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A Complex Systems Approach to Financial Markets, Social Learning, and Socioeconomic Phenomena

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Table of Contents

Acknowledgement	1
Table of Contents	2
Summary.....	4
Chapter 1 - Introduction	5
1.1 Nonlinearity and Dynamics.....	10
1.2 Agent-based Computational Modeling	11
1.3 Bounded Rationality.....	14
1.4 Emergence	15
1.5 Cellular Automata	16
1.6 Small-World Networks.....	19
Chapter 2 - Complex Interactional Dynamics Of Investors: Mass Psychology and Investor Sentiments	22
2.1 Introduction	22
2.2 Investor Behaviors.....	27
2.3 A Heterogeneous Agent-based Model	29
2.4 Modeling Financial Markets	36
2.5 Comparative Studies and Theoretical Implications	46
2.6 Conclusion.....	50
Chapter 3 - The Wisdom of Social Links: Learning, Interaction and Self-organized Efficiency	53
3.1 Introduction	53
3.2 Social Interaction and Wisdom of Crowds.....	56
3.3 Stochastic Model	59
3.4 Simulation of A Social Learning Economy	65
3.5 Comparative Studies: Impact of A First-mover Advantage.....	68
3.6 Theoretical Implications: Social Learning as the Hidden Half of the Invisible Hand	77
Chaper 4 - Complexity in Socioeconomic Phenomena	82
4.1 Introduction	82

4.2 Herding Behavior	86
4.3 Stochastic Model	89
4.4 Stimulating Socioeconomic Phenomena	94
4.5 Entomological Puzzle Revisited.....	103
4.6 Model Implications and Conclusion.....	105
 Chaper 5 - Summary and Conclusion	 109

Summary

This thesis studies complexity in financial markets, social learning and socioeconomic phenomena. Economies and societies are complex systems, with decentralization and local interaction of numerous people with heterogeneous behavior. The thesis departs from the independent rational agent paradigm and adopts the generativist approach of how a population of bounded rational and heterogeneous agents, through micro-interactions, can emerge to a different kind of macro-behavior of the system.

Chapter 1 describes the research background/approach of this thesis and relates complexity to the history of economic thought.

Chapter 2 explicates how the salient characteristics of financial prices emanates from mass psychology and investor sentiments explicitly by modeling the interactional dynamics between herding and contrarian behavior of investors in financial markets using a computational agent-based approach. Utilizing a cellular automaton agent-based model with heterogeneous agents, herding and contrarian investors make their investment decisions based on interactions with other investors in a regular network. The agents in our model determine their investment decisions based on the actions of other agents in their network neighborhood which in turn are based on the actions of others in their respective network neighborhoods. The model succeeds in providing a generative explanation of rich and complex characteristics of financial markets such as chaotic price fluctuations, punctuated equilibria, fat tails, extreme values, market cycles, non-periodic bubbles and crashes, and switching regimes of bull and bear markets.

Chapter 3 utilizes an agent-based model to explore the non-pecuniary impact of social learning on the utilitarian efficiency of the population in decision-making between discrete choices. The model embeds a small-world network into a cellular automaton framework. Consumers augment their limited private information by learning and deriving information from social interaction and imitation in their social network. The social learning between individual consumers in a small-world network is an efficient aggregation mechanism of information which overcomes the frictions of imperfect information and bounded rationality of individuals. Social learning in liberal economies generates aggregate rationality from individual bounded rationality,

resulting in the emergence of self-organized efficiency of consumers in optimal decision-making.

Chapter 4 explores the dynamics of socio-economic phenomena using a complex systems approach. Using a stochastic cellular automata network model (CANM), bounded rational agents herd to the actions of other agents in their social network, a convergent social behavior resultant of social influence. The CANM model allows for an interdependent multiple-agent paradigm which structures the local interaction of agents in a small-world network. This paper offers a generative explication of various socio-economic phenomena as the emergence of Quasi-herding interaction among individuals, and in addition relates the results to examples not restricted to skirts, cohabitation, political revolutions and individualism. A parsimonious model of quasi-herding behavior elucidates outcomes of fleeting fads, (cyclical) fashion, non-periodic cycles of bubbles and crashes, changing regimes of social norms, and lock-in of cultures.

Chapter 5 summarizes and concludes the thesis.

Chapter 1

Introduction

The philosophy of economic thinking in this thesis revolves around complexity. At the dawn of the twenty-first century, physicist Stephen Hawking said, "I think the next century will be the century of complexity." In a seminal paper by Weaver (1948), he addressed the significance of "problems of organized complexity". A classification of problems that cannot be reduced to formulas/equations of a few variables (problems of simplicity) nor can such problems be studied by the numerous-variables (problems of disorganized complexity) method of statistical probability analysis. "Organized complexity" involves problems with a moderate number of variables and interrelationships which are often nonrandom and complicated, resulting in a system that is more than the sum of its parts. Logically, the problems of society and economics fall into the category of "organized complexity" due to the nature of strong nonlinear interdependencies within such systems.

Complexity refers to a system with strong nonlinear interaction between its individual components and, as a result, the behavior of the system at the macro level exhibits a supervenience of properties nonexistent at the micro-level. The complexity approach to economics (complexity economics) has been slowly growing over the last decade. While criticized for its vagueness since there is no consensus to the definition of complexity (Mitchell 2009), complexity explores new ways of thinking which have the potential to create solutions for many unexplained problems in economics.

While the neoclassical general equilibrium paradigm in economics has been widely successful, there are limitations. The proof of a static existence of equilibrium does not affirm the dynamic attainment of such an equilibrium, or if attainment is reached in reasonable time scales (Simon and Saari 1978; Epstein 2006), after all, "in the long run we are all dead." A pluralistic view of economics encompassing diverse perspectives overall is beneficial as it enriches the theoretical and methodological toolkit of the discipline. Complexity economics departs from the neoclassical paradigm in that the economy is not necessarily in equilibrium, but in disequilibrium as well. Increasing and diminishing returns can exist simultaneously in an economic situation (Arthur 2013). Much of economics has long been built on the concept of equilibrium (Arrow

and Debreu 1954). The assumption of equilibrium allows for solutions by mathematical analysis, giving rise to a theoretical world of order, determinism and perfect rationality. As opposed to this platonic world is a reality of uncertainty, randomness and bounded rationality (Simon 1991). A different framework of economic thought has been provided through complexity economics, removing the filter of equilibrium broadens the perspective of the workings and outcomes of markets.

Arthur (2013) states three phenomena that cannot exist in tandem with the concept of equilibrium: The first phenomenon is self-reinforcing asset price changes or bubbles and crashes; the second phenomenon is volatility clustering, which has been modeled by the arsenal of ARCH/GARCH models (Engle 1982; Bollerslev 1986); the third phenomenon is sudden percolation which is related to phase transitions and cascading effects.

Bubbles and crashes are known to have existed since markets came into being. Market prices have been observed to have larger movements than fundamentals. The dichotomy between prices and fundamentals has been studied in markets such as housing; Glaeser et al. (2008) documents the dichotomy between fundamentals and price volatility of housing. The contrariety can hardly be explained using an equilibrium framework. In fact the notion of equilibrium does not accord to bubbles and crashes as they are largely considered to be far-from-equilibrium or disequilibrium outcomes. The cycle of bubbles and crashes can be seen as a disequilibrium process in which the price overshoots and undershoots the fundamentals (Shaikh 2010). Some economists have questioned the possibility of a perpetual persistent equilibrium as theorized by the efficient market hypothesis; as the world is continually changing and prices have to adjust instantaneously to changes to achieve a persistent equilibrium which is paradoxical (Beja and Goldman 1980).

Farmer (2012) further opine that the equilibrium markets paradigm cannot explain phase transitions or structural breaks. The point made so far should not be mistaken for a criticism of the notion of equilibrium in economics. Equilibrium in economics has yielded many contributions over the years, but to explain many stylized facts and perplexing aspects of the economy, the added study of disequilibrium is useful and necessary. Economic disequilibrium causes propagation of changes (Arthur 2013) and

the study of such changes can be done by utilizing dynamic systems modeling. By embracing complexity and disequilibrium, numerous potentially useful (if not already useful) concepts can be unleashed onto the study of the economy. The concepts include positive feedbacks, path dependence, phase transitions, fat tails, cascading effects and extremistan randomness (Taleb 2010).

While complexity has been criticized as being a new fad in science, complexity ideas are in fact abundant in the history of economic thought. Ages ago, Adam Smith, the “father of modern economics”, adopted a complexity perspective with an emphasis on surplus and increasing returns. Also in *The Theory of Moral Sentiments*, he studied the advent of basic social institutions/norms from social coordination and moral approvals/disapprovals. John Stuart Mill, the English political economist, stressed the significance of path dependency (Arrow 2000) and the inseparability of social and economic phenomena (Colander 2008).

There are strong complexity aspects to Keynes' central notions of uncertainty (Keynes 1921) and animal spirits. In his magnum opus, Keynes (1936) writes:

"Most [...] of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as the result of animal spirits [...] and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities." (Keynes 1936)

Keynes' animal spirits, and his metaphor of stock market as a beauty contest, perceive human action to be inter-relational of social interaction, psychology and economics. In addition, Keynes' beauty contest metaphor involves decision-making riddled with notions of uncertainty, imperfect information and collective action (as opposed to an individual representative being).

Decision-making under limited knowledge/information and cognitive capacity is a notion redolent of the 'unclassifiable' Herbert Simon. Arguably his most famous concept is bounded rationality (Simon 1955), relating to the fact that humans make decisions under uncertainty, imperfect information and limited cognitive computation, rather than with the utopian mind of a Laplacian demon. He advocated that the study of rational decision-making cannot be separate from the environment. The complexity

of human systems and environment outstrips the ability of man to attain perfect information and compute the “global maximum over the whole solution space” (Elsner et al. 2014).

The concept of circular cumulative causation by the Swedish Nobel economist Gunnar Myrdal relates to positive feedbacks in complexity, as opposed to equilibrium-enforcing negative feedbacks. In Myrdal (1957), he writes:

“The notion of stable equilibrium is normally a false analogy to choose when constructing a theory to explain the changes in a social system. What is wrong with the stable equilibrium assumption as applied to social reality is the very idea that a social process follows a direction [...] towards a position which in some sense or other can be described as a state of equilibrium between forces. Behind this idea is another and still basic assumption, namely that a change will regularly call forth a reaction in the system in the form of changes which on the whole go in the opposite direction to the first change. The idea [...] is no such tendency towards automatic self-stabilization in the social system. The system is by itself not moving towards any sort of balance between forces, but is constantly on the move away from such a situation. In the normal case a change does not call forth countervailing changes but, instead, supporting changes, which move the system in the same direction as the first change but much further. Because of such circular causation as a social process tends to become cumulative and often gather speed at an accelerating rate” (Myrdal 1957)

Circular cumulative causation tends to dynamical disequilibrium outcomes of virtuous or vicious cycles. Myrdal highlights the limitations of an equilibrium paradigm as it assumes countervailing changes that leads to stabilization of the system. There is no adequate reason to believe that the economy will settle into an equilibrium through automatic self-stabilization from circular causation perspective.

Joseph Schumpeter developed the evolutionary concept of creative destruction to describe entrepreneurial and innovation processes of endogenous structural change within the economy. In Schumpeter (1942), he writes of,

“The opening up of new markets, foreign or domestic, and the organization development from the craft shop and factory to such concerns as U.S. Steel illustrate the same process of industrial mutation [....] that incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one. ” (Schumpeter 1942)

He postulates that it is this process of creative destruction that leads to continuous endogenous growth and long-run fitness of the free-market economy. The constant competition and interaction between firms, entrepreneurs and technology do not tend to stability or equilibrium, but incessant mutation, and perhaps with discernible patterns.

Hayek (1945) holds the view that information is locally distributed throughout the economy. Synonymous to Herbert Simon's bounded rationality, Hayek makes the case that, due to the nature of dispersed information, there is no single entity that holds or is capable of holding all knowledge/information in a concentrated form. Thus, a solution of rational order of the macro-economy must account for the micro-interaction of individuals with dispersed and imperfect information. Also, Hayek (1989) reiterates the reductionist approach which brought much success to the natural sciences is not applicable to economics due to its complex phenomena.

The above-mentioned ideas of many prominent economists in history were overlooked or trivialized due to a lack of conventional mathematical tools for modeling purpose. The advent of the computer age provided increased computational power for methodologies, such as agent-based modeling, which are classes of constructive mathematics that enable the study of complex systems. A discussion into features of complexity and modeling methodology will be covered in the rest of the introduction.

1.1 Nonlinearity and Dynamics

Traditional economics look upon economies as closed¹, equilibrium systems. This thesis takes a different conceptual view of seeing economies as complex systems. One feature of such systems is their nonlinear dynamical nature. Dynamic systems include

¹ Here, closed systems are not referring to closed economy without imports and exports.

time factor. Despite its importance, the time factor has not been included in many traditional models.

Sterman (2002) writes, "Understanding complex systems requires mastery of concepts such as feedback, stocks and flows, time delays, and nonlinearity." Economies and Societies are in fact complex systems (Farmer 2012). To understand them, the mastery of the above concepts stated in Sterman (2002) is necessary. Campbell et al. (1997) claim that many aspects of economic behavior are nonlinear. Numerous studies have argued that nonlinearity is present in economic relationships, encouraging interest and development in nonlinear processes. The assertions result in the basis of nonlinear approaches. Nonlinearity has become an accepted feature in economic and financial time series.

Barnett and Serletis (2000) hold a nonlinear chaotic dynamical view to the behavior of asset prices. They found evidence that suggests nonlinear dependence and chaos in financial markets based on the results of numerous researchers, namely Serletis and Gogas (1997), Abhyankar et al. (1997), Hsieh (1991), Frank and Stengos (1989), Scheinkman and LeBaron (1989). However, this proves controversial among economists. A faction of economists insists that linearity remains a good assumption, electing to disregard the existence of chaos or nonlinearity in economic and financial data. The other view is that sensitivity to noise distorts the test results for chaos.

1.2 Agent-based Computational Modeling

The general methodology for the studies in this thesis is agent-based computational modeling (ABM). The introduction to this methodology is best phrased in Epstein and Axtell (1996),

"What constitutes an explanation of an observed social phenomenon? Perhaps one day people will interpret the question, "Can you explain it?" as asking "Can you grow it?" Artificial society modeling allows us to "grow" social structures in silico demonstrating that certain sets of micro-specifications are sufficient to generate the macro-phenomena of the true, observed, structures and the ones we grow. but the ability to grow them[...] is what is new. Indeed,

it holds out the prospect of a new, generative kind of social science." (Epstein and Axtell 1996)

With ABM as a tool, Epstein (2006) proposes the generative standard of explanation in the social sciences. To achieve the standard, one must show how decentralized local interactions of autonomous micro-agents generate a regularity or pattern at the macro-level.

Deductive explanations usually involve the notion of linear causality. The generative explanation extends or transcends the deductive explanation in demonstrating how a set of micro-specifications can generate the macro-phenomenon of the subject in interest. This is paramount in studies of complexity due to the nature of entangled webs of causation/interactions in complex systems. In such systems, there is an inadequacy of linear cause and effect thinking as a form of explanation. Because of that, the study of complex systems requires the notion of generative explication, where a set of outcomes can be generated and made explicit from a set of initial of conditions.

Albert Einstein once said that, "It can scarcely be denied that the supreme goal of all theory is to make the irreducible basic elements as simple and as few as possible without having to surrender the adequate representation of a single datum of experience." Scientific modeling seeks simplicity and clarity in presenting and understanding a complex world; the study of complex systems by the use of agent-based computational modeling does not depart from the parsimony principle of scientific modeling.

Researchers of computational modeling have advocated a 'Keep Models Simple' standpoint (Axelrod 1997; Miller and Page 2009). Simple agent-based models can generate complex behavior that resembles real-world phenomena associated with economic change. Complex macro-behavior can emerge from the interaction between simple micro-rules. The deterministic interactions among agents can also produce irregular non-periodic outcomes. Agent-based modeling allows for a bottom-up approach to studying the emergence of macro-behavior from micro-rules (Schelling 1971; Wolfram 1994). Borrill and Tesfatsion (2011) assert that agent-based modeling

is the "right mathematics for the study of social sciences", capable of simulating plausible real-world social systems.

The key features of ABM are heterogeneity, autonomy, explicit space, local interactions and bounded rationality (For an elaboration of the features, see Epstein and Axtell 1996)

Epstein and Axtell (1996) build an artificial economy using computer simulation via a bottom-up approach. In their experiment, they simulated a landscape with resources, sugar and spice, and multiple economic agents (humans). They collected statistics of their simulations and found out that the results were consistent with many of the trends and patterns in the real world.

The main findings showed: 1) the distribution of wealth follows a power law, and 2) a downward-sloping demand and upward-sloping supply curve existed despite no assumptions made. However, the equilibrium, a cornerstone of economic theory, did not exist in the simulated world. Due to time delays, continuous change and other factors, the arbitraging agents cannot drive the prices to equilibrium. This presents a sounder description of the real world as we do get different prices of the same product at different supermarkets. The ticks of stock prices happen so quickly such that the prices change before we can place an order.

Arthur et al. (1997) constructed an artificial stock market model. The market setup is a one-period, myopic, constant absolute risk-aversion utility framework in which agents must decide on their asset allocation between a risk-free bond and a risky stock. The experiment converged to a homogeneous rational expectations equilibrium. From here, the model is modified: agents' individual expectations are created by a classifier system. The agents make their asset allocation decisions based on their expectations of future risk and return. The agents start to employ technical trading tools to buy and sell stock. The result is increased trading volume and persistent price volatility.

Day and Huang (1990) introduced a deterministic excess demand model. In the model, there are heterogeneous agents, alpha-traders (information trader), beta-traders (noise traders) and market makers. The model generates irregular bull and bear markets without exogenous shocks; the prices are unpredictable, stochastic and normally-

distributed despite being generated from a completely deterministic model. Arthur et al. (1997), Day and Huang (1990) have modeled the oscillatory nature of markets that emerged from the interaction of micro-agents. Many examples of agent-based models do not necessarily converge to an equilibrium.

1.3 Bounded Rationality

The common postulate of rational choice theory in economics is that agents behave as if they are perfectly rational optimizers. The rational choice paradigm, however, is limited by computability undecidable problem and computational complexity (Albin 1998). Humans make decisions and inferences about the world under limited time, information and cognitive capacity. The platonic ideal of perfect rationality, as characterized in rational choice theory, requires the mind of a Laplacian Demon with limitless time, knowledge and computation power. The assumptions of perfect rationality and perfect information characterized by rational choice theory are implausible. Simon (1955) introduces the idea of bounded rationality, a rational adjustment in which humans make choices according to payoffs that are ‘good enough’, known as ‘satisficing’. A satisficer simply experiences and evaluates choices, then continues to select the choice if the degree of satisfaction exceeds an acceptable threshold. To satisfice is to accept a good enough option, rather than a possibly endless search for the best option.

Kapteyn et al. (1979) find that consumer behavior of durables tend towards ‘satisficing’ rather than maximizing. While satisficing is generally regarded as an inferior to optimization, the study of Schwartz et al. (2002) establishes that satisficers are generally happier than maximizers; feelings of depression, perfectionism and regret are positively correlated with optimizers. Simon (1972) continues to illustrate the implausibility of perfect rationality with the game of chess, where he infers that there are approximately 10^{120} possible games of chess; a perfectly rational agent will have to evaluate 10^{120} possibilities to deduce an optimal strategy for chess. Instead, what expert chess players do is to examine a small number of possibilities and select the one which is satisfactory (De Groot 1965). If perfectly rational optimality is hard to achieve in a perfect information 8 x 8 grid universe even by the grandmasters of chess, reality is infinitely more complex. Good economics should consider all benefits and costs, if the attainment of perfect rational ‘optimality’ incurs the astronomical

costs of unlimited time, knowledge and computation power, such ‘optimality’ might not be truly optimal. Conlisk (1980) asserts that if optimization is costly, cheap imitators can achieve the same level of utility as optimizers. If optimization incurs astronomical deliberation cost due to computational complexity, and the benefit of ‘upgrading’ from bounded rationality to perfect rationality is small, it might not be best for agents to optimize (Conlisk 1996).

1.4 Emergence

The study of emergence is paramount in the study of complexity and could yield important insights to economic patterns such as business cycles, boom and bust. *Emergence* refers to collective phenomena or behaviors in complex systems that are not present in their individual components; it occurs when micro-level interactions form complex macro-level patterns/structures in a complex system with a supervenience of properties across hierarchical levels. More is different (Anderson 1972). Kirman (1993) puts forth the percept of economy analogous to an ant colony, a prime example of the emergence of an immensely efficient system (capable of food foraging and self-defense) from the numerous interaction of much simpler components (ants).

Pines (2014) offers an excellent proposition to the study of emergent behavior: “Understanding such behavior requires a focus on the emergent properties that characterize the system as a whole and a search for their origin. It means identifying emergent collective patterns and regularities through experiment or observation, and then devising models that embody candidate collective organizing concepts and principles that might explain them.”

Mosekilde and Laugesen (2007) document how human behavior and asymmetric information results in boom and bust in prices through experiments such as the beer game. Mathematician Benoit Mandelbrot coined the term ‘Joseph effect’ defined as almost trends and cycles in financial and commodity prices (Mandelbrot and Hudson 2014). Novel and coherent structures, patterns and properties arise through self-organization in complex systems (Goldstein 1999). Emergence is thus spontaneous, self-organized and endogenous.

