financial Market," 6).

The implications of this finding are troubling: it is possible that agents do not remain in the market long enough to learn the logics that govern market activity. This possibility is affirmed in the SFI ASM, where Ehrentreich observed "the closer the mean-reverting dividend process gets to a random walk, the more difficult it is for the agents to arrive at the zero-bit level. It implies that pure random asset behavior in real financial markets is much harder to detect than more predictable asset behavior" (118). In essence, even complex learning strategies, with dynamic θ values, might not differentiate between between random variation and long term trends. Ehrentreich continues, "In real financial markets, the constant departure of experienced traders and the arrival of new traders might lead to constant out-of-equilibrium behavior…any practical learning speed could put us in the region where it is extremely difficult to discover the randomness of asset prices." It is likely, given the divergent character of human chronos and market chronos, that the logics through which human agents learn do not correspond to the logical intervals that govern market action. When this finding is reflected back onto rhetorical formulations of time, chronos cannot be understood as an exclusively extrinsic device. It is instead a rhetorical figure, a component in interactive logics. It is likely, given the conditional elements of chronos, that it is an oft-neglected instrument of logical circumscription. It remains, in other words, a mechanism to "hold, close, or envelop."

3.2 ONTOLOGICAL KAIROS IN COMPLEX SYSTEMS

While chronos is the most important determinant of a logic's veracity, kairos is the most important element both of a trader's memory and of a market's elasticity, or its ability to reconcile divergent agendas. In the first place, traders relativize their experience of a rule's accuracy through a single function, an exponential weighted moving average. That function is intended to reflect the creative capacity of memory; however, it implies that an agent's recursive evaluation is coextensive with its knowledge creation, and thus, evidences formulations of rhetorical memory in which memory is operationally connected with invention. In the second place, when the SFI ASM runs, a market professional generates a clearing price based on agent's demands. And yet, not all clearing prices will generate market activity. Arthur et al. explain, "our market-clearing mechanism simulates an auction in which the specialist declares different prices and agents continually resubmit bids until a price is reached that clears the market" (40). Whether or not a given price will generate market is a function of the market's form. Different market forms reconcile different levels of difference between agent logics. This behavior calls attention to the ontological dimensions of kairos, both as a creative restructuring of time, and as the intrinsic ability of some states to motivate action. In order to understand the full significance of ontological kairos in the SFI ASM, it is necessary to review rhetoric's formulation of kairos itself.

Like value, or like complexity, kairos is easy to identify but difficult to define. In its basic form, kairos refers to qualitative rather than quantitative time. While its formative delineation is found in the work of Aristotle, Plato beat him to the punch in the *Phaedrus*:

> "it is only when [the rhetor] has the capacity to declare to himself with complete perception, in the presence of another, that here is the man and here the nature that was discussed theoretically at school…to which he must apply this kind of speech in this sort of manner in order to obtain persuasion for this kind of activity—it is when he can do all this and when he has, in addition, grasped the concept of propriety of time (*kairos*)…that the finishing and perfecting touches have been given to his science" (27I-27b).

In Plato's formulation, kairos is divided between two phenomena: an actual opportune moment, and a speaker's recognition of that opportunity. It is, therefore, the dynamic interplay between experienced actuality and perceived potentiality. Aristotle's formulation is rather more formulaic. It consists of three elements. First, timing (the right time). Second, a time of tension which calls for decision. Third, an opportunity to accomplish some purpose. (Smith, "Time, Times, and the Right Time," 6). Again, kairos is characterized by a peculiar quality whose preexistence is nevertheless dependent upon a rhetor's discovery. In this regard, Eric White's definition is rather more provocative. White defines kairos as a " radical principle of occasionality establishing the living present as point of departure for rhetorical invention" (*Kaironomia*, 161), although in so writing, White perhaps too much emphasizes kairos as a point from which rhetoric departs instead of a point to which persuasion converges.

As a construct, kairos calls attention to the conditional element of time. For this reason, the element of perceived opportunity often supersedes the ontological element of kairos. Rämö writes that "from an Aristotelian point of view, the notion of kairos still remains closely connected with *human right moments to act*" (Rämö, 313, emphasis in original). Or, as Miller, with signature frankness, argues, "A rhetoric that involves kairos…is necessarily relativist" ("*Kairos* in the Rhetoric of Science," 314). Still, kairos contains a unique ontology whose significance to complexity theory is paramount. In their work on chaos theory, which prefigures complexity theory, Ilya Prigogene and Isabelle Stengers adapted Lucretius's physics from *De Rerum Natura* in order to describe kairos as the right moment for system emergence. Kairos, in their work, describes the stochastic quality of time, which is the necessary prerequisite for complex system formation. Moreover, Bitzer's foundational description of the rhetorical situation described kairos as an objective quality which elicited a speech act from the rhetor ("The Rhetorical Situation," 5). And, as John E. Smith observed, "while the watchword of pre-

Socratic ethics was 'Know the opportunity' in the context of human action, the Pythagoreans regarded *kairos* as 'one of the laws of the universe.' This Cosmological dimension of *kairos* must not be lost, as indeed it could be if it were supposed that the *chronos* aspect of time is physical and metaphysical in import, while *kairos* is mainly anthropological or practical" ("Time and Qualitative Time," 5). In the SFI ASM, the ontological dimension of kairos is especially productive, for while the algorithms do operationalize their knowledge in relationship, they do not interact with one another directly, and so do not persuade or recognize distinct opportunities in any conventional sense. Their interactions with time are formal. As I have already indicated, there are two distinct time-based properties whose character is kairological: the agent application of memory (the variance estimate), and the reflective period through which agents learn (weighted recursive evaluation).

A rhetor's experience of time is relativized by that rhetor's memory. In the canons of rhetoric, memory plays a vital role in determining proper action. It is linked to the knowledge of precedent, and therefore to an individual's understanding of cause and effect. For human actors, memory is elected from a continuum of experience and is considerably difficult to delineate. Still, in order to imitate human action, the algorithmic agents require some form of memory, and in the SFI ASM, it is represented by an agent's recursive evaluation. That evaluation is primarily chronological: the period, θ, an agent considers when evaluating the accuracy of its rule. In their description of their model, LeBaron et al. emphasize the significance of θ to an agent's ability to produce efficacious knowledge. Their language is provocative: "Fixing [θ], the period of evaluation, at 75 is a crucial design question. The value of [θ] determines the horizon length that the agent considers relevant for forecasting purposes. It does this in a smooth exponentially weighted fashion, but it does set an arbitrary cutoff on information. If agents used all past data, then they would be making the implicit assumption that the world they live in is stationary" (1496).

