CHAPTER 2

NETWORKS: A PARADIGM SHIFT FOR ECONOMICS?

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> Yet it is likely that one day we will know much more about how economies work—or fail to work—by understanding better the physical structures that underlie brain functioning. Those structures—networks of neurons that communicate with each other via axons and dendrites—underlie the familiar analogy of the brain to a computer—networks of transistors that communicate with each other via electric wires. The economy is the next analogy: a network of people who communicate with each other via electronic and other connections. The brain, the computer, and the economy: all three are devices whose purpose is to solve fundamental information problems in coordinating the activities of individual units—the neurons, the transistors, or individual people. As we improve our understanding of the problems that any one of these devices solves—and how it overcomes obstacles in doing so—we learn something valuable about all three.
>
> —Robert Shiller 2011

It was Thomas Kuhn in his 1962 book *The Structure of Scientific Revolutions* who developed the idea of a "paradigm shift" in a discipline. He argued that such a shift occurs when scientists encounter anomalies that cannot be explained by the universally accepted paradigm which has provided the framework for the existing theory. He suggested that when such a change occurs what he referred to as the "world view" of the scientists in the discipline changes. A number of economists and policy-makers have suggested that, with the experience of the current economic crisis we have reached the point at which such a shift will occur in the discipline of economics.

Yet, it might seem pretentious to suggest that the development of network theory and its applications would be at the heart of such a change in economics. Underlying the development of economics in the last two centuries has been a commitment to the principles of what might be called "classical science" (for example, Morin 2006), the most relevant of which, for this discussion, can be summarized as follows: *The principle* *of reduction*, that consists in knowing any composite from only the knowledge of its basic constituting elements.

While accepting that the behavior of the aggregate is the result of the behavior of the components, the important idea, and one which has pervaded economic theory, is that it is enough to know how those components behave without worrying about the direct interaction and feedbacks between them. This is the core of methodological individualism, and indeed Robert Lucas went as far as to say that it is, for him, an article of faith that one should only make assumptions about individuals. However, this leads us directly to the basic problem with recent events. What has been the major source of dissatisfaction with current economic theory, and macroeconomic theory in particular? It has been the absence of major endogenous upheavals in the models. Major changes are attributed to exogenous shocks but do not emerge from the internal dynamics of the system. This is not surprising given the structure of modern macroeconomic models, which do not allow for direct interactions among the individuals in the economy or for the consequences of the network that governs those interactions, and thus exclude one of the major sources of intrinsic volatility. One gets a glimpse of how understanding the network of linkages between asymmetric firms may generate large systemic shocks in the work of Acemoglu et al. (2011) and Gabaix (2011), and this is discussed in Acemoglu's chapter in this book. But this has not penetrated modern macroeconomics other than as justification for a more fat-tailed distribution of aggregate shocks. The importance of the direct interaction between firms, which is an essential ingredient of the evolution of the economy, is not recognized. Macroeconomic models remain in the tradition of a set of actors taking essentially independent decisions with the mutual influence of these actions relegated to the role of inconvenient externalities.

But to understand why we have come to this point, it is worth just casting a brief glance at the path that economics has followed from Adam Smith to the present. Our current theory, particularly in macroeconomics, is the result of a long evolution in which economics has tried to produce a coherent model to underpin the laissez faire liberal, social, and philosophical approach, which has become dominant. This suggests that, left to their own devices, participants in an economy will self-organize into a satisfactory state. Yet, within the standard General Equilibrium framework, this cannot be proved. Thus, theoreticians and policy-makers are confined to studying equilibria and changes in the latter without any convincing argument as to why the economy should be in such a state. Suppose instead that we base our paradigm on a view of the economy as a complex interactive system. This would mean taking as a starting point the direct interaction between market participants who may vary widely in their characteristics and their information. Such a system may show no tendency to self-equilibrate, and endogenous crises and aggregate changes will be a standard feature of our models.