The bottom-up approach of agent-based modeling enables the computational simulation of the strong nonlinear interaction of micro-level agents to study the emergence of complex macro-behavior of the system as a whole. As Aristotle famously said, "The whole is more than the sum of its part." This thesis studies financial markets, social phenomena, learning, norms and economies through the perspective of complex systems, using cellular automata and network models to elucidate and explicate some of their salient patterns and properties.

1.5 Cellular Automata

The specific modeling methodology in the main chapters of the thesis involves the combination of cellular automata and networks. Cellular automata (CA) are discrete dynamical systems consisting of simple elements that model complex behavior based on simple local rules. The promise of CA lies in the discreteness of space, time and states. CA allow for idealized modeling of complex systems with no central control but are capable of exhibiting self-organization. A cellular automaton is a stylized universe, where time advances in discrete steps; the stylized universe comprises a large number of components / agents with interaction within their local neighborhoods. Every cell takes on a state based on a finite number of possible states. The transition from one state to another is based on simple micro-rules. In each time period, each cell can transit to a new state based on its previous state and the states of cells in its neighborhood. Low dimensional models are promising for understanding the real world of higher dimensions (Hegselmann and Flache 1998).

There are two common classifications in the locality of neighborhoods in two-dimensional CA: Von Neumann neighborhood and Moore neighborhood.

Fig. 1 Common Neighborhoods in Two-dimensional Cellular Automata

The Von Neumann neighborhood of a cell (red) consists of four orthogonally adjacent cells (blue). The Moore neighborhood of a cell (red) consists of four orthogonally adjacent and four diagonally adjacent cells (blue).

Wolfram (1984, 2002) classifies CA behavior into four classes:

- Class 1: Initial configurations converge to a homogenous fixed state after a transient period.
- Class 2: Initial configurations converge to either a homogenous fixed pattern or some periodic cycle of states after a transient period.
- Class 3: Initial configurations result in chaotic, unpredictable space-time behavior after a transient period.
- Class 4: Initial configurations converge to complex localized structures.

In Class 1 CA behavior, there is no change in the final state: the outcome is a state of equilibrium. The degree of predictability in Class 1 CA is high. In Class 2 CA behavior, changes occur in a finite region: the outcome is periodic and cyclical. In Class 3 CA behavior, changes propagate over an increasing region: the outcome is chaos. The behavior is effectively unpredictable due to sensitivity to initial conditions. In Class 4 CA, there are irregular changes despite the emergence of structure and patterns: the outcome is complex.

The first practical CA, the Game of Life, was pioneered in John Conway (1970) and later popularized in Martin Gardner (1970). The objective of the Game of Life is to create unpredictable behavioral outcomes in the population using the simplest rules of life. The environment can be envisaged as a checkerboard in which each square contains a single cell. Each cell has four orthogonally adjacent neighbors and four diagonally adjacent neighbors, comprising a total of eight neighbors. The Game of Life assumes a Moore neighborhood. The genetic rules of life are as follows:

- Isolation: a live cell dies if it has one or zero live neighbors.
- Overcrowding: a live cell dies if it has four or more live neighbors.
- Sustainability: a live cell continues to live into the next period if it has two or three live neighbors.

- Birth: a dead cell becomes a birth/live cell in the next period if it has exactly three live neighbors. Reproduction occurs.

Complex emergent behavior arises from the simple genetic rules of life. Emergent patterns include - but are not restricted to - glider, glider-gun, beehive, block, blinker, boat, fishhook, buckaroo, and space rake. The Game of Life fulfills a basic complex system paradigm where many interacting agents engage in distributed and locally determined actions. The Game of Life exhibits Class 4 CA behavior.

Another famous study using CA was done by Thomas Schelling, whom many consider to be a “father” of agent-based modeling. Schelling was intrigued by the prevalence of racial segregation of neighborhoods despite the decline in racial prejudice and the passing of the Rumford Fair Housing Act (1963).

Schelling (1971, 1978) created a CA model to show that segregation need not reflect the preferences of the individuals and could be self-organized as a result of the dynamic interaction of the people. Schelling did not use a computer in his research. Beginning with a checkerboard, he used dimes and pennies to represent two different races of people. The dimes and pennies were placed randomly on the checkerboard. Each individual coin could have up to eight neighbors: four orthogonally adjacent and four diagonally adjacent. In other words, Schelling assumed a Moore neighborhood. The rules of the individual were simple: an individual will move to live in another location if less than one-third of the neighbors are of similar race as him. The individual will stay only if more than one-third of the neighbors are of the same race. This implies that an individual is highly receptive to having neighbors of a different race. The individuals (dimes and pennies) moved about or were relocated until each fulfilled the rules of the individual, thereby converging to a static equilibrium. The Schelling (1971, 1978) model exhibits Class 1 CA behavior. The equilibrium outcome shows that neighborhoods are still highly segregated by race, in spite of the stipulated rules promoting high tolerance of racially different neighbors. The micro-motives of the individuals result in the emergence of a different macro-behavior.

Hegselmann & Flache (1998) present a simple model of opinion dynamics. The model assumes a two-dimensional CA with Von Neumann neighborhoods. All cells are individuals with opinions, and individuals form new opinions by averaging

the opinions of all their neighbors, a consequence of social influence. The model postulates that the higher the number of diverse opinions, the more probable it is for a universal consensus of opinions. The wide range of diverse opinions of agents at the micro-level emerged into a convergent consensus of opinion in the macro-behavior. CA models are capable of studying the emergence of macro-behavior from the interaction of micro-behavior.

1.6 Small-World Networks

Milgram (1967) conducted a small-world experiment in the United States. In the experiment, participants were to send letters to someone they knew on a first-name basis until the letters arrived at the target person. The objective is to investigate the number of links between any two randomly chosen people. The results show that on average, two randomly chosen people are separated by five intermediaries. The social network of humans is typical of short path lengths, popularized as ‘six degrees of separation’.

Granovetter (1973) postulates the indispensability of weak ties of enhancing social diffusion while strong ties lead to fragmentation of society due to clustered local groups. To reframe the conclusion of Granovetter (1973) in the mathematical terms of network science, enhanced social diffusion implies that the network has a short average path length, while strong ties create local groups that exhibit high clustering coefficient of networks. A follow-up study (Granovetter 1995) finds that a large percentage of people in the US found jobs through social contacts who are acquaintances (weak ties), rather than close friends and relatives (strong ties). From Granovetter’s (1973) perspective, human social networks are characteristic of short average path length and high clustering coefficient.

Fig. 2a Simplified Regular Network, 10 cells/nodes and 4 connected neighbors (2 connected neighbors on each side)

Fig. 2b Regular Network, 100 cells/nodes and 8 connected neighbors, Average Path Length = 6.7, Clustering Coefficient = 0.64

Fig. 3a Simplified Random Network, 10 cells and 4 randomly connected cells

Fig. 3b Random Network, 100 cells and 8 randomly connected cells, Average Path Length = 2.39, Clustering Coefficient = 0.06

Fig. 4a Small World Network, 10 cells and 4 connected neighbors with a rewiring probability of 0.05

Fig. 4b Small World Network, 100 cells and 8 connected neighbors with a rewiring probability of 0.05, Average Path Length = 2.99, Clustering Coefficient = 0.49

In the discussion on cellular automata (two-dimensional), cells are arranged in a two-dimensional lattice; with simple networks, it is preferred to arrange the nodes in

circles. Regular networks exhibit long average path length and high clustering coefficient (See Fig. 2a, b). Erdos-Renyi random graphs are of short average path length but low clustering coefficient (See Fig. 3a, b). No network type fulfilled both conditions of the research on human social structures until Watts and Strogatz (1998). Watts and Strogatz (1998) created small-world network models (See Fig. 4a, b) by randomly rewiring the edges of a regular network. Small-world networks exhibit short average path lengths and high clustering coefficient; other complex systems such as power grids, neural network of *Caenorhabditis elegans*, and collaboration networks of film actors are found to have small-world networks. Social networks also exhibit the properties of small-world networks.

Wilhite (2001) shows that trade occurring in small-world networks rapidly arrives at the Pareto optimal equilibrium. Jackson and Rogers (2007) create a ‘friends of friends’ network model that exhibits many features of social networks beyond short average path length and high clustering; the networks generated by the dynamic model also reflect ‘fat tail’ degree distributions and assortativity. For parsimony, the network structure in the models (in the subsequent chapters) utilizes the small-world networks of Watts and Strogatz (1998) rather than the more complicated dynamic model of Jackson and Rogers (2007).

Chapter 2

Complex Interactional Dynamics of Investors: Mass Psychology and Investor Sentiments

2.1 Introduction

Stock prices do not adhere strictly to random walk processes (Lo and Mackinlay 2011). Financial prices exhibit several characteristics and invariant aspects. For example, the price fluctuations of stocks are too large to be ascribed to the fundamentals - a phenomenon or puzzle labeled as excess volatility (Grossman and Shiller 1981; Shiller 1981; Flavin 1983; Bondt and Thaler 1985; Campbell and Shiller 1988; West 1988; Dumas et al. 2009).

Also, the efficient market hypothesis (EMH) states that in weak-form efficiency, prices reflect information about all historical prices. Thus, if the market is weak-form inefficient, it renders the common financial practice of technical analysis inefficacious in providing incremental information about financial prices. Despite the academic dissension of technical analysis, studies have shown that technical analysis (chart patterns) is effectual in extracting useful information from historical prices (Allen and Karjalainen 1999, Lo et al. 2000).

Another salient characteristic of prices is that the extreme values of stock price changes such as market crashes are consequential extreme events which occur more frequently than predicted or expected (Sornette 2009a).

Trading occurs due to the heterogeneity of agents in the market. Farmer (2012) postulates that the richness of the economy emerges from the interaction of a large number of heterogeneous agents. There have been numerous studies modeling heterogeneous agents in financial markets. These studies reflect many salient characteristics of financial prices.

Day and Huang (1990) create a heterogeneous agent model (HAM) capable of generating chaotic fluctuating prices and switching regimes of bull and bear markets. LeBaron et al. (1999) find statistical properties of leptokurtosis or 'fat tail' distribution of asset prices in a computer-simulated stock market. Corcos et al. (2002) model hyperbolic bubbles and crashes using an agent-based approach. Gallegati et al. (2010)

examine disturbing crashes by modeling interacting heterogeneous agents while Huang et al. (2010) investigate various types of financial crashes using a heterogeneous agent model. Nevertheless, none of the existing theoretical models are capable of exhibiting all the important issues/characteristics of financial markets addressed in all of the above literature.

The objective of this study is to establish theoretical basis that mass psychology and investors' sentiments influence asset prices significantly (Keynes 1936). We examine a simple agent-based model with behavioral foundations regarding investors which are well-found in existing financial literature. The results elucidate the multiple characteristics of asset prices that are discussed in the last paragraph and establish a propagating mechanism of bubbles and crashes.

In financial markets, it is widely known that two kinds of behavior exist: contrarian and herding behavior. Generally, contrarian behavior can be defined as individual behavior that is negatively correlated with actions of others while herding behavior can be defined as individual actions that are positively correlated with actions of others. The logic and evidence behind the herding and contrarian behavior in financial markets are well-documented although more interest has been placed in the former than the latter. What is interesting is not the existence of herding and contrarian behavior but the result of the interaction between the two. The approach of this study explores if the interaction between herding and contrarian investors can result in changes in investor sentiments that translate to price dynamics of bubbles and crashes, and elucidate multiple salient characteristics of financial prices.

In this chapter, the modeling methodology is based on a cellular automaton model. The discrete dynamical system nature of the cellular automaton model enables the study the interaction between investors in order to elucidate the complexity of stock markets. We depart from other studies utilizing cellular automata models as artificial stock markets (see e.g. Wei et al. 2003; Fan et al. 2009) in aspects namely the inclusion of heterogeneity, its significance expounded in Farmer (2012), and the exclusion of exogenous information. The motivation of the latter is the exploration of isolated psychological effects of investors on markets.

Another research strand that is similar to the study is mixed minority-majority games (see e.g. Marsili 2001; De Martino et al. 2003). Many studies of this kind are based on

the premise of the interplay between fundamentalists and chartists, which is well-established in HAM research (Day and Huang 1990; Huang et al. 2010). Instead, the study focuses on the interplay of investor behavior/psychology in a locally distributed system. The combination takes the perspective of the local-distributed nature of human interaction in Hayek (1945) and that of the Keynes Beauty Contest (Keynes 1936): the action of an investor depends on the collective action of others.

The model assumes heterogeneous agents: two types of investors - herding and contrarian agents. The investors make decisions on whether to buy, hold or sell a risky asset in each time period. The investors are organized in a regular network embedded in a cellular automata framework, which can be simply described as a two-dimensional Euclidean network space. The agents are subjected to incomplete information and bounded rationality. The information and social coverage of an agent extends only to the immediate Moore neighborhood in a cellular automata framework. Agents act and update their beliefs/sentiments on the risky asset in discrete time.

A market maker sets prices in response to excess demand and supply. The model exhibits rich and complex outcomes. Generally, it is found that the deterministic interactions between herding agents and contrarians can result in chaotic irregular macro-behavior. Moreover, the modeling of heterogeneous behavior among economic agents can provide insights to the continuous fluctuation of prices in financial markets. Despite the simplicity of the model, multiple aspects of financial markets are exhibited: chaotic fluctuating prices, switching regimes of bull and bear markets, fat tails, non-periodic bubbles, various types of crashes, and punctuated equilibria (occasional ‘bursts’).

The study can be summarized in the flowchart as follows:

The model exhibits the respective endogenous phenomena summarized as follows:

1. Punctuated equilibria: The buying action of an investor is 'information' for other investors, and this information can lead to the buying action of another investor - in some cases relatively large volumes of buy orders in a small segment of the network result in information cascades across the global network. The information cascades result in massive buying behavior within a short period of time causing huge spikes in demand and asset price. The reverse can happen when the selling action of an investor conveys information

to trigger the selling action of other investors. In essence, there exists a positive feedback loop of investors' actions which can result in punctuated equilibria of demand and prices.

2. Chaotic Price Fluctuations: Erratic, perpetual price fluctuations arise due to the deterministic interactions between herding and contrarian investors. The fluctuations result in excess volatility of prices that cannot be explained by fundamentals as the fluctuations are not a result of fundamental changes but investor interactions. Furthermore, there are switching regimes between bull and bear markets where the prices follow rising or falling trends in general. The regimes are non-periodic, with some being longer than others.
3. Fat Tails: The price changes exhibit the stylized fact of leptokurtosis or fat tails.
4. Extreme Events / Values: The absolute price changes are observed to have extreme values without the imposition of large exogenous shocks. The interactional dynamics of herding and contrarian agents can result in the emergence of endogenous extreme events / values.
5. Bubbles and Crashes: The erratic price fluctuations with punctuated equilibria can lead to endogenous formation of bubbles and crashes. The bubbles are resultant of the herding behavior of investors, creating positive feedback loops of buying behavior. The price movements exhibit qualitative features of sudden, disturbing and flash crashes.

The philosophy of this chapter follows the concept of complex systems where interaction between simple micro-agents results in the emergence of a complex macro-behavior with characteristics and patterns absent at the micro level. The system is more than the sum of its component parts. The model in this chapter is capable of simulating a financial market displaying multiple salient characteristics from the interaction of heterogeneous investors with simple behavior, and establishes the interactional dynamics between herding and contrarian investor behaviors as a propagating mechanism of bubbles and crashes.

The rest of the paper is organized as follows:

- Section 2 discusses the investors' behaviors and methodology of cellular automata.

- Section 3 describes the model.
- Section 4 simulates a financial market with multiple characteristics of asset prices: punctuated equilibria, erratic price fluctuations, bubbles and crashes.
- Section 5 considers alternative specifications to study the effects of the variation in the market proportion of herding and contrarian agents.
- Section 6 concludes the paper.

2.2 Investor Behaviors

2.2.1 Herding Behavior

Why do individuals herd? The behavior of an individual is hardly independent of the actions and opinions of his social companions and environment. Time and again, we are susceptible to patronizing a restaurant or purchasing a stock due to the recommendation of a social contact (Shiller and Pound 1989). As economic agents possess limited knowledge and cognitive abilities, the tendency is to rely on traditionally acquired heuristics such as herding². One of the reasons why individuals herd is information uncertainty. Uncertainty results in ambiguity which can cause herding, leading to short-run mispricing. Ford et al. (2012) suggest that herding and contrarian behavior can arise when market makers and / or traders face informational ambiguity - herding can occur when both market makers and traders face informational ambiguity whereas contrarian behavior can appear when only traders face informational ambiguity.

Herding is generally regarded as irrational behavior³. However, imitation and mimicry are basic evolutionary instincts. As argued in Cosmides and Tooby (1994), the human mind exhibits a high level of performance in evolutionarily recurrent computation tasks. Cognitive tools that emerged through evolution can be ‘better than rational’. Herding can be rational if herding arises due to payoff externalities, principal-agent problems and informational cascades (Devenow and Welch 1996).

² Herding can arise due to investors’ animal spirits. (Shiller 2005)

³ Quote from Mackay (2004): “Men, it has been well said, think in herds; it will be seen that they go mad in herds, while they only recover their senses slowly, one by one.”

Economic modeling commonly assumes that economic agents behave as if they are optimizers with perfect rationality. However, behavioral psychology tells us that humans are only moderately efficient in deductive logic. It might not be best for economic agents to optimize if optimization incurs astronomical deliberation cost and the benefit of upgrading from bounded rationality to perfect rationality is small (Conlisk 1996).

In the presence of bounded rationality (Simon 1955), economic agents turn to heuristics such as imitation and herding especially if the cost of optimization is high (Conlisk 1980). Moving from a cost standpoint to a benefit perspective, generally better information can be obtained through social influences as compared to information obtained independently. As a result people can be exceedingly docile, increasing the propensity to herd and follow the crowd (Simon 1993).

The rationality of herding behavior in economic activities should not be absent in the domain of financial markets. In financial markets, profits can be gained through speculation; herding behavior can be rational as the speculator focuses on the behavior of other investors rather than the objective factors of demand and supply (Orlean 1989). The existence of herding in specific financial activities has been documented in numerous studies: corporate takeover (Bikhchandani *et al.* 1992), initial public offering (Welch 1992), and investment recommendations (Scharfstein and Stein 1990; Graham 1999; Welch 2000).

2.2.2 *Contrarian Behavior*

An all-encompassing theory of investor behavior cannot be constrained to solely herding behavior. In the implementation of an investment strategy, an investor wishes to be slightly ahead of the herd hence he purchases the asset at a lower price before the market goes on a bullish trend. This is the goal of the contrarian investor who endeavors to be in the minority when taking a position. Iconoclastic genius is usually linked with the notion of contrarian behavior (Berns 2008).

Famous investors and star fund-managers such as Warren Buffett, David Dreman and Bill Miller are associated with contrarian investing behavior. Contrarian behavior can be formalized in the framework of the famous El-Farol's bar problem (Arthur 1994).

A variation of El-Farol's bar problem is known as the minority game (Challet and Zhang 1998). A minority game is a repeated game in which players have two choices at each time step; selecting the choice of the minority results in a winning outcome whereas selecting the choice of the majority is a losing outcome. To put it simply, the contrarian choice is the winning decision. Minority game models have been capable of reproducing stylized facts of financial markets such as fat-tailed distributions and clustering volatility (Challet et al. 2001).

2.3 A Heterogeneous Agent-Based Model

Consider a market with K investors making decisions on whether to buy or sell a risky asset when the price of the asset in the next period is uncertain. According to standard economic theory, the price of an asset is determined by the objective factors, the market clearing equilibrium of demand and supply subjected to the preferences and budget constraints of the consumer, and the production possibilities of the firm. In the case of equities, the market fundamental value is the expected discounted value of the dividends over time. Shiller (1981) postulates the failure of the 'efficient market' model stated in Eq. (2.1) as he establishes that measures of stock price volatility are too high to be ascribed to new information about future real dividends. The volatility of stock prices cannot be generally explained by their underlying fundamentals.

$$v_t = d_t + d_{t+1}^e/(1+r) + \dots + d_{t+n}^e/(1+r)^n \quad (2.1)$$

Where v_t is the fundamental value at period t , d_t is the dividend declared at period t , d^e is the expected dividend, and r is the discount rate.

The fundamental value of equity is the sum of discounted dividends over n future periods or its lifetime. The computation of this fundamental value requires forecasts of the dividends into infinite future periods or the lifetime of the equity. The accuracy of the calculation is subjected to the quality of the forecasts, and forecasts over long periods of time are generally dismal. When uncertainty is taken into account, the computation of the fundamental value expressed in Eq. (2.1) lacks robustness.

Knight (1921) argues that the concept of uncertainty must be distinct from the notion of risk. Risk is a quantity susceptible to measurement and appears to be a measurable 'uncertainty'; a paradox presents itself here as risk - which is measurable - is not

effectively ‘uncertain’. Knightian uncertainty refers to non-quantifiable cases⁴ - randomness with unknowable probabilities.

Time breeds uncertainty in the Knightian sense. The immense difficulty of investors’ decision-making lies in the computation of the long-run fundamental value of the asset; with Knightian uncertainty, the computation of a robust long-run fundamental value is an elusive impossibility. Investment decision-making that relies on the computation of long-run fundamental value does not present itself as an optimal strategy.

The perspective that investors do not behave with reference to the fundamental value is also given in Keynes (1936); Keynes utilizes a newspaper beauty contest as a metaphor for the stock market. In the contest, participants are to select six prettiest faces from a hundred photographs. The winning participant will be the one whose selections are closest to the average selections of all participants. One should not select what one thinks are the six prettiest faces but to select the faces one thinks others will think are the prettiest. A better strategy will be for one to select the faces that one thinks others will think that others think are the prettiest.