Recall, when an agent calculates a rule's accuracy, it relativizes that figure according to an exponential moving average (a weighted average) of current and past errors. That weighted average is problematic: it suffers a periodic diminution. The trouble with an exponential moving average is that it does not differentiate between degrees of relevance. A vital error could be dismissed only because it appeared very early in the market's action. Worse, an exponential moving average fails to reflect real-world action: human traders do not interact with time as a linear logic, but instead relativize their strategies in the light of mistakes to which they attribute value, and those could happen at any time. The sole advantage of an exponential moving average is that it prevents a trader from dismissing either a very general or a very specific rule—the persistent small errors of general rules would otherwise add up to unworkable magnitudes, while a specific rule, with its wide margins of success and failure, would be dismissed after only one or two inaccurate appearances. The agent's focus on the present tense levels the probable playing field. Nevertheless, an agent's chronologically-mediated memory is problematic. Palmer et al. do no address this difficulty; the model's success suggests that it works out, somehow.

But there is no magic in math. The oversights, which are evident in the model's structure, are corrected, perhaps unintentionally, in its operation. In their appearance as quantities, all times, however, distant, are transfigured into degrees of magnitude. Thus, while the arithmetical progression imitates spatial perspective (and so suffers the problems of diminution and chronological inaccuracy) the quantitative character of those figures corrects at least part of this problem. Put another way, insofar as they are numerical values, all temporalities are perceived as immediate. From emergent quantitative distinctions, the algorithms relativize their logics and create structures of knowledge. In this process, the algorithms do not interact with serial order, or with chronos at all. Instead, their experience of time is a probability: it is the likelihood that particular structures of knowledge, with their corollary causal logics, are advantageous tools relative to certain goals.

In this regard, the algorithmic agents embody classical conceptions of memory. As medievalist Mary Carruthers has argued, what is now considered either intuition or imagination was in classical understanding memory (*The Book of Memory*, 8). Elsewhere, media theorists such as Geoffrey Bowker (*Memory Practices in the Sciences*) have productively argued that memory is coextensive with knowledge production, codifying the structures through which experience is mediated. In Bowker's formulation, memory is an inventive act directed toward some purpose. As Bowker writes "memory work develops and is enacted within functional systems" (261). The knowledge production, which is enabled through the act of memory, is directed at some object. Of course, the agents represent the performative extreme of this canonical formulation. They do not reflect on passing time at all, except as a tool to construct knowledge through varying degrees of causal probability. And yet, in so doing, the algorithmic agents of the SFI ASM represent several productive avenues of analysis for time and memory in computational space.

First, and most evident, the algorithmic equivalent of memory suggests that an agent's experience of time is coextensive with the formal structure of its knowledge, or how it organizes cause and effect. Second, insofar as market action requires action on the part of the algorithmic agents, it suggests that the time which emerges in a market is created by this process in a literal sense. And third, the agent's memory offers an explanation for how computational atemporality might interact with a dynamical system in motion: the time which emerges through market action is outlined by differentials of data, which in turn outline the causal efficacy of a logical structure. In a marketplace, time could represent an interdependent process between a conditional logic's accuracy and the amount of action that will emerge as a consequence.

Since each agent's experience of time is relativized by its memory, each agent represents a distinct temporal organization. They do not experience time in the same way, and thus diverge both in their expectations of causality and in their understanding of market logic. And yet, market action requires some level of logical congruence. After each agent calculates its expectations for the next period's prices and determines its corollary demand, it submits that demand to a market professional. The professional averages those demands and sets a clearing price. However, not all clearing prices generate market action. It is possible, if the expectations of the agents were not compatible, for the agents to reject the clearing price. When this happens, the professional sets another trial price, with which the agents calculate another demand, and, eventually, the professional tries another clearing price. This circular action can take place up to ten times, beyond which the professional simply rations half the market and the whole thing starts over. To generate market activity, the professional must discover an appropriate degree of logical equivalence. The range of necessary equivalence is dependent upon market form.

Consider, again, the creation of periodic trial prices. While the professional generates those prices, no time passes. Instead, distinct potentialities emerge, expressed as a degree of difference between an agent's own demand and the mean demand, or the standard of deviation.

Interestingly, there is no definitive range for a standard of deviation with which the market will move. Instead, different market forms correspond to different ranges of acceptable difference. Put another way, different market forms can coordinate distinct levels of logical equivalence. It is a kairological quality: the form of the market represents a unique opportunity. The character of this market kairos is unique: it is the ability to coordinate discrete agendas in the space of an exchange and make time move. It is, furthermore, intrinsic to the market. In other words, at least in financial markets, some kairos is the precondition of periodic chronos.

This formulation of kairos has tremendous heuristic value, and complicates prevailing notions of market action and stability. In their work on periodic stability and chaos theory in financial markets, Youngna Choi and Raphael Douady defined the limited capacity of markets to balance divergent agendas as "metastatic equilibrium" ("Financial crisis dynamics," 1352). In their analysis, periodic stabilities are, in fact, predicated upon narrow margins of compatible logics, beyond which the economy slips into chaos. It is a quality otherwise defined as elasticity, the ability of financial markets to coordinate variant strategies. However, in this line of analysis it is common to attribute varying levels of elasticity to distinct industrial agendas, or else with levels of economic connectivity in an economy. The variegated composition of underlying actors, especially in their divergent risk aversion and utility maximization strategies, cumulatively creates a periodic stability. Elasticity then describes the inclination of market actors to respond to one another, and theorists have developed complicated instruments to measure that inclination. However, the fact that similar phenomena emerge in the SFI ASM challenges these attributions—even in market populated by homogenous traders, who are specifically incapable of divergent risk aversion or utility maximization, emergent market forms contain a corollary quality, a range of compatible logics with which they will continue to operate. It is a sort of *argumentum a contrario*: the SFI ASM suggests that emergent market forms, rather than divergent trader qualities, contain an internal level of elasticity which elicits market action from the traders. In this formulation, a complex market's negentropy, or convergence across time, is dependent upon kairos, the precondition for movement.

3.3 ECONOMIC TEMPORALITY

In the SFI ASM, time is indeed an organizing dimension, but not in a conventional sense, as an external interval. Instead, time plays two major roles. As chronos, time represents the contingent nature of logic: different trading rules correspond to different lengths of time. As kairos, time represents a quality that emerges in a market and allows action to occur. The formulation of time represented in the SFI ASM has tremendous heuristic value. It offers explanatory insight into real-world market behavior, and further, it challenges the excesses of the regnant economic models.

In the first place, complex temporality offers a rationale for market irrationality: at certain moments, a market might fail to reconcile the divergent logics of real world traders, even if those logics were almost identical. Thus, the SFI ASM contains a useful framework for analyzing contradictory market downturns. Still more, an ontological interpretation of market kairos can be extended to analyze the phenomena of value. Insofar as value represents a node in which noncommensurable agendas can reconcile in an exchange, it is a kairotic element, and could itself serve as an instrument to measure a market's current ability to reconcile noncompatible logics.

In the second place, complex temporality calls attention to the difficulties surrounding the rising form of economic analysis, econophysics. Econophysics applies insights from the physical sciences to economic phenomena and represents time as a motion, the aggregate movement of a marketplace. Multiple-threshold models, adaptive compositional models, and high-dimensional stochastic regression models, to name but a few, begin by assuming that time is a function of force and is therefore composed of its underlying processes. The problem in these models is that time is unidirectional; it is a consequence of motion, and so like motion, inclines towards entropy. While the insights afforded by these models are significant, it remains that if econophysics intends to reflect economies composed of human actors, it will need to account for the nonequivalence of its own presuppositions with observed social phenomena. Psychology's distributed cognition, for example, is predicated upon a theory of multidirectional causality, in which the extension of a psyche across time creates multiple entangled causal processes (Sutton, Harris, Keil, Barnier, "The psychology of memory," 524), rather than unidirectional causal processes.

