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Agent-Based Models for Financial Crises

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agent-based model, financial crisis, complexity, representative agent, heuristics, leverage, liquidity, contagion

Abstract

This article describes the agent-based approach to modeling financial crises. It focuses on the interactions of agents and on how these interactions feed back to change the financial environment. It explains how these models embody the contagion and cascades that occur owing to the financial leverage and market concentration of the agents and the liquidity of the markets. This article also compares agent-based models to the standard economic approach to crises and shows the ways in which agent-based models overcome limitations of economic models when dealing with financial crises. In particular, this article demonstrates how agent-based models replace homogeneous, representative agents with heterogeneous agents and optimization with heuristics, and how such models move away from a focus on equilibrium, allowing non-ergodic dynamics that are manifest during financial crises to emerge.

INTRODUCTION

The performance of economics during crises is a litmus test for its performance during other times, when limitations might be ignored and cast aside as rounding errors. Crises are a testing ground for economic models, a stress test for economic theory. Understanding the performance of a model during periods of crisis provides us a window into any broader weaknesses. If an economic model fails in crises, we are left to wonder what failings exist in the non-crisis state, failings that might not be so apparent or that can be covered by a residual error term that appears, to use Lucas's (2009) phrase, "too small to matter."

Looking at our recent experience, economics does not seem to fare too well in times of crisis. Despite having an army of economists and all the financial and economic data one could hope for, on March 28, 2007, Ben Bernanke, then Chairman of the Federal Reserve, stated to the US Joint Economic Committee that "the impact on the broader economy and financial markets of the problems in the subprime market seems likely to be contained." Less than 3 months later, this containment ruptured when two Bear Stearns hedge funds that had held a portfolio of more than $20 billion failed, marking a course that blew through one financial market after another over the following 6 months. In February, 2008, as the market turmoil raged, Bernanke gave his semiannual testimony before the US Senate Committee on Banking, Housing, and Urban Affairs. He said there might be failures within the ranks of the smaller banks, but "I don't anticipate any serious problems of that sort among the large internationally active banks that make up a very substantial part of our banking system." That September, Washington Mutual became the largest financial institution in US history to fail. Another bastion of economic brainpower, the International Monetary Fund (IMF), fared no better. In its spring 2007 *World Economic Outlook*, the IMF (2007) forecast that the storm clouds would pass: "Overall risks to the outlook seem less threatening than 6 months ago."

It is not surprising that economics fails during financial crises when, as Trichet (2010) noted, "the serious limitations of existing economic and financial models immediately became apparent. Arbitrage broke down in many market segments, as markets froze and market participants were gripped by panic." Economic models do not incorporate the panics, and they do not have mechanisms that allow markets to freeze. Rather, economics thrives in a world of equilibrium; indeed, most economic models impose regularity conditions to assure that movements away from equilibrium and stability rebound. Lucas (2009) recognized that economics is ill-suited to dealing with crises when he stated that "the simulations were not presented as assurance that no crisis would occur, but as a forecast of what could be expected conditional on a crisis not occurring."

In this article I discuss a recent approach to modeling crises that has been proposed to overcome the limitations of standard economic tools and models (Helbing & Kirman 2013, Haldane 2016, Bookstaber 2017). The methods to do this are drawn from complexity science and employ computer simulations to take a bottom-up approach of examining the behavior of the many heterogeneous individuals that compose the financial system and seeing what emerges from their activities for the system overall. The specific application of the simulations to problems like this is known as agent-based modeling.

Agent-based modeling starts with the agents of the system. In the case of the financial system, these are the investors, providers of funding, and market makers. The model follows the interactions of the agents and examines how the interactions alter the environment and the future actions of one another. The agents operate in their own microenvironments, having no more of a view of the state or the dynamics of the overall system than a driver has of the traffic across a network of roads. The result is a dynamic that can lead to complex outcomes that often do not seem related to the actions of the individuals and from which a crisis emerges.

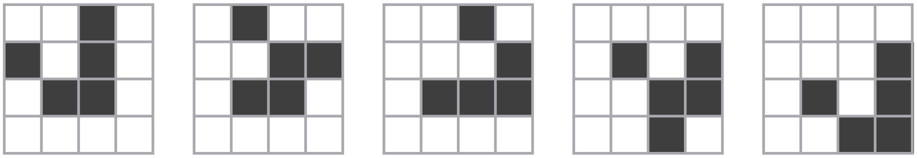

Figure 1

An illustration of Conway's Game of Life. The periods move from left to right. Dark cells are alive; white cells are dead. A cell is determined to be alive or dead on the basis of its local environment:

1. Each living cell with four or more living neighbors dies.
2. Each living cell with only one living neighbor or no living neighbor dies.
3. Each living cell with two or three living neighbors continues to live.
4. Each cell that is dead and that has exactly three living neighbors becomes alive in the next period.