Thus, in the stock market, the prediction of the eventual outcome based on the reasoning of agents is not to select the issue of the highest objective value or the average opinion of the highest value, but the third degree of the expectation of the average opinion of the average opinion. The prediction of others’ assessment of value might be more paramount than the estimation of the objective value.

Hence, in this model, there is no reference of the decisions of agents to the fundamental value of asset⁵. The investors’ choice is a price expectation problem since the main objective of the investor is to maximize capital gains. An investor buys when he has a price expectation of the asset higher than the current price and sells when the price expectation of the asset is lower than the current price. The investor’s expected profit or capital gain is the difference between the price expectation and the current price. Price variations are determined by the sum of investors’ actions. In order to

⁴ Keynes (1921), *A Treatise on Probability*, discussed a similar concept which he termed as ‘irreducible uncertainty’. Makridakis, Hogarth, and Gaba (2009) playfully suggested a similar concept which they termed as ‘coconut uncertainty’.

⁵ Caballero (2010) advocates a reduction in the amount of knowledge economic agents are assumed to possess for a better representation of reality.

make investment decisions, an agent obtains information about the collective judgment from other investors in his localized network - or Moore neighborhood - to form his state of opinion of the asset, i.e. “bullish” or “bearish”. The proposition is that investor sentiments are integral in determining asset prices. The concept follows that the state of opinion/sentiment of agent i at period $t + 1$, $S_{i,t+1}$, is a function of all the opinions/sentiments of the network ‘neighbors’ (a total of 8) of agent i at period t :

$$S_{i,t+1} = f\left(\sum_{j \in N_i} S_{j,t}\right) \quad (2.2)$$

Where N_i denotes the domain of network neighbors, the Moore neighborhood, of agent i .

The elements of the model comprise a regular network embedded in a cellular automata framework, two kinds of investors (herding agents and contrarians), and a market maker.

2.3.1 Investors

2.3.1.1 Herding Agents

We assume an equal proportion of herding and contrarian agents in a population of investors in the standard model. Herding agents believe in the wisdom of crowds (Surowiecki 2005) and they follow the majority. A herding agent demands the asset in period $t + 1$ if half the number of investors in his local network buy the asset in period t , in other words, the herding agent is bullish. However, recall from our earlier discussions on the rationality of herding behavior: a herding agent is not a mindless follower. When the demand for the asset of the investor population reaches a certain high threshold, the herding agents recognize that the expected profit (upside of the asset price changes) is small and the risk (downside of the asset price changes) is large. The herding agents will sell the asset once they deem the asset ‘over-bought’. The behavioral rules of the herding agents are as follows:

$$H_{i,t+1} = \begin{cases} 1, & \text{if } 4 \leq \sum_{j \in N_i} S_{j,t} \leq 5 \\ 1, & \text{if } H_{i,t} = 1 \text{ and } (6 \leq \sum_{j \in N_i} S_{j,t} \leq 7) \\ 0, & \text{otherwise} \end{cases} \quad (2.3)$$

Where $H_{i,t+1}$ is the state of herding agent i in period $t + 1$, and $\sum_{j \in N_i} S_{j,t}$ is the number of bullish investors in the agent's network demanding the asset in period t .

Each herding agent i adopts two simple states: 'bullish' or 'bearish' denoted by 1 or 0 respectively. The agent demands the asset (buying the asset if he is not holding the asset and holding the asset when he has bought the asset) when he is bullish and sells the asset if he is holding the asset when he is bearish. As each agent's local network is his Moore neighborhood, the total number of investors in his network is 8, the investors in the local network can be herding agents and contrarians. The herding agent buys the asset in period $t + 1$ once 50% to 62.5% of the number of investors in his network demands the asset in period t , $4 \leq \sum_{j \in N_i} S_{j,t} \leq 5$; the agent will hold the asset in period $t + 2$ if $6 \leq \sum_{j \in N_i} S_{j,t} \leq 7$. The agent profits from following the trend of the crowd. The herding agent reaches his selling threshold when more than 90% of the total investors in the agent's network demand the asset and the agent will sell the asset in period $t + 3$ if $\sum_{j \in N_i} S_{j,t+2} = 8$; 90% is the threshold at which the herding agents recognize that the expected profit (upside of the asset price) is small and the risk (downside of the asset price) is large. The agent will also sell the asset in the next period if the investors demanding the asset are less than 4 as this indicates a minority demand and low likelihood of a trend developing.

2.3.1.2 Contrarian Agents

Contrarians abide by the idea of the madness of crowds (Mackay 2004) and they do not follow the crowd. A contrarian investment paradigm used by many investors is known as value investing (Graham 1934, 2009). The crux in value investing lies in buying assets which are undervalued - the undervaluation of the assets can be due to a multitude of reasons for which the asset is ignored or unloved by the crowd. In this model, a contrarian demands an asset only if a minority of the investors in his network demand the asset based on the assumption that if too many investors demand the asset, the asset is not undervalued. The behavioral rules of the contrarian are as follows:

$$C_{i,t+1} = \begin{cases} 1, & \text{if } \sum_{j \in N_i} S_{j,t} = 2 \\ 1, & \text{if } C_{i,t} = 1 \text{ and } (3 \leq \sum_{j \in N_i} S_{j,t} \leq 4) \\ 0, & \text{otherwise} \end{cases} \quad (2.4)$$

Where $C_{i,t+1}$ is the state of contrarian agent i in period $t + 1$, and $\sum_{j \in N_i} S_{j,t}$ is the number of bullish investors in the agent's network demanding the asset in period t .

Each contrarian agent i adopts two simple states 'bullish' or 'bearish' denoted by 1 or 0, similar to the herding agent. The contrarian agent has a local network of a Moore neighborhood comprising 8 other investors, herding agents and contrarians. The contrarian agent buys the asset in period $t + 1$ if a quarter of the investors in his network demand the asset in period t , $\sum_{j \in N_i} S_{j,t} = 2$; the contrarian agent prefers to buy an asset with a minority demand but excessively low demand can signal an inferior asset. The agent will then hold the asset in period $t + 2$ if $3 \leq \sum_{j \in N_i} S_{j,t} \leq 4$; once the majority of the investor population demands the asset, the contrarian deems the asset overvalued. The agent profits by purchasing an undervalued asset and selling when the crowd starts demanding the asset. The contrarian agent reaches his selling threshold when more than 50% of the total investors in the agent's network demand the asset, the agent will sell the asset in period $t + 3$ if $\sum_{j \in N_i} S_{j,t+2} \geq 5$. The agent will also sell the asset in the next period if the investors demanding the asset are less than 2, $\sum_{j \in N_i} S_{j,t} < 2$, as this signals that demand is almost non-existent, interpreted as a huge lack of interest in the asset. The ideal for a contrarian is to be a minority buyer when entering into a position⁶, and be a minority seller again when closing the position⁷.

2.3.2 Regular Network

Now that we have defined the characteristics and rules of the investors, a partial representation of the global regular network is presented in Fig. (2.1). (The connecting edges of the agents are removed in future representations for neatness and simplicity of the diagrams.)

⁶ Note that $N_i = 8$, $\sum_{j \in N_i} S_{j,t} = 2$, $\frac{\sum_{j \in N_i} S_{j,t}}{N_i} = 0.25$

⁷ $\sum_{j \in N_i} S_{j,t} \geq 5$, $1 - \frac{\sum_{j \in N_i} S_{j,t}}{N_i} \leq 0.375$

Fig. 2.1 Regular Network

Each investor makes his decision based on the actions of the other ‘connected’ investors in his localized network space, N_i in Eq. (2.2), (2.3) and (2.4). Information gathering and processing costs present frictions for perfect rational behavior. The notion of bounded rationality (Simon 1955, 1956) and incomplete information leads to the assumption that an agent cannot have perfect information about the buying and selling decisions of all agents. Even if it were possible to obtain all information, it is not optimal to do so when search costs are considered. The model assumes that an agent only has access to information from his local network of a Moore neighborhood.

Fig. 2.2 Agent and Demand Screens

Figure (2.2) shows the cellular automata model with two different representations. The square diagram on the left shows the dispersion of herding agents and contrarians in the network space. The blue cells denote the contrarians and the red cells denote the herding agents. The square diagram on the right shows the demand of the corresponding investors in the global network space. A black cell (agent state = 1) denotes that an investor is ‘bullish’, and demands (either buying or holding) the asset. A pink cell (agent state = 0) denotes that an investor is ‘bearish’, with no intention of buying the asset or had sold the asset. The two diagrams refer to the same context.

2.3.3 Market Maker and Price Dynamics

A market clearing equilibrium in every time period is difficult to achieve and it does not reflect the continuous trading prevalent in financial markets (Lebaron 2006). In a market maker framework, the market maker provides liquidity and facilitates transactions in the market, setting price in response to excess demand or supply (Day and Huang 1990). When there is excess demand, the market maker supplies from its inventory; in contrast when there is excess supply, the market maker accumulates inventory. The market maker plays the role of a price setter. The market maker framework allows for the absence of a Walrasian market clearing equilibrium in the market price formation.

Typically the buy and sell orders of investors do not match so the market does not clear. In the market maker framework, market orders are always filled. Investors trade assets with the market maker. When investors place a buy order, the market maker sells; when investors place a sell order, the market maker buys. The market maker sets price in response to aggregate excess demand. Here, we define general demand, denoted by D , as the sum of investors holding or buying the asset. The difference in general demand between period t and period $t - 1$ is the aggregate excess demand (+) or supply (-). Following Farmer (2002) and Corcos et al. (2002), we propose a variant of a price impact function used by the market maker to set price where the price P is linearly proportionate to a net order imbalance, aggregate excess demand or supply.

$$P_t = P_{t-1} + \gamma(D_t - D_{t-1}) \quad (2.5)$$

Where γ is the inverse price elasticity of demand for the risky asset and,

$$D_t = \sum_{i=1}^K (H_{i,t} + C_{i,t}) \quad (2.6)$$

Where $H_{i,t}$ denotes the state of herding agent i at period t , $C_{i,t}$ denotes the state of contrarian agent i at period t , and the general demand at period t , D_t , is the aggregate of all bullish herding and contrarian agents.

$$\Delta P_t = \gamma(\Delta D_t) \quad (2.7)$$

Eq. (2.5) can be simplified into Eq. (2.7) where the change in price is linearly proportionate to the change in general demand. If γ is high, the magnitude of price adjustment is large to changes in general demand. If $\Delta D_t = 0$, the market is in equilibrium and there is no change in price. If $\Delta D_t > 0$, the general demand increases from period $t - 1$ to period t , there is excess demand and some of the buy orders are not filled in. The market maker responds by selling its inventory to buyers at a higher price. If $\Delta D_t < 0$, the general demand falls, indicating that there is excess supply and some sell orders are not filled in, the market maker accumulates inventory at a lower price.

$$P_t = P_{t-1} + \gamma \left(\sum_{i=1}^K (H_{i,t} - H_{i,t-1} + C_{i,t} - C_{i,t-1}) \right) \quad (2.8)$$

$$\Delta P_t = \gamma \left(\sum_{i=1}^K (\Delta H_{i,t} + \Delta C_{i,t}) \right) \quad (2.9)$$

Eq. (2.8) is obtained by substituting Eq. (2.6) into Eq. (2.5). The change in price is linearly proportionate to the aggregate change in sentiments of the investors, herding and contrarian agents.

2.4 Modeling Financial Market

The model is set up by randomizing herding and contrarian investors' placement in the cellular automata model, denoted by red and blue cells respectively. The initialization induces demand in a small proportion of the population of investors randomly. The herding and contrarian investors then interact, creating general demand. The market maker sets price in response to changes in general demand.

Fig. 2.3 Demand Dynamics

The dynamics of the general demand in the investor population is shown in Fig. (2.3). The three diagrams indicate the agent and demand screens at different time periods, $t = 100, 500, 1000$ respectively. The agent screen is fixed for all time periods as the positioning of herding and contrarian agents in the network does not change in a single simulation. The demand screen changes over time, representing the demand dynamics of the investors. The general demand of the investors does not converge to any equilibrium, cyclical or periodic state. The general demand of the investors exhibits chaotic and unpredictable space-time behavior after a transient period. The cellular automata model exhibits class 3 behavior. The first interesting feature observed is that some investors choose to buy and hold the asset for long periods of time while some choose to buy and sell the asset at short time intervals. A macro-behavior of long-term and short-term investing emerges from the interaction between herding and contrarian investors.

2.4.1 Result 1: Punctuated Equilibria

In the model, an agent derives information from the actions of other agents. The buying actions of agents can induce more buying actions of other agents: a positive feedback loop in which buying begets more buying. In extreme cases, the positive feedback loops develop into buying cascades⁸ across the global network. As stipulated by the rules of herding and contrarian agents, once too many investors have bought the asset, the agents recognize the limited profit expectation and increased risk (expectation of loss) and proceed to sell the asset. Selling can beget more selling. At times, the selling actions of agents too result in selling cascades across the global network. In extreme cases, information cascades result in a large magnitude change in the general demand of investors. In other times, the changes in general demand - which in turn translates into changes in market price - vary but they are generally small in magnitude. In such times, the volume of trading is small, resulting in relatively small fluctuations in price.

A bar diagram of the absolute change in general demand is shown in Fig. (2.4). The absolute change in general demand exhibits one of the characteristics of complex systems: punctuated equilibria. Extended periods of relative stasis are punctuated by occasional bursts of excess demand or supply. These bursts of large magnitudes in excess demand or supply are periods where the market is far-from-equilibrium, and - in extreme cases - result in bubbles and crashes. In certain periods, these bursts tend to cluster.

Fig. 2.4 Punctuated Equilibria

⁸ In the computer simulation, this is seen as a sudden proliferation of black or pink cells across the global network.

2.4.2 Result 2: Financial Price Series

2.4.2.1 Price Fluctuations and Excess Volatility

The time series of the asset price is shown in Fig. (2.5). The interactions between heterogeneous investors, herding agents and contrarian agents result in chaotic price fluctuations. It can be observed that in extreme cases, the chaotic price fluctuations along with punctuated equilibria can result in endogenous, non-periodic bubbles and crashes. As the model does not incorporate the fundamental value of the asset, the results suggest that the interaction between herding and contrarian investors can cause price variations without reference to fundamental values. The changes in aggregate investor sentiments due to the social interaction among investors can move prices. This explains the excess volatility of prices found in numerous studies (Grossman and Shiller 1981; Flavin 1983; Bondt and Thaler 1985; Campbell and Shiller 1988; West 1988; Dumas et al. 2009).

Fig. 2.5 Simulated Price Series

2.4.2.2 Switching Regimes of Bull / Bear Markets and Cyclical Behavior

A moving average is a mathematical operation that smooths out short-term fluctuations and accentuates the trends and cycles. Fitting a 50-period simple moving average to the price series (See Fig. 2.5),

$$P_t^{SMA} = (P_t + P_{t-1} + \dots + P_{t-48} + P_{t-49})/50$$

There are relatively long periods when the price is above or below the 50-period simple moving average, indicative of a general rising or falling price trend. The price series switches between regimes of bull (rising) markets and bear (falling) markets. Furthermore, the 50-period moving average exhibits non-periodic cyclical behavior, reminiscent of market cycles. The simulated price series is reminiscent of the ‘Joseph Effect’: almost trends and cycles (Mandelbrot and Hudson 2014).

2.4.2.3 Fat Tails and Risk

The price series also exhibits quantitative features similar to real asset prices. Price changes or returns are assumed in standard finance theory to follow a normal distribution. One stylized fact of financial prices is that asset price changes do not follow a Gaussian distribution. Asset price changes have fat-tailed distributions. A simple measure of the ‘fatness’ of tails is the fourth standardized moment or kurtosis.

$$Kurt(X) = \frac{E[(X - \mu)^4]}{\{E[(X - \mu)^2]\}^2}$$

Assuming that liquidity is constant, the kurtosis of the simulated price change series of Fig. 2.5 (1,000 observations) is 3.65 - in excess of 3 - which implies that the simulated price changes have ‘fatter’ tails than a normal distribution, indicating leptokurtosis. If parameter γ is varied, allowing for periods when γ is high or low, the kurtosis of price returns can be significantly higher.

The Grossman-Stiglitz paradox states that a perfectly information-efficient market is impossible (Grossman and Stiglitz 1980). If the perspective of market inefficiency is taken, the increased money supply can push prices into far-from-efficient territory and exacerbate the animal spirits of investors. This result contradicts the conventional perspective that liquidity necessarily results in more efficient pricing in markets.

2.4.2.4 Technical Analysis and Price Patterns

Technical analysis has shown to be useful in extracting information about future prices from historical prices (Allen and Karjalainen 1999, Lo et al. 2000). The model simulates price series that are consistent with technical price patterns. Some of the common technical indicators are illustrated as follows:

- Head-and-shoulders top reversal pattern: The head-and-shoulders reversal pattern consists of a left shoulder, head, right shoulder and neckline (See Fig. 2.5a). The troughs between the head and shoulders form the neckline or support; when the price falls below the neckline support, it indicates a reversal to a downward trend.
- “V” top reversal pattern: The “V” top is an inverted V-shaped price pattern that consists of a rising price trend with no or few disruptions before reversing sharply to the initial price (See Fig. 2.5a).
- Ascending triangle continuation pattern: The ascending triangle consists of a right-angled triangle indicator (See Fig. 2.5b). Two or more equal peaks form the top line (red) and two or more rising troughs form the hypotenuse of the triangle. The top horizontal line formed by connecting two or more equal peaks is the resistance line. When the price rises above the resistance line, it indicates the continuation of a price uptrend.

Fig. 2.5a Technical Price Patterns (Reversal) in Simulated Price Series

Fig. 2.5b Technical Price Patterns (Continuation) in Simulated Price Series

2.4.2.5 The Extreme Values of Absolute Price Changes

The histogram of the absolute price changes are shown in Fig. (2.6). The frequency is larger where absolute price changes are smaller and the frequency is smaller where absolute price changes are larger. Generally, the frequency decreases with increasing magnitudes in price changes. Extreme events have been studied as Black Swans, power laws and Dragon Kings (Sachs et al. 2012). The distribution of the absolute price changes exhibits a ‘long tail’; this illustrates graphically the phenomena of extreme values that are more common than stipulated in a Gaussian distribution which is assumed as the distribution of price changes in standard risk management models. The emergence of the extreme values is endogenous⁹, without the imposition of large exogenous shocks.

Fig. 2.6 Histogram and “Long Tail” (Red) of Absolute Price Changes

⁹ Endogenous extreme events are consistent with the notions of power laws and Dragon Kings. Black swans do not distinguish between exogeneity or endogeneity but revolves around the concept of epistemology.

2.4.3 Result 3: Bubbles and Mimetic Behavior

The time series of general demand of herding and contrarian agents are shown in Fig. (2.7). The vicissitudes of the general demand of herding agents (Fig. 2.7) tend to follow the vicissitudes of the price series¹⁰ (Fig. 2.5). The general trends in the price series are largely caused by aggregate herding demand behavior; aggregate contrarian demand behavior is relatively constant. In extreme cases, trending prices result in bubbles and crashes. The underlying cause is the mimetic contagion or positive feedback of herding behavior (Orlean 1989; Shiller 2005; Sornette 2009b). The positive feedback loops of herding behavior create a self-reinforcement of rising prices when buying begets more buying, resulting in bubbles.

Fig. 2.7 Herding and Contrarian Investors

2.4.4 Result 4: Market Crashes

This subsection further seeks to demonstrate that the deterministic price fluctuations have similar qualitative features with some of the market crashes observed historically. Huang et al. (2010) classify financial crises into 3 types: disturbing crises, smooth crises and sudden crises. The differences in the type of crises could be endogenous. Financial crises that cannot be explained by a change in fundamentals - such as Black Monday¹¹ - could be due to interactions between heterogeneous investors. Replication aids understanding. As voiced by Richard Feynman: “What I cannot create, I do not understand.” The focus in this subsection is to illustrate that the model can simulate

¹⁰ An ordinary least squares regression of change in price on change in general demand of herding agents is statistically significant.

¹¹ Black Monday refers to the stock market crash in October 1987 where stock markets all over the world lost a significant portion of their value in a single day. The Dow Jones Industrial Index fell by 23%.

price series with qualitative features similar to some historical market crashes, mainly sudden crashes and disturbing crashes.

2.4.4.1 Sudden Crash

In sudden crashes, prices decline sharply from the peak to the bottom over a relatively short amount of time (Huang et al. 2010). A slight rebound tends to occur when the price hits the bottom, which is usually referred in traders' lingo as a 'dead cat bounce'. The stock market crash of 1987 is a typical example of a sudden crash. In the study, we examine if the qualitative features of a sudden crash as exemplified by the historical daily price series of the Dow Jones Industrial Index (DJIA) in October 1987 could be replicated by the model. The simulation of the model generates the price series with partial segments qualitatively similar to that of the DJIA stock market crash. One example is shown in Fig. (2.8). This suggests that a market crash could be endogenous rather than exogenous, and could have occurred without any exogenous shocks.

Fig. 2.8 Sudden Crash of Dow Jones Industrial Index October 1987

2.4.4.2 Disturbing Crash

In disturbing crashes, the price decline is more gradual than that of a sudden crash. The time period of disturbing crashes is generally longer than that of sudden crashes. The financial distress between the price peak and bottom that manifests as volatility clustering is characteristic of disturbing crashes (Gallegati et al. 2010). A good example of a disturbing crash is the global financial crisis of 2008/09 triggered by the sub-prime mortgage crisis and the fall of Lehmann Brothers.