What econophysics approaches lack is the insight afforded by the SFI ASM: time and logic are discrete, interdependant entities. As I have demonstrated, in the SFI ASM, temporal progression is a function of logical equivalence, mediated by qualities internal to the market form. Further, in a complex marketplace, an individual's interaction with time is limited to logics: an agent can organize history through rules of cause and effect, or make assumptions about the future through forecasts rooted in particular statistical theories, but it cannot interact directly with the dynamic process the market is. In the SFI ASM, time is a complicated figure. It is both an extended progression within which logics correspond to particular intervals, and it is a quality intrinsic to and emergent in market forms.

CHAPTER 4

COMPLEX SPATIALITY

In a complex system, space emerges through interaction; it is conditional, emergent, and dynamic. Moreover, distinct spatial types reflect distinct interactive modalities. The type of interaction constrains the type of space that will emerge in a system. As a consequence, even apparently stable spatial phenomena, such as distributive distances, represent the organizational counterpart of interactive structures. This is true in the SFI ASM, where space is a both a consequence and an illustration of the type of interaction taking place. In this section, I analyze three distinct spaces in the SFI ASM—trading nodes, cascades, and belief space—and argue that each space emerges as a consequence of a distinct interactive form—identification, competition, and persuasion.

An example of spatial emergence through interaction is evident in a series of maps for the city of Cambridge, Massachusetts. In 2014, the Social Computing group at MIT Media Lab, a consortium of computer scientists, mathematicians, and designers, began a project to map cities with dynamic dimensions: *You Are Here.* The three maps below represents three complex systems in a single city. The top left map shows every coffee shop location in the city and its corresponding walking area. The top right map shows the efficiency of distinct modes of transportation in distinct regions. The bottom left map shows the city's street greenery.

Figure 4.1 Coffee Shops

youarehere.cc/w/coffeeshops/cambridge

Figure 4.2 Transit Efficiency

youarehere.cc/w/bestmode/cambridge

Figure 4.3 Greenery

youarehere.cc/p/green/cambridge

The differences evident in the maps are consequences of distinct interactive modalities. In the first, individuals can self-select into shops. The consequent spatiality is therefore contingent upon the amount of people self-selecting in a single area. In the second, transportation efficiency, individuals are constrained. Assuming similar transportation needs, the further an individual person lives from the city center, the more likely it becomes that they will need a car. The meaning of distance, relative to transportation, is shaped by populations densities and also by wealth. The third map, city greenery, is perhaps the most complex. People are free in that they can choose to plant trees and shrubs, by are constrained, somewhat, by their environment. Interestingly, the oldest neighborhoods tend to be the most green, rather than the wealthiest. Greenery is a thus semi-free environment shaped by time. It is important that while each map partly corresponds to its underlying geography, it reflects spaces shaped by predominantly non-geographic variables.

In the course of this argument, the vocabulary of space is restrictive. This is chiefly because “space” as such implies a system of coordinate planes, the actual constitution of which is unclear: even a Euclidean plane functions by relativizing the behavior of one variable (usually a unit description) according to another (usually quantity), and so the significance of a space is contingent upon whatever relational characteristics receive emphasis. Moreover, developments in geography have for more than a century indicated that space is an epistemological instrument, and thus varies with epistemology (Merriman et al., "Space and spatiality in theory," 4). In algorithmic learning theory, and in financial markets, it is more common to speak of "environments." Insofar as an environment describes a rigid pattern of traits constraining action, the term is a better fit. In addition, there is a growing body of research that indicates rationality employs spatial constructs. As Christian Freska, Nora Newcombe, Peter Gärdenfors, and Stefan Wölfl argue, "Cognitive agents process various kinds of spatial knowledge for learning, reasoning, and talking about space…A particularly interesting feature is that much of the internal representations of the meanings of words seem to have a spatial structure. This also holds when we are not talking about space as such" ("Preface," vi). Characteristics such comparative sizes, relative location, and operational distance emerge as spatial figures from rational processes. This is true in financial markets, where space emerges as a material expression of the *type* of action going on.

In order to clarify the significance of space in the following argument, I employ three distinct terms: space, spatiality, and spatial phenomena. A space describes an environment, a situation in which two or more objects, ideas, or actions, are relativized, either according to a common schema or to one another. A spatiality describes a situation which is related to space in concept but not yet constrained by an interpretive schema. A spatial phenomena describes a situation with spatial characteristics, i.e. relativizing structure, mass, distance, that nonetheless exists only in the knowledge structure of an agent.

Space, spatiality, and spatial phenomena are also useful because, taken together, they emphasize the dynamic, contingent character of a market's materiality. In a market, space is not stable in itself, but instead reflects the stability of interactive modalities, which define environments in a way that has consequences on subsequent action.

In the first section, I define a market so as to circumscribe the actual entity within which space emerges. In the second section, I analyze the knowledge clusters that operate as stable strata over which agents scaffold complex knowledge structures and indicate the similarities of those strata to Burke's theory of substances. In the third section, I analyze the "avalanches" of knowledge the characterize competitive intelligence and interrogate the connection between those avalanches and ideological imposition. In the fourth section, I analyze the "belief space" that describes an agent's application of novel knowledge and delineate the connections between an emergent belief space and an agent's persuasive faculty.

4.1 A SPATIAL MARKET

In an economy, a market refers to the agencies of supply and demand, albeit in an abstracted form. It is a consuming public, and the avenues of access to that public, as well as the productive forces arranged to compete for that public. The most widely-used definition is attributed to Augustin Cournot, but seems instead to have originated in Alfred Marshall's *Principles of Economics*, where it is quoted: "Economists understand by the term Market, not any particular market place in which things are bought and sold, but the whole of any region in which buyers and sellers are in such free intercourse with one another that the prices of the same goods tend to equality easily and quickly" (Book V, Chapter 1). From this definition, it is clear that a market does not describe any evident object, but a pattern of activities bound through common interpretation; "such free intercourse" could signify almost any stable state.

It should be clear, even with little definition, that a "market" functions as a vehicle to describe an object of otherwise prohibitively complexity. A public includes hopes, beliefs, labors, needs, and an epistemological structure to interpret them; the forces of production are similarly variegated. Moreover, as Yannis Iaonnides demonstrates, the designation and corresponding interpretation of these structures governs what can happen in their underlying spaces (129). Still, for the present, it is enough to define a market as a social formation of exchange. A market's structure is more definite. It describes the mechanisms of transaction, and includes laws, regulations, and transactive mediums, such as money, stocks, or commodities.