WHAT ARE AGENT-BASED MODELS?

A Simple Agent-Based Model: Conway's Game of Life

Conway's Game of Life (Gardner 1970) is a zero-player game (because once the initial conditions of the cells are set, there is no further interaction or input as the process evolves) with a simple set of rules. Each cell on a grid can be either alive (dark) or dead (white). Each cell on a grid has eight neighboring cells, and the fate of each cell for the next period is determined by the number of neighboring cells that are alive in the current period:

1. Each living cell with four or more neighbors that are alive dies because of overpopulation.
2. Each living cell with only one neighbor alive or with no neighbor alive dies because of isolation.
3. Each living cell with two or three neighboring cells that are alive survives to the next period.
4. Each cell that is currently dead and has exactly three neighbors that are alive is in just the right nurturing environment to be a birth cell, and becomes alive in the next period.

Figure 1 shows how one initial configuration plays out over a few periods.

The game starts by distributing living automata on a grid. Once the initial state of the grid is set with the various alive and dead cells, the process might end after a few periods, with all the cells having died off, or it might continue, with all sorts of structures emerging and changing.

The Game of Life is one of the simplest examples of an agent-based model. The living cells are agents that operate according to a simple heuristic laid out by the four rules. All the agents use the same rules, and this homogeneity simplifies away from one of the key elements of an agent-based model. But as an agent-based model, the Game of Life still presents two key characteristics that differentiate agent-based models from standard neoclassical models.

First, simple rules can lead to complex, unexpected outcomes, including outcomes that do not seem to relate in any natural or predictable way to the individual agents that are acting on the basis of those rules. Any one cell/agent reacts only to eight other agents and can act only in one of two ways, yet the aggregate result of the individual actions is rich and complex. That is, the Game of Life displays emergence. Emergence means the overall effect of individuals' actions is different from what the individuals are doing. The actions of the system differ from the actions of the agents that comprise the system, sometimes in a dramatic way, such as when a crowd exiting a stadium suddenly turns into a stampede. Any individual is doing what seems innocuous or unavoidable given the immediate surroundings. No individual knows what is happening or why it is happening except as it affects them and those in close proximity, and there is no governing force or body or mind that has that knowledge (Helbing, Farkas & Vicsek 2000).

If we have an emergent phenomenon, then although each agent is acting according to the world around them, and perhaps can know perfectly their part of the world, the overall effect is something different and cannot be determined by what any agent observes. The model for the system as a whole needs to examine the decisions of each agent on the basis of what each agent individually observes, change the agents and the environment accordingly, and then proceed to do the same period by period. This is the essence of the procedure of an agent-based model.

Emergence explains why we can all be doing what we think makes sense and indeed be doing what manages our risk, but with an end result that is disastrous. Our individual worlds can look stable, yet the system can be globally unstable; what is locally prudent can be globally imprudent.

Second, even though the Game of Life is the essence of simplicity, in general it is impossible to predict whether a configuration will die off at a given period. That is, the Game of Life is computationally irreducible (Davis 1958). A computationally irreducible problem is one without mathematical shortcuts; the only way to determine the outcome is to perform each step of the program. If you want to see what a system will be like at a distant time, the computer program that is modeling the system must be run step by step from now until that distant time. By contrast, a computationally reducible system can be described by mathematical formulas that give the outcome at any chosen instant of time without working through all the time steps. Computational reducibility is a critical property for standard economic methods, and absent it, we must rely on simulation methods that follow the path as it occurs.

Components of an Agent-Based Model

Moving from an agent-based model as a game to an agent-based model as a tool, consider modeling traffic (Zheng et al. 2013). Traffic has readily identifiable agents: the drivers and their cars. It is a great laboratory for emergent phenomena, as anyone who has seen the inexplicable and broad variations in congestion can attest.

Drivers operate in their own microenvironments, seeing a small subset of the other cars on the roadway. One minute they might be part of a coordinated, smoothly flowing stream of traffic; another, they are unaccountably contributing to the ripple effect of congestion. It is no wonder that agent-based modeling is a popular tool for evaluating traffic flows. Each driver uses different heuristics. They drive at different speeds; some switch lanes to avoid lane-specific congestion, others go slowly in the left lane.

Think about what is happening on the roadway:

- Agents (cars, drivers) are typically heterogeneous and employ various heuristics to act with some degree of independence or autonomy, so there is no centralized control of the system.
- At the start of each time period each agent observes its environment and acts according to its heuristic. The agent's environment is only a local view of the overall system.
- The agents' actions change the environment.
- In the next period, each agent sees its new environment, altered on the basis of the actions of the previous period, and takes action again. Thus, there is an interaction between the agents and the environment, and between one agent and another.

These are the threads of agent-based models.