Although the crisis is a result of fundamental reasons (Shiller 2008; Crotty 2009), the extreme price fluctuations and volatility of stock prices cannot be explained by fundamentals. In the study, we examine if the qualitative features of a disturbing crash as exemplified by the historical daily price series of the Standard & Poor's 500 Index (S&P 500) from September 2008 to April 2009 could be replicated by the results from the model. The model has been able to simulate a price series that replicates the qualitative features of a disturbing crash and is not too dissimilar from that of the S&P 500 Index during the global financial crisis of 2008/09 (see Fig. 2.9a). Price fluctuations, even during times of crisis, can arise out of the interactions between heterogeneous agents which imply that prices can move without efficiently reflecting the fundamental value of assets.

Fig. 2.9a Disturbing Crash of Global Financial Crisis 2008/09

2.4.4.3 Flash Crash

We include another type of market crash as an update due to recent events: a flash crash. The May 2010 *Flash Crash*, also known as The Crash of 2:45, where major market indexes in the United States fell by approximately 9% only to recover a large part of the losses within minutes. A definition of flash crash is proposed as follows: a large decline in asset price that is followed by an immediate rebound to approximately the same price over a relatively short period of time. The interactions between heterogeneous agents in the model are capable of producing large price movements with similar qualitative features of a flash crash (see Fig. 2.9b).

Fig. 2.9b Flash Crash

2.5 Comparative Studies and Theoretical Implications

The interaction between simple heterogeneous investors can result in the emergence of chaotic price fluctuations (see Fig. 2.5) along with punctuated equilibria (see Fig. 2.4); in extreme cases, the price movements are large, emanating into bubbles and crashes (see Fig. 2.7, 2.8a, 2.9a, 2.9b).

We proceed further to explore alternative specifications to study the results of the variation in the market proportion of herding agents and contrarians. The proportion of herding and contrarian agents in the investor population is changed to study the effects of varying degrees of herding and contrarian behavior in the market to the asset price.

Experiment (i): From the 50/50 investor distribution of herding and contrarian agents in the standard model, we specify the investor population to consist of all contrarian agents; there is no herding agent in this experimental simulation. The results show that the price converges to an equilibrium state after a short transient period (see Fig. 2.10). The interactions among contrarian agents do not result in any fluctuations of price.

Fig. 2.10 Equilibrium Price

Experiment (ii): Previously in experiment (i), the investor population consists of all contrarian investors. In experiment (ii), the investor population consists of all herding agents. The outcome is that there is no market demand and price is zero in this experiment. Intuitively, this is so because if the investor population consists of all herding agents, there is no contrarian investor to create ‘initial’ demand for the herding investors to imitate. In this case, the investors herd towards not buying the asset. The results of experiment (i) and (ii) have reinforced that trading occurs due to the heterogeneity of investors - a population of solely herding or contrarian investors results in no trade and an equilibrium price. In experiment (ii), the result is a trivial equilibrium price of zero.

Using the specifications of experiment (i) as a starting point, the proportion of herding agents is increased by deciles from experiment (iii) to (x).

Experiments (iii) – (vi): In experiment (iii), the proportion of herding agents is specified at 10% and contrarian agents comprise the remaining 90%. Experiment (iii) proceeds from experiment (i) by including a minority proportion of herding agents into the population. The outcome is similar to that of the standard model in which there are price fluctuations but the magnitude of price fluctuations is significantly smaller (see Fig. 2.11). The price volatility emerges out of the interactions between the herding and contrarian investors even when there is a minority of herding investors. Experiments (iv) – (vi): By increasing the proportion of herding agents, increasing price fluctuations are observed (see Fig. 2.12, 2.13, 2.14). The proportion of herding agents in experiments (iv) to (vi) is 20, 30 and 40 percent respectively.

Experiments (vii) – (x): In experiment (vii), the proportion of herding agents is 60% and that of the contrarian agents is 40%, the level of price fluctuation is similar to that of experiment (vi) (See Fig. 2.14). In experiment (x), the proportion of herding agents is 90% and that of the contrarian agents is 10%. The outcome of experiment is similar to experiment (iii) (See Fig. 2.11).

Generally, increased proportion of herding agents in experiments (iii) to (vi) increases the magnitude of price fluctuations. However, in experiments (vii) to (x), increasing the proportion of herding agents lowers that of the price fluctuations, indicating a nonlinear and non-monotonic relationship between herding behavior and price volatility.

Fig. 2.11 Unstable Prices

Fig. 2.12 Price Fluctuations

Fig. 2.13 Experiment (v)

Fig. 2.14 Experiment (vi)

Further exploration on the varying degrees of herding and contrarian behavior suggests that there is no monotonic relationship between the level of herding behavior in the market and the price volatility. Intuitively, when there are high levels of herding behavior, there is largely a consensus on the price of the asset, resulting in a stable equilibrium price.

When there is no herding behavior, a high level of independence in investors' decision-making also results in a stable equilibrium. It is between high levels of presence and absence of herding behavior that results in large fluctuations in price and price reversals due to strong interaction between herding and non-herding investors. The increased heterogeneity leads to greater volatility in financial prices. Trading occurs due to the heterogeneity of investors.

The agents in the model determine their investment decisions based on the actions of other agents in their network neighborhood, which in turn are based on the actions of

others in their respective network neighborhoods. In other words, in the model, the agents act based on the average true opinion of the average true opinion.

Social interaction is a mechanism for learning and information transfer. The modeling of time and network space of agent interaction yields periods of stasis and occasional ‘bursts’ of activity. In a networked economy, the assumption of independent decision-making of a representative agent has limitations for economic modeling; agents can derive information from or imitate the actions of other agents. This is especially so in financial markets, as the price can be seen as the collective judgment and action of all participants. The payoff of an investor is tied to the actions of others. Even without changes in fundamentals of an asset, social interaction among investors can move asset prices.

The interaction among heterogeneous investors alone can reflect many qualitative features of asset prices; it also shows that interaction among investors can push prices into far-from-efficient territory. Investor sentiments matter in financial markets. The non-periodic bullish or bearish sentiments in localized network components can socially diffuse into the global network of traders and investors, resulting in switching regimes of bull and bear markets. In a network of interdependent investors who are influenced by each other, local interaction can propagate spontaneously into global cascades. The global cascades among herding investors can result in self-organized behavior which leads to the emergence of bubbles and crashes.

2.6 Conclusion

The aim of this chapter is to study how group psychology and investor sentiments explicitly translate to the general behavior of financial prices. For that purpose, we construct a parsimonious model of interacting agents that is capable of expounding the multiple salient characteristics of financial prices and, simultaneously, propose a propagating mechanism of bubbles and crashes.

The chaotic dynamics of our results highlight the unpredictability of market prices due to the psychological heterogeneity of investors. The unpredictability extends to the spontaneous emergence of endogenous bubbles and crashes. This illuminates the consequential uncertainty of markets.

We show that the interdependent actions of heterogeneous investors can result in continuous trading, excess volatility and endogenous extreme events. Herding behavior is explicated as the driving force in the endogenous formation of bubbles. The internal price dynamics replicate trajectories of different types of crashes. The existence of fat tails and extreme high impact events evokes the requirement of risk management techniques that are robust to large deviations and outliers.

The emergence of non-periodic cyclical behavior of prices is observed as almost-trends and reversals (Joseph Effect). The endogenous price effects of interaction between investors have implications on market efficiency.

Agent-based methods are capable of modeling the complex dynamics of asset prices by incorporating interaction of heterogeneous investors, network space and time. The model in this chapter incorporates parsimonious rules of the herding and contrarian behavior of investors in a regular network. It describes a system comprising interdependence and autonomy of agents with locally distributed actions that result in macro-behavior of prices emerging from deterministic micro-rules. Thus, it qualifies as a complex system.

In essence, the model expounds that financial price, is an emergent behavior from the interaction of mass psychology and investor sentiments. Individual investor behavior presents only a starting point to understanding the financial system as a whole. The concept of emergence in complex systems implies a supervenience of properties between the individual and the system.

Finally, the model reflects multiple characteristics of financial markets: erratic price fluctuations, punctuated equilibria, fat tails, extreme values, market cycles, non-periodic bubbles and crashes, switching regimes of bull and bear markets.

Shiller (2014) opines that the fluctuations of economies are mainly due to social interaction between people where narratives can simulate and inhibit ‘animal spirits’. This chapter holds a parallel perspective in the context of financial markets where the interaction between heterogeneous investors can result in changing investor sentiments, which in turn propagate into complex price behaviors.

Future research can embed the model with fundamental values of various financial variables for study of how co-existence of fundamentals, investor sentiments and

social interaction can unearth improved insights and understanding of financial markets. Another direction for research will be to employ more realistic network structures such as small-world networks or scale-free networks to study whether different networks result in other interesting implications. Even so, in its present state, our parsimonious model of interacting heterogeneous agents that incorporates herding and contrarian micro-behavior can elucidate the macro-behavior and prominent characteristics of asset prices.

Chapter 3

The Wisdom of Social Links: Learning, Interaction, Self-Organized Efficiency

3.1 Introduction

“The peculiar character of the problem of a rational order is determined precisely by the fact that the knowledge of the circumstances which we use never exists in concentrated or integrated form, but solely as the dispersed bits of incomplete and frequently contradictory knowledge which all the separate individuals possess..... The problem is thus in no way solved if one can show that all of the facts, if they were known in a single mind, would uniquely determine the solution; instead we must show how a solution is produced by the interactions of people each of whom possesses only partial knowledge.”
(Hayek 1945)

This chapter proposes an explicit model of social learning to the above Hayek's problem. Granovetter (1985) argues that most economic behavior is embedded in interpersonal networks and social contexts. Economic behavior is ultimately rooted in the context of human society. The behavior of an individual can be influenced by the behavior of others.

Asch (1956) line experiments exemplify the extent of social influence. In the Asch (1956) experiments, participants are asked to select a matching line to the reference line from a series of options, and to then announce their answers sequentially. All participants, except for the last, are actors/confederates who intentionally chose the blatant incorrect answer in several of the trials, essentially pitting the correct private judgment of the last participant against the incorrect consensus. The results show that majority of the participants elected to go with the incorrect consensus instead of their correct private judgment.

Berns et al. (2005) investigate the neural basis of conformity behavior apparent in the Asch (1956) results; using functional magnetic resonance imaging, the scans show activity in the occipital-parietal network when wrong information is transmitted from others, establishing the biological evidence of perceptual and emotional processes of social influence.

In an increasingly hyper-connected world, increased social interaction and information dissemination are ubiquitous. The element of social interaction has long taken a secondary role in standard economic analysis. The relevance of social interaction to economic decision-making should be obvious. A simple fact is that it is perfectly common for people to patronize a restaurant, consume a product, or invest in a stock due to the recommendation of a friend (Shiller and Pound 1989).

Social interaction is a mechanism for information transmission and learning. The access to information is largely dependent on the social structure and connections of individuals (Ioannides and Loury 2004). Simple learning in social networks can lead to the wisdom of crowds (Golub and Jackson 2012). Consumer choice and preference are not independent of social interaction; social interaction can exert an inordinate amount of influence on one's choice and preference. This begs questioning of the effects of social interaction and learning with regard to utilitarian optimality and efficiency.

Free markets are favored for their decentralization of resource allocation optimality, as if guided towards a self-organized efficiency by an 'invisible' hand. The Arrow-Debreu general equilibrium connotes the optimal outcome by involving the centralized price-setting market mechanism of a Walrasian Auctioneer. The price mechanism is, however, not infallible. Becker (1991) presents a puzzle of prices where restaurants, cinemas and book publishers do not increase price when demand exceeds supply. This warrants a study of the non-pecuniary aspects of the free market economy.

The 'freedom' of free markets can be categorized into two halves: one half involves the freedom of firms in producing the type and quantity of goods and services, the other half involves the free choice of consumers in selecting what they purchase. The focus of this chapter deals with the autonomous choice of consumers with reference to the non-pecuniary interdependence of social interaction, but departs from the idea of social interaction as externalities (Brock and Durlauf 2001).

Social interaction occurs locally, and local interaction of micro-agents can result in interesting global behavior (Schelling 1971, Ellison 1993). We seek to explore if social interaction, as a mechanism of information transmission and learning, can be a 'force' for self-organized utilitarian efficiency.

This chapter explores the notion that social learning is an efficient information aggregation mechanism in achieving optimal decision-making of the crowd in a context of discrete choices. In order to model social learning, the model has to ideally comprise numerous agents and social networks.

The objective is to investigate if the social interaction of numerous agents in the structure of small world networks, which characterizes social networks, can result in the wisdom (rational choice) of crowds. Such a problem is well-suited to the applicability of agent-based modeling. Agent-based models with simple rules can generate complex behavior that resembles real world phenomena (Reynolds 1987). The whole is more than the sum of its parts. Agent-based modeling allows for a bottom-up approach to studying macro-behavior from micro-rules (Schelling 1971, Wolfram 1994).

Utilizing a cellular automata agent-based model, we examine if the local interaction of social learning micro-individuals in a market can emerge into a macro-behavior that exhibits aggregate rationality, or, the wisdom of crowds. The model considers the context of a market with binary choices. Hence, the economic agents have to choose between two discrete choices.

The model comprises multiple agents embedded in a small-world network in a two-dimensional cellular automaton universe. The agents are subjected to bounded rationality and imperfect information with regard to the choices. The behavioral rules of agents are stochastic. Agents act and update their beliefs in discrete time. In essence, it is found that the interaction and social learning between bounded rational agents act as an efficient information aggregation mechanism which can propagate the wisdom of the population in selecting the superior choice.

The model in this chapter encapsulates social learning as an efficient information aggregation mechanism, which leads to aggregate rationality from individual bounded rationality. The information aggregation results in decision cascades of uniform crowd behavior. The model elucidates a number of interesting (non-exhaustive) implications:

- Decision cascades: When bounded rational agents augment their private information through social learning, this causes a correct cascade where every agent of the group selects the superior choice, hereby eliminating the inferior

choice, resulting in a utilitarian efficient outcome illustrating the wisdom of crowds.

- Efficiency of social learning: In a first-mover model where the incumbent (inferior choice) has a significant market dominance over the entrant (superior choice), the information aggregation mechanism of social learning is capable of displacing the inferior choice, resulting in a utilitarian optimal outcome despite the first-mover advantage of the inferior product.
- Small-world networks: Small-world networks, which are characteristic of social networks, allow for rapid and efficient aggregation of information.
- Robustness and fragility of decision cascades: The correct cascades are robust and not susceptible to exogenous shocks. In rare situations of incorrect cascades, the incorrect cascades are fragile to exogenous shocks; which makes them susceptible to reversals to correct cascades.

The paper is organized as follows: Section 2 discusses social interaction and the wisdom of crowds. Section 3 outlines the model. Section 4 discusses the results and the corresponding theoretical implications of the standard model. Section 5 conducts a first mover experiment with different types of networks. Section 6 discusses the theoretical implications and concludes.

3.2 Social Interaction and Wisdom of Crowds

Social interaction has a tendency towards collective/herding behavior, an evolutionary adaptation to capitalize on the information of others. Learning entails imitation of the behavior of others (Bikhchandani et al. 1998). Successful learning in complex environments relies heavily on copying (Rendell et al. 2010).

In an attempt to explain herd behavior, Shiller (1995) states two reasons: 1) information is obtained by observation of the actions of others (Banjee 1992, Bikhchandani et al. 1992); 2) information is transmitted through social interaction mechanisms such as conversation (Heritage and Goodwin 1990).

While fads, fashion and bubbles are generally regarded as irrational behavior due to the mindless imitation of individuals, herding is not necessarily irrational. Social imitation and mimicry are basic evolutionary instincts and ways of learning.

The common postulate of rational choice theory in economics is that individuals behave as if they are perfectly rational optimizers who eventually arrive at the optimal outcome. Optimality can be excessively hard to achieve, otherwise a game of chess is meaningless as both players can easily arrive at the optimal strategy. Optimality is hard to achieve in an 8 x 8 grid, two-dimensional artificial universe of chess; reality is infinitely more complex.

Simon (1972) lists three limits on perfect rationality: 1) Uncertainty about the outcomes of each alternative, 2) Incomplete information about the range of alternatives, 3) Computational complexity. The platonic ideal of perfect rationality requires the mind of a Laplacian demon endowed with limitless time, knowledge and computational power (Gigerenzer and Goldstein 1996). The inability of economic agents to transcend the limits on perfect rationality suggests that it is more appropriate to classify individuals as bounded rational agents.

Economic models with bounded rationality have described economic behavior with success (Conlisk 1996). Considering the intangible costs of computation, it might be best for economic agents to turn to low-cost heuristics such as herding when the cost of achieving perfectly rational optimality is high (Conlisk 1980). There is a tradeoff between deliberation cost and optimization benefits. Economic agents are not only constrained by the limited cognitive abilities of bounded rationality; the accessibility of information is far from perfect, searching and processing of information are costly. From a benefit perspective, social interaction can facilitate information exchange resulting in better information as compared to information obtained independently which increases the propensity for herding (Simon 1993).

Herding can also be rational if it arises due to payoff externalities, principal-agent problems and informational cascades (Devenow and Welch 1996). In complex environments, humans have developed efficient cognitive mechanisms such as social imitation in dealing with information. This chapter explores the conditions in which social interaction and imitation lead to the wisdom or madness of crowds.

Surowiecki (2005) proposes three conditions under which the wisdom of crowds can be achieved: diversity, independence, and decentralization. The wisdom of crowds is best exemplified by Galton's ox weight-judging competition in which competitors had to guess the weight of a selected fat ox at a country fair (Galton 1907). Galton

aggregated the estimates of all competitors and found that the mean and median of the estimates were within 1% of the true value. The true weight of the ox was 1,198 lbs while the median and mean were 1,207 lbs and 1,197 lbs respectively. As a whole, the crowd was capable of estimating the true weight of the ox simply based on observation.

In Galton's experiment, the estimates of the competitors were averaged by Francis Galton, the 'experimenter'. In reality, there is no entity or 'Galtonian Aggregator' that aggregates the actions or information of the crowd. The problem becomes more complicated when one considers a context of discrete choices. There are numerous scenarios in life where one has to select between discrete choices, say selecting product A or product B in a supermarket, or voting for candidate A or candidate B in an election. We will further this discussion in considering a thought experiment of discrete choices in relation to the ox weight-judging contest.

Assume the rules of the competition are changed in such a way that competitors now have to guess if the weight of the ox is heavier or lighter than 1,200 lbs. Since the median guess is 1,207 lbs, the slight majority of the crowd would have guessed the ox to be heavier than 1,200 lbs, which is essentially the wrong choice since the true weight of the ox is 1197 lbs. To achieve the wisdom of crowds in the context of discrete choices, an efficient aggregation mechanism or 'Galtonian Aggregator' will have to perform beyond mathematical averaging.

The wisdom of crowds draws parallel with the rational expectations hypothesis (Muth 1961). The concept of rational expectations asserts that outcomes do not differ systematically from expectations. In the famous words of Abraham Lincoln, "*You can fool some of the people all of the time, and all of the people some of the time, but you cannot fool all of the people all of the time.*"

Due to the non-systematic randomness of the errors, the errors cancel out on average. In essence, the hypothesis states that individual expectations of the future may be in error but over time they are correct on average, akin to Galton's ox weight-judging competition. This also implies that the rational expectations hypothesis can falter when faced with discrete choices, as the errors do not average out to naught. Furthermore,

the average of two discrete choices is impossible¹²; consumers cannot select the average of a BMW and a Mercedes Benz, they are to choose one or the other. The concepts of rational expectations and wisdom of crowds might not hold in the context of discrete choices.

3.3 Stochastic Model

Following Watts and Strogatz (1998), we introduce disorder into the structure of the ‘neighborhoods’ in a cellular automaton universe. While Watts and Strogatz randomly ‘rewire’ the edges of a regular network, we impose the addition of a random ‘weak tie’ on the Moore Neighborhood to create a small world network as shown:

Small World Neighborhood

The agent in red has a network of ‘companions’ who are presented in blue. As compared to the Moore neighborhood, the small-world ‘neighborhood’ has a random connection to an agent further away in the network space. This ‘faraway’ agent can be interpreted as an acquaintance. The eight blue agents close to the red agent can be interpreted as the red agent’s ‘close friends and relatives’. The links of the agents are removed in subsequent diagrams for clean and neat presentation.

The small-world ‘neighborhood’ allows the incorporation of small-world networks into cellular automata models, exhibiting high clustering and low average path length of the cells in a two-dimensional cellular automaton universe.

Consider a population with K agents in a context of binary choices (i.e. choosing between two products, two technologies, two innovations, two scientific theories or two medical practices). The agents are embedded in small-world social networks in a two-dimensional cellular automaton universe as described in the previous section.

¹² The average of discrete choice problem is reminiscent of the Schrödinger's Cat thought experiment where the cat is both alive and dead; in the binary choice problem, the outcome is 0 or 1, rather than a number in between 0 and 1.

Agents are subjected to imperfect information and bounded rationality. As argued in Conlisk (1980), imitation is cheap. In a quest to learn better information about the choices, consumers observe the actions of the other agents in their social network (Banjee 1992, Bikhchandani et al. 1992, Simon 1993).

In this model, social learning is simplified as observing and copying the previous actions of other agents (Bikhchandani et al. 1998). The actions of other agents are information signals regarding the quality of the product. The information signal received by an agent i in the period t is a function of the aggregate actions of his social companions/agents in the previous period $t-1$ which can be represented as follows:

$$S_{i,t} = f \left(\sum_{j \in N_i} C_{j,t-1} \right) \quad (3.1)$$

Where $S_{i,t}$ is the information signal received by agent i in period t , N_i denotes the domain of ‘neighbors’ or social companions of agent i , and $C_{j,t-1}$ is the choice or action of social companion j in period $t-1$.