A financial market, of which the SFI ASM is a type, is still more abstract. It is abstract because it is isolated. Unlike real-world markets, a financial market is not relativized by alternative spatial designations. It exists in and through exchange. A financial market's "architecture" describes the whole of its delineated processes: how an asset will be weighted, how an agent can gather knowledge about trading activity, how an agent can apply its knowledge, etc. For the SFI ASM, the architecture of the market consists of its trader's structure: their learning mechanisms, their profit maximization strategies, and the behavior of a price in response to their bids and offers—in short, the procedural rationality outlined in Chapter 1. The SFI market *form* is composed of multiple intersecting knowledge structures in the emergent environment of exchange.

Significantly, a financial market originates in a trader's motivation to participate in economic activity. In the SFI ASM, the traders are already motivated to trade. In some ways, this already-existent motivation is disappointing, because it obscures both the intuitive fact that trader's might not enter a market with compatible logics, or even compatible learning mechanisms, and the fact that the market could emerge as an instrument of overcoming these differences. The market could, in other words, be a methodology of remedying miscommunication. If it were, that would have substantial consequences on the formation of market spaces. Nevertheless, the agents of the SFI ASM are good analogues for already-existent agents whose combined interaction composes the entity of the market.

For financial markets, graphs, charts, and tables remain the preferred means of making market dynamics visible. The advantages offered by these graphs are significant; as Edward Tufte argues, "Graphics *reveal* data" (*The Visual Display of Quantitative Information*, 13). In financial markets, these charts, tables, and graphs are unified by a series of conventions, the most common of which is to organize market activity on a bivariate scatter plot with a range of orthogonal coordinates. Time and trading volume, which together compose the "time series," are usually the variables of interest: the NASDAQ, the DOW Jones indices, and the NYSE composite index, to reference but a few examples, organize market activity between volumes of trade and time.

The time-series convention is itself problematic, since bivariate scatter plots imply a certain degree of causal correlation, as though time were the medium through which value moved, rather than knowledge or language or some external instrument. Worse, at least so far as Tufte's enjoiner that graphs should "avoid distorting what data have to say" (13) is concerned, is that bivariate charts allow analysts to import external logics into their market analysis. Rises are positive. Dense clusters of jagged fluctuations are dangerous. Like low hills, long, slow rises indicate stability, continuity, and, most of all, ease of access. In other words, financial time series communicate through a series of spatial metaphors and cultural associations that together distort the situation of the marketplace. That situation is further obscured by the language describing markets: unstable markets contain a "rich psychology," while upswings and downswings together determine a market's "moods;" slow adjustments are market "hesitance," while large upswings indicate market "optimism." In the field of financial analysis, it does not seem to bother very many people that a time series, by which a market is made visible, is treated as a personality, or a *mind*.

Even so, time series graphs do reveal spatial phenomena, but only when they are read through the market's underlying interactive structure. The SFI ASM's time series graph, for example, evidences the primary spatial element of a financial market, scaffolded knowledge, but only when that time series is read as a reflection of the agent's interactive modalities.

4.2 KNOWLEDGE CLUSTERS.

In the artificial stock market, the process of adaptation sometimes halts, for some traders, when those traders converge into compatible knowledge structures. As Arthur et al. observe "the market can self-organize into mutually supporting subpopulations of predictors" ("Asset Pricing Under Endogenous Expectations in an Artificial Stock Market," 36). In other words, agents with compatible intelligences tend to form stable connections, even though this behavior contradicts the Arthur et al.'s explanation of perpetual novelty in a competitive environment. The inclination of agents to self-select into stable relationships reflects the rhetorical phenomenon of identification. It would be difficult to locate this phenomenon in the model's code, but it is evident in the market's time series graph:

Figure 4.4

"Asset Pricing Under Endogenous Expectations in an Artificial Stock Market" Arthur et al, 30. FIGURE 1

In the case of the SFI ASM time series, one quality is evident at a glance: volatility, how much the market moves, and how often. The lower line, representative of the rich psychological regime, is considerably more volatile, and its trading costs are generally lower, since persistent volatility lowers the cost at which risk-averse traders are willing to trade. And yet, in a market where traders can only reason inductively, the emergence of even periodic stability is surprising. For example, between roughly 253080 periods and 253100 periods, trading volume rose almost uninterrupted, even though Arthur et al. admit that there is no theoretical reason why a market should not persist in continuous volatility (36). The fact that the market does stabilize is an indication of a mediating dimension. That dimension is agglomerated trader knowledge. As Arthur et al. explain in the passage quoted earlier, “the market can self-organize into mutually supporting subpopulations of predictors” (36). By this, Arthur et al. refer to the ability of a market to develop endogenous, self-consistent relational nodes. The predictor part of some agent trading rules eventually corresponds to the behavior of a trader subclass: those individuals are then united by their compatible behavior, and they form a trading node.

In geographic market analysis, this is referred to as a lattice structure: individuals effect the expectations of persons with whom they have contact, and so economic knowledges correspond to topological geographies. Of course, in the SFI ASM, the traders cannot move per se. They are not closer to any one trader than to any other, mediated, as they are, by the market. They can, however, develop logical compatibilities, which correspond to market features. In so doing, the trader’s exhibit a rhetorical behavior.

In an oft-quoted passage in *A Rhetoric of Motives*, Kenneth Burke defines rhetoric as identification. Burke writes, “A is not identical with his colleague, B. But insofar as their interests are joined, A is identified with B. Or he may identity himself with B even when their interests are not joined, if he assumes that they are, or is persuaded to belief so” (20). As Burke later explains, in a formulation well-known to rhetorical scholars, this occurs through a process of identification. Agents attempt to emphasize shared attributes; those attributes may be assumptions, expectations, values, and even logics. The more they succeed, the more stable a relationship becomes. Burke’s formulation fits the algorithms almost exactly: the traders form stable spatial clusters when they attribute the same statistical significance to the same trading rules. The more trading rules they have in common, the more significantly they converge to a shared market logic, and the more stable their sub-strata becomes. Moreover, as agents identity into common logics, the domain of their potential market interaction narrows. Except by random mutation, which itself occurs within given predictor frameworks, it is increasingly difficult, even for an algorithmic trader, to operate outside of the boundaries of its sub-strata. This logical relativity reaches its climax when Arthur et al. "freeze" certain trader knowledges early in the market's action, only to reinsert those traders later on. Without continuous relational evolution, the frozen traders cannot continue to participate effectively in the marketplace (36). Market stability, and its corresponding spatial phenomena, are therefore an indication of ideological convergence. Two models, in relationship to whom Arthur et al. situated the SFI ASM, clarify this point.

The first is the asset pricing model developed by William Brock and Cars Hommes, created to study instability in heterogenous markets. In their study, Brock and Hommes seek to identify the dynamics of "Adaptive Belief Systems" through complexity mathematics. Their market shares an architecture with the SFI ASM: agents interact through applied condition-action rules, learn recursively, and trade a risky asset. As with the SFI ASM, Brock and Hommes's market exhibits time-series volatility.

