CHAPTER 12

# Social Science in Between

> The machine does not isolate man from the great problems of nature but plunges him more deeply into them.
>
> —*Antoine de Saint-Exupery, Wind, Sand, and Stars*

> If you want to build a ship don't herd people together to collect wood and don't assign them tasks and work, but rather teach them to long for the endless immensity of the sea.
>
> —*Antoine de Saint-Exupery, Wisdom of the Sands*

> Our inventions are wont to be pretty toys, which distract our attention from serious things. They are but improved means to an unimproved end.
>
> —*Henry David Thoreau, Walden*

HERE WE DISCUSS THE IMPACT of complex adaptive systems on the social sciences. Our book's central theme, "The Interest in Between," provides a framing for this discussion. The complex adaptive social systems view of the world allows us to explore the spaces between simple and strategic behavior, between pairs and infinities of agents, between equilibrium and chaos, between richness and rigor, and between anarchy and control. These spaces lie between what we currently know and what we need to know. They are not subtle refinements on the landscape of knowledge but represent substantial deviations from what we typically assume. The story is told of a geologist who walks to the rim of the Grand Canyon and remarks "something happened here." Social scientists seem to be haunted by their own canyons, and it is time that we actively engage these mysteries and begin to explore them.

The social sciences have pursued a variety of methodologies. Techniques like empirical research, natural and laboratory experiments, historical investigations, qualitative methods, mathematical and game theory, and computational models have all been used. In some cases, these methods have been deployed and refined by thousands of scientists over many, many decades. In other cases (like computational models), they have been used by just a handful of scientists only recently. Each approach can be both a complement and substitute for the others.

Thus, careful empirical work can both substitute for, and complement, laboratory experiments; computational models can enhance, or replace, mathematical ones; and so on.

In the absence of any one method or idea, science would continue to advance, albeit perhaps at a slower pace or in a different direction. Nonetheless, sometimes the changes in the pace and direction brought by a new methodology or set of ideas can be significant. In this chapter, we outline some initial contributions we attribute to the complex adaptive social systems view of the world. We also highlight some of the new frontiers that can now be explored—the interest in between the usual boundaries.

## 12.1 Some Contributions

It is still too early in the development of complex adaptive social systems ideas to fully assess their contributions. We know that some of the results that have been found can be replicated using more traditional techniques, though it is often the insights and discoveries made with the new methods that allow the old ones to be applied. Ultimately, the complex adaptive systems approach has focused our attention on new possibilities. Even though the applications of these ideas are still in their infancy, they have already begun to contribute to our understanding of key social processes.

A key contribution of complex systems has been a better appreciation of the power and mechanism of emergence. Models of self-organized criticality show how systems can locally adapt to a critical region in which the global properties of the system take on regular behavior, such as a power-law distribution of event sizes. Such ideas are likely to serve as fodder for explaining various social scaling laws, like the distribution of incomes or firm sizes (Axtell, 2001).

Perhaps many features of social systems are the result of self-organization. Computational models of market behavior have highlighted key features that allow the emergence of predictable prices and trading patterns in markets (Rust, Miller, and Palmer, 1992, 1994; Gode and Sunder, 1993). In particular, this work has shown that a sufficient requirement to see such behavior emerge is the presence of simple institutional rules that force new offers to better existing ones. Such an insight radically altered the existing view—one that relied on the innate cleverness of self-interested traders—of the driving force behind Smith's invisible hand (see figure 12.1). The emergence of organization via decentralized means is apparent in the example of voting with your feet explored in chapter 2.