Each binary choice is assigned a fundamental fitness, reflecting the quality or payoff of the choice. For ease of discussion, the binary choices in this model¹³ are assumed to be two products, A and B, where product A is represented by 1 and product B is represented by 0. In other words, we consider a market with K consumers and binary choices of products. Assume that there is no switching cost. Each consumer selects a product in each time period. The consumers act simultaneously but they are able to observe the actions of their companions of the previous period and hence derive information from the observed actions. Product A is assigned a fitness denoted by α , and product B’s fitness is denoted by β . Under uncertainty, the fitness of the products is subjected to a random perturbation. The fitness or payoff of the products is represented as follows:

$$V_{A,t} = \alpha + \varepsilon_t \quad (3.2)$$

$$V_{B,t} = \beta + \varepsilon_t \quad (3.3)$$

¹³ Note that the model can be generally extended for applications regarding choice of technologies, innovations, ideas or practices.

Where $V_{A,t}$ denotes the fitness of product A at period t , $V_{B,t}$ denotes the fitness of product B at period t , and ε_t is a normally distributed random disturbance with zero mean, $\varepsilon_t \sim N(0, \sigma^2)$.

Proposition 1: Assume a bounded rational satisficing consumer is endowed with a uniformly distributed random aspiration level over time, $\omega_t \sim U(\gamma, \delta)$, the consumer continues selection of the same product in period $t + 1$ if the payoff in period t exceeds ω_t , but switches his selection if the reverse occurs. When faced with two products A and B, a satisficer will consume or select product A with a higher probability than product B over time if $\alpha > \beta$.

Proof: A consumer with the current selection of product m at period t , if $\omega_t < V_{A,t}$, consumer selects product A in period $t + 1$, if $\omega_t > V_{A,t}$, consumer selects product B, in period $t + 1$. The probability of selection of product m ,

$$P_{t+1}(A) = \begin{cases} P_t(\omega_t < V_{A,t}), & \text{if } c_t = A, & \{\text{Staying}\} \\ P_t(\omega_t > V_{B,t}), & \text{if } c_t = B, & \{\text{Switching}\} \end{cases}$$

Where c_t is the choice selection in period t .

$$P_{t+1}(B) = \begin{cases} P_t(\omega_t < V_{B,t}), & \text{if } c_t = A, & \{\text{Switching}\} \\ P_t(\omega_t > V_{A,t}), & \text{if } c_t = B, & \{\text{Staying}\} \end{cases}$$

If $\gamma < \beta < \alpha < \delta$,

$$E[P_t(\omega_t < V_{A,t})] = P_t(\omega_t < \alpha)$$

$$E[P_t(\omega_t < V_{B,t})] = P_t(\omega_t < \beta)$$

$$E[P_t(\omega_t > V_{B,t})] = P_t(\omega_t > \alpha)$$

$$E[P_t(\omega_t > V_{A,t})] = P_t(\omega_t > \beta)$$

Then,

$$E[P_t(\omega_t < V_{A,t})] > E[P_t(\omega_t < V_{B,t})], \quad \{\text{Staying}\}$$

$$E[P_t(\omega_t > V_{B,t})] > E[P_t(\omega_t > V_{A,t})], \quad \{\text{Switching}\}$$

The expected probability of staying with product A is higher than the expected probability of staying with product B. This implies that a consumer with the current choice of product A is more probable to stay with the same product in the next period as compared to a consumer with the current choice of product B.

The expected probability of switching to product A is higher than the expected probability of switching to product B. This implies that a consumer with the current choice of product B is more probable to switch to product A in the next period as compared to a consumer with the current choice of product A switching to product B.

As a result,

$$E[P_{t+1}(A)] > E[P_{t+1}(B)]$$

Thus, a satisficing consumer selects product A with a higher expected probability than product B if $\alpha > \beta$. Q.E.D

The consumer seeks to maximize his utility by selecting the product with the higher fitness or payoff in each period. However, we assume that bounded rational consumers do not know the true generating functions¹⁴ of the fitness of products (Eq. 3.2 and 3.3). The probability of a consumer selecting a particular choice is determined by the fundamental value of the product and information signal received from his social companions.

To determine the effects of product fitness on the probability of selection, the information signal is first omitted. This represents the decision-making of consumers based on limited private information. Omitting information signals from the social environment, a simple assumption is to formalize consumer selection based on fitness proportionate selection, also known as roulette wheel selection (Goldberg 1989, Melanie 1999). The fitness proportionate selection is a technique used in evolutionary computation algorithms. A variant of the fitness proportionate selection is proposed - fundamental value proportionate selection¹⁵. The probability of product m being selected is:

¹⁴ We find this assumption to be of utmost realism as people generally do not know the true payoff or utility of a decision choice beforehand.

¹⁵ Using a Markov chain process we can show that the choice selection of satisficing agents with random aspiration levels approximates the proportionate selection equation given in equation (4).

$$p_m = \frac{E[V_m]}{\sum_{n=1}^N E[V_n]}, \text{ for } m = 1, 2, \dots, N \quad (3.4)$$

Where $E[V_m]$ is the fundamental value of product m .

The independent choice selection of bounded rational consumers is formulated to be consistent with Proposition (1). Omitting social information signals, the probability of product A being selected by consumer i based on fundamental value of the product at time t can simply be represented as follows:

$$p_{A,i,t} = \frac{E[V_{A,t}]}{E[V_{A,t}] + E[V_{B,t}]} \quad (3.5)$$

And the probability of product B being selected by consumer i based on fundamental value of the product at time t is,

$$p_{B,i,t} = \frac{E[V_{B,t}]}{E[V_{A,t}] + E[V_{B,t}]} \quad (3.6)$$

Where $E[V_{A,t}] = \alpha$ and $E[V_{B,t}] = \beta$.

Eq. (3.5) and (3.6) represent a kind of ‘bounded rational expectations’. In a large population, over time, agents have a higher probability of selecting the product with the higher fundamental value. The probability of the superior product being selected increases with an increasing magnitude of the differential between the two product fitness.

Holding a perspective parallel with that of the rational expectations viewpoint¹⁶ discussed in the introduction, we opined that “the correct decisions can be made by some people all the time or by all the people some of the time, but the correct decisions cannot be made by all the people all the time.” The bounded rational expectations of Eq. (3.5) and (3.6) clearly shows this: the majority of the population can select the superior choice most of the time but the postulate of the entire population coming to the correct choice independently all the time is an elusive impossibility.

¹⁶ Quote by Abraham Lincoln: “You can fool some of the people all of the time, and all of the people some of the time, but you cannot fool all of the people all of the time.”

We can now focus on the probability of a product being selected by incorporating information signals into the fundamental value proportionate selection. A high number of social companions selecting a particular product will signal to consumers that the particular product is of better fitness. The probability of product A being selected (based on fundamental value and information signals) by consumer i at time t can be represented by:

$$p_{A,i,t} = \frac{\alpha \sum_{j \in N_i} C_{j,t-1}}{\alpha \sum_{j \in N_i} C_{j,t-1} + \beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})} \quad (3.7)$$

Where η_i denotes the number of social companions, $\sum_{j \in N_i} C_{j,t-1}$ represents the aggregate selection of product A of the social companions of agent i at time $t-1$, and N_i denotes the domain of social companions.

The probability of product B being selected by consumer i at time t can be represented by,

$$p_{B,i,t} = \frac{\beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})}{\alpha \sum_{j \in N_i} C_{j,t-1} + \beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})} \quad (3.8)$$

Where $(\eta_i - \sum_{j \in N_i} C_{j,t-1})$ represents the aggregate selection of product B of the social companions of agent i at time $t-1$.

With social interaction, the stochastic rules of the consumers are represented in Eq. (3.7) and (3.8). The probability of consumer i selecting product A is represented in Eq. (3.7). The numerator $\alpha \sum_{j \in N_i} C_{j,t-1}$ is a combination of the product fitness α and the number of social companions selecting product A in the previous period.

Recall that binary choice of product A is denoted by 1. A high number of social companions selecting product A equates to a large magnitude of the term $\sum_{j \in N_i} C_{j,t-1}$. The probability of selection of product A increases with its product fitness and the number of social companions selecting product A in the previous time period. The denominator $\alpha \sum_{j \in N_i} C_{j,t-1} + \beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})$ is a normalization factor so the probability is between 0 and 1. The probability of consumer i selecting product B is represented in Eq. (3.8). The numerator $\beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})$ is a combination of the product fitness β and the number of social companions selecting product B in the previous period. Recall that the binary choice of product B is denoted by 0. The term

$\eta_i - \sum_{j \in N_i} C_{j,t-1}$ increases with the number of social companions selecting product B. The probability of selection of product B increases with its product fitness and the number of social companions selecting product B in the previous time period.

The consumers interact in a small-world network embedded in a two-dimensional cellular automaton universe. The cellular automata network model (CANM) incorporates the social interaction among consumers in an imperfect information and bounded rational context. The social interaction (communication and observation of companions' actions) acts as an information mechanism to complement their private information on the product fitness.

3.4 Simulation of a Social Learning Economy

In order to determine if the market with K consumers is able to select the optimal product, an experiment is set up with variables as follows: $K = 1089, \alpha = 10.1, \beta = 10.0$. The stage is set with 1,089 consumers and a product A which has a fitness marginally better than product B. We assume the products are otherwise identical except for a difference in quality or fitness. Hence, there is no reason for inferior selection such as a preference for variety. A utilitarian efficient outcome entails that all consumers select the superior product, hence eliminating the inferior product from the market.

3.4.1 Result 1: Independent Decision-Making

In the first simulation, the cellular automata model is initialized with an equal proportion of consumers selecting product A and product B (See Fig. 3.1). The consumers who selected product A are denoted by blue cells while the consumers who selected product B are denoted by green cells.

Fig. 3.1 The Cellular Automaton Universe initiated with equal proportion of consumers selecting product A (blue) and product B (green)

The computational model is first simulated without the effects of social interaction based on simple stochastic rules of Eq. (3.5) and (3.6). The choice selections of the consumers over 1,000 time steps are shown in Fig. (3.2). Under uncertainty and imperfect information, the consumers' selection of products fluctuates randomly around the attractor of $0.5(1089) = 544.5$.

At times, the majority of the consumers select product B, the inferior product. Here, the independence of the consumers does not result in the efficiency of the market. Without the aggregation of information among the agents, agents act based on their limited private information which is essentially inadequate in arriving at an efficiency outcome of the selection of the superior product. The 1% advantage of product A over product B, as reflected in the values of α and β , could be too small, implying no considerable advantage of product A over product B.

The numerical experiment is repeated with the values as follows: $K = 1089, \alpha = 15.0, \beta = 10.0$. The choice selections of the consumers over 1,000 time steps are shown in Fig. (3.3). The market of consumers as a whole is still incapable of fully adopting the superior product and eliminating the inferior product over time. The utilitarian efficient outcome will be for all consumers to select product A.

The outcome without social interaction shows that some consumers select the inferior product, however these consumers can be made better off by switching from the inferior product to the superior product. The decision-making of consumers independent of social interaction results in an outcome that is not utilitarian efficient due to the imperfect private information of individuals.

Fig. 3.2 Choice Selection without Social Interaction, $\alpha = 10.1, \beta = 10.0$, Product A (Blue), Product B (Green)

Fig. 3.3 Choice Selection without Social Interaction, $\alpha = 15.0$, $\beta = 10.0$

3.4.2 Result 2: Decision-Making with Social Learning

We consider the same context with the variables of the numerical experiment set up as follows: $K = 1089$, $\alpha = 10.1$, $\beta = 10.0$. The consumers act and update their information based on stochastic rules represented in Eq. (3.7) and (3.8). The cellular automata model is initialized with an equal proportion of consumers selecting product A (blue) and product B (green).

With social interaction, the consumers make their decisions with probabilities based on their private information (expected proportionate fitness selection) and information signals from their social companions (observations of the choices of social companions in the previous period).

The same equilibrium outcome emerges from 500 repeated simulations. A decision cascade is observed¹⁷ (see Fig. 3.4). Moreover, the cascade of product A is a correct cascade whereas a cascade of product B is an incorrect cascade since product A is superior to product B. The consumers with imperfect private information can arrive at the optimal selection over time by augmenting their limited information with learning from the previous aggregate actions of their social contacts. The actions of social contacts serve as information signals with regard to the fitness of the product. This results in rational herding behavior where all consumers converge on the correct choice selection.

Social learning acts as an information aggregation mechanism or “Galtonian Aggregator”. By aggregating the limited information of individual consumers, the

¹⁷ A similar cascade (blue) is observed over 100 repeated simulations.

crowd is capable of selecting the superior product and eliminating the inferior product from the market, hence a utilitarian efficient outcome.

Fig. 3.4 Choice Selection with Social Learning

3.5 Result 3: Comparative Studies - Impact of a First-Mover Advantage

To test the robustness of the result in the previous section, the computational experiment is repeated with product B having a significant first-mover advantage. The variables of the experiment are still as follows: $K = 1089$, $\alpha = 10.1$, $\beta = 10.0$. Before the entry of product A, product B possesses monopoly status in the market. The entrant is superior to the incumbent. However, the incumbent has a dominant market share. Assume the initial entry of product A achieves a market share of 1%, this implies that product B has a market share of 99%. The model is initialized with 1% of consumers selecting product A and 99% of consumers selecting product B (see Fig. 3.5). The binary choices of product A or product B in this case can be interpreted as the adoption or rejection of the new product, A.

Fig. 3.5 Market Dominance of Incumbent (Product B)

By repeatedly simulating the model with the stipulated values and conditions, the outcome is observed to have multiple equilibria. Two equilibrium outcomes are observed (see Fig. 3.6 and Fig. 3.7).

Equilibrium outcome (1) is the cascade of product B (see fig. 3.6). The stochastic rule of the consumer selecting product B is given by $p_{B,i,t} = \frac{\beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})}{\alpha \sum_{j \in N_i} C_{j,t-1} + \beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})}$. The initial dominance and ‘popularity’ of product B implies a large number of consumers selecting product B in the beginning. The initial dominance of product B entails that the actions of social companions signal that product B is the better choice, hence the magnitude of the term $(\eta_i - \sum_{j \in N_i} C_{j,t-1})$ tends to be large. Despite an inferior product fitness ($\beta < \alpha$), the popularity of product B from its initial dominance results in a path-dependent cascade of the inferior product.

The above result is synonymous with studies on path dependence. David (1985) illustrates the path-dependent dominance of the QWERTY keyboard, due to its first-mover advantage, over the more efficient DSK (Dvorak Simplified Keyboard). In the video-cassette recorder market, the increased market share of VHS recorder resulted in dominance over the technically superior Betamax format (Arthur 1989).

The lack of diversity in the eventual choice selection forbids the social interaction of numerous consumers in converging to the rational outcome. The consumers engage in herding behavior which results in an irrational outcome. The equilibrium of an incorrect cascade of product B is inherently unstable; a small exogenous shock of 1% market share of product A is able to displace the equilibrium in favor of equilibrium outcome (2). The cascading behavior here is fragile to small exogenous shocks¹⁸.

Equilibrium outcome (2) is the correct cascade of product A (see Fig. 3.7). While product A is the superior product, product B is the incumbent with a huge market share. The previous equilibrium outcome is a path-dependent lock-in of product B. The initial dominance and huge market share of product B result in barriers to its monopoly in equilibrium outcome (1). Equilibrium outcome (2) results in the adoption of the superior product.

The cascade behavior follows an ‘S’ curve consistent with studies on diffusion and adoption of new innovation and technologies (Ryan and Gross 1943, Griliches 1957, Rogers 2010). In this case, consumers engage in herding behavior which results in a rational outcome.

¹⁸ See Bikhchandani et al. (1998) for a discussion on the fragility of cascades.

The social interaction between consumers results in the displacement of an inferior product from the market, hence a utilitarian efficient outcome where all consumers select the superior product over the inferior product. The equilibrium outcome in this case is stable: An exogenous shock of 1% of market share of product B is unable to displace the equilibrium.

Fig. 3.6 Path-Dependent Lock-In of Product B

Fig. 3.7 Utilitarian Optimal Outcome

3.5.1 Result 4: Comparative Studies of Different Networks

The first-mover experiment is conducted under different types of networks: regular network, small-world network, and random network. With a regular network, every agent has a social network of a Moore neighborhood: an agent is only connected to the eight adjacent neighboring agents (See Fig. 3.8). The regular network results in overlapping locally connected communities. There is no weak links to serve as local bridges to an agent or community ‘far away’ in the network. The standard first-mover experiment conducted in the previous section assumes a small-world network (See Fig. 3.8). The first-mover experiment with a random network envisages an idealized world where all agents are connected with every other agent. In each time period, an

agent can derive information from a number of randomly selected agents (see Fig. 3.8).

Fig. 3.8 Network Types

Fig. 3.8 illustrates the social companions of agents in different network structures; blue agents are the social companions of the agent in red. In a regular network, every agent has a social connection to his eight adjacent ‘neighbors’ in the network space. In a small-world network, an agent is connected to his seven adjacent agents and one agent distant in the network space. The connection to the agent distant in the network is a weak link. In a random network, an agent is connected to seven randomly selected agents in each time period.

The simulation results of the first-mover experiment of 500 virtual economies of each network type are shown in Table 1.

Table 1

Network	Average Degree ¹⁹	Correct Cascade (Product A)	Incorrect Cascade (Product B)	Speed of Convergence of Correct Cascades
Regular	8	11%	89%	568.85
Small World ²⁰	8	10%	90%	456.99
Random	8	9%	91%	387.85

In the first-mover experiment, the inferior product, product B, has a significant market share advantage over the superior product, product A. The model is initialized with product B comprising 99% of the market share. Despite the adverse priori conditions, the superior entrant, product A, has been capable of displacing product B. Social

¹⁹ Average degree refers to the number of social companions connected to an agent, averaged over all agents.

²⁰ For consistency of average degree, the small-world network differs from that of the main model as the ‘weak’ link is a rewiring from the regular network.

interaction in a local network has been the most efficient²¹ in information aggregation; 11% of the simulations result in the correct cascade of product A which is the utilitarian optimal outcome. However, the average time taken for the cascade to occur is 568.85 time steps. Despite the greater efficiency of regular networks due to high clustering, the low speed of convergence implies that the system lies in sub-optimal territory for longer periods of time. In random networks (the idealized networks where an agent can derive information from any other agent), only 9% of the simulations result in the correct cascade of product A. The average time taken of correct cascades is 387.85 time steps, approximately 70% of the average time of correct cascades in regular networks. The high speed of convergence is resultant from the short average path length of random networks. In small-world networks, 10% of the simulations result in the correct cascade of product A; the average time taken of correct cascades is 456.99 time steps.

The different ways in which agents are connected result in different characteristics of the whole. A random network allows for more rapid aggregation of information as compared to a regular network due to its short average path length. Regular networks with high clustering are more efficient in information aggregation. A short average path length results in rapid information aggregation, and high clustering results in efficient information aggregation. The small-world network, with its ‘weak’ link, has short average path length and high clustering, resulting in rapid and efficient information aggregation. The characteristics of small-world networks in social networks enhance the transfer of information through social interaction, leading to the wisdom of consumers in selecting the optimal outcome, hence the wisdom of social links.

3.5.2 Result 5: Robustness and Fragility of Decision Cascades

The actions of individuals can influence the behavior of others as agents learn and receive information signals from one another. The result of this process of social interaction is that, with time, the behavior of agents as a crowd generally converges to a uniform social behavior, or cascade. The instances of uniform social behavior are aplenty. Examples include 1) the adoption of monogamy in most cultures; 2) the reliance on written examinations as the main form of student assessment in schools; 3)

²¹ Efficient information aggregation refers to the utilitarian optimal outcome of the correct cascade.

the widespread use of utensils to consume food. The investigation of the robustness and fragility of correct and incorrect cascades will enable better understanding for the use of intervention in reversing incorrect cascades²².

The experiment for the robustness and fragility of cascades is as follows:

- 1) The standard model will be initialized with the cascade of product A (correct) or product B (incorrect).
- 2) Various degrees of exogenous shocks (1% - 5%) will be introduced.
- 3) Simulations will be conducted for 100 virtual worlds of correct and incorrect cascades (for each degree of exogenous shock).

In a correct cascade, the probability of product A being selected (based on fundamental value and information signals) by consumer i at time t is equal to one,

$$p_{A,i,t} = \frac{\alpha \sum_{j \in N_i} C_{j,t-1}}{\alpha \sum_{j \in N_i} C_{j,t-1} + \beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})} = 1 \quad (3.9)$$

A one-time exogenous shock, ζ , is introduced to displace the cascade in the time period τ .

$$p_{A,i,\tau} = \frac{\alpha \sum_{j \in N_i} C_{j,t-1}}{\alpha \sum_{j \in N_i} C_{j,t-1} + \beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})} - \zeta = 1 - \zeta \quad (3.10)$$

In an incorrect cascade, the probability of product B being selected (based on fundamental value and information signals) by consumer i at time t is equal to one,

$$p_{B,i,t} = \frac{\beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})}{\alpha \sum_{j \in N_i} C_{j,t-1} + \beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})} = 1 \quad (3.11)$$

A one-time exogenous shock, ζ , is introduced to displace the cascade in the time period τ .

$$p_{B,i,\tau} = \frac{\beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})}{\alpha \sum_{j \in N_i} C_{j,t-1} + \beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})} - \zeta = 1 - \zeta \quad (3.12)$$

The results of the computational experiment are summarized in Table 2.

²² In cases where the benefits and costs can be subjective, it may be hard to determine whether the cascade is correct or incorrect. We will omit the discussion of such cases in this chapter.