However, Brock and Hommes employ an additional analytical tool, bifurcation models, to study the emergence of strange attractors, or organizing vectors, in phase space, a space representing every possible state of a system. A bifurcation represents a separation from a stable state, characterized by certain statistical properties. Methodologically, bifurcation models allow Brock and Hommes to visualize knowledges clusters, the agglomeration of traders, relative to similar knowledges, around particular vectors of market potentiality. The corresponding scatter plot is attractive in its own right. In this visualization, a single moment of market activity is frozen, and trader knowledge structures are organized alongside the causal vectors to which they correspond:

Figure 4.5

"Heterogeneous beliefs and routes to chaos in a simple asset pricing model" Brock, Hommes, 1250. Fig. 1.

The visible knowledge structures together create spatial phenomena, through interaction, which correspond to a market's stability. From a rhetorical standpoint, the interesting element of this model is that space only emerges as agents's knowledge structures converge, over time, to distinct structural forms. That is to say, not all action counts as interaction, and not all action results in spatial phenomena. Only interactive agents *who are inclined towards identification* create spatial phenomena. In this formulation, space emerges when agents are capable of identifying, or adopting compatible knowledge structures, and choose to do so.

The second model, Lawrence Blume and David Easley's study of evolution and market behavior, represents a compelling example, since their traders are not equipped to interact, and do not create spatial phenomena. In Blume and Easley's study, heterogeneous agents, equipped with a recursive learning mechanism, attempt to discover a homogeneous rational expectations equilibrium by analyzing active market formations—specifically, prices (*Learning to be Rational*, 341). In the model, agents select a price vector, or model, from their endowed set, and then evaluate the accuracy of that vector over time; the process is similar to the SFI ASM condition bit evaluation. Yet, unlike the SFI ASM, the agents do not trade. Instead, the price progresses along a rational expectations time series (341). There are therefore no conditional rationalities, only objective evaluations. In Blume and Easley's work, no spatial phenomena appear; the agents do not develop knowledge clusters, as the model's adaptive framework is limited to an arrangement of accurate price vectors intrinsic to each agent. Further, while Blume and Easley's agents can combine their market models, their knowledges do not scaffold (345). Without interaction, the market does not move through the sophisticated states to which scaffolded knowledges would correspond. Blume and Easley's market is not a spatial entity. The slow-learning regime of the SFI ASM, the counterpart of the "rich psychological" regime, is similarly limited. As LeBaron *et alia* explain, in the slow-learning regime, no non-rational expectations equilibrium condition bit can take hold ("Asset Pricing Under Endogenous Expectations in an Artificial Stock Market," 31). Without the ability to continuously interact, the agents do not create complex knowledge structures, since only the most general rules prevail over long periods of time. On account of this, the agents do not converge into temporary sub-strata, but instead adapt their knowledges to reflect a few basic principles. A spatial marketplace, of which a real world marketplace is a type, is first and foremost an interactive marketplace.

In agent-based markets, spatial phenomena emerge when agents are able to identify and choose to do so. The question that follows is whether or not real-world spaces are similarly composed. The short answer is yes. While it is conventional to think of spaces as stable and the interaction in them as dynamic, recent work in sociospatial theory instead suggests that the real nature of space is relationally-contingent. Deborah Cowen, for example, outlines the ways in which the real dynamics of space— the measurement of the distance, the energy needed to cross it, etc.—are predicated upon interactive modes in industrial logistics (*The Deadly Life of Logistics*, 2). As in financial markets like the SFI ASM, in real-world economies, spatial phenomena are rhetorically composed. Still, few spatial phenomena emerge as a consequence of interaction. Many spaces reflect a much more competitive environment.

4.3 CASCADES

Most market spatialities emerge as a consequence of competition and reflect the ability of knowledge structures to construct space. As Arthur et al. further observe, the "agent's hypotheses and expectations adapt to the current pattern of prices and dividends; *and the pattern of prices changes to reflect the current hypotheses and expectations of the agents*" (22); intriguingly, the earlier adaptive relationship, in which agent's adapt their knowledge to suit the state of the market, occurs only in the early stages of the market. Over time, the structure of the agent's knowledge unilaterally constrains the market form that emerges as a consequence.

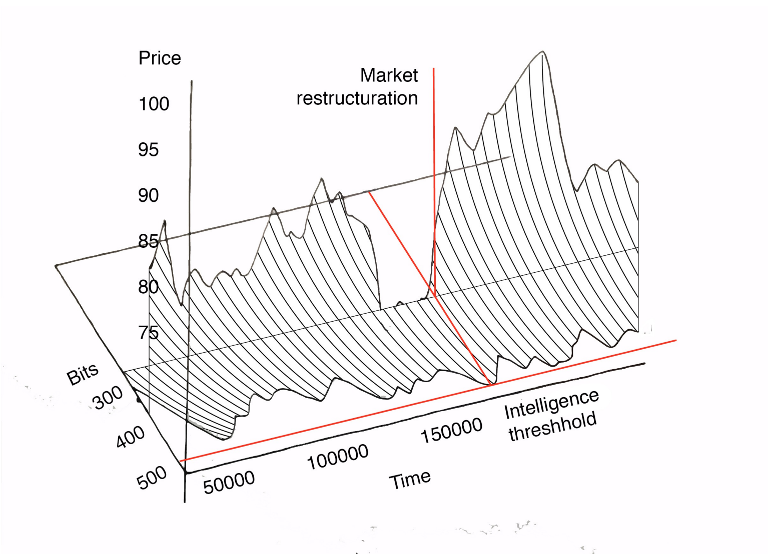
This causal transition, in which knowledge structures begin to constrain market forms, rather than adapting to reflect the learned significance of a form, is visible in the dissemination of new knowledges across the market. Arthur et al. write, “Once in a while, randomly, more successful expectations will be discovered. Such expectations will change the market, and trigger further changes in expectations, so that small and large ‘avalanches’ of change will cascade through the system” (33). When agents discover novel trading strategies, those discoveries transform market behavior and, over time, disparate agents are forced to adapt their knowledge structures to fit the novel market.

The chosen language of this transition is misleading; while it is nice to imagine streams of adaptation rushing over the market’s nodular structure, it is inaccurate. “Cascade” and “avalanche” reflect a spatial construct in which transformation originates in a particular node and transitions across an environment through proximal nodes. Lattice structures or contagion models of information distribution, for example, both exhibit phenomena that “cascade.” In the SFI ASM, no two traders exist in a contiguous relationship. Instead, in a market, “cascades” of information are illustrated by market shocks. The creation of new knowledges, formalized through novel condition bits, transforms the formal structure of the market. This transformation follows as a consequence of a causal transition, as market forms, which would usually force logics to adapt, adapt to fit novel logics. These transitions are accompanied by stochastic behavior and downturns; the market enters a paroxysm, which only stabilizes when agents restructure their knowledges to suit the new logical modality which the market illustrates. In order to analyze the spatial characteristics of this behavior, some abstraction is useful. Consider, again, the time series from Figure 1. The time series data is complicated by the corresponding casual complexity, or intelligence, of the market, indicated by the number of technical descriptor bits in use. Arthur et al. illustrate the transition to intelligence in Figure 3.