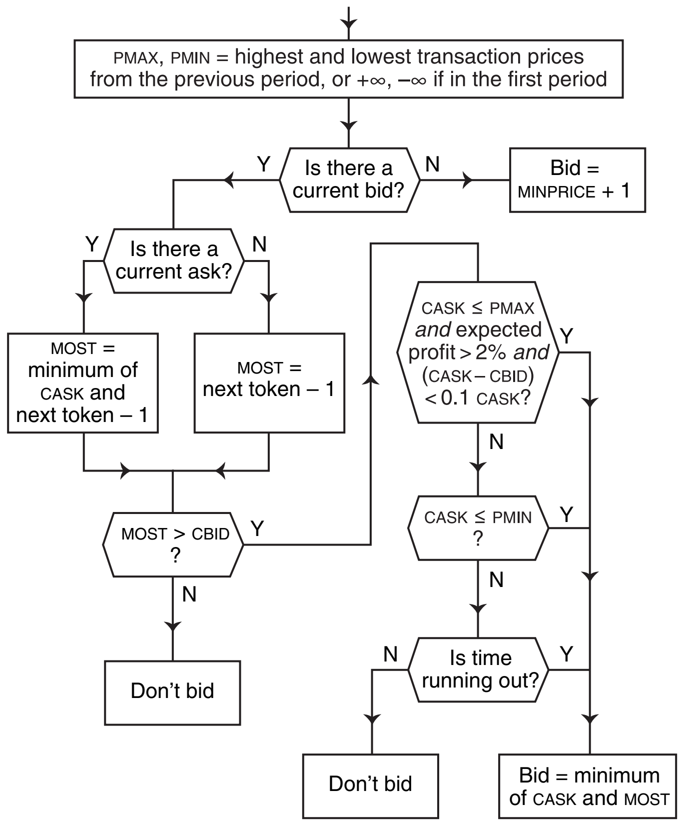


Figure 12.1. Simple trading strategies dominated the Double Auction Tournament (see Rust, Miller, and Palmer, 1994). Notwithstanding the presence of some very complicated strategies based on various economic and statistical theories of trading, it was the simple strategies that won the tournament. Depicted is a schematic of Kaplan's winning strategy. It allowed other traders to submit bids and asks, and took advantage of any profitable opportunities when the spread between the bids and asks was small. This strategy was an "information parasite" that fed off of the actions of the other agents in the ecosystem.

Models of emergence also provide insights into the robustness of the underlying system, as the essence of emergence requires entities to be able to maintain their core functionality despite what are often radical changes from both within and without. Using emergence ideas, we can begin to understand the robustness of systems such as markets, cultures, and organizations like firms and political parties.

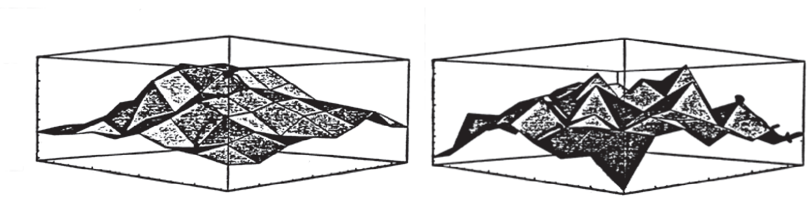


Figure 12.2. Two landscapes generated by nonlinear interactions. As nonlinear interactions increase in a system, the numbers of peaks and valleys increase as well and the landscape becomes more rugged. Agents with limited search abilities can get trapped easily on local optima when the underlying landscape is rugged. Landscape models have been used in the social sciences to study topics ranging from politics to technological innovation.

Another contribution of complex adaptive social systems has been a recognition of the importance of nonlinearities and interactions. To take one example, consider agents that must blindly search across the world to achieve some goal. To keep such models mathematically tractable, we often need to assume that agents are completely blind (and hence just randomly search), are completely omniscient (making search trivial), or exist in a smooth and single-peaked world (where groping results in optimality). All of these assumptions are both unsatisfying and unrealistic. The complexity approach considers landscapes in which the various elements of the space interact in nonlinear ways, resulting in a convoluted world with many peaks and valleys (see figure 12.2). Once agents are placed in such a world, a whole new realm of behavior opens up. Agents find themselves in a path-dependent world, in which early choices determine future possibilities (Page, 2006). Tipping points and critical junctures emerge, where a given system can rapidly change its characteristic behavior.