Table 2

Degree of Exogenous Shock, ζ	Incorrect Cascade to Correct Cascade (100 simulations for each degree of exogenous shock)	Correct Cascade to Incorrect Cascade (100 simulations for each degree of exogenous shock)
1%	25%	0%
2%	34%	0%
3%	53%	0%
4%	66%	0%
5%	74%	0%

An incorrect cascade occurs when all consumers choose product B. When an exogenous shock of 1% is applied to the market, implying that 1% of the consumers switch to product A, there is some chance that the incorrect cascade will be reversed and a correct cascade will occur instead. The probability that an incorrect cascade will reverse towards a correct cascade increases with the degree of exogenous shock. When an exogenous shock of 3% is introduced to the model, there is a more than 50% chance that the incorrect cascade will reverse to a correct cascade. The probability becomes 74% when the degree of the exogenous shock is increased from 3% to 5%²³.

The model draws parallel to Chaos Theory; the sensitivity to initial conditions underlies the inherent unpredictability of cascades and social behavior. The incorrect cascade is fragile to exogenous shocks; small shocks can propagate the system to a cascade in the other direction. The equilibrium of the incorrect cascade is unstable.

A correct cascade occurs when all consumers select product A. When exogenous shocks of various degrees are introduced to the correct cascade, the shocks are transient and the system eventually reverts to the correct cascade. The correct cascade is robust to exogenous shocks; small shocks cannot displace the cascade. The equilibrium of the correct cascade is stable.

²³ An exogenous shock of 5% to the incorrect cascade implies that 95% of the consumers select inferior product B while 5% of the consumers select superior product A. Recall the discussion of the discrete Galton or weight-judging contest in the introduction. If the majority of the agents select the incorrect choice, an efficient information aggregation mechanism should be able to reverse the non-optimal outcome. Here, there is a 74% chance of reversing the incorrect cascade to the Utilitarian optimal outcome of a correct cascade.

3.5.3 Result 6: Informational Cascades

According to Bikhchandani et al. (1992), an *informational cascade* “occurs when it is optimal for an individual, having observed the actions of those ahead of him, to follow the behavior of the preceding individual without regard to his own information.” In this chapter, the differences between decision cascades and information cascades are as follows:

1. Informational cascades occur when agents disregard their private information and choose to follow the actions of others before, whereas decision cascades occur when agents augment their private information with information signals from social interaction (communication and observation of the previous actions of others).
2. Information cascades are studied in the context of sequential decision-making, whereas decision-cascades are studied in the context of simultaneous repeated decision-making.

By making adjustments to the model in this chapter, we can incorporate the notion of information cascades into the context of simultaneous repeated decision-making and study the differentiated effects between informational cascades and decision cascades. Informational cascades occur when agents disregard their private information. Recall the stochastic decision rules of the agents in Eq. (3.7) and (3.8):

$$p_{A,i,t} = \frac{\alpha \sum_{j \in N_i} C_{j,t-1}}{\alpha \sum_{j \in N_i} C_{j,t-1} + \beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})} \quad (3.7)$$

$$p_{B,i,t} = \frac{\beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})}{\alpha \sum_{j \in N_i} C_{j,t-1} + \beta(\eta_i - \sum_{j \in N_i} C_{j,t-1})} \quad (3.8)$$

The private information with regard to the product fitness are represented by the constants, α and β . The act of agents disregarding their private information in informational cascades can be incorporated to the stochastic decision rules of Eq. (3.7) and (3.8) by removal of the private information constants, α and β . This results in the decision rules as follows:

$$p_{A,i,t} = \frac{\sum_{j \in N_i} C_{j,t-1}}{\eta_i} \quad (3.13)$$

$$p_{B,i,t} = 1 - \frac{\sum_{j \in N_i} C_{j,t-1}}{\eta_i} \quad (3.14)$$

Where η_i denotes the number of social companions, $\sum_{j \in N_i} C_{j,t-1}$ represents the aggregate selection of product A of the social companions of agent i at time $t-1$, and N_i denotes the domain of social companions.

The standard model with the behavioral rules of Eq. (3.13) and (3.14) is initialized (similar to that in Section 4) with an equal proportion of consumers selecting product A and product B.

Fig. 3.9 The Cellular Automaton Universe initiated with equal proportion of consumers selecting product A (blue) and product B (green)

The results are shown in Fig. (3.10) and (3.11). The results show the outcome of multiple equilibria of correct and incorrect cascades.

Fig. 3.10 Incorrect cascade

Fig. 3.11 Correct Cascade

When agents augment their private information with information signals from social interaction as in Section 5, the agents always arrive at the equilibrium of the correct cascade. However, in the case of informational cascade, the disregarding of private information results in multiple equilibria of correct and incorrect cascades. Social interaction is an information aggregation mechanism. In the case of decision cascade (Section 5), social interaction aggregates the private information of the agents to arrive at the Utilitarian optimal outcome. In the case of informational cascades, the agents disregard their private information; social interaction does not aggregate the information of agents but the noise of agents' mimetic behavior, resulting in the possibility of an incorrect cascade.

3.6 Theoretical Implications: Social Learning as the Hidden Half of the Invisible Hand

Hayek (1945) has long argued in his seminal paper "The Use of Knowledge in Society" that information in an economy is dispersed:

"The peculiar character of the problem of a rational order is determined precisely by the fact that the knowledge of the circumstances which we use never exists in concentrated or integrated form, but solely as the dispersed bits of incomplete and frequently contradictory knowledge which all the separate individuals possess..... The problem is thus in no way solved if one can show that all of the facts, if they were known in a single mind, would uniquely determine the solution; instead we must show how a solution is produced by the interactions of people each of whom possesses only partial knowledge."

The model clearly shows how the interactions between agents with limited private information can result in the emergence of the self-organized efficiency of the

economy in total selection of the superior choice through the mechanism of social learning. A study was done by Gode and Sunder (1993) on slightly similar grounds, where the authors showed that a double auction market is capable of achieving aggregate rationality from individual irrationality. However, recall that the Becker (1991) price puzzle suggests that the market price mechanism is not necessarily responsive and infallible, hence the focus of this chapter on non-pecuniary aspects of the free market economy. The autonomous consumer choice is a characteristic of the free market and a necessary condition for a self-organized aggregate rationality. The results in the model is an attempted solution to Hayek's problem of rational order under dispersed information.

The notion of the invisible hand is commonly related to the market price mechanism. In *The Theory of Moral Sentiments*, Adam Smith asserts that social exchanges can bring about the greater good of the community. Studies, such as Vernon Smith (1998), focus on the apparent contradiction between the two major works of *The Theory of Moral Sentiments* and *Wealth of Nations*. The implications of the model give a partial reconciliation to the contradiction between the two: we postulate that the two works document different 'solutions' to the common problem of the attainment of a greater whole. As social learning is the exchange of knowledge, information and ideas from interaction within social networks (which relates to the theme of social exchange in the *Theory of Moral Sentiments*), the model establishes social learning as the mechanism of generating aggregate rationality from individual bounded rationality.

Apart from market mechanisms, the social learning between agents in a liberal laissez-faire system comprising free autonomous choice leads to a utilitarian optimal outcome, a self-organized efficiency as if guided by an invisible hand. There is a neurobiological basis to Adam Smith's apparent 'conflicting yet not contradictory' ideas, as the human brain seeks overlapping solutions to problems (Eagleman 2013).

Decentralized decision-making is characteristic of super-organismal insect societies as centralized control requires an inefficiently immense amount of information to be integrated in a single entity (Gigerenzer and Selten 2002). Liberal systems, free markets or democracies, involve decentralized decision-making that comprise multiple agents with autonomous choice.

Through the process of social learning, multiple bounded rational agents can form a decentralized optimal decision-making system, synonymous to a super-organismal ant colony comprising individual ants capable only of relatively simpler functions. The model also elucidates the robustness of the decentralized system: the removal or destruction of a proportion, 20% for example, of the agents does not eliminate the optimal decision-making capability of the system as a whole. The decentralized system consists of redundancies: agents can be eliminated or easily replaced²⁴ without the system losing its decision-making function, as opposed to a top-down centralized system²⁵ where removal of certain vital components will result in dysfunction. The model exhibits redundancy, a key element of complex systems, highlighting the sustainability and robustness in the combination of social networks and liberal systems.

The caveats to the optimistic view of self-organized efficiency are shown in Section 6. Under conditions of path dependence and information cascades, the system can fixate or converge to an inefficient outcome. Numerous studies have shown that there is a tendency for human beings to ignore our private information in various contexts (Asch 1956, Bikhchandani et al. 1992, Berns et al. 2005, Lorenz et al. 2011). Accounting for such evidence, when the private information variable in the model is omitted from the model, social learning does not take place and inefficient outcomes are possible; however, they are not more probable than efficient outcomes.

The results of the computational model presented in Section 6 state that the system is generally efficient, with the exception of special conditions such as path-dependent lock-ins and information cascades. This relates to the controversy in financial economics which suggests that financial markets are efficient (Fama 1970, 1991) but are punctuated by periods of irrational exuberance (Shiller 2000) - a statement that two polar opposites are true. Similarly, social learning between investors in financial markets can lead to efficient pricing of assets. However, under conditions of

²⁴ There are no vital agents in the social learning model. No agent possesses the mind of a Laplacian demon. Every agent is bounded rationally and follows simple rules.

²⁵ In a free market economy, the system can function well despite agents lacking in rationality. In a centrally planned economy, planners require a sufficiently high level of information and rationality for the functioning of the system. This highlights the robustness of the decentralized free market system and the fragility of the centralized system.

information cascades²⁶, bubbles²⁷ can emerge from the positive feedback²⁸ of mimetic contagion and irrational exuberance.

Conclusion

The topic of this chapter is to investigate if the collective intelligence of a crowd can emerge from social learning between individuals. Humans are embedded into their social fabric. The results show that the constant interaction between agents propagates learning and coordination, leading to a non-pecuniary, self-organized efficiency. The collective intelligence of the crowd results in an emergence from the social learning of the bounded rationality of individuals. Through the mechanism of social learning, a distributed system of group decision-making emerges with optimal rationality from elements of individual bounded rationality and imperfect information. Society is robust computational device.

The social interaction between individuals can also result in irrational aggregate behavior although such irrational decision cascades tend to be fragile. Under conditions of path dependence and information cascades, social interaction and herding behavior does not necessarily lead to rational behavior and efficient outcomes (Bikhchandani et al. 1992, Lorenz et al. 2011).

The model in this chapter gives an optimistic perspective regarding social interaction and enables better understanding of the conditions that lead to the madness and wisdom of crowds. In a context of simultaneous repeated decision-making under conditions in which individuals augment their private information of the fundamental fitness of the choice with information derived from social interaction, social learning is an efficient information aggregation mechanism leading to optimal decision-making. When private information is ignored, the wisdom of crowds fails to emanate from the social interaction of numerous agents since noise is aggregated rather than information - this is the case where irrational behaviors emerge from social interaction and imitation.

²⁶ Bikhchandani et al. (1992) use the concept of information cascade as an explanation for fads and fashions.

²⁷ Robert Shiller describes bubbles “as fads resulting from excessive optimism” in his Nobel Prize lecture.

²⁸ Path dependence is generally associated with the notion of positive feedbacks.

The computational agent-based approach allows for the modeling of social learning among numerous agents within various networks that results in multiple equilibrium outcomes. The approach in this chapter steps away from the standard independent representative agent paradigm and towards an interdependent multiple-agent paradigm. The model illustrates a socio-economic system based on individual decisions and self-organization where there can be coordination of successes and failures, and systemic stabilities and instabilities²⁹.

Further research can incorporate the existence of network externalities into the model; the addition of network externalities might trigger inefficient outcomes due to the greater likelihood of path-dependent, inferior lock-in.

Even so, in its present state, our parsimonious model that incorporates economic decision-making with social interaction suggests that social learning can be an efficient information aggregation mechanism capable of transcending the frictions of uncertainty, bounded rationality and imperfect information in achieving an optimal outcome of aggregate rationality, or, the wisdom of crowds.

The social interaction mechanism of information aggregation allows for the emergence of the rational choice of the market from the interactions of individuals with bounded rationality. Furthermore, social interaction occurs in structures of social networks that exhibit characteristics of small-world networks. Small-world networks enhance the speed and efficiency of information aggregation, hence the wisdom of social links.

²⁹ Helbing and Kirman (2013) envisage a socio-economic system approach with features such as individual decisions and self-organization which are consistent with the model in this chapter.

Chapter 4

Complexity in Socioeconomic Phenomena: Ice buckets, Skirts, Tulips, Cohabitation and Individualism

4.1 Introduction

The existence of fads, fashion, bubbles, social norms and customs are some of the most prevalent phenomena in society over the ages. Fads, fashions, riots, and market bubbles are largely due to interactional effects, especially in a hyper-connected world. This chapter explores how the interdependent micro-behavior of agents in decision-making results in the macro-behavior of fads, fashion, bubbles, social norms and customs.

In many economic models, the representative agent paradigm examines the aggregate behavior of the economy by postulating a typical agent who rationally computes and adopts the optimal action; the behavior of such an agent is absent of major fluctuations, cycles and extreme events. More importantly, the representative agent paradigm disregards the interaction among agents, arguably the essence of societies and economies- a large number of people do not entail a society or economy if they do not interact or transact with one another. As asymmetric behavior can arise from the interaction of identical agents, examining the behavior of a system based on an isolated agent can lead to inaccurate inferences (Kirman 1993).

The study of non-market and social interaction is familiar to economists. Non-market interaction can lead to aggregate behavior with properties different from that of a single agent. Schelling (1971) establishes that micro-motives of individuals do not necessarily translate into a similar macro-behavior of the population. The resultant whole can be more than - and is often significantly different from - the sum of its parts. Blume (1993), Brock and Durlauf (2001) study non-market interaction in the economic context of discrete choices. Interaction models³⁰ can exhibit interesting effects such as path dependence, punctuated equilibria, coordination success and failure (Arthur 1989, Buchanan 2008).

³⁰ For a review of theoretical models of non-market interaction, see Glaesar and Scheinkman (2000)

A seminal study on socio-economic phenomena was done by Bikhchandani et al. (1992) where a theory of fads, fashion, custom, and cultural change as informational cascades is proposed, leveraged with a model using the concept of perfect Bayesian equilibrium. In contrast, the approach of this chapter is to model the socio-economic phenomena of fads, fashion, bubbles, social norms, and customs using a complex systems approach where interaction between simple micro-agents result in the emergence of a complex macro-behavior with characteristics and patterns absent at the micro level. A complex system can be defined as a system with strong non-linear interaction among components and without centralized control; emergent behaviors are typical of complex systems. Societies and economies can be better thought of as complex systems rather than equilibrium systems (Farmer 2012).

The ubiquity of herding behavior is observed in socio-economic phenomena such as fads, fashion, bubbles, social norms and customs (Orlean 1989, Banerjee 1992, Bikhchandani et al. 1992, Shiller 1995, Sornette 2003, Raafat et al. 2009); this begs the following questions:

- If a fad is due to herding behavior, why do fads not continue infinitely but instead reverse and die off?
- How does herding behavior in fashion result in cyclical behavior instead of a monotonic increasing trend? (cyclical behavior as observed in the fashion of skirt lengths for example)
- The positive feedback from herding behavior in bubbles entail that buying begets more buying. Why do bubbles burst then? Exogenous shocks?
- Why do the social norms or perceptions reverse or exhibit changing behavior across time?
- Why or how do different communities cascade and fixate on opposing customs?

Some studies postulate that exogenous shocks are the cause for reversals and ‘switching’; Bikhchandani et al. (1992) stress the fragility of informational cascades and Sornette (2003) claims the fragility and unsustainability of bubbles lead to increased susceptibility of the resultant bubble to any exogenous shocks.

This chapter instead holds an endogenous perspective regarding the phenomena of fads, fashions, bubbles, social norms and customs. The objective is an all-encompassing model of herding behavior to examine the emanations and reversals of fads, fashions, bubbles, social norms and customs. In order to fulfill the conditions of local interaction and no centralized coordination, we utilize a cellular automaton model which incorporates multiple agents in a two-dimensional Euclidean space. To define the localized boundaries of interaction, the use of small-world networks is applied. The computational agent-based model in this chapter can be described as a Cellular Automaton Network Model (CANM), which organizes numerous agents into a two-dimensional network space.

In a decision-making context of binary choices, agents choose to purchase or not purchase a stock, to buy short or long skirts, et cetera. They are subjected to conditions of bounded rationality and imperfect information. As argued in Conlisk (1980) and Simon (1993), economic agents seek to overcome the frictions of bounded rationality and imperfect information by turning to the heuristic of herding. Agents cannot have knowledge of the actions of all agents but they are capable of observing the actions of socially connected agents in their social networks, which are characteristic of small-world networks. These social connections are essentially friends, relatives, acquaintances and other social contacts. Individuals are as much social beings as rational actors, if not more. While much focus has been placed on the self-interested, rational aspect in economic modeling, humans are also fundamentally social creatures. The model in this chapter seeks to account for the social aspect.

Multiple studies demonstrate that social influence creates a tendency towards herding behavior (Asch 1956, Zimbardo 1972, Milgram 1974, Cialdini and Goldstein 2004, Berns et al. 2005). The probability of an agent taking a particular action increases with the number of socially connected agents taking the same action. Our parsimonious model of quasi-herding behavior elucidates outcomes of fleeting fads, (cyclical) fashion, non-periodic cycles of bubbles and crashes, changing regimes of social norms, and differing cascades in customs.

A fad is any form of behavior that is adopted by large numbers of people enthusiastically for a short period of time. Examples of fads in recent years include self-portraits (or ‘selfies’) and the ALS (Amyotrophic lateral sclerosis) ice bucket

challenge. The ALS ice bucket challenge has been taken by celebrities and prominent political figures such as former US president George Bush. The popularity and support of the challenge is disproportionate to the severity of ALS as a health problem, drawing needed attention away from other more urgent public health issues. There is generally nothing convenient about pouring a bucket of ice water on oneself. People did it apparently because other people are doing it: a manifestation of herding behavior.

In financial markets, a fad can be defined as over-valuation resultant from the excessive optimism of investors. Aggarwal and Rivoli (1990) find that returns of common stock initial public offerings (IPO) are significantly negative after one year; this is attributed to the existence of fads in early aftermarket trading of IPOs. Similarly, Ritter (1991) finds underperformance of IPOs over a longer period of three years due to the over-optimism of investors.

Fashion is generally regarded as a popular style for a period of time, usually referring to clothing. Over the years, fashion has been one of the prevalent aspects of consumer behavior. Fashion usually entails herding to the latest behavioral trend, hence the phrase “follow fashion”. Examples of fashion trends in 2013 include bold neon colours and the mid-length skirt. Belleau (1987) investigates the fashion trends of women’s dresses using time series data and found cyclical patterns in the features of clothes such as skirt length, waist emphasis and silhouette.

Shiller (2012) interestingly defines a speculative bubble as “*a social epidemic whose contagion is mediated by price movements.*” The positive feedback loop of herding behavior in which buying begets more buying fuels the development of bubbles (Sornette 2003); Orlan (1989) labels herding leading to market bubbles as a form of mimetic contagion. The prevalence of bubbles dates back centuries ago. Mackay (1841) provides one of the first accounts on the existence of bubbles, chronicling historical bubbles such as the Mississippi bubble in 1719-20, the South Sea Company Bubble in 1711-20, and the tulip mania of the 1630s.

Bikhchandani et al. (1992) exemplify the large shifts in social behavior by commenting on the cohabitation of unmarried couples in America, which was socially perceived as scandalous in the 1950s, flaunted in the 60s, and socially indifferent in

the 80s. The differences of social behavior exist not only across time but also across geography, race and religion. Social norms exhibit rare regime changes over time.

A custom or culture can be deemed as a ‘stronger’ form of a norm. Cultures exhibit persistence and lock-in as opposed to switching regimes in social norms. Asian cultures are typical of collectivist interdependent self-construals; on the other hand, American culture tends towards individualism and independence (Markus and Kitayama 1991). Evidence of this cultural difference on cognitive process is given by Liew et al. (2011): people in collectivist cultures respond more quickly to the facial image of their bosses than to their self-image whereas such a ‘boss effect’ is absent in individualistic cultures. Consensus behavior in different communities cascades to different cultures.

The rest of the paper is organized as follows:

- Section 2 reviews herding behavior
- Section 3 outlines the details of the model.
- Section 4 discusses the simulated phenomena and the corresponding theoretical implications.
- Section 5 re-examines the entomological puzzle of Kirman (1993), Deneubourg et al. (1987) and Pasteel et al. (1987).
- Section 6 summarizes the model implications and concludes.

4.2 Herding Behavior

Herding can be defined as a form of convergent social behavior that aligns the behaviors of individuals via local interaction and without centralized coordination (Raafat et al. 2009). Socio-economic phenomena such as fads and fashions are deemed to be caused by social interaction and herding. Most human behavior is embedded in interpersonal relationships and social contexts (Granovetter 1985). Happiness, risk of smoking and obesity are partially dependent on one’s social network, highlighting the collective phenomena of social influence and behavioral imitation (Christakis and Fowler 2007, 2008; Fowler et al. 2009). The study of compliance and conformity has demonstrated striking behavioral phenomena that resulted from the forces of social influence (Cialdini and Goldstein 2004).

Social compliance is best exemplified by the Milgram (1974) experiment on obedience to authority figures. In the experiment, under the pretext of research on learning, participants were tasked to administer deadly electric shocks to a human subject when the human subject gave a wrong answer to questions asked. Participants were unaware that in truth the human subject was an actor and no electric shocks were actually administered to the human subject. The results of the Milgram (1974) experiment show that ordinary humans disregarded moral concerns under the instruction of authority as they continued to administer increasing to fatal levels of electric shocks to the human subject/actor despite agonizing screams and pleas from the human subject/actor to stop the experiment³¹.