Where then do networks come into play? As Lucas (1988) said, somewhat paradoxically given his insistence on restricting assumption to those on individual characteristics, "Applications of economic theory to market or group behavior require assumptions about the mode of interaction among agents as well as about individual behavior."

If we are to understand aggregate economic behavior, we have to not just make assumptions about the individual characteristics and motives of the actors in isolation and the economy, but also the structure that links them together. Sociologists have long adopted the idea that the individual is embedded in a social network and that his or her choices and actions are influenced, directly and indirectly, by those to whom he is linked. This has been pushed in many directions, such as the development of the Actor Network Theory (ANT) in sociology. Whittle and Spicer (2008) believe that ANT prefers to seek out complex patterns of causality rooted in connections between actors. In other words, what generates causal relations cannot be understood by looking at individuals in isolation. Furthermore, as Vega-Redondo emphasizes in his chapter in this book, the links between actors are also chosen by the actors themselves, and this further complicates the analysis.

James Coleman noted, with regret, the efforts by some empirical sociologists to move to an approach more akin to that of economists, taking samples of independent purposeful individuals and leaving to one side the conflict between the micro and macro level:

> There was no comparable development of tools for analysis of the behavior of interacting systems of individuals or for capturing the interdependencies of individual actions as they combine to produce a system-level outcome. The far greater complexity required of tools for these purposes constituted a serious impediment to their development and continues to do so (though some methods such as those generally labeled "network analysis" move in that direction). The end result is extraordinarily elaborated methods for analysis of the behavior of a set of independent entities (most often individuals), with little development of methods for characterizing systemic action resulting from the interdependent actions of members of the system.
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> —Coleman 1986, p. 1316

These remarks were made some 30 years ago but should still resonate with economists. The tradition on which modern economic analysis is based goes back a long way, at least as far as Hobbes. Hobbes' view (1651) is now referred to as atomism and is a more extreme form of methodolological individualism. He envisioned society as a group of unconnected individuals whose current characteristics were unaffected, now, or in the past, by those to whom they are linked. He proposed to "consider men as if but even now sprung out of the earth, and suddainly (like Mushromes) come to full maturity without all kind of engagement to each other."

Later economists did not reject interaction out of hand, though it was often limited to market interaction over which the actors involved had no strategic control, and where agents were essentially negligible price takers. This is, of course, the basic vision of the Walrasian General Equilibrium model.

To caricature, if we take the Walrasian model seriously, it consists of agents linked to some central but unspecified agent who calls out prices for all goods. Thus the basic network is a star, and the agent in the center is often referred to as the "Walrasian auctioneer."[1] The Walrasian road does not seem to offer a vision of the economy that would place network theory in the forefront.

The evolution of game theory can be considered as the natural sequel to a development in economic theory that is very different from that followed by general equilibrium theory and which opened the door for network theory to play a central role. To caricature again, one could think of a full blown game theoretic model of the economy as made up of agents, all of whom interact consciously and strategically with all the others. In this case the network of links between the agents would correspond to the complete graph. One might argue that, from a macroeconomic point of view, a fully game-theoretic analysis would seem to attribute knowledge and calculating capacity to agents, which is so far beyond what can reasonably be postulated that it is best to assume that agents simply act in isolation. Yet this would seem to negate the interest of a great deal of economic analysis. Indeed, the natural reaction to this would be to suggest that agents interact strategically with only a limited number of other agents, and once we admit this then we can use network theory to specify who is "playing with whom," as do Bramoullé and Kranton in their chapter. But, at least for the moment, the use of game-theoretic analysis puts quite severe restrictions on the sort of models we can analyze; perhaps the most important of these that the network effects are small. If we are to put network theory at center stage, then this must be because the interaction effects can sometimes be large.