The notion of search across a rugged landscape provides a new purchase from which to consider ideas like innovation and political platform formation. For example, we can model firms competing against one another to develop good technologies, where a given technology is described by, say, a binary string in which each bit encapsulates some technological feature that interacts with the other bits (the wing shape of an airplane interacts with its power plant choice, which interacts with its fuselage materials, and so on). Now the process of technological invention becomes a search problem across a rugged landscape, where past triumphs and new discoveries form the basis of new technologies that are brought to the market.

The new network theory has also been a major advance facilitated by the complex systems approach (Newman, 2003). While networks—and, more important, the interactions among agents they facilitate—have long been considered by social scientists, especially sociologists, a wave of recent interest has been prompted by computational and mathematical models created by complex system researchers. Rather than focusing on any particular network, this new work considers the generic properties of social connections. Computational modeling allows researchers to create massive numbers of networks that share particular connectivity patterns, and from these derive generic patterns of behavior. These same researchers have begun to mine new sources of on-line data, providing new examples of networks that heretofore would have been impossible to collect and analyze.

Complex systems ideas have also led to new advances in the modeling of adaptation. Adaptive agents can often radically alter the behavior of our models. For example, consider the formation of political platforms by competing parties. If the parties are able to optimize with perfect knowledge, then we predict that incumbents always lose elections and the party platforms we observe will forever follow a chaotic path. Under adaptive agents (see figure 12.3), the platform dynamics behave in a way that is much more consistent with the real world—they slowly converge to good social outcomes that can be tied to the underlying preferences of the voters (Kollman, Miller, and Page, 1992). Moreover, incumbency advantages spontaneously arise due to the inherent search problems faced by adaptive parties. In such models, the search landscape of each party is coupled to those of the other parties, and the landscapes dance around with one another as one party alters its platform in response to platform changes made by the other parties.

Computational models have opened up vast new frontiers for exploring the learning behavior of agents. To take one example, consider learning in games. The last half of the twentieth century witnessed a tremendous intellectual effort aimed at refining various game solution concepts. Toward the end of this period, good experimental data on how agents actually played games began to emerge, and it was found that many of the formal solution concepts failed to predict what was happening in the experiments. Over the past decade or so, computational learning models have arisen to explain the divergence. For example, Andreoni and Miller (1995) showed how a simple model of learning based on a genetic algorithm can be used to reconcile differences between the theoretical and experimental results arising in various auction markets (see figure 12.4).

Similarly, computational models have played a pivotal role in illuminating issues surrounding the emergence of cooperation. For example,

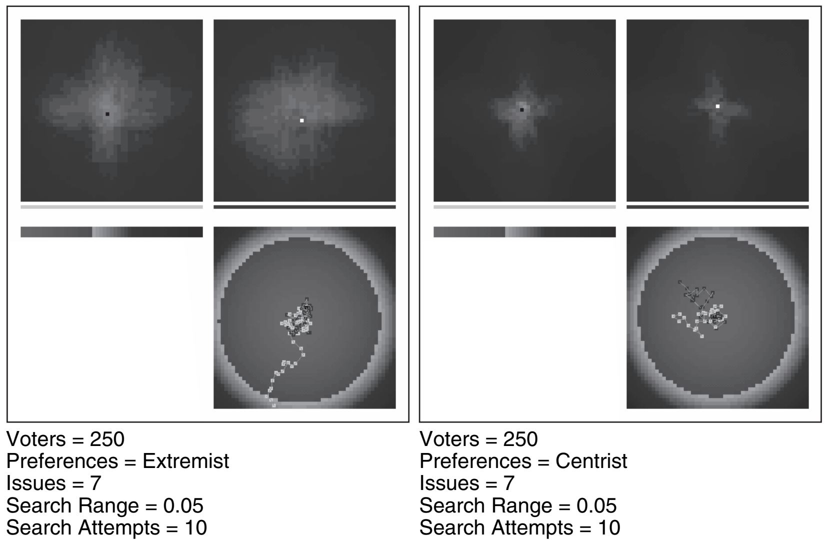


Figure 12.3. Political landscapes and platform search. The political landscape facing a party is tied to the preferences of the underlying voters and the position of the opponent. When voters have extreme preferences (*left half*), the landscapes facing each party become more rugged and diffuse (*upper panels*), while under centrist voters (*right half*) they become much more concentrated. In both cases, the platforms of adaptive parties tend to converge on good social outcomes (*lower right of each diagram*).