Another famous experiment demonstrating social compliance is the Stanford prison experiment (Zimbardo 1972) in which a group of participating college students was divided into prison guards and prisoners in an artificial prison environment. The results show that the 'prison guards' internalized their designated identity to the extent that they psychologically abused the 'prisoners' (who were fellow college students); the 'prisoners' responded with passive susceptibility to the tyranny and abuse of the 'prison guards', indicating a high propensity of social compliance.

Social conformity is best exemplified by the Asch conformity experiment (1956) which required participants to select a matching line to the reference line from a range of options; participants announce their answers sequentially. All participants except the last participant were confederates/actors. The actors intentionally choose the blatant incorrect matching line for some of the trials. In essence, the experiment pitted the correct private judgment of the participant against the incorrect consensus of the group; majority of the participants elected to go with the incorrect consensus for conformity reasons. Berns et al. (2005) investigate the neural basis of conformity behavior apparent in Asch (1956) results; using functional magnetic resonance imaging, the scans show activity in the occipital-parietal network when wrong information is transmitted from others, establishing the biological evidence of perceptual and emotional processes of social influence.

The suggested primary mechanisms of herding behavior are summarized by Devenow and Welch (1996) as follows: 1) sanctions on deviants, 2) positive payoff externalities,

³¹ Burger (2009) replicated the experiment with similar results.

3) conformity preference, and 4) communication. Bikhchandani et al. (1992) demonstrate that conformity of behavior can be optimal for an individual when an information cascade occurs. Herding is not only a trait of humans; other species do exhibit herding behavior. Birds and fishes herd together in flocks/schools of cooperative defensive formations to fend off predators (Werner and Dyer 1993). Ants herd along the pheromone trails of other ants in a self-organized system for food foraging.

Kirman (1993) describes the similar phenomenon between economic and ant behavior by leveraging on the experiments of Deneubourg et al. (1987) and Pasteel et al. (1987) in which two constantly replenished, identical food sources (say, A and B) were placed equidistant from an ants' nest. The logical guess would be for the system to stabilize when approximately half of the ants gather food from each food source. The results of Deneubourg et al. (1987) and Pasteel et al. (1987) indicate asymmetry feeding and non-periodic reversals, i.e. 80% of the ants gather from food source A and 20% gather from food source B, and at times, a switch occurs when 80% of the ants gather from food source B and 20% of the ants gather from food source A.

Herding behavior can explain the asymmetry feeding as ants herd or are 'recruited' towards the stronger pheromone trail, causing a positive feedback; as more ants gather from a particular food source, increasingly more ants forage from the same food source. The same phenomenon can be observed in human consumer behavior. The ubiquity of herding behavior in biological species further evinces its evolutionary merits.

Why do individuals herd rather than optimize? The common postulate in standard economic theory is that economic agents behave as if they are perfectly rational optimizers. Conlisk (1980) establishes that if the cost of optimizing is high, cheap imitators can have as high a fitness as optimizers. There is a tradeoff between the costs of deliberation and the benefits of optimization. Herding excels as a low-cost heuristic. A benefit perspective is taken by Simon (1993): people are docile as better information can be obtained by learning from others as compared to information gathered independently; herding contributes to the fitness of man in transcending the bounded rationality of the individual. Herding behavior in financial activities has been documented in many studies as follows: corporate takeover (Bikhchandani *et al.*

1992), initial public offering (Welch 1992), and investment recommendations (Scharfstein and Stein 1990, Graham 1999, Welch 2000).

Learning often entails imitation of the actions and behavior of others (Bikhchandani et al. 1998). Rendell et al. (2010) shows that successful learning in complex environments relies heavily on copying. As a researcher writing this (which can be considered a form of learning), citing the works of others is generally ‘herding’ to the perspectives, conclusions or results established by other researchers, other than the exceptions when we critique or offer an alternate perspective. This chapter provides an explanation of how herding behavior can result in the phenomena with salient characteristics of fads, fashion, bubbles, social norms and customs. But first, we describe the methodology of the model.

4.3 Stochastic Model

If the two-dimensional lattice in a cellular automaton is assumed as a network space, the regular network can be represented by common classifications of Von Neumann neighborhood and Moore neighborhood where each cell is connected to its nearest neighbors. There is high clustering but long average path length. In network analysis, small-world networks are modeled by rewiring the edges of the regular network so as to keep the average degree constant for comparison (Watts and Strogatz 1998).

The small-world network is applied as a structure for localized interaction of agents. To discuss in the sociological context of Granovetter (1973), the connections to nearest neighbors can be interpreted as strong ties, resulting in highly clustered groups (i.e. two close friends of an agent are likely to be close friends with one another as well, forming a triad); the crossover links can be interpreted as weak ties, acquaintances who are not part of the ‘inner’ social circle of the agent. The inclusion of an acquaintance to an agent does not necessarily entail the exclusion of a close friend. Therefore, we impose the addition of a random ‘weak tie’ to the Moore Neighborhood to create a small world network in a cellular automata framework as shown:

Small World Neighborhood

Fig. 4.1 Cellular Automata Small World Network

The small-world ‘neighborhood’ of every cell (illustrated by the red cell) comprises 8 adjacent neighbors (blue) and a random agent (blue) ‘far away’ in network space - a total of 9 network neighbors. The small-world ‘neighborhood’ allows the incorporation of small world networks into cellular automata models, exhibiting high clustering and low average path length of the cells in a two-dimensional cellular automaton universe. The links (green) are removed from subsequent diagrams for clean and neat representation.

Consider a society with K agents faced with a decision-making problem between binary choices, 1 or 0, in each time period. Agents are subjected to bounded rationality and imperfect information. Under the conditions of bounded rationality and imperfect information, herding can be individually rational (Conlisk 1980, Orlean 1989, Scharfstein and Stein 1990, Bikhchandani et al. 1992, Welch 1992, Simon 1993, Devenow and Welch 1996, Graham 1999, Welch 2000, Raafat et al. 2009).

Agents are assumed to adopt herding behavior to overcome the frictions of bounded rationality and imperfect information. The global network space of K agents is organized in a two-dimensional cellular automata lattice. Agents have imperfect information of the actions of others; it is impossible for agents to interact with every other agent in the global network and observe their actions.

The local interactions of agents are restricted to a small-world ‘neighborhood’ as discussed. Furthermore, agents act simultaneously and can only have knowledge of the actions of others of the previous time period. Due to the existence of the following

mechanisms: 1) sanctions on deviants, 2) positive payoff externalities, 3) conformity preference, 4) communication, and 5) information cascades, the utility of an agent i in selecting binary choice 1 at period t , $U_{i,1,t}$, can be defined as,

$$U_{i,1,t} = f\left(\sum_{j \in N_i} C_{j,t-1}\right) \quad (4.1)$$

Where $U_{i,1,t}$ is a non-monotonic increasing function of the number of network neighbors selecting choice 1 in the period $t-1$, where N_i is the small world neighborhood (the domain of network neighbors) and $C_{j,t-1}$ is the choice selected by network neighbors in the previous time period.

Similarly, the utility of an agent i in selecting binary choice 0 at period t , $U_{i,0,t}$, can be defined as,

$$U_{i,0,t} = g\left(\sum_{j \in N_i} C_{j,t-1}\right) \quad (4.2)$$

Where $U_{i,0,t}$ is a non-monotonic increasing function of the number of network neighbors selecting choice 0 in the period $t-1$, where N_i is the small world neighborhood (the domain of network neighbors) and $C_{j,t-1}$ is the choice selected by network neighbors in the previous time period.

Assume that the bounded rational agents do not know the true utility functions³². The utility functions are defined as follows,

$$f\left(\sum_{j \in N_i} C_{j,t-1}\right) = \sum_{j \in N_i} C_{j,t-1} + \varepsilon_{1,t} \quad (4.3)$$

Where $\sum_{j \in N_i} C_{j,t-1}$ is the number of network neighbors selecting choice 1 in period $t-1$, and $\varepsilon_{1,t}$ is a normally distributed random disturbance, $\varepsilon_{1,t} \sim N(0, \sigma^2)$.

³² We find this assumption to be of utmost realism as we do not know the true utility/pay-off generating functions of our decisions. In reality, we can observe the eventual pay-off/utility but not the ‘generator’.

$$g\left(\sum_{j \in N_i} C_{j,t-1}\right) = \eta_i - \sum_{j \in N_i} C_{j,t-1} + \varepsilon_{0,t} \quad (4.4)$$

Where η_i is the total number of network neighbors, $\eta_i - \sum_{j \in N_i} C_{j,t-1}$ is the number of network neighbors selecting choice 0 in period $t - 1$, and $\varepsilon_{0,t}$ is a normally distributed random disturbance, $\varepsilon_{0,t} \sim N(0, \sigma^2)$.

We proceed with the agent's individual bounded rational (satisficing) decision-making rules in choice selection: expected utility proportionate selection. In each period, the expected utility proportionate selection for choice 1 can be represented by,

$$p_{1,t} = \frac{E[U_{1,t}]}{E[U_{1,t}] + E[U_{0,t}]} \quad (4.5)$$

Where, $p_{1,t}$, the probability of selecting choice 1 is proportionate to the expected utility of choice 1 relative to aggregate expected utility of choice 1 and 0.

In each time period t , the probability of agent i selecting choice 1 is proportionate to the expected utility of choice, in addition to an endogenous independent will of agent i , which can be defined as follows,

$$p_{i,1,t} = \frac{E[U_{i,1,t}]}{E[U_{i,1,t}] + E[U_{i,0,t}]} + \varphi_{i,t} = \frac{\sum_{j \in N_i} C_{j,t-1}}{\eta_i} + \varphi_{i,t} \quad (4.6)$$

Where $\varphi_{i,t}$ is the independence parameter³³, a normally distributed random variable, $\varphi_{i,t} \sim N(0, \sigma^2)$.

The probability of agent i selecting choice 1 in period t increases with the number of network neighbors/social companions selecting choice 1 in period $t-1$, a representation of herding behavior. The independence parameter φ_i can be interpreted as the probability that agent i will select choice 1 when no one selects choice 1; or when everyone selects choice 1, the independence parameter is the probability that agent i will not select choice 1. As this is a model of herding behavior, the independence parameter is minuscule in magnitude.

³³ The inclusion of the independent parameter is partially to prevent the model from getting 'stuck' at $K=0$. A similar technique is used in Kirman (1993).

Here, we introduce the concept of *Quasi-herding Behavior*:

The notion of bounded rationality was coined by Herbert Simon as an adjustment to the implausible notion of perfect rationality (Simon 1955). While humans do herd by conformity, compliance, and imitative learning to an extent, herding behavior as blind adherence with perfect certainty cannot be an accurate depiction of human behavior. A clear distinction from perfect herding behavior is mathematically represented by the inclusion of the independence parameter to explicate a notion we coin as ‘quasi-herding’. Quasi-herding can be defined as a tendency to engage in herding behavior with inclusion of independent behavior. The notion of quasi-herding allows for an adjustment that humans can be independent, contrarian or iconoclastic (Berns 2008).

The probability of agent i selecting choice 0 in each time period is defined by,

$$p_{i,0,t} = \frac{E[U_{i,0,t}]}{E[U_{i,1,t}] + E[U_{i,0,t}]} - \varphi_{i,t} = \frac{\eta_i - \sum_{j \in N_i} C_{j,t-1}}{\eta_i} - \varphi_{i,t} \quad (4.7)$$

Where the probability of agent i selecting choice 0 in period t increases with the number of network neighbors/social companions selecting choice 0 in period $t-1$, indicating the herding behavior of agent i .

The probability of agent i selecting either choice 1 or 0 can be summed up to 1.

$$p_{i,1,t} + p_{i,0,t} = \frac{\sum_{j \in N_i} C_{j,t-1}}{\eta_i} + \varphi_{i,t} + \frac{\eta_i - \sum_{j \in N_i} C_{j,t-1}}{\eta_i} - \varphi_{i,t} = 1 \quad (4.8)$$

The foundations of the basic herding model have been described. By making minor adjustments to the magnitude of variance σ_2 in the independent parameter φ , we seek to extend the model to study fads, fashions, bubbles, social norms and culture.

4.4 Simulating Socio-economic Phenomena

“What I cannot create, I do not understand.” - Richard Feynman

“What constitutes an explanation of an observed social phenomenon? Perhaps one day people will interpret the question, ‘Can you explain it?’ as asking ‘Can you grow it?’ ”
- Epstein and Axtell (1996)

This section demonstrates the simulation results of the various socio-economic phenomena generated by the model. Let $K = 1089$.

4.4.1 Result 1: Fads - Spontaneous Emergence, Punctuated Equilibrium, and Endogenous Extreme Event

The model is initialized with 1% of the agents adopting an existing behavior. This 1% can be viewed as potential fad ‘leaders’ if the particular behavior propagates to a fad. The black cells indicate agents who do not adopt the behavior (binary choice 0) and the orange cells indicate agents who adopt the behavior (binary choice 1). Every agent is connected to a small-world ‘neighborhood’ as shown in Fig. (4.1). The connecting links are removed for a simple and clean representation of the diagram. The initialized herding model is shown in Fig. (4.2).

The main results of the fad-herding model are shown in Fig. (4.3) and Fig. (4.4). Many simulated behaviors die off without ever propagating to become fads. Occasionally, fads emerge.

Figure (4.3) shows the occurrence of a strong fad where approximately half the population adopts the behavior at the peak of the fad before reversing and eventually dying off; the herding of agents in localized, overlapping social groups can emerge into global macro-behavior of rising and reversing trends.

Figure (4.4) shows a weak fad where approximately 10% of the population adopts the behavior at its peak; such fads propagate rapidly and retrocede rapidly into oblivion. The emergence of the fad is congruous with the notion of punctuated equilibria, where there is an occasional burst of activity after periods of stasis.

In the context of IPOs, herding behavior can propagate the optimism of investors which results in a large initial buying interest (Aggarwal and Rivoli 1990, Ritter

1991). Over time, the optimism subsides. This implies caution on the part of the investor before jumping on the IPO bandwagon upon the observation of a rising price trend.

The existence of fads in free societies has implications on allocative efficiency. An example will be the success of the faddish ALS ice bucket campaign which attracted a relatively disproportionate amount of attention and monetary donations, resulting in relative allocation neglect of more pressing medical issues such as Ebola.

The dynamics of the Fad model is characteristic of spontaneous emergence, punctuated equilibrium and endogenous extreme event.

The Fad herding model exhibits the rapid rise and endogenous reversal of a fad.

Fig. 4.2 Initialized Fad Model. Black Circle (Choice 0 = Ignore). Orange Triangle (Choice 1=Adopt)

Fig. 4.3 Strong Fad

Fig. 4.4 Weak Fad

4.4.2 Result 2: Fashion - Non-periodic Cycles and Switching Regimes

The model is initialized with 50% of the agents selecting choice 0 and the other 50% selecting choice 1. The binary choice 0 and 1 are competing items of fashion (for example, short and long skirts). The red cells are agents selecting choice 0 (short skirts) and the green cells are agents selecting choice 1 (long skirts). The initialized Fashion herding model is shown in Fig. (4.5).

Fig. 4.5 Initialized Fashion Model. Red Circle (Short Skirts). Green Triangle (Long skirts)

The results of the Fashion model show trending fashions with cyclical behavior (See Fig. 4.6). Figure (4.6) shows the trend in long skirts (green) emerging from time $t = 0$ to time $t = 2000$. The fashion of long skirts waned and short skirts came into fashion until approximately time $t = 4000$. The fashion of short skirts retroceded and long skirts emerged as the fashionable item once again. Following that, there was a relative short period around $t = 5000$ where the population as a whole is generally indifferent between long and short skirts. Subsequently, short skirts were again in fashion and eventually displaced by long skirts.

The trends of short and long skirts along with the cyclical behavior continue indefinitely. The Fashion model exhibits the transient trends of consumer behavior and

the resultant cyclical behavior of fashions (Young 1966, Belleau 1987). The trends and cyclical behavior in the model are endogenous, not as a result of exogenous shocks, and emergent from interaction of micro-agents.

The dynamics of the Fashion model is characteristic of non-periodic cyclical behavior and switching regimes.

Fig. 4.6 Cyclical Fashion

4.4.3 Result 3: Bubbles - Spontaneous Emergence, Cycles, and Switching Regimes

The model is initialized with 10% of the agents selecting choice 1. The binary choice 0 refers to not buying or selling the asset, if the asset is being held in the current time period. The binary choice 1 refers to buying or holding the asset, if the asset has already been bought in the previous time period. The black cells indicate agents with choice 0 and light blue cells indicate agents with choice 1. The initialized Bubble herding model is shown in Fig. (4.7).

The results of the Bubble model show the emergence of recurring bubbles and crashes (See Fig. 4.8). Figure (4.8) shows the general demand (buying/holding) of the agents in the population for the asset across time. The results of the model are congruous with Shiller's (2012) perspective of bubbles without markets, where a misallocation of resources can occur from an uninformed enthusiasm for a particular good or action. The huge spikes in general demand are mediated by the interaction between agents, thus a bubble can occur without market prices but can arise from mimetic contagion³⁴. As opposed to a fad, a bubble can be sustained for an extended period of time. In addition, the model shows that the reversals of bubbles can be endogenous.

³⁴ Orlean (1989) postulates that bubbles arise from what he calls 'mimetic contagion'.

Returning to the context of markets, assuming a price-demand relationship where an increase in demand raises the price and a decrease in demand lowers the price, the large increases in general demand result in asset bubbles while the large decreases in general demand result in market crashes. The herding behavior³⁵ of investors can result in bubbles and crashes (Sornette 2003). The financial crisis of 2008/09 has been associated with the notions of contagion, networks and coupling interdependence. The interdependent positive feedback of herding behavior on general demand and price in the system results in the contagion emergence of bubbles and crashes, macro-behavior of rising and falling prices, and switching regimes of bull and bear markets. Information transmission between agents can lead to social herding and information cascades (Bikhchandani et al. 1992). Local interaction and transmission of information and opinions from one agent to another can emanate in collective panic and exuberance (Kirman 2010). This is, in part, exhibited by the Bubble model in the emergence of endogenous bubbles and crashes from the endogenous quasi-herding interaction between agents.

The dynamics of the Bubble model is characteristic of endogenous/spontaneous/contagion emergence of bubbles/crashes, cyclical behavior and switching regimes of bull/bear markets.

Fig. 4.7 Initialized Bubble Model. Black Circle (Choice 0). Blue Triangle (Choice1)

³⁵ The existence of herding in specific financial activities has been documented in numerous studies: corporate takeover (Bikhchandani *et al.* 1992), initial public offering (Welch 1992), and investment recommendations (Scharfstein and Stein 1990, Graham 1999, Welch 2000).

Fig. 4.8 Bubbles and Crashes

4.4.4 Result 4: Social Norm - Endogenous Regime Change, Punctuated Equilibrium, and Self-organized Restoration of Order

The model is initialized with half of the total number of agents selecting each choice. The binary choices 0 and 1 are conflicting behaviors for a social norm. Generally, the behavior of the majority of the population is the social norm. For ease of discussion, we will proceed with the scenario of cohabitation of unmarried couples. Binary choice 0 implies the agent selection of no cohabitation before marriage. Binary choice 1 implies the agent selection of cohabitation before marriage. The dark blue cells indicate agents with choice 0 and the turquoise cells indicate agents with choice 1. The initialized Social Norm herding model is shown in Fig. (4.9). In the scenario envisaged, the agents in this artificial society make the choice of cohabiting or not. The behavior adopted by the majority of the population becomes the social norm of the time period. The results of the Social Norm model show that, in the artificial society, for an extended long period of time, the social norm is for people to not cohabit before marriage (see Fig. 4.10). This results in a minority of the population cohabiting before marriage. The perception towards cohabitation eventually shifts between time $t = 10000$ and time $t = 11000$. Subsequently, it becomes a social norm for unmarried couples to cohabit.

The evolutionary dynamics exhibit the creation of a new order when the (majority) population engages in endogenous switching from one social norm to another. A punctuated equilibrium is apparent as a regime change is observed slightly after time $t = 10000$, a rare burst of change after extended periods of relative stasis. The Social

Norm herding model exhibits the qualitative features of long periods of social norms and rare shifts, illustrating a perspective that shifts in social norms can occur endogenously.

The local interactions between agents in the system spontaneously approach a critical point leading to large-magnitude regime shift. The critical behavior is followed by an extended period of relative stasis - an endogenous creation of new order, exhibiting a self-organized restoration of relative stability. The exhibited self-organization of order in a system of autonomously-interacting agents is similar to the effect of homeostasis observed in complex systems (Tregonning and Roberts 1979).

The 2011 Arab Spring was an escalation of demonstrations and protests across the Middle East and North Africa, resulting in the overthrow of governments in Tunisia, Egypt, Yemen and Libya. Political leaders Zine El Abidine Ben Ali (Tunisia), Hosni Mubarak (Egypt), and Muammar Gaddafi (Libya) were exiled, convicted or killed. The revolutionary wave of protests led to considerable/significant political repercussions which included the dismissal of ministers, economic concessions, reform of government and release of political prisoners in Jordan, Oman, Bahrain, Kuwait, Morocco and Saudi Arabia. In Syria, a civil uprising led to the Syrian Civil War.

The Arab Spring was an endogenous regime change that resulted from a sudden swing of social norm perception. The dynamics of a similar-type endogenous regime change can be illustrated by the model (See Fig. 4.10), where the majority choice of the population goes from dormant submission to the regime (choice 0) to an aggressive rebellion (choice 1).