The other extreme, the pure Walrasian approach, would suggest that individuals essentially only interact through large, impersonal markets, and that who trades with whom, can safely be ignored. Indeed, some network models have been criticized precisely because they assume that agents only trade or interact with a limited number of others, and as Durlauf (2012) has rightly indicated, there are large, even anonymous markets on which many individuals trade without being specifically linked to the other participants. However, the purpose of this chapter is to suggest that such markets are, in fact, the exception, and that closer empirical inspection of most markets shows that the networks of interactions between individuals do play an important role. Indeed, to assert that what individuals choose to do, on the apparently large, anonymous markets, is not influenced by those with whom they are linked through family, social, or other connections is unrealistic. In fact, individuals, firms, and collective entities are all embedded in many different sets of relations. To obtain a reasonably complete picture of how aggregate activity emerges, we cannot afford to ignore the influence of individuals on each other, and the important fact that not only do these influences change over time, but the structures of the networks themselves are constantly being endogenously modified.

We have to acknowledge that the direct interaction between agents and the way in which that interaction is organized has fundamental consequences for aggregate

[1] Walras never mentioned the auctioneer himself, as Walker (1996) has indicated, but as De Vroey (1999) has pointed out, the auctioneer seems to be the only device consistent with Walras' arguments.

outcomes. To reiterate, when agents are directly linked to and influence each other, the relationship between the behavior of individuals and the behavior of aggregate variables will be different than in the anonymous market situation in which all agents are linked to each other only through the price system. What we observe at the aggregate level will not mimic what we observe at the individual level, nor will it correspond to the behavior of some "representative individual." Moreover, that rationality we attribute to economic individuals, in order to justify and analyze the behavior of aggregates, may have to be modified. Just as neurologists would not think of explaining behavior by studying the changes in a representative neuron, neither should economists try to explain aggregate phenomena in this way. This does not mean that one should not be interested in what happens at the micro-level, but rather that the passage to the aggregate level is mediated by the network structure in which individuals find themselves. Neurologists will continue to examine what happens at the molecular level but would not argue that there is some simple passage from that level to the aggregate activity of the brain that does not involve the network of interactions between neurons. Of course, as economists, unlike neurologists, we do not usually descend as far as the level of the neurons of economic agents, but as interest in so-called neuro-economics has developed, it has been argued that economic behavior is very much determined by the network of neurons that is activated in a certain situation, and that as the situation changes another network may become active. Thus even at this level it is the network structure of the neurons that is important (see Oullier et al. 2008).

To use another analogy, we would not expect to be able to explain how much food is stored by a colony of ants by looking at the behavior of individual ants in isolation. The organization of the ants plays an essential role. This example raises an important point. Far from complicating things, taking direct account of interaction and the networks which organize it, actually makes life simpler for the economic theorist. This is because the reasoning and calculating capacities we need to attribute to economic agents may be of a lesser order than in standard models.

Two examples of direct interaction are, perhaps, worth evoking at this stage. The first concerns the vexed question of the stability of general equilibrium. Here, most of the attention has focused, as I have remarked, on the idea of some central market clearing mechanism that might lead an economy to equilibrium. However, many economists from Edgeworth (1881)[2] to Hayek (1945)[3] have insisted on the fact that direct interaction between agents plays a crucial role in determining aggregate

[2] Indeed Walras (*Letter no. 927 to Von Bortkiewicz*, in Jaffe 1965) complained that Edgeworth considered all his work on price adjustment as worthless and that the only realistic assumption was that prices emerged as the result of haggling between individuals.

[3] Hayek (1945), for example, explicitly argued that information is never available to all the participants in the economy but that it is transmitted by means of transactions between individuals, each of whom possesses some small part of that information. He argued that prices would emerge that would encapsulate all this information. However, he was unable to specify the precise mechanism through which this would happen.

outcomes. Edgeworth (1881) was dismissive of the Walrasian idea of a market as a set of isolated individuals:

> You might suppose each dealer to write down his demand, how much of an article he would take at each price, without attempting to conceal his requirements; and these data having been furnished to a sort of market-machine, the price to be passionlessly evaluated.
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> —Edgeworth 1881, p. 30