Axelrod's (1984) landmark study relied on a tournament of computerized strategies to investigate strategic behavior in the Prisoner's Dilemma game, and Miller (1988) showed how such cooperation can emerge among adaptive agents. Work is also ongoing that incorporates processes of social learning whereby agents learn by observing others (see, for example, Vriend, 2000).

## 12.2 The Interest in Between

The preceding discussion provides a few examples of where the complex adaptive social systems approach has made contributions to advancing the frontiers of the social sciences. While dwelling on past accomplishments is useful, we are more interested in the future opportunities that are potentially available. The study of complex adaptive social systems opens up vast new frontiers in the social sciences. These frontiers exist in the space between the current boundaries imposed by traditional ideas and methods.

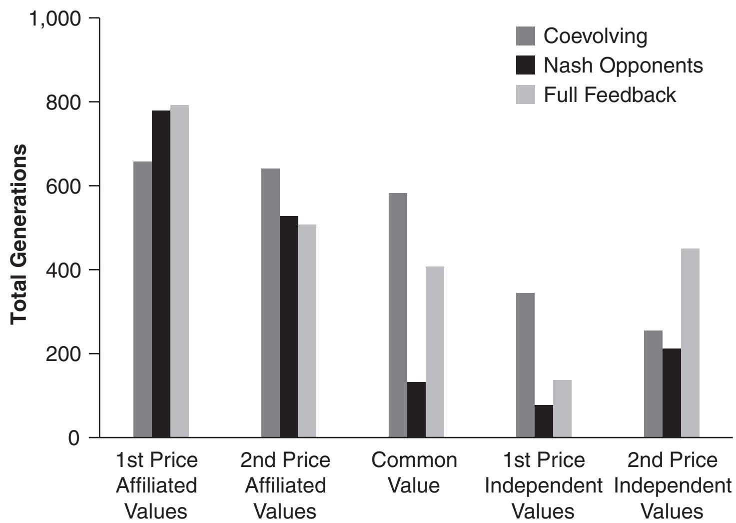


Figure 12.4. Coevolution and learning in auction markets. Here, artificial adaptive agents "learned" to bid in various single-sided auction markets using a genetic algorithm. The patterns exhibited by these artificial agents paralleled those observed in laboratory experiments with humans. Note that agents that coevolved with other learning agents spent more time using optimal bidding strategies ($y$-axis) than agents that learned in an environment populated by expert strategies. More details can be found in Andreoni and Miller (1995).

### *12.2.1 In between Simple and Strategic Behavior*

Consider a simple game like tic-tac-toe (aka noughts and crosses). Few adults actively play tic-tac-toe, as after a fairly short learning period almost anyone figures out how to force the game to end in a draw and thereafter it is not of much interest. Technically, tic-tac-toe is a sequential game with perfect information. Such games can be solved by mapping out all of the possible paths of play and then working backward through the resulting tree and selecting moves that will force the play of the game down favorable paths. Even though the possible paths in tic-tac-toe are enormous, some symmetries in the game that can be exploited (for example, the nine possible first moves can be collapsed down to three) allow adults to intuit the game tree and do the necessary backward induction without too much effort. Indeed, even chickens can be trained to play the optimal strategy (Stuttaford, 2002).

Although adults do not get much joy out of tic-tac-toe (other than playing games against chickens), children—who are unable to do the necessary calculations—can enjoy the game for hours. Lest adults feel too superior to their children, adding even slightly more complication can quickly overwhelm our own cognitive abilities. Three-dimensional tic-tac-toe might qualify here, as would the game of chess.

Chess has fascinated players in its modern version for over half a millennium. Alas, it is a simple game, with sixty-four squares, sixteen pieces of six possible types on each side, and a limited set of movement and engagement rules. Nevertheless, it has generated a vast literature, rancorous scholarly debates, challenging philosophical quests, and the occasional international incident. The odd thing is that chess is identical to tic-tac-toe, in that it has a well-defined game tree that, in theory, we could work our way through and develop an optimal strategy. If our cognitive abilities were just a bit higher, all of the fuss about chess might be a bit embarrassing (to put this in perspective, imagine "Fischer versus Spassky, the tic-tac-toe match of the century").