Figure 4.4	Figure 4.6
"Asset Pricing Under Endogenous Expectations in an Artificial Stock Market" Arthur et al, 30. FIGURE 1	"Asset Pricing Under Endogenous Expectations in an Artificial Stock Market" Arthur et al, 31. FIGURE 3

The addition of intelligence, relative trade volume, creates a multi-dimensional masseous structure. The consequent figure, represented in Figure 4, illustrates the market's size.

Figure 4.7



With high trading volumes and significant strategic intelligences, the market is a wide space rife with possibility. Usually, the most significant changes take place under such conditions, although they do not last; when other agents converge to comparable intelligences, trading volume declines.

Figure 4 makes the causal transition, which accompanies the advent of a "rich psychological" regime, visible. LeBaron et al. observe, "The artificial markets in this paper often end up with agents conditioning on variables that should be of no value, but become valuable since others are paying attention to them" (1489). This occurs because increasingly-accurate condition bits can constrain the causal dimension of a market's form. Highly specific rules, developed through algorithmic evolution, allow traders large gains. In turn, those gains have large effects on the market's form. As a consequence, other traders are driven to restructure their knowledge to reflect the form which allows the most significant gains. Thus, a highly-specific condition bit will restructure the logics of the marketplace, even though that logic will rarely be the best logic imaginable. In common language, the best guess of how agents will act will impose that action on those agents by controlling what knowledge is advantageous. These impositions are visible in the 1999 iteration of the SFI ASM, where the application of the GA in period X is followed by a long trend of high volume trade, indicating that traders are converging to a novel knowledge.

Figure 4.8

"Time Series Properties of an Artificial Stock Market" LeBaron et al, 1500. Fig. 1.

This phenomenon, in which complex knowledges sublimate real market operation, is reminiscent of Althusser's ideology, "*material actions inserted into material practices governed by material rituals*" (1354), except that the market's pre-complex causation avoids Althusser's determinism. That is, early market action converges to homogeneous rational expectations equilibrium, rather than to a complex knowledge structure. Even so, once the market moves, knowledge structures superimpose logical structures on the form of the market. While knowledge "cascades" do not actually describe the spatial dimension of adaptation, the knowledge transformations to which the language of "cascade" is applied do reveal a far more interesting spatial element: market knowledges shape market forms. It is still more accurate to argue that space, in a market, is a consequence of knowledge. The competitive process of adaptation reconstructs existent spatiality.

In order to clarify this point, it is useful to consider a model whose architecture is analogous but whose agents do not interact for long periods. The 2006 revision of the SFI ASM, created by Norman Ehrentreich, is such a model: the algorithmic architecture remains the same, but Ehrentreich reconstructs the genetic algorithm's mutation operator. In so doing, Ehrentreich seeks to correct an upward bias on technical trading; he may have done so, but the operational effect of Ehrentreich's revision is to simulate a market in which agents do not participate in trade activity for the long term. Mutation routinely reduces agents to basic knowledge structures. Thus, Ehrentreich's agents cannot co-create highly-sophisticated, conditional knowledges. Intriguingly, in Ehrentreich's model, knowledges do not cascade; the departure of old agents removes the impetus for younger agents to adapt to complex knowledge structures. In Ehrentreich's model, this behavior is more difficult to locate, since Ehrentreich does not represent his market in a conventional time series. Nevertheless, the absence of conditional knowledges is visible in Ehrentreich's time series data.

Figure 4.9

Agent-Based Modeling. Ehrentreich,

119. Table 7.1.

An ARCH (Autoregressive Conditional Heteroskedasticity) process implies that the error terms of a process have a standard variance. In the SFI ASM, it implies that the trading volume was generally stable. In Ehrentreich's model, with an active GA, this was almost always the case (the ARCH hypothesis was rejected in only .007 percent of the tests), while in the earlier SFI ASM versions, the ARCH was much less stable (rejected in .065. processes), indicating that agents were required to adapt, periodically, to highly-specific knowledges that made their accuracy high-variant and the trading volume volatile.

The spatial distinctions between the earlier versions of the SFI ASM and Ehrentreich's revision suggest that the ability of agents to use their adaptive process as a persuasive process requires long-term interaction. This further indicates that as agents persist in interaction, the spatial elements of the market are increasingly-conditional, as knowledges create increasinglynuanced adaptations. This transition, which is observed in algorithmic markets, further suggests that an agent's ability to adapt eventually functions as its ability to persuade: in the early action of the market, an agent's adaptation represents an effort to survive in a market by developing a suitable form of knowledge for that market. However, when knowledges reach a degree of sophistication that can effect a swift market restructuration, an agent's ability to survive becomes contingent upon its ability to effect the behavior of other agents, to develop a complex knowledge *which is only successful if its changes others's behavior*.

The spatial phenomenon of the "cataract," which is visible in real markets, illustrates a process in which knowledge is applied in order to constrain consequent action. A "cataract" indicates that space is reshaped to reflect the dominant knowledge structure in a competitive environment. The connections between adaptation, competition, and spatiality are further illuminated by what may be the market's most abstract spatial phenomenon, belief space.

4.4 BELIEF SPACE.

A belief space, otherwise described as a fitness landscape, refers to the characteristics of a data environment relative to a particular interactive modality. In the SFI ASM, a belief space refers to a temporary pattern of intelligences as seen from the perspective of a single agent; it represents the difficulty with which each agent can develop advantageous behavior and is, moreover, distinct to each agent. In a rhetorical sense, a belief space is the material counterpart of each agent's persuasive faculty. Intriguingly, belief space receives only cursory attention in the SFI ASM; Arthur et al. describe the degree to which agents institute novel condition bits as explorations in "belief space" (29), but do not define the significance of that space. Arthur et al.'s apparent disinterest in belief space represents something of a missed opportunity. In the SFI ASM, belief space emphasizes the persuasive dimension of each agent's adaptation, and situates spatiality as a phenomena that *only* emerges from persuasive interaction.

Before further analyzing the location and significance of belief space in the SFI ASM, it is useful to delineate the characteristics of belief space as a theoretical construct; for belief space, John Holland's 1991 conference presentation, "The Royal Road for Genetic Algorithms: Fitness Landscapes and GA Performance" remains the foundational text.

In their work, John Holland, Melanie Mitchell, and Stephanie Forrest describe the dimensions that organize a belief space, or a fitness landscape. The dimensions are hardly Euclidean; they are deception, sampling error, and "ruggedness." Deception describes data structures whose differences would not be evident to particular learning mechanisms. Sampling error describes a system in which low-order schema are highly variant. And the last, "ruggedness," is a bit of figurative language from Stuart Kauffman and Edward Weinberger. It describes a data structure where solutions form multitudinous, isolated optima. A learner therefore moves through a variegated "badlands" ("The NK model of rugged fitness landscapes," 211), rather than up a single high hill toward an isolated optimum. To these, Holland adds a structural attribute: "the extent to which the fitness landscape is hierarchical, in the sense that crossover between instances of fit low-order schemas will tend to yield fit higher-order schemas."