In applying agent-based models to study the nature of traffic congestion, the precise nature of the cars on the roadway, including their location and heuristics (that is, individual driving characteristics), is unknown. So the model is run many times, with the agents drawn repeatedly from a distribution of drivers with various heuristics. Sometimes traffic will move along smoothly, sometimes not. The end result will be a distribution of roadway characteristics such as incidents of emergent congestion. The model can be run to test the effects of different configurations of exit and entrance ramps or to determine how best to cycle a traffic light.

The end result is derived from the dynamics of interactions driven by the environment and heuristics the various agents apply in that environment. A heuristic is a decision rule that could be based on optimization, but usually it is not. More typically, a heuristic is based on simple rules of thumb and might ignore information in the process. Heuristics are where issues from behavioral economics can find their home within an agent-based model, because the heuristics can be structured to take biases and idiosyncrasies into account. Heuristics do not try to capture all the nuances of the possible states and their probabilities but, in their simple approach, might be robust with respect to changes in states or to new, unanticipated states.

Take the well-known gaze heuristic for catching a fly ball (Gigerenzer & Brighton 2009). One way to catch the ball is to measure the velocity and spin of the ball immediately after it leaves the bat, take into account air resistance and wind, feed these factors into a differential equation, and then identify the spot on the field that corresponds to the output. Another way to catch the ball is the way ballplayers actually go about the task. If the ball is already high in the air by the time you react, fix your gaze on the ball, start running, and adjust your running speed so that the angle of gaze remains constant.

Another example is to examine how heuristics are used in the animal world (Bookstaber & Langsam 1985, Gigerenzer & Brighton 2009, Gigerenzer & Gaissmaier 2011). Many creatures that use simple heuristics nonetheless have great records of survival. For instance, the survival of the cockroach comes from a basic and seemingly suboptimal escape heuristic: The cockroach simply scurries away when little hairs on its legs vibrate from puffs of air, which might signal an approaching predator. Heuristics are also used in other decisions critical to survival such as foraging and mate selection. For foraging, we can refer to the gaze heuristic. Dragonflies and other species use a variant of it to catch prey (Olberg, Worthington & Venator 2000). For mate selection, the peahen uses a take-the-best heuristic, in which she looks at three or four males and then selects the one with the most eyespots.

COMPARING NEOCLASSICAL AND AGENT-BASED APPROACHES

The behavior described above is at the opposite end of the spectrum from the rational expectations theory that dominates economics, about which Thomas Sargent (quoted by Evans & Honkapohja 2005, pp. 566–67) has said: "Agents inside the model, the econometrician, and God share the same model." Sargent calls this the "communism of models" within the rational expectations hypothesis, and it comes from the fundamental view that those who are being modeled must act in a way that is consistent with the model that is being used to model them.

Agent-based models present an alternative paradigm to neoclassical economics. Whereas neoclassical economics seeks its roots in the mechanics of physics, agent-based modeling is spawned from dynamic networks and complexity theory (Arthur 1999, Colander et al. 2009, Kirman 2010, Page 2011). It is short on theoretical structure and is a slippery subject for parametric testing. It is more of a direct approach, serving as a quantitative basis for developing and inspecting a narrative rather than as a deductive model that gives a solution to the world. Notable distinctions between the two approaches are discussed in detail below.

Interactive Heterogeneity Versus the Representative Agent

To allow for mathematical tractability, economics holds to homogeneous agents, even to using one representative agent. Gathering all the agents in a system into a representative agent prevents a meaningful analysis of interactions, which is at the core of the agent-based approach. Groups of people display patterns and structures of behavior (such as emergent behavior) that are not present in the behavior of the individual members, which is of obvious importance throughout the social sciences. These are the characteristics agent-based models display (Scarf 1960, Kirman 1992, US House 2010).

But the representative agent is used nonetheless, because it is hard to harness the machinery of mathematical economics without it. If one is going to assume the homogeneity that is implicit in a rational expectations model, in which all agents are acting in a lockstep, consistent manner using the same (and correct) model, then one may as well collapse the world into one representative agent.

Complexity and Computational Irreducibility Versus Mathematical Tractability

The interactions that come from our social nature and the shifting preferences that come from experience and context are inherent to humanity. We interact in society, and certainly within markets, and all the more so during periods of crisis, when we are anything but robots with fixed, mechanistic responses to inputs. We face a changing world, which in turn changes the context in which we view the world, and that changes us, again all the more so during periods of crisis. The critical implication is that we cannot plug numbers into a model and solve for the future. We cannot know where we will end up until we take the journey.

Emergence Versus Equilibrium

Complex dynamics result from the agents' interactions, which can lead to emergent phenomena and the prospect of surprises. These surprises include point-of-no-return disruptions from equilibrium, in contrast to perturbations around equilibrium, which are perturbations with stability that are built into most economic models; equations of equilibrium constitute the center of the economic discipline.