The strategic space between tic-tac-toe and chess is an interesting one. On one hand, both games are isomorphic and, in a very real sense, trivial to play. On the other hand, while this statement has some meaning for tic-tac-toe (at least for adults), it seems rather empty for chess. Although we could assume the existence of a chess god, through which chess becomes a trivial game using backward induction, such an approach yields little insight into how chess is really played by humans. While toward the end of a chess game we may indeed fall onto an equilibrium path of play, most of the game is played in a wilderness far from any known equilibrium.

Recent developments in computerized chess programs are instructive in terms of the interest in between simple and strategic play. Like humans, computers are unable to generate the entire game tree for chess except toward the end of the game. Therefore, programs must rely on various heuristics (for example, queens are more valuable than rooks), calculations of localized portions of the game tree (often using clever pruning to avoid pursuing likely dead ends), and other means to decide on their moves.

Social science has struggled to come to grips with how to model human behavior. Simple behavioral rules such as price-taking behavior and voting along party lines dominated social science a half century ago. Then, the tide turned toward models that relied on rational actors who were able to do extraordinary calculations on simple problems. More recently, we have seen a movement toward behavioralism and learning models. At each point along this path, social scientists have struggled with what to assume about behavior. A complex adaptive systems approach allows the level of agent sophistication, and even the behavior itself, to adapt. The appropriate level of strategic behavior is not always clear, as we might expect people to be strategic in some contexts and rule following in others. Nonetheless, we have good evidence that humans do not always act like rational agents and that adaptive behavior may lead to very different outcomes, and thus we need some flexibility to be able to explore the interest in between the strategic extremes we have come to rely on.

### *12.2.2 In between Pairs and Infinities of Agents*

Most social science models require either very few (typically two) or very many (often an infinity) agents to be tractable. When an agent interacts with only a few other agents, we can usually trace all of the potential actions and reactions. When an agent faces an infinity of other agents, we can average out (in physics-speak, take a mean field approximation of) the behavior of the masses and again find ourselves back in a world that can be easily traced. It is in between these two extremes—when an agent interacts with a moderate number of others—that our traditional analytic tools break down.

Unfortunately, most economic, political, and social interactions involve moderate numbers of people. Sometimes two firms do compete for a single account, but more often than not dozens of firms compete for dozens of accounts simultaneously. Once we find ourselves in such a world, our traditional analytic tools fail us. Of course, notwithstanding the futility of our tools, actual firms do continue to operate in such contexts, so there must be some mechanisms, albeit imperfect ones, that come into play and allow firms to survive. Similarly, the world of politics is not fully captured by either two-person or large population games. While we do see two candidates squaring off in an electorial battle, this is typically the exception rather than the rule. A United States senator interacts with ninety-nine other senators. To be effective, senators must navigate a vast strategic landscape that involves voting, amendments, interest groups, lobbyists, constituents, bureaucrats, and other branches of the government. Perhaps some of these domains can be isolated and distilled to interactions with only a few or infinitely many other agents, but such an approach quickly succumbs to the reality of the situation. Moreover, even when the interaction is limited to one dimension, it is difficult for the repercussions to be fully isolated. Almost all actions taken by an agent have implications across many games simultaneously, and even if each of these games has a single opponent, the constellation of them does not.

As we start to increase the number of agents we consider in a model, the mechanisms facilitating the interactions among agents become important. One way to keep things tractable is to assume that agents exist in a soup and randomly pair off with one another for an occasional clash. Models of the spread of disease often make this type of assumption. Alternatively, we can assume that everyone interacts with everyone else simultaneously. General equilibrium market models and political models often make this assumption.