The best visualization of a belief space is, I believe, Stuart Kauffman and Edward Weinberger's Boolean cube, both for its ability to synthesize theoretical constructs, and for its ability to reflect a series of spatial movements that do not occur in conventional dimensions.

Figure 4.10

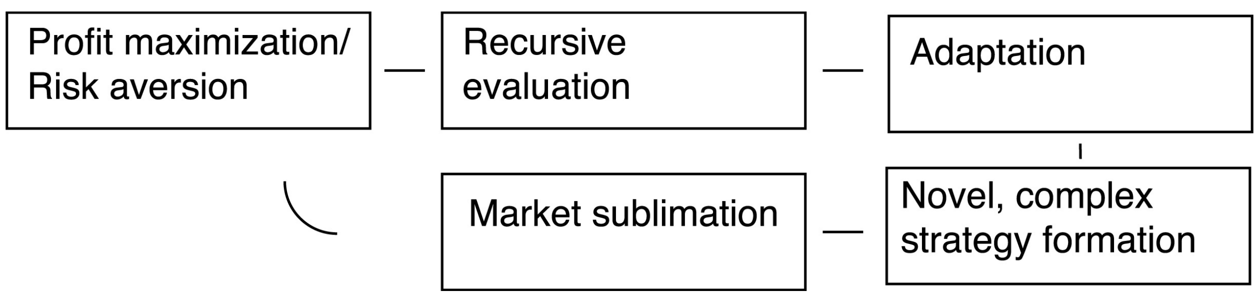
"The NK Model of Rugged Fitness Landscapes." Kauffman, Weinberger, 214. FIG. 1(a).

In this graph, amino acids are arranged according to their mutational similarities, a scenario that requires a great deal of subjective differentiation on Kauffman and Weinberger's part. The interesting element of this graph is its combination of two theoretical localities: the observed similarity of amino acids and the statistical probability of a transition between them. But for this project, the tesseract (concentric cubes) within which they are organized is still more interesting: its orthogonal structure implies an environment which is much less dynamic that the agents operating within it. There are optimal solutions, objective evaluations of successful strategies, and progressive development. In an artificial marketplace, those attributes do not hold.

As I have already explained, in the SFI ASM, it is not appropriate to reference a single belief space: the agents are adaptive, and the environment is an agglomeration of their expectations, so each agent experiences a distinct belief space. Instead, in each agent's belief space represents the spatial counterpart of its persuasive faculty. This is evident in each agent's operation, in which the knowledge structure of competitive agents is the operational counterpart of each agent's adaptation. In other words, as a temporary pattern of intelligences, a belief space foregrounds the fact that an agent can only succeed long-term if it succeeds in reshaping its competitors knowledge structure.

Recall, in the SFI ASM, market action occurs in cycles: agents receive data, generate expectation and corollary demand, trade, and evaluate the success of their rule set. In these market cycles, the operation of the agents is itself a cycle of the following form:

Figure 4.11



In the market, agents adapt their knowledges in an attempt to control the progression of the marketplace; that act of sublimation is analyzed in Section II. However, an agent can only control the progression of the marketplace if its actions succeed in reshaping the knowledge structures of other market participants. For this reason, an agent's operation, which begins and ends with profit maximization, situates the knowledge structures of competing traders as the counterpoint of its own adaptation. In simple terms, each agent adapts in order to effect the knowledge structures of other participants. A belief space emerges as a consequence of each agent's attempt to do so, and reflects the difficulties it encounters in the attempt.

In contrast, models in which agents cannot effect the meaning of a market form by adapting their knowledge structures do not contain the phenomenon of a belief space. There are numerous examples of this kind; the slow-learning regime of the SFI ASM is one, simply because the agents adapt too slowly to actually create a complex knowledge structure and therefore entice other agents to adapt their knowledge structures as well. A belief space only emerges if an agent can produce some effect on other agents through its own adaptation. For this reason, a belief space describes the spatial figure which is a consequence of an agent's rhetorical faculty. It is the competitive situation each agent encounters, and includes both the available material from which to develop a strategy, and the resistance to that strategy represented by competitive agencies. In the SFI ASM, the realized space of interaction, the market, is constrained by the antecedent form of persuasion, belief space.

In the SFI ASM, a market's spatiality is a material consequence of rhetorical interaction: it both reflects and is composed of the knowledge structures enacted to effect some end. This, more than any other single feature, contributes to the success of the SFI ASM. When agents are constructed to perform "a more realistic level of exploration in belief space…complex patterns [form] in the collection of beliefs, and the market [displays] characteristics that differ materially from those in the rational-expectations regime" (Arthur et al., 29). Otherwise put, when the actors are constructed in such a way as to reflect competitive interaction driven by persuasion, the market takes on the form of a real-world market.

4.5 RHETORICAL SPATIALITY

The heuristic value of assuming a persuasive faculty is a precondition for space is considerable; in the early 2000s, the relational dimension of economic geography received significant development in the work of David Harvey, Doreen Massey, and Ilya Prigogine, to name only a few, and has popularized poststructural mathematics, rhizomatic thinking, and nonlinear dialectics. The impetus for this work is the observed nonconvergence of economic geography with conventional spaces. Oil, for example, can move more quickly, with less energy, across larger spaces, than almost any other consumer good. Moreover, oil is chiefly accessed through financial infrastructures in which it is, in a very real sense, everywhere. In this field, the SFI ASM is enigmatic because it arrived too early. Ilya Prigogine's foundational text on complex systems and materiality, *The End of Certainty*, did not appear until 1996. Doreen Massey's now canonical work on relational space, *For Space,* did not arrive for another decade. In other words, the SFI ASM modeled economic spatiality before the complexity theory was considerably developed.

In their analysis, Arthur et al. attribute this success to the creation of algorithmic analogues for inductive intelligences (37). This is certainly true in part, but LeBaron et al. also created *rhetorical* actors, agents who create a purposive rationality in interaction, and then employ that rationality to effect some purpose—in the model's case, financial gain. More importantly, in equipping their agents with a genetic algorithm, the capacity of invention, Arthur et al. also constructed a market in which an environment, or a spatiality, originates in the persuasive constitution of their agents: the motive to enact some purpose on alternative agencies through purposive action creates space.

The three spatialities investigated in this project do not represent an exhaustive list of complex spatiality, but they do represent a good starting point for a rhetorical analysis of complex space. First, trader knowledge structures, which form the stable strata of the market, appear as a consequence of an agent's inclination to identify. The principle, of which these stable strata is an example, is extensive. In real markets, identifications often form the stable basis upon which complex structures are built. In this line of analysis, even dollar values, which require an enormous amount of identification to function, indicate a complex of underlying rhetorical processes. Second, the dissemination of novel knowledge across the market in “cascades” reflects the ability of agents to constrain space with knowledge. This process is readily evident in real-world markets, where knowledge, whether in the form of treaties or technology or forms of ownership, shapes the geography that underlies markets. And third, the emergence of belief space foregrounds the persuasive element of each agent’s adaptation; agent’s adapt in order to effect the knowledge structures of competitive agencies. This process emphasizes the persuasive dimension of all market activity, in which agents operationalize the totality of their interactive potentialities in order to effect the behavior of competitive agencies. So understood, production, distribution, and even patterns of buying and selling represent persuasive activities performed in a fundamentally rhetorical environment.