The natural setting within which to study Edgeworth's own bargaining approach would seem to have come with the development of game theory. Nevertheless, frustratingly, the various discussions of price formation mechanisms in which individuals trade directly with each other have almost invariably left the structure of trade to one side. The various non-tatonnement processes, or trading mechanisms, a la Feldman (1973, 1974) assume that individuals are drawn at random to trade with each other. If one thinks of bargaining processes such as that of Rubinstein and Wolinsky (1985), for example, nothing is said about who bargains with whom, just that there are individuals in a bargaining situation. There has, of course, been a later literature on bargaining in networks (see, e.g., Abreu and Manea 2012 and Manea 2011). However, the general question as to how individuals through their direct interaction might generate equilibrium prices did not involve the explicit use of networks. Manea, in his chapter in this handbook, looks at a number of the questions associated with bargaining in networks and highlights the importance of the discount factor that players use when evaluating outcomes as bargaining proceeds. This is an interesting problem, since it is not clear to what extent, in empirical situations where the market functions for a limited and specified period of time that discounting plays a real role; for example, it might be that the discount factor is a proxy for the uncertainty as to how many units are left to be sold.

It might also be worth observing that a great deal of the game-theoretic literature on this subject has concentrated on the convergence of the process to an equilibrium, and often a Nash equilibrium. But, as Von Neumann and Morgenstern suggested, the nature of the game theory that they developed was fundamentally unsatisfactory because of its static nature, and Morgenstern said that Von Neumann's aversion to the Nash equilibrium was precisely that it avoided the non-equilibrium dynamics involved. Manea also emphasizes the fact that we need to take into consideration the extent to which individuals know the structure of the network, and what the matching mechanism is.

A second example of how local interaction has long been envisaged as playing a part in the evolution of the economy is that involving the simple idea that individuals rarely obtain information independently and then act on it, but rather tend to be influenced by what others are doing. It was Poincaré (1908) who put his finger firmly on this. He was critical of Bachelier's (1900) thesis for which he was the external arbiter. Bachelier laid the foundations of what has come to be called the efficient markets hypothesis, by assuming that individuals observe information independently of each other and by acting upon it, that information is incorporated into prices. Yet, Poincaré objected to this and argued that in fact markets and financial markets are characterized by "herd behavior." He explained that he there is a natural trait in human nature which is to herd, like Panurge's sheep, and this undermined the mathematical structure that Bachelier developed.

Thus, there was imbedded in Poincaré's vision of how markets functioned a notion of contagion. Yet, nothing was specified about how this contagion spread, other than to say that individuals have a direct influence on each other. The idea of isolated individuals receiving idiosyncratic information and, somehow, through the way in which they interact, transmitting this information to others, was very different from a network of mutually observing participants.

However, if one wants to be more specific about the consequences of direct interaction, one has, as Lucas observed, to say more about how this interaction is organized and, in particular, who interacts with whom. To analyze this, we need to know about the network of links between the individuals, whether these are consumers, firms, or other collective entities. As I have said, networks and network analysis have played a central role in many disciplines, both in the social sciences and in the "hard sciences," but for a long time their role in economics was ambiguous. Direct interaction and the results of that interaction were classified as "externalities" and were considered as "imperfections" from the point of view of the benchmark model in which the participants only interact through the price system.

For many economists the study of networks was limited to analysis of the functioning of physical networks such as the railway, the telephone system or, now, the Internet. Yet, more recently it has been recognized that networks, in fact, are much more fundamental and pervasive than this, and this is well illustrated by the work of Goyal (2007), Jackson (2008), Vega-Redondo (2007), and Ioannides (2013) on economic and social networks. Indeed, almost any serious, detailed analyis of economic activity leads to the conclusion that network structures both within and between organizations are important. Nevertheless, a consensus seems to have developed among economists that networks and graph theory are useful tools to complement standard economic analysis but do not constitute the basis for rethinking the model to which we have become accustomed. These authors are regarded with great respect but are not generally thought of as the basis for a new paradigm. The whole purpose of this chapter is to suggest, to the contrary, that founding economic theory on a network-based benchmark model would provide insights and answers to enigmas which the standard model does not let us handle. One effort to develop such an approach is that of Easley and Kleinberg (2013), but there are few signs that their textbook will be commonly used at the undergraduate level.