Owing to the complexity of interactions, the behavior of the system cannot be constructed as the aggregate of the models of the individuals (Saari 1995, 1996; Kirman 1989). Although a statement such as "assume everyone knows sufficient data to understand the implications of interactions" might be taken as a starting point, that is not how things really work. Keynes (1978) wrote that the material to which economics is applied "is, in too many respects, not homogeneous through time." If this is ever the case, it is during crises.

In addition to computational irreducibility and emergence, another characteristic at variance with the assumptions required for economics is that the world is not ergodic. The future is unknown, and the past does not provide a dependable guide to the future.

Heuristics Versus Optimization

We are seeking reality, and the agents in an agent-based model, rather than being mathematicians or logicians, are rooted in the real world; they are experienced and savvy professionals, working together to determine the best rules and heuristics to perform their job. This remains the case as the crisis emerges. That is, if a heuristic and an objective function with its optimization were placed before financial professionals, they would likely find the heuristic more reflective of how they think and what they do. Indeed, the professional might not even recognize as rational the formalized notions of optimal behavior or the rationality that the economists are presenting.

A Narrative Versus a Solution

Neoclassical models work toward a solution. They are constructed to ensure a straight, unambiguous answer. The final step in building these models is what is termed closing the model, finding a way to tie everything together so that solving for any *x* results in a unique *y*. As Romer (2016) has pointed out, the economist's unwavering drive to this end can lead to severe, often opaque assumptions and restrictions. By contrast, an agent-based model, with its host of heterogeneous agents, is not closed—it can be overidentified. To the economic theorist who seeks elegance and parsimony, an agent-based model might look like a scrum. But clearly, the financial system is overspecified, with hundreds, or even thousands, of entities. Many worlds might come out of its dynamics, and the simulation presents a distribution for these possible worlds. The result is not a number, but more like a story line or narrative of the ways the world might evolve. And it is narratives, not numbers, that dominate the high-level meetings on trading floors and board rooms over the course of a crisis.

AGENT-BASED MODELS FOR FINANCIAL CRISES

The underpinnings of agent-based models in finance, heuristics, interaction, and heterogeneity go as far back as 1908, as described by Henri Poincaré (quoted by Helbing & Kirman 2013, p. 9):

> When people are in close contact they do not act randomly and independently of each other; they react to each other. Many factors come into play, and they perturb people, and move them right and left.

In finance, agent-based models were first applied to the dynamics of trading (Zeeman 1974, Rieck 1994). A notable early effort in applying agent-based models of finance is the Santa Fe Institute's Artificial Stock Market project in the 1990s (Palmer et al. 1994; LeBaron, Arthur & Palmer 1999; Ehrentreich 2008), which was an offshoot of a broader, interdisciplinary project centered at the Santa Fe Institute examining economies as complex systems (Anderson, Arrow & Pines 1988). These models had markets that were populated by agents with varying trading strategies and exhibited peaks and troughs that belied the simplicity of the heuristics of the underlying agents.

From there, the work on agent-based models expanded to include, for example, models of mortgages and the housing market (Geanakoplos et al. 2012), the effects of leverage on volatility (Thurner, Farmer & Geanakoplos 2012), and liquidity in the face of capital constraints (Cifuentes, Ferrucci & Shin 2005). The work on agent-based models through the decade after the Artificial Stock Market effort is surveyed by LeBaron (2006a). Leigh Tesfatsion maintains a website for agent-based models used in economics and finance: **http://www2.econ.iastate.edu/tesfatsi/ace.htm**.

Interest in agent-based models has been spurred in the wake of the 2008 crisis (Buchanan 2009, Farmer & Foley 2009, Farmer & Geanakoplos 2009) for the very arguments that standard economic models failed and that the agent-based models can shed light where the standard models struggle, dealing with the complexity, interactions, and emergence that were manifest over the course of the crisis.

To explain how agent-based models can deal with crisis risk, I analogize the sources of a stampede as people escape from a fire—an example to which agent-based models have been applied (Shi, Ren & Chen 2009)—to the components of a market crisis. For a fire marshal the critical question is whether people can get out in the case of fire, and the answer depends on three factors: the number of people in the space, how many people can exit per minute based on the number and size of places of egress, and the time available to exit based on the flammability of the space. Modeling the number of people that can exit per minute is difficult because people are not walking through the exit in an orderly way. There is the potential for panic and stampedes. So this needs to be modeled on the basis of how people behave in a crisis—a role for agent-based models.

Using this example as an analogy for the financial system, market concentration measures the number of people in the market; liquidity determines the rate at which people can exit; and leverage, or more generally, the potential for forced selling, determines the flammability of the market and thus the number of minutes available to exit.[1] For financial markets, the situation gets more complicated. The exits shrink as investors push through them to liquidate. That is, liquidity dries up during a crisis. And for financial markets it is as if the building becomes more flammable as the exits become smaller, because a drop in liquidity can fuel cascades.

So a crisis-focused agent-based model feeds off of concentration, leverage, and liquidity. But the first ingredient of a crisis is the environment in which the agents interact, which is affected by their actions.