New modeling techniques, combining both mathematics and computation, allow us to make the more realistic assumption that social activity takes place in between these extremes. In these models, agents interact with one another over well-defined networks of connections; for example, diseases are transmitted because two people share the same place of work or travel via the same airline hub and agents trade with one another because they find themselves in the same marketplace (whether this is a city on an ancient trade route or an online auction).

Moving in between the old boundaries alters how we think about, and attempt to change, the world. For example, previous disease models assumed random mixing and were solved using a system of coupled differential equations. Although random mixing may be a good assumption if we are modeling the spread of a cold in an elementary school classroom, it is much less useful if we are trying to model the spread of a sexually transmitted disease such as HIV-AIDS. The assumption of widespread promiscuity that knows no geography (random mixing) fails to appreciate the reality of sexual contact structures. When such contact structures are explicitly incorporated into the model, we get more accurate predictions and better policy prescriptions.

### *12.2.3 In between Equilibrium and Chaos*

The rise of complex adaptive systems and its core ideas stems partly from the intrinsic power of the metaphor. If you consider the data from key political, social, and economic processes, it is not clear whether equilibria are the exceptions or the rule. Stock markets soar and crash (LeBaron, 2001). Political parties rise and topple (Jervis, 1997). Terrorist acts emerge from, and are perpetuated by, loose networks. While the notion of social equilibria is an important one, and perhaps even these phenomena are best reflected as a series of (apparently rapidly changing) equilibria, we may need to go beyond equilibria to truly understand the social world.

Complex adaptive systems models allow us to explore the space between equilibrium and chaos. In the starkness of neoclassical models, exchange markets result in a single, stable price equating the quantity supplied with the quantity demanded. Unfortunately, our experiences with real, experimental, and artificial markets indicate that the actual behavior of a market is not so easily captured. In real markets phenomena like clustered volatility and excess trading remain difficult to explain, in experimental markets traders seem to be less strategic and far more irrational than expected, and in artificial markets even minimally rational traders cause the market to achieve high levels of ex post efficiency, even though the observed price path is very noisy.

The equilibrium predictions of the standard market model in economics contrast sharply with those of spatial voting models from political science. With even minimal complication, spatial voting models rarely have equilibria (Plott, 1967). Yet, political parties do seem to demonstrate a fairly high degree of stability on many issues. As previously mentioned, in a model using adaptive political parties, parties tend to converge and dance around the social center of the policy space (Kollman, Miller, and Page, 1992). This latter result is related to the coupled landscape metaphor we discussed earlier. Consider a landscape where the coordinates are positions on policy issues and the height gives the number of votes such a platform would receive. Adaptive political parties move around such landscapes in search of the (metaphorical) high ground. As one party alters its policy positions, however, the landscapes of the other parties are changed. Thus, the political process is one in which parties must actively seek the high ground, even as the landscape underneath them constantly undulates. Although such a process has the potential to generate a collection of aimlessly wandering parties, we find that most of the time the high ground, while ever changing, tends to be concentrated in a contained region of the policy space resulting in relatively stable platforms.

Equilibria, when they exist, are an important organizing force in social systems. Nonetheless, there is no a priori reason to think that equilibria must exist. If we want to understand social systems, we must also account for those that are complex. As shown by the spatial voting model, the lack of equilibria does not necessarily mean a lack of predictability and insight. Using the techniques of complex adaptive social systems, we now have the capability to explore those systems that lie in between equilibrium and chaos.

### *12.2.4 In between Richness and Rigor*

Early proponents of complex adaptive social systems models were optimistic about the prospects for using these models to combine the richness of more qualitative methods with the rigor of mathematics. Qualitative methods provide great flexibility in terms of the types of problems that can be analyzed. At the same time, these methods are often vague, inconsistent, and incomplete. Mathematical methods tend to be more rigorous with exacting notions of how models are formed and solved. Yet, the cost of this rigor is often a loss of richness in what can be studied. Complex systems models may be able to bridge the gap between richness and rigor.