To make the basic point, I will present some illustrations as to how networks can produce phenonema that are often difficult to generate with standard models. The suggestion then is that direct interaction is the benchmark and pure competition but an exceptional and very special case that does not necessarily provide the best basis for the analysis of empirical phenomena. As a Chinese philosopher said, "Water that is too pure has no fish in it."

2.1 Markets

In the first example that I mentioned, that of price adjustment in the general equilibrium model, the mechanism can be characterized as akin to an auctioneer who calls out the prices for all goods. But what happens if, as Edgeworth (1881) envisaged, trade takes place between individuals—who sets the prices and why should the same price prevail for units of the same good? Those who have studied the *theory of value* seriously would argue that if we observe different prices, these are for units at different times and places even if they have identical physical characteristics. This means that technically they are different goods. But, leaving this objection to one side for a moment, would one then expect to find different units of the same good at the same place being traded over a limited period of time at the same price? Consider Cournot's definition of a market:

> . . . not any particular market place in which things are bought and sold but the whole of any region in which buyers and sellers are in such free intercourse with each other that the prices of the same goods tend to equality easily and quickly.
>
> — A. Cournot, *Recherches sur les Principes Mathématiques de la Théorie des Richesses*, Chapter IV

He does not explain how this might happen but does suggest that, unlike in a network view, all participants interact with all the others and somehow this eliminates price discrepancies. However, if this were to be essentially the case, the vast literature on searching for the lowest price or wage when there is a distribution of prices for the same good would be of no empirical interest. To see why this is not the case, consider the following example of a real market, that of the wholesale fish market in Marseille, where the conditions for such a process to work would seem to be ideally fulfilled.

This market is situated at Saumaty on the coast at the northern edge of Marseille, which for the period for which the data was collected was open every day of the year from 2 a.m. to 6 a.m. At this market, over 500 buyers and 45 sellers come together, although they are not present every day and transact more than 130 types of fish. Prices are not posted. All transactions are pairwise. There is little negotiation and prices can reasonably be regarded as take it or leave it prices given by the seller.

The data set consists of the details of every individual transaction made over a period of three years. The data was systematically collected and recorded by the Chamber of Commerce, which managed the market. The following information was provided for each transaction:

(i) The name of the buyer
(ii) The name of the seller
(iii) The type of fish
(iv) The weight of the lot
(v) The price per kilo at which it was sold
(vi) The order of the transaction in the daily sales of the seller.

The data runs from January 1, 1988 to June 30, 1991. The total number of transactions for which we have data is 237,162.

Two specific questions can be asked about the functioning of this market. Do all traders trade with each other, or do networks of buyers and sellers form? Does this result in different units of the same fish being transacted at the same price as Cournot seemed to suggest? In other words, does the market self-organize into a state characterized by what is traditionally assumed, or does it exhibit rather different features?

2.1.1 A Simple Model

It is often useful to build on a very simple theoretical model for which we have analytical results, and then to add more realistic features that make exact results more difficult to obtain. Then the model can be simulated, to see whether the results obtained in the simple case still hold.