The Environment

If you want to follow a crisis, you need to follow the money. The money flows along a course to be processed into assets, to be delivered to those who need funding to transform into securities, and to be sent as collateral. If one of the pipes gets clogged or breaks under pressure, we have the makings of a crisis. If it fails to feed what is downstream, or backs up to spill into other systems, that crisis will spread.

If we keep things abstract and general, the mechanics of a crisis are not so difficult. But abstraction does not get us far. We need to start with a schematic of this plumbing. For an agent-based approach, or for almost any simulation approach, the key is to understand the structure: where the agents are operating, their environment, their heuristics, and the resulting dynamics, all of which are specific to the financial system.

The fastest way to appreciate the real world of the financial system and the degree to which economics has abstracted it away is to look at how funds travel, where cash is borrowed, how assets are bought and then used as collateral, and how the collateral is then used a second time to borrow even more cash (Aguiar, Bookstaber & Wipf 2014). As assets are moved from one institution to another, things change, much as the flows within a chemical plant are altered as they pass into the various processing units. Flows moving from depositors to long-term borrowers are subject to a maturity transformation. The flows of funding from cash providers through secured funding and prime brokers to hedge funds undergo a credit transformation. The flows between the financial institutions on either side of the bank or dealer's trading desk are subject to a liquidity transformation. Finally, the participants in the derivatives area are subject to risk transformations. Interactions matter.

The Agents and Their Heuristics

Syll (2016) asks why economists "consider it worthwhile and interesting to make evaluations of real economies based on abstract imaginary fantasy worlds," which he likens to "telling physiologists to

[1] Although I am focused on forced selling because of leverage, other avenues for forced selling include risk limits that force selling when breached (and that are more likely to be breached when there is a market shock and volatility increases) and preprogrammed selling strategies, such as portfolio insurance, volatility targeting, and risk parity strategies.

evaluate the human body from the perspective of unicorns." An agent-based approach can do away with abstraction, homogeneity, and generalization. It can start with the decisions of real-world, individual agents. Why start off by saying, "Assume there are N banks and K asset managers" when we know those banks and asset managers? Banks such as JPMorgan Chase (JPM) and Citi are the agents, as are hedge funds such as Citadel and Bridgewater, not to mention the various security lenders, asset managers, pension funds, and money market funds.

Each agent interacts with others. Some agents are sources of funding; others use funding. Some are intermediaries and market makers. Some act as conduits for collateral; others take on counterparty risk. Each agent has its own business model, a different level of risk taking, and a different culture. Each agent has its own set of heuristics. Some of the heuristics are spelled out in their governance structure and policies and procedures, and some are communicated to their investors. During times of crisis, some of the heuristics are hardwired; the agents unable to alter their course, most notably when the heuristics relate to margin calls or forced liquidations due to reduced availability of funding.

Interactions

The agent-based approach allows agents' actions to change the environment, and the changed environment changes their actions. What one agent does next depends on what it and other agents have just done. The result is a system imbued with complex dynamics that can defy direct mathematical analysis and trigger emergent phenomena. Financial crises envelop a wide swath of the landscape; therefore, the financial system, including the roles of the various participants and the interrelationships between the various financial functions, needs to be well mapped.[2] There are various types of agents in this system.

1. **Bank/dealers.** The term bank/dealer refers to both banks and broker-dealers, most of which have become aligned with banks post-2008. The bank/dealer can be considered a singular agent in the financial system, but it contains various agents, such as the prime broker, trading desk, and financing desk, such that each agent interacts with different agents and operates with a share of independence.
2. **Hedge funds.** Hedge fund agents borrow from the bank/dealer's prime broker to support their long and short trading positions. Hedge funds trade with the bank/dealer's trading desk, as well as with various exchanges.
3. **Cash providers.** Cash providers are agents that include asset managers, pension funds, insurance companies, securities lenders and money market funds.
4. **Institutional investors.** The institutional investors encompass agents ranging from asset managers to pension funds, sovereign wealth funds, and insurance companies. These agents are critical for providing liquidity to the market.[3]

The agents have various roles related to liquidity and can be recast in those terms (Preis et al. 2006, Tirole 2011). Returning to the fire marshal analogy, liquidity is the means of egress for financial environments. Consistent with the dictum that the markets operate to extract the

[2]The central bank and other government entities can be added as other agents. Here, we focus strictly on the agents within the financial system.

[3]Because of their tendency to become embroiled in forced selling, thus having a special role in fostering crises, hedge funds are presented here as a specific agent type, but hedge funds really are a special class of institutional investor that can borrow money to put on leveraged positions, take on short positions, and enter into illiquid and unusual investment opportunities.

maximum pain, when investors really need to get out, the door to liquidity begins to close. There are three types of agents when it comes to liquidity: liquidity demanders, which buy or sell, the archetype being leveraged investors such as hedge funds; liquidity suppliers, which meet the liquidity demand—for a price—such as asset managers and pension funds; and market makers, which adjust the price to meet the demand with supply.