The dynamics of the Social Norm model is characteristic of endogenous regime change, punctuated equilibrium and self-organized restoration of order.

Fig. 4.9 Initialized Social Norm Model. Dark Blue Circle (Choice 0). Turquoise Triangle (Choice 1)

Fig. 4.10 Shifting Social Norms

4.4.5 Result 5: Custom and Culture - Path-Dependent Lock-in and Self-organized Cascades

Consider two societies, A and B, where agents are faced with a decision-making problem between binary choices 1 or 0 in each time period. The binary choices 1 and 0 are opposing behaviors for a culture. Societies adopt either choice 1 or 0 as culture. Blue cells indicate agents selecting choice 1 and orange cells indicate agents selecting choice 0. Each artificial society is initialized with 50% of the agents adopting each binary choice. The initialized Custom model is shown in Fig. (4.11). Both societies are initialized with 50% of the agents adopting each binary choice.

Fig. 4.11 Initialized Custom Model. Orange Circle (Choice 0). Blue Triangle (Choice 1)

A custom is a form of uniform social behavior. Figure (16) shows the behavior of society A. Society A cascades to the custom of choice 0. Figure (17) shows the behavior of society B. Society B cascades to the custom of choice 1. Both societies are initialized with same conditions and comprise agents with the same generating behavior rules. However, both societies cascade to different cultures. Recall the example of collectivist and individualist cultures in different societies: the model makes clear that path-dependent herding behavior can explicate, in general, how different societies cascade to different cultures. Due to sanctions on deviants, externalities and conformity preference, a culture, custom or tradition is locked in and cannot be broken by a few individuals.

The positive feedback and self-reinforcement of cultural behavior results in historical path dependence and, in this case, eventual lock-in of different cultures (Page 2006). Path dependence implies a choice can become dominant as a result of ‘historical accidents’ along its time path. This is reminiscent of David’s (1985) illustration of the path-dependent dominance of the QWERTY keyboard due to its first-mover advantage which restricted the entry of other more efficient keyboard products designed later such as the DSK (Dvorak Simplified Keyboard). In the video-cassette recorder market, the technically superior Beta format was edged out by and eventually eliminated due to the larger market share of VHS recorder in the early stages of competition (Arthur 1989). The increasing returns of gaining market share result in the path-dependent lock-in of technologies. When a choice starts being adopted by a majority of the population, it is synonymous to the choice gaining ‘market share’ and eventually cascading to a consensus. The consensus behavior of the population without central coordination is a form of self-organization of culture.

As opposed to the previous phenomena already studied, we observe a fixation of customs that remains unchanged across extended periods of time. This explains a persistence of irrational behavior in customs such as human sacrifice - the self-organized persistent behavior of the group cannot be undone by a few dissidents.

Guiso et al. (2006) conclude that research on culture and economics leaves an important question unanswered: How does culture come about? How does it persist? From the results of the model, we offer a parsimonious proposition: the network interactions of quasi-herding behavior lead to the emergence and persistence of culture. The dynamics of the Culture model is characteristic of path dependence, lock-in and self-organized cascades.

Fig. 4.12 Custom of Society A: Cascade of Choice 0

Fig. 4.13 Custom of Society B: Cascade of Choice 1

4.5 Entomological Puzzle Revisited

The entomological puzzle of Deneubourg et al. (1987) and Pasteel et al. (1987) is revisited. The recruitment behavior in ants entails a form of herding behavior in the quest of food foraging. We believe that the herding model in this chapter can be extended to model the herding behavior of ants with a few improvisations. Ants are

not constrained by the human-like social networks of small-world networks in foraging for food. Without further inference on the interactions between ants, we simply assume that ants ‘herd’ randomly to nearby ants. Over time, in a large population of ants, the proximity between two ants can be treated as random. Hence, in the ants’ herding model, the connecting edges in the ants ‘network’ follow a random network (See Fig. 4.14) instead of a small-world network. The connecting edges are randomized in each time period for this model. Let the independence parameter be $\varphi_{i,t} \sim N(0, 2.5 \times 10^{-3})$.

Fig .18 Random Network (2-D Cellular Automata)

In general, without the influence of a colony, individual ants move randomly. When ants encounter and gather food, they excrete pheromones, leaving a pheromone trail which attracts other ants. The pheromones can be seen as a kind of ‘information’ to communicate with other ants as to the location of the food source. The other ants follow the pheromone trail to forage for food and, in turn, excrete pheromones themselves that reinforce the pheromone trail. As long as the food source does not run out, more ants are attracted to the pheromone trail to forage for food; more pheromones are excreted, resulting in a positive feedback of herding behavior. As more ants gather from a food source, increasingly more ants gather from the same food source³⁶. In the absence of reinforcement, the pheromone will subside. The strength of the pheromone trails reflects the collective information of the colony, and this collective information is constantly adapting to the changes in the environment.

The constantly randomized network assumes that an ant ‘herds’ randomly towards the pheromones of a number of other nearby ants, since the proximity of two randomly chosen ants can also be regarded as random, reminiscent of random search-theoretical models in labor markets (Rogerson et al. 2005).

³⁶ This ant behavior is synonymous with the mimetic behavior of investors in a bubble: as more investors buy a stock, increasingly more investors buy the same stock, a form of mimetic contagion.

Greene and Gordon (2007) find that greater interaction rates between ants heighten foraging activity due to increased information. This draws parallel with Simon's (1993) explanation that the herding behavior of humans results due to more and better information of the group. The recruitment behavior of ants is also accordant with herding and evolution between strategies in financial markets (Kirman 1993).

Let the independence parameter be $\varphi_{i,t} \sim N(0, 2.5 \times 10^{-3})$. The model is initialized with ants having an equal chance of foraging from food source A or B. The binary choices 1 and 0 in the model are the two equidistant food sources, A and B. Purple cells denote the ants choosing to forage from food source A. Black cells denote the ants choosing to forage from food source B.

Fig. 4.15 Initialized Ants Model. Purple Triangle (Source A). Black Circle (Source B)

The model exhibits the asymmetric feeding between the two food sources; occasionally the asymmetric feeding 'switches' from one food source to another food source, resulting in switching regimes of asymmetric feeding (See Fig. 4.16).

Fig. 4.16 Switching Regimes of Asymmetric Feeding

4.6 Model Implications

A stochastic cellular automata network model has been utilized as a computational agent-based approach to studying herding behavior. In this model, agents act based on quasi-herding behavioral rules. A simple model, with minor adjustments of an independence parameter, has been capable of exhibiting a series of endogenous, self-organized, emergent phenomena as follows:

- **Fads:** The localized herding of agents in the adoption of a particular behavior can result in the rise and reversals of fads. It illustrates the rapid rise and fall of fads in a relatively short period of time.
- **Fashions:** The interaction of consumers with herding behavior can result in trends and cyclical behavior of fashions.
- **Bubbles and crashes:** The herding behavior of investors in localized groups can result in endogenous formation of bubbles and crashes. Herding behavior in a complex system of the economy can result in cyclical and shifting investor sentiments.
- **Social norms:** The macro-behavior of rigid, long-lived social norms with rare ‘switching’ emerges from the interactions of herding micro-agents.
- **Custom and culture:** The cascades of different societies to different customs emanate from the path-dependent herding behavior of agents in different societies. Customs and cultures are fixed and difficult to displace even if the practices are irrational or inefficient.
- **Ants:** The random network model exhibits switching regimes and asymmetric feeding of ants.

The complex functions and efficiency of an ant colony arises from the self-organization of numerous interacting ants. Societies and economies are a similar form of decentralized systems that self-organize through the interaction of individuals. The complexity in socioeconomic behavior emerges from social interactional effects which can be asymmetric and unpredictable, but with discernible patterns.

Herding is rational when taking into account the integration of moral approvals/disapprovals into an individual utility function (Elsner et al. 2014), or it can be treated as valuation, based on the actions of others, that is unrelated to the objective

utility. The dynamics of the endogenous process in the model exhibit positive feedbacks, related to Gunnar Myrdal's concept of circular cumulative causation (Myrdal 1957). Positive feedbacks/circular cumulative causation contradicts the view of 'switching' between multiple equilibria, where the underlying mechanism is due to negative feedbacks that is mediated by exogenous shocks.

Complex asymmetric behavior can arise from the interaction of homogenous agents. Despite knowledge of the underlying generating functions and initial conditions, the reversals and switching regimes of the processes are inherently unpredictable. This inherent unpredictability is evident in a wide range of economic and social phenomena. Moreover, the existence of self-organized extreme events illustrated in the simulated outcomes of socioeconomic phenomena implies significant consequences for such inherent unpredictability. How do we design policy and systems to cope with unpredictable, rare extreme events? (For an account of solutions to effects in unpredictable consequential events, see Taleb 2009.)

The emergence and evolutionary dynamics of several macro-phenomena from the micro-interactions of numerous autonomous and interdependent agents highlight the ubiquity of social herding behavior in society and economics. The bottom-up approach of the model is a move away from the independent representative agent paradigm and towards an interdependent multiple-agent approach which is more reflective of the economy and society. The interdependent multiple-agent approach, with a focus on process and emergence, is consistent in the shift toward sciences becoming more algorithmic and Turingesque (Arthur 2015).

The study identifies / proposes quasi-herding behavior as a counter-intuitive explanation to the various kinds of social and economic behavior. Herding and embeddedness are salient aspects of a society or economy. Utilizing quasi-herding behavior as a building block, the endogenous dynamics of the model explicate various social phenomena.

Concluding Remarks

In this chapter, the model of quasi-herding behavior illuminates the core dynamics in fads, fashions, bubbles, social norms and diverse cultures. The propagating mechanism of the socioeconomic phenomena is counter-intuitive in the sense that

localized quasi-herding behavior of differing degrees can result in sharp ‘rises’ and ‘falls’, cyclical behavior, asymmetric concentration with rare shifts, and fixated lock-in behavior. The results can be exemplified with a multitude of issues, not limited to the under-performance of IPOs, consumer behavior of fashion apparel, endogenous formation of market bubbles, and the irrational persistence of customs.

The dynamics of the model is congruous with the definition of dynamical complexity by Day (1994) which posits that complex processes fail to converge to a periodic or balanced pattern due to endogenous causes, and are characteristic of irregular fluctuations, non-periodic cycles and switches in regime or structural change.

The propagation mechanism of stochastic quasi-herding micro-behavior can create a fascinating array of non-linear dynamical and complex behavior. The stochastic cellular automata network approach allows for the modeling of herding behavior among numerous agents within network structures. The localized interaction of micro-agents results in the emergence of trends, reversals and switching regimes of several real-world phenomena. The self-organization of the agents leads to an evolutionary system that is difficult to predict or is path-dependent, thus illuminating uncertainties of socioeconomic systems.

A complex system can be viewed as one where the interaction between agents of simple behavior results in an emergent complex macro-behavior of the system. The model in this chapter qualifies as a complex system. It also satisfies Macy and Willer’s (2002) four key features of agent-based modeling in social science where agents are autonomous, interdependent, followers of simple rules and backward-looking, and elucidates the generic characteristics of complexity in socio-economic phenomena: interdependence, positive feedback, self-organization, emergence, path dependence, punctuated equilibria, spontaneous creation of new order, and endogenous extreme events.

Furthermore, the model incorporates small-world networks which are characteristic of social networks as structures defining the boundaries of agent interaction. The approach taken in this chapter is compatible with Helbing and Kirman’s (2013) vision of a self-organized socio-economic system based on individual decisions.

The parsimonious model in this chapter seeks to provide an elegant "generative explanation" (Epstein 2006) for a wide range of complex socio-economic phenomena - ranging from fads (*ice buckets / IPOs*), fashions (*skirts*), bubbles (*tulip mania*), social norms (*cohabitation*) to culture (individualism / QWERTY) - as the emergence of non-linear interaction of quasi-herding micro-behavior.

Chapter 5

Conclusion

"The human passion to be efficient - to summarize the complex, to wrap it all up in '25 words or less' - is often an enemy to real understanding." (Hood, Hill, Spilka 2009)

Complexity is ubiquitous in economic and social processes. This thesis adopts a complex systems approach to the study of financial markets, social learning and socioeconomic phenomena. In complexity, the notion of causality has analytical limitations as complexity deals with 'webs of dynamic causation'. One common theme is resurfacing throughout the thesis is the concept of emergence which relates to the notion of generative explanation. Can we generate the emergence of a given macro-regularity so as to explain it? When dealing with complexity, a generative explanation of emergence transcends the limited notion of linear causality.

Chapter 2 expounds on the salient characteristics of financial markets as the emergence of the local interacting heterogeneous investors between herding and contrarian behavior, aligned with the perspectives of Hayek's vision of localized interaction. It highlights the inherent unpredictability of complexity in financial markets especially the consequentiality of endogenous extreme events. The endogenous nature downplays the notion of causality in explaining financial bubbles and crashes.

Chapter 3 shows the emergence of aggregate rationality (wisdom of crowds) from the limitations of bounded rationality, limited information and uncertainty. It elucidates the supervenience of macro-properties of a rational order from the decentralized local interaction of bounded rational agents through processes of social learning. Also, it highlights the imperfection of such processes under conditions of path dependence and information cascades, leading to aggregate irrationality (madness of crowds). The complexity of bottom-up decentralized processes can result in explicit duality from an implicit source.

Chapter 4 provides a generative explication of socioeconomic phenomena of fads, fashions, bubbles, social norms and culture/custom - as the emergence of quasi-

herding interaction in a small-world network. It relates to Myrdal's concept of circular cumulative causation and elucidates the generic characteristics of complexity in socioeconomic phenomena. The emergence of complex dynamics from simple behavior highlights the supervenience of properties across hierarchical levels from the self-organization of decentralized interacting agents.

Epstein (2008) outlines 16 goals of modeling to emphasize the rationale of explicit modeling. From such a modeling perspective, Chapter 2 provides a generative explanation, illuminates core dynamics and uncertainties/unpredictability of investor behavior and financial markets. Chapter 3 explicates how the process of social learning achieves aggregate rationality in a decentralized system. It also suggests efficiencies/inefficiencies and reveals complex duality from simple learning behavior. Chapter 4 provides a generative explanation, illuminates core dynamics and core uncertainties/unpredictability of socioeconomic phenomena. It demonstrates the dynamical analogies between ant colonies and societies, and elucidates complex behavior from simple micro-specifications.

The history of economic thought consists of rich complexity ideas from great economists of the past. Regrettably, most complexity ideas have been passed up or studied sparingly in economics due to the inability to formalize them with conventional mathematics of the equilibrium sort.

From the nonlinear interdependence of investor behavior in Keynes Beauty Contest (Keynes 1936), extreme events of bubbles in Charles Mackey's *Madness of Crowds* (Mackay 1841), self-organized supervenience of rationality from locality of imperfect information (Hayek 1945), themes of social coordination and social exchange in Adam Smith's *Theory of Moral Sentiments* (Smith 1759), positive feedbacks of circular cumulative causation (Myrdal 1957), to bounded rationality (Simon 1955), this thesis revisits some of the complexity themes of historical economic thought with the nouveau paradigm of complex systems.

Appendix

Netlogo Programming Codes for Chapter 2

```
breed [cells cell]
```

```
breed [dells dell]
```

```
breed [fells fell]
```

```
to setup
```

```
  no-display clear-all
```

```
  set-default-shape cells "circle"
```

```
  set-default-shape dells "circle"
```

```
  ask patches[
```

```
    set pcolor white
```

```
    ifelse random 10 < 5
```

```
      [sprout-cells 1 [set size 0.8 set color pink set label-color green]]
```

```
      [sprout-dells 1 [set size 0.8 set color pink set label-color green]]
```

```
  ]
```

```
  reset-ticks display
```

```
end
```

```
to randomize
```

```
  no-display reset-ticks
```

```
  ask turtles [set color pink set label ""]
```

```
  ask n-of round (count turtles * percent-black / 100)
```

```

    turtles [set color black]

display

end

to edit

    if ticks != int ticks [go] ;; start on a whole step

    if mouse-inside? and mouse-down?          ;; when clicked,

        [ask turtles-on patch mouse-xcor mouse-ycor ;; toggle color

            [set color ifelse-value (color = black) [pink] [black]]

        wait 0.16 display]

end

to go

    ;if ticks >= 10000 [ stop ]

    no-display

    ifelse ticks = int ticks          ;; go in half-steps:

    [

        ask cells [count-black-nbrs] ;; first all cells count neighbors,

        ask dells [count-black-nbrss]

    ]

    [

        ask turtles [change-color]    ;; and only then do they change color.

```

```

]

tick-advance 0.5 display    ;; tick counter on display only shows integers

tick

end

to count-black-nbrs          ;; mark only the cells with 'just enough' neighbors

  let n count (turtles-on neighbors) with [color = black]

  let m count (turtles-on patch-right-and-ahead random 360 (2 + random 10) ) with
[color = black]

  if ( n = 2 or n = 3 or ( color = black and n = 4) or ( color = black and n = 5) ) [set
label "•"] ;; 'live' next generation

end

to count-black-nbrss        ;; mark only the cells with 'just enough' neighbors

  let n count (turtles-on neighbors) with [color = black]

  let m count (turtles-on patch-right-and-ahead random 360 (2 + random 10) ) with
[color = black]

  if ( n = 5 or n = 6 or ( color = black and n = 7) or ( color = black and n = 8) ) [set
label "•"] ;; 'live' next generation

end

to change-color

  set color ifelse-value (label = "•") [black] [pink]

```

```
set label ""
```

```
end
```

Netlogo Programming Codes for Chapter 3

```
breed [cells cell]
```

```
to setup
```

```
no-display clear-all
```

```
set-default-shape cells "circle"
```

```
ask patches
```

```
[set pcolor black
```

```
  sprout-cells 1 [set size 0.8 set color green set label-color green]]
```

```
reset-ticks display
```

```
end
```

```
to randomize
```

```
no-display reset-ticks
```

```
ask turtles [set color green set label ""]
```

```
ask n-of round (count turtles * percent-blue / 100)
```

```
  turtles [set color blue]
```

```
display
```

```
end
```

to edit

if ticks != int ticks [go] ;; start on a whole step

if mouse-inside? and mouse-down? ;; when clicked,

[ask turtles-on patch mouse-xcor mouse-ycor ;; toggle color

[set color ifelse-value (color = blue) [green] [blue]]

wait 0.16 display]

end

to go

no-display

ifelse ticks = int ticks ;; go in half-steps:

[ask cells [count-black-nbrs]] ;; first all cells count neighbors,

[ask cells [change-color]] ;; and only then do they change color.

tick-advance 0.5 display ;; tick counter on display only shows integers

tick

end

to count-black-nbrs ;; mark only the cells with 'just enough' neighbors

let n count (turtles-on neighbors) with [color = green]

let m count (turtles-on patch-right-and-ahead random 360 (2 + random 30)) with
[color = green]

```

    ifelse ( random 10000 < ((1.01 * (m + n) ) / ((1.01 * (m + n) ) + ( 1 * (9 - (m + n)
) )) * 10000) ) [set label "•"] [set label ","] ;; 'live' next generation
end

```

```

to change-color

```

```

    if (label = "•") [set color green]

```

```

    if (label = ",") [set color blue]

```

```

end

```

Netlogo Programming Codes for Chapter 4

```

breed [cells cell]

```

```

cells-own [

```

```

    live?

```

```

]

```

```

to setup

```

```

    no-display clear-all

```

```

    set-default-shape cells "circle"

```

```

    ask patches

```

```

    [set pcolor white

```

```

        sprout-cells 1 [set size 0.8 set color black set label-color green]]

```

```

    reset-ticks display

```

```

end

```

to randomize

no-display reset-ticks

ask turtles [set color black set label ""]

ask n-of round (count turtles * percent-blue / 100)

turtles [set color violet]

display

end

to edit

if ticks != int ticks [go] ;; start on a whole step

if mouse-inside? and mouse-down? ;; when clicked,

[ask turtles-on patch mouse-xcor mouse-ycor ;; toggle color

[set color ifelse-value (color = blue) [red] [blue]]

wait 0.16 display]

end

to go

no-display

ask cells [count-black-nbrs] ;; first all cells count neighbors,

ask cells [change-color] ;; and only then do they change color.

tick

display

end

```

to count-black-nbrs          ;; mark only the cells with 'just enough' neighbors

  let a count (turtles-on patch-right-and-ahead random 360 (2 + random 30) ) with
[color = violet]

  let b count (turtles-on patch-right-and-ahead random 360 (2 + random 30) ) with
[color = violet]

  let c count (turtles-on patch-right-and-ahead random 360 (2 + random 30) ) with
[color = violet]

  let d count (turtles-on patch-right-and-ahead random 360 (2 + random 30) ) with
[color = violet]

  let f count (turtles-on patch-right-and-ahead random 360 (2 + random 30) ) with
[color = violet]

  let g count (turtles-on patch-right-and-ahead random 360 (2 + random 30) ) with
[color = violet]

  let h count (turtles-on patch-right-and-ahead random 360 (2 + random 30) ) with
[color = violet]

  let i count (turtles-on patch-right-and-ahead random 360 (2 + random 30) ) with
[color = violet]

  let j count (turtles-on patch-right-and-ahead random 360 (2 + random 30) ) with
[color = violet]


  ifelse ( random 10000 < (((1 * (a + b + c + d + f + g + h + i + j) ) / ((1 * (a + b + c +
d + f + g + h + i + j) ) + ( 1 * (9 - (a + b + c + d + f + g + h + i + j))) ) * 10000) +
random-normal 0 100 ) [set live? true] [set live? false] ;; 'live' next generation

end

```


to change-color

set color ifelse-value (live?) [violet] [black]

end

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