In the market, there are n buyers indexed by i and m sellers indexed by j. The buyers update their probability of visiting sellers on the basis of the profit that they obtained in the past from them. If we denote by $J_{ij}(t)$ the cumulated profit, up to period t, that buyer i has obtained from trading with seller j where

$$J_{ij}(t) = \Pi_{ij} + (1-\gamma)J_{ij}(t-1) \tag{2.1}$$

and where Π_{ij} is the profit that the buyer i makes if he visits seller j and the latter still has fish available (assume for the time being that the profit does not vary over time). Then the probability $p_{ij}(t)$ that i will visit j in that period is given by

$$p_{ij}(t) = \frac{e^{\beta J_{ij}(t)}}{\sum\limits_{k} e^{\beta J_{ik}(t)}} \tag{2.2}$$

where β is a reinforcement parameter which describes how sensitive the individual is to past profits. This nonlinear updating rule will be familiar from many different disciplines and is also widely used in statistical physics. It is known as the "logit" rule or, in game theory, as the "quantal response" rule. The rule is based on two simple principles. Agents make probabilistic choices between actions. Actions that have generated better outcomes in the past are more likely to be used in the future.[4]

To simplify matters at the outset we will start with a continuous approximation of our model which is actually in discrete time. Furthermore, we will replace the random variables by their expected values. This is referred to as the "mean field" approach. In

[4] Such a process has long been adopted and modeled by psychologists (see, e.g., Bush and Mosteller 1955). It is a special form of reinforcement learning. It has also been widely used in evolutionary and experimental game theory (see Roth and Erev 1995), and a more elaborate model has been constructed by Camerer and Ho (1999).

this way it is easy to see that the change in cumulated profit for the buyer is given by

$$\frac{dJ_{ij}}{dt} = -\gamma J_{ij} + E(\Pi_{ij}). \tag{2.3}$$

Using the learning rule that I have given, we know the probability for agent i to visit seller j and can therefore calculate the expected gain from that visit. Recall that there are two things involved here—the probability that the seller j still has fish available when buyer i arrives, and the probability that the latter chooses seller j. So the expectation is given by

$$E(\Pi_{ij}) = \Pr(q_j > 0)\Pi_{ij}\frac{\exp(\beta J_{ij})}{\sum\limits_{k}\exp(\beta J_{ij})}. \tag{2.4}$$

Now consider an even simpler case where the seller is sure to have fish, in which case we have

$$\Pr(q_j > 0) = 1. \tag{2.5}$$

Now simplify even further and look at the case where there are just two sellers (and furthermore each time a buyer visits one of the sellers he receives a fixed profit of Π) and find the equilibrium level for the cumulated profit for a buyer from seller 1. This will, of course, be when

$$\frac{dJ_1}{dt} = 0. \tag{2.6}$$

Substituting this gives

$$\gamma J_1 = \Pi\frac{\exp(\beta J_1)}{\exp(\beta J_1) + \exp(\beta J_2)}. \tag{2.7}$$

Now take the difference between the profits from the two sellers and we have

$$\Delta = J_1 - J_2. \tag{2.8}$$

If we now substitute we have the following expression

$$\Delta = \frac{\exp(\beta\Delta - 1)\Pi}{\exp(\beta\Delta + 1)\gamma}. \tag{2.9}$$

We now have simply to solve this equation for Δ and this gives two cases. First, consider

$$\beta < \beta_c = \frac{2\gamma}{\Pi}. \tag{2.10}$$

In this case, when the importance attached to previous experience is below the critical value β_c we have

$$\Delta = 0 \quad J_1 = J_2\frac{\Pi}{2\gamma}. \tag{2.11}$$

There is a single solution and the cumulated profits from both sellers, and hence the probabilities of visiting them, are the same.

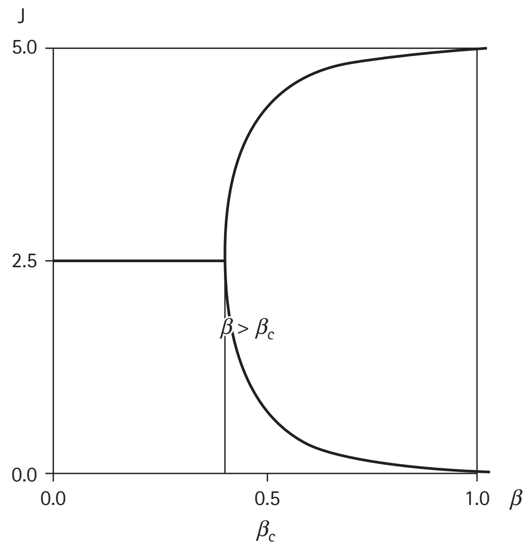


FIGURE 2.1 Source: Weisbuch et al. (2000).