Modeling liquidity during market crises is difficult because of the complex, nonlinear dynamics of the interactions among market participants. Measuring relatively small transactions does not provide much insight. Liquidity can be subject to emergent phenomena. This arises from the feedback that occurs during periods of market shock and illiquidity. Liquidity becomes an endogenous element of the broader market behavior, and it cannot be analyzed without attention to issues of leverage, funding, and the resulting changes in investor behavior. The complexity also arises from the heterogeneous decision cycles among those in the market, specifically the difference in time frames between the liquidity demanders, which require immediacy, and the liquidity suppliers, which do not (Duffie 2010; Bookstaber, Foley & Tivnan 2016; Leal et al. 2016).

DYNAMICS

The end result of the agents interacting in the environment creates the dynamics of the agent-based model. Each agent in the financial system observes the environment in its purview, which includes the effects of other agents' actions, and acts on the basis of its own heuristics. The agent does this without integrating how all others in the world are operating, much less how all of what it and all others are doing will add up in aggregate. We are developing a methodology that examines the activities of the individual participants and uncovers the global phenomena that emerge.

Once we have laid out the environment through the system map and the agents of the system, we can turn the model on and see how the dynamics unfold. The key dynamic of market crises is the fire sale, which is induced by asset shocks or funding runs, each of which can feed into the other (Brunnermeier & Pedersen 2009, Shleifer & Vishny 2011).

The fire sale dynamic is driven by the anvil and hammer of leverage and liquidity. If the markets are highly liquid, selling can be accommodated without a notable price decline, and there will be no cascades or contagion. If there is little leverage in the market, there will not be a need for substantial deleveraging, even in the face of a market event. Because forced deleveraging leads to asset sales and asset sales lead to price declines (which then lead to further deleveraging), both leverage and illiquidity are essential components of a market crisis.

I illustrate the objectives of the agent-based model by showing how the model can trace a shock as it reverberates through the system (Bookstaber, Paddrik & Tivnan 2017). Despite my comments arguing for agent-based models to be oriented toward the detailed reality, here I use a simplified, stylized example. The model can be applied to a system with many agents, but here I apply it to a tractable network of three assets, two hedge funds, two bank/dealers, and a single cash provider.

Figure 2 shows the progression of one simulation run of the agent-based model with five agents operating in three assets: two hedge funds, HF1 and HF2; two bank/dealers, BD1 and BD2; three assets, A1, A2, and A3; and a cash provider, CP. HF1 and BD1 hold A1 and A2, and HF2 and BD2 hold A2 and A3. The CP holds collateral in all three assets. BD2 is exposed to counterparty risk from BD1.

The first stage begins with an initial shock: A1 drops in price, which affects the three agents that hold this asset. Each stage in the figure, which is a snapshot of the model at different points in the progression from the initial shock, is depicted by showing which agents influence other agents.