CHAPTER 5: CONCLUSION

RHETORICAL ECONOMICS AND DYNAMICAL RHETORIC

"To address the possibilities of a new medium as a type of rhetoric, we must identify how inscription works in that medium, and then how arguments can be constructed through those modes of inscription." —Ian Bogost (Persuasive Games, 24).

In his Preface to the 2013 compendium *Complexity and the Economy*, William Brian Arthur explains that complexity economics studies "agents who must make sense out of the situation they face, who need to explore choices using whatever reasoning is at hand, and who live with and must adjust to an outcome that their very adjustments may cause perpetually to change" (xxii). In Arthur's definition, complexity economics is the study of agency and interaction, the study of dynamic agencies converging to create a common world. In that regard, complexity economics is fundamentally rhetorical. While I have emphasized the implications of rhetoric for economics in this project, the view that complexity economics is a rhetorical science means as much for rhetoric as it does for economics. In the epigraph above, Ian Bogost explains that a new rhetoric is defined by a new exigency, a new medium of inscription. In general, economics operates in existent mediums: in text, in images, in mathematics and procedures and even in things. The SFI ASM is no exception: it is inscribed in code, mathematics, and text. However, economics also studies dynamics, the dissipation of persuasion in a system. As Arthur writes, "Complexity studies the propagation of interconnected behavior" ("Complexity Economics, A Different Framework for Economic Thought," 11). In so doing, complexity economics calls attention to those elements of persuasive activity that remain largely neglected in conventional rhetorical analyses. While rhetoric has extensively studied the composition of rhetorical activity, complexity economics emphasizes persuasive dynamics. The consequences of persuasion on an environment, as seen in complexity economics, represents both a challenge and an extension to existent formulations of rhetoric.

In general, complexity economists has done a better job than rhetoric at identifying the long-term consequences of interaction. In order to understand how persuasive activity effects interactive environments, it would be advantageous for rhetoric to analyze and adopt some of complexity economics's presuppositions: that time "clusters," that knowledge "cascades," and that whole systems go through "phase transitions," changing macro-behavior when an interactive modality reaches a certain level of representation (Arthur, "Complexity Economics, A Different Framework for Economic Thought,"10). In other words, it would be advantageous for rhetoric to treat persuasion both as an action and as an extension of action across a system.

The study of persuasive dynamics, as illustrated by complexity economics, represents a methodological extension for rhetoric. It also represents an ethical extension. At its Aristotelian roots, economics is an ethical science, the study of action as it relates to the good of the community (*Politics,* 1256a:11-13). While few economists would argue that all economic activity benefits any community, it remains that economics is driven by an ethical imperative: to understand the consequences of particular actions on communities. In order to operate both effectively and ethically in an interconnected world, rhetoric must adopt a similar imperative: to understand the long term effects of persuasive activity in an interconnected environment. In this endeavor, the study of complexity economics represents an ideal starting point.

FOOTNOTES

1. Rama Prasad Kanungo's 2004 paper, "Genetic Algorithms: Genesis of Stock Evaluation," outlines how genetic algorithms shape real-world markets, while while Li Lin, Longing Cao, Jiaqi Wang, and Chengqi Zhangs contemporaneous paper, "The applications of genetic algorithms in stock market data mining optimization," represents a larger study of the effect of computation on asset pricing and financial market mapping.
2. James Arnt Aune's book, *Selling the Free Market: The Rhetoric of Economic Correctness*, is an excellent complement to McCloskey's project, insofar as Aune explores the rhetorical formulation of proper economic behavior. Robert McChesney's book *Rich Media, Poor Democracy: Communication Politics in Dubious Times* also considers the rhetoric employed by economics; while McChesney's book is mostly about socialism, he does extend his analysis to rhetorics of ownership and commercialization. Dana Cloud's review essay, "Rhetoric and economics: Or, how rhetoricians can get a little class," also does a good job of outlining how economics use rhetoric to "mystify, justify, naturalize, and universalize elite interests" (343).
3. The proliferation of SFI ASM iterations makes citation difficult: the original cohort of creators did not collaborate on every paper. It is important to remember that the different attributions refer to different papers, and to different models. When referencing the model in general, I cite Palmer et al., the original team and the 1994 paper. When referencing the 1997 iteration from *The Economy as an Evolving Complex System II*, I cite Arthur et al. Only two other papers receive anything like regular attention: the 1999 paper, to which John Holland

and Richard Palmer did not contribute, is cited as LeBaron et al., and the 2008 Java version, which is found in *Agent-based Modeling* as cited as Ehrentreich.

4. The SFI ASM code is hosted by Paul Johnson at http://ArtStkMkt.sourceforge.net.
5. In the course of this analysis, I often refer to algorithms as agencies, and so allow them the verbiage of an agency: they think, assume, guess, organize, forecast. From these acts alone, one might wonder whether or not the following investigation was an argument for the humanity of expert systems. It isn't. The algorithms of the SFI ASM are not human persons. And still, the only way to really write about them is to act as though they were. This methodological difficulty stems, to some degree, from the history of statistics itself, and the inclination, as Lorraine Daston has pointed out, to conflate statistical coherence with epistemological activity: statistical solutions are expressed as "degrees of certainty." Really, the entire history of statistics, from which algorithms developed, is littered with tropological errancies. As Daston has further argued, statistical logics were adapted from legal logics. For example, Pascal described his early statistics as an attempt to determine relative equity between persons, while Huygens and Johann De Witt described their statistical calculus as a series of social contracts (*Classical Probability in the Enlightenment*, 7). Thus, statistics is a science whose composite logics are either entangled with or derived from sociology. It could be argued that insofar as statistics is a language of epistemological balance it goes all the way back to Hesiod: observe due measure in all thing. Algorithms are instead thought clusters. As a consequence, they indicate particular conceptions of thought and knowledge. It is hardly surprising that even the physicist John Holland rooted his work in the philosophy of induction; his algorithmic traders are meant to illustrate knowledge taking a form in

relationship with an environment, "mental modes" which are "based in part on static prior knowledge, [but] they are themselves transient, dynamic representations of particular unique situations. They exist only implicitly" (*A Framework for Induction*, 14). In Holland's formulation, an algorithm is the process that connects knowledge to an environment.

6. I draw this observation from a close reading of all SFI ASM models to which the original team contributed. In the 1994 model, Palmer et al. equate rationality with a quality of behavior and write "The evolutionary approach is generally inductive, not deductive; the agents typically generalize patterns obsessed in the past to guide their behavior to the future…This inductive approach is much closer to normal human behavior." (266) While Palmer et al. do not define the behavior they expect in their initial model, it is clear in later iterations that behavior is connected to intelligence, or bit-specificity. For example, in the 1997 model, Arthur et al. explain "in the complex regime, [technical trading bits] bootstrap in the population, reaching a steady state value" (31).

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