Consider the problem of getting people seated on a commercial airplane. Airlines can realize considerable savings by reducing boarding times because with faster boarding they can fly the same number of routes with fewer planes. Suppose we have a group of, say, one hundred people waiting in the passenger lounge that we need to get seated as quickly as possible on the waiting aircraft. Passengers must board the aircraft, travel down a lone aisle that is easily obstructed by other passengers, stow any baggage, and get to their seat and sit down. The only real control the airline has over this process is the order (based on seat assignments) in which it allows the passengers to board. A very common system in current use is to allow passengers to enter the plane starting at the rear of the aircraft and moving forward, but a number of alternatives exist, including allowing window-seat passengers to board first, alternating between the two sides of the aircraft, and so on.

We can construct a model of this process in a variety of ways. One approach would be to use the average time it takes a passenger to walk, stow baggage, and get seated, and from this develop a mathematical queuing model. As an alternative, we could incorporate much more fidelity into the model via an agent-based model, in which passengers have connections to one another (say, business travelers versus families), alter their behavior in response to other passengers (stow their bags up front if they cannot immediately get to their seat), and so on. Even if we use an agent-based model, we still must decide on how much detail to build into the model. At one extreme the model would look very much like a mathematical queuing model (with the only difference being that we are using the computer to solve it rather than formal equations), whereas at the other it could be a very detailed simulation of every aspect of the passenger experience.

The agent-based model will be much messier than the one that relies on gross averages. Given that we strive to have stark models, this is a disadvantage. Yet, we also strive to have useful models, and depending on the questions we wish to tackle, we need to be willing to trade off starkness for usefulness. Through stark models we can develop broad intuitions. Through empirical analysis and case studies we can get very detailed accounts of what happens under exacting circumstances. Rich computational models allow us to explore the delicate interactions inherent in a system in a much more expansive way and fill in the space in between.

### 12.2.5 *In between Anarchy and Control*

The stock market exemplifies the space between anarchy and control. Our theorems tell us that the market should efficiently aggregate information through the price mechanism. Yet, fluctuations in price appear to far outstrip variations in information. The market sometimes appears to have a mind of its own, yet it does not collapse into complete anarchy. Computational models allow us to mimic such processes (Arthur et al., 1997). They produce behavior not unlike real markets, and we can use them to begin to experiment with attempts to control such worlds. For example, we can see if increasing the amount that can be bought on margin will reduce or eliminate bubbles.

We can extend this idea to think about institutions more broadly. Attempts to assist developing countries through institutional reforms and large projects have, on the whole, been unsuccessful (Lewis and Webb, 1997). People who study development have learned that it may be difficult to find a common method that works across all environments. An institution that works in one culture may not work in another. Ostrom (2005) explains these differences by reference to context. Institutions do not sit in isolation from one another, but are linked to each other and the culture within which they exist. Cultural features like the level of trust, the set of common behavioral rules, and the density of social networks all provide an important context for an institution (Bednar and Page, 2006). We can use computational models to explore these contexts and develop appropriate institutional designs.

Harnessing emergence may be an important means by which to create institutions that can use apparent anarchy to create control. As we saw in chapter 2, a well-designed political institution can introduce noise into a decentralized system in such a way that it promotes the emergence of productive global organization. We also know that institutions like markets can be effectively used, say, to aggregate opinions about political races and world events. We suspect that complex systems ideas will lead to a new appreciation of the importance, and potential for exploitation, of the space between anarchy and control.

## 12.3 Here Be Dragons

The complex adaptive social systems approach provides many opportunities to explore the interest in between the usual scientific boundaries. This vast unexplored territory is home to many of the most interesting and ultimately important scientific questions. Nevertheless, we have tended not to stray too far from known waters for fear that *hic sunt dracones*.

We now have within our grasp the ability to explore these uncharted waters. Like any such exploration, perils abound. It may be that our intellectual conveyances are inadequate to the task, and that we will founder upon the many shoals that surely exist beneath the inviting seas. Or, perhaps this territory is one of false promises, and our explorations will uncover little of value. Nonetheless, the early expeditions prove that the seas can be sailed and suggest at least the possibility of potential riches, so explore we must, even if, as T. S. Eliot (1942) wrote, “the end of all our exploring will be to arrive where we started and know the place for the first time.”