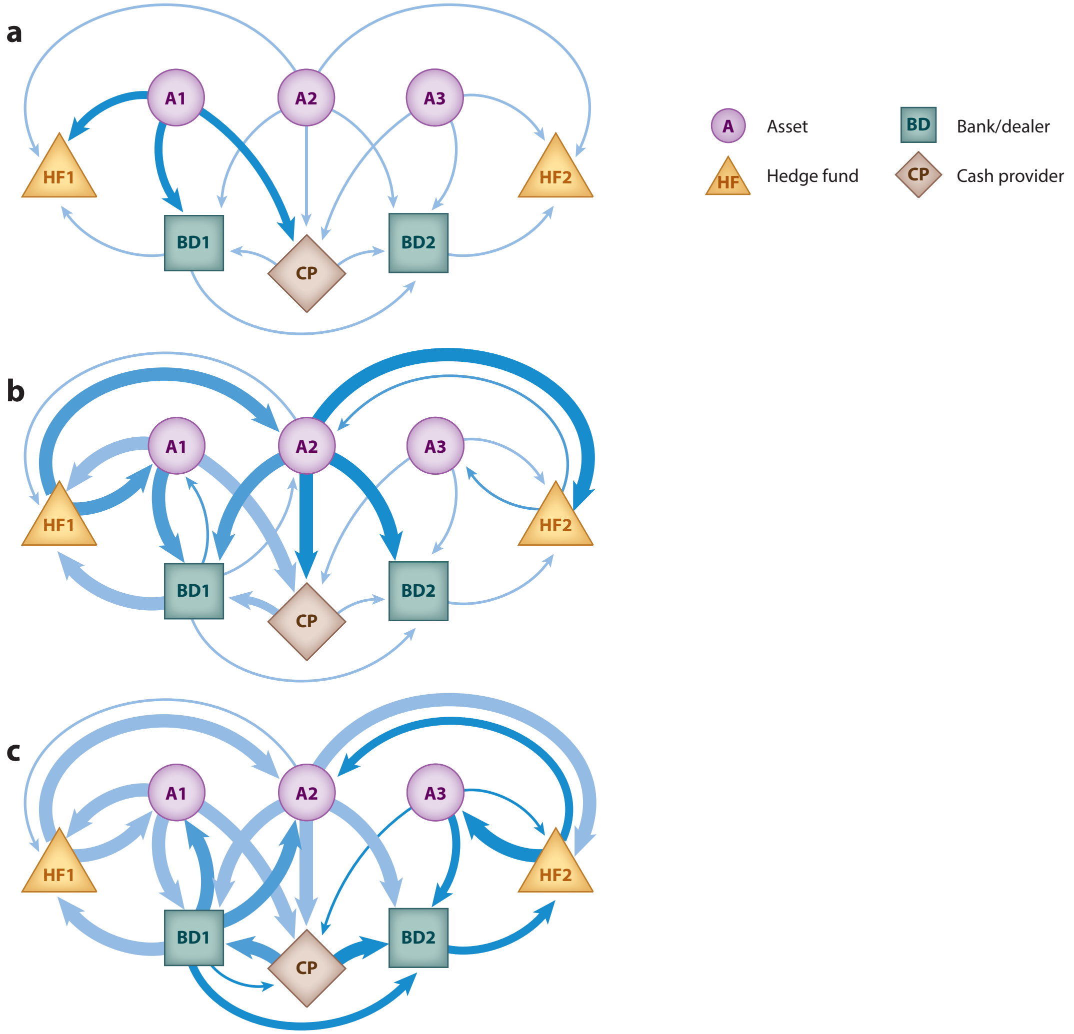

Figure 2

(*a*) The first stage shows the effects of a price shock to asset 1 (A1). The shock affects hedge fund 1 (HF1) and bank/dealer 1 (BD1) because they have exposure to A1. It also affects the cash provider (CP) because it holds A1 as collateral. A new pathway of effects is indicated by a dark blue line, and continuation of a shock along a pathway is indicated by a lighter line, the shading being indicative of the intensity of the effect. (*b*) The second stage shows the propagation to A2, which is also held by HF1 and BD1, and to HF2 and BD2, which, although not holding A1, have exposure to A2. The CP is further affected because of the pressure on A2. (*c*) The third stage shows the feedback, which creates a cascade for A1 and A2. It also shows A3 embroiled because it is held by HF2, BD2, and the CP. Counterparty exposure from BD1 to BD2 creates a further route for propagation. Figure adapted from Bookstaber, Paddrik & Tivnan (2017).

In the second stage, the effects of the initial shock propagate to affect A2 because both HF1 and BD1 sell positions in their portfolio to meet margin calls. A2 also drops in price. This has the same sort of effect on HF2 and BD2 that the shock in A1 had on HF1 and BD1. And A1 will drop further owing to continued pressure on HF1 and BD1. The value of CP's collateral drops even further, and because BD2 has used its assets as collateral, it is now also affected by reductions in funding from the CP.

By the third stage, A3 is embroiled in the effects from the initial shock, because HF2 and BD2 have exposure to A3. In the face of forced selling, HF2 and BD2 will start to liquidate their holdings of A3. Also, with funding restricted for the two bank/dealers, a new channel of contagion opens. The credit relationships between the bank/dealers weaken. BD2 observes BD1 weaken from the drop in its asset holdings and the reduction in funds. From the first stage through the third, the initial shock washes throughout the system, affecting all the assets and all the agents, creating the financial equivalent of a multicar pileup.

Each period in the agent-based model simulation can be represented by a network with the agents as nodes. The links can represent market flows and contractual relationships. The markets are part of the environment, and contractual relationships, most notably for lending, collateral and margin requirements, and counterparty arrangements, are generally embodied in the heuristics. But the network is only a snapshot; nodes and links change, and may even disappear, from one period to the next.[4]

Imagine a hedge fund that invests only in A3. It does not have any exposure to A1, where the initial shock occurs, and it does not even have exposure to agents that share the same assets as those that hold A1. Yet the hedge fund's portfolio drops as a result of the initial shock. That is real collateral damage!

ESTIMATION

The structure of an agent-based model allows estimation and calibration to occur at two levels, the heuristics of the agents and the dynamics of the resulting system. The model is evaluated by comparing its results to stylized facts, characteristics that are considered essential to properly reflect the target dynamics. LeBaron (2006b) illustrates calibration and testing in a market application, where the stylized facts include distributional properties such as the kurtosis, volatility clustering, and autocorrelation of market prices. Ashraf, Gershman & Howitt (2016) calibrate their macroeconomic model using a multistage approach that matches the model to stylized facts regarding economic variables and to measures of internal model consistency. The housing model of Geanakoplos et al. (2012) compares the model output to the pattern of actual housing foreclosures and related housing metrics.

Using stylized facts and internal consistency may be more akin to the methods of estimation for deep-learning artificial intelligence (AI) systems than to the parametric methods of most economic models, although an agent-based model does provide more structure than neural network–driven AI models. This structure no doubt is less than satisfying for researchers who enjoy the rigorous statistical foundations of econometric methods. But for the application of crisis modeling, stylized facts and consistency may be the best researchers can do. Historical data are of limited value when evaluating a present crisis, which is different not only from the more stable pre-crisis world but also from past crises. People are inventive; they construct new financial instruments and strategies (which, being untested and aggressively marketed, often are in the middle of a crisis). People adjust to the past crisis with new governance principles, risk management structures, and refined heuristics. And the path of a new crisis will bypass newly formed pockets of resistance that come from regulations that have been set up in the wake of the previous crisis.

[4]Monin & Bookstaber (2017) show the relationship between agent-based models and dynamic networks, and demonstrate that under suitable conditions both of them are representations of a Markov chain. Additional insight into the network representation can come from considering it as a multilayer network, with the layers being execution, financing, and collateral. Bookstaber & Kenett (2016) construct such a network.

CONCLUSION

A crisis is neither an equilibrium state nor a little nudge from that state. A crisis is not a bad draw from the urn. It is a draw from a new urn, a new distribution. A crisis cannot be pinned down if it is not ergodic, and it cannot be mechanistically predetermined if there is computational irreducibility. A crisis also is not a regime shift except in the obvious, tautological sense in that it is a new dynamic, where "regime shift" dresses up the statement "sometimes things are normal, and sometimes they are not" in the same way that "fat-tailed event" gives a more scientific ring than saying "something really bad happened."

Lucas (1981, p. 8) wrote: "In general, I believe that one who claims to understand the principles of flight can reasonably be expected to be able to make a flying machine, and that understanding business cycles means the ability to make them too, in roughly the same sense." In other words, if you want to understand crises, you have to develop a system that can create one. And to create one, you should note and address the following points.

- The dynamics are likely to be computationally irreducible, so follow the paths rather than trying to find a mathematical shortcut for getting to the end of the story.
- Interaction matters, so allow interaction (which means do not compress the world into representative agents).
- Interactions are based on heuristics, so understand the (heterogeneous) agents' heuristics.
- The interactions can change the environment and lead to emergent phenomena, so be sure the model is constructed in such a way that emergence is not smothered.

How a shock propagates and cascades, including how it changes the environment, our perceptions, and our experience, creates a dynamic for the future course of events, and this dynamic is at the core of agent-based modeling methodology. Agent-based models allow us to recognize some essential aspects of the world that are particularly apparent during crises.

There Is a Real World

The real world is rich and complex. There are many different players and institutions, and many different components have a bearing on how people act. Each person operates according to their particular heuristics, which likely differ from those of others and differ by more than the setting of some parameters. People interact in complex and sometimes unexpected ways, and actions work through the system with surprising and nonlinear results. Institutions such as Morgan Stanley, Goldman, Citadel, Bridgewater, Fidelity, and BlackRock bring their own idiosyncrasies. Inelegant regulations (e.g., Dodd–Frank, Volcker, and the Basel Accords) affect the agents' heuristics; they might reduce risk and constrain activities, but they also can lead to collateral damage and create vulnerabilities.

Using agent-based models, researchers are not starting with axioms and deriving a top-down deductive theory. They are not trying to build a general, abstract model that would work for some economy that might be discovered on Mars.

Agents Are Different

The real world requires us to understand real financial entities and the actual structure in which they operate. Homogeneity cannot be assumed nor can all agents be lumped together into a single representative agent, especially if the goal is to model interactions and emergent phenomena.

Agents Affect the Environment

Large financial institutions cannot take meaningful action in the face of a crisis without affecting the broader system, owing to their liquidation of large positions and their effect on the funding market and related counterparty and credit risk. They can take actions that are locally prudent but imprudent when the effect is extended to the broader system. Sometimes actions are taken to deliberately alter the environment. And a changing environment changes how agents act.

Agents Affect One Another

Contrary to the notion of a representative agent, many forces are interacting. Even similar forces, which we would think could be compressed into a representative agent, generate a complex and unpredictable world. If these forces affect the environment, and the environment affects them, then they all affect each other.

All these characteristics reside within the critical limit to knowledge that we only know the future as we live it. If we alter the environment on the basis of our actions, and if that in turn affects others who then change the environment further, and if all this occurs within actions that depend on the resulting changes in context, the deductive approach of neoclassical economics needs to be reconsidered. It will work some of the time, such as when people are atomistic and mostly the same, and do the same sorts of things as they always do. But they are not, and they do not, especially during periods of crisis.

DISCLOSURE STATEMENT

The author is not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

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