However, when $\beta > \beta_c$ then there are three solutions and $\Delta = 0$ is unstable and there is a rapid transition at $\beta > \beta_c$. By this we mean that as soon as β passes above the critical value, the probabilities of visiting each seller rapidly become very different. All of this is illustrated in Figure 2.1.

Note that even in this most basic case, which would seem to have simplified away all the interesting features of the market, a small change in one parameter, β, the sensitivity to past profits, leads to a radical change in the behavior of the buyer who will, when β is high, not treat the two identical sellers identically but will attach himself with high probability to one of them. Furthermore, it is easy to show that there is considerable inertia, or hysteresis, in the system. Once attached, the other seller would have to have a considerably lower price to be able to attract the buyer back (see Weisbuch et al. 2000). However, suppose that we start to introduce some more realistic features into the model. For example, sellers no longer have a fixed predetermined amount of fish, but decide each day in the light of their experience how much to buy, while buyers reinforce on their previous experience. Initially, suppose that sellers keep their price fixed, and adjust the amount of fish that they buy and then put on offer each day. Each seller forecasts his sales on the basis of past sales. Suppose that we then simulate the evolution of the purchases of the individuals in the market. As shown in Weisbuch et al. (2000), we observe that when buyers have a β below their critical value β_c, they keep shopping around. Since sellers are faced with varying numbers of clients, they find it difficult to anticipate demand. As a result, considerable amounts of fish remain unsold at the end of the day, and some sellers find themselves unable to satisfy the demand. If, on the other hand, buyers have coefficients β above their critical value, β_c then buyers become

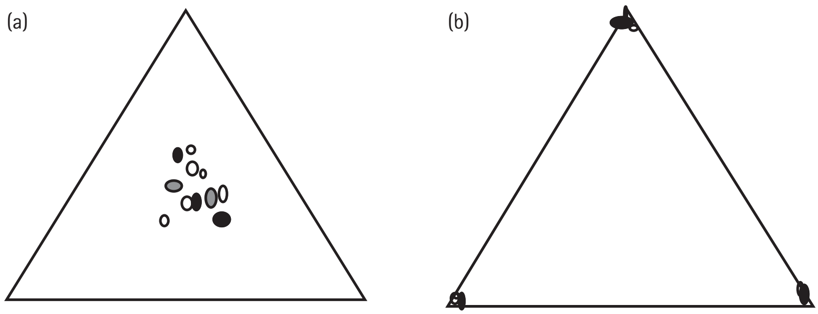


FIGURE 2.2 Source: Kirman (2010).

loyal to their sellers and the latter can then forecast the demand correctly and much less fish is wasted.

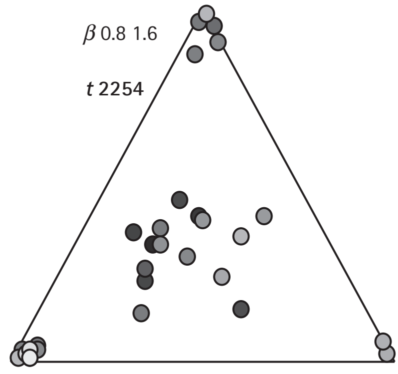
This would seem to be in contradiction with the overall efficiency of the market since buyers who become locked on to a particular seller can no longer benefit from the fact that another seller may provide more profit. Nevertheless, it became clear from the simulations that the overall efficiency of the market, in terms of the percentage of fish purchased which was then sold, was higher in the presence of loyal buyers. Thus, an informational loss was compensated for by an efficiency gain.

The buyers and sellers in the market structured themselves into a network which improved the throughput of fish, even though this might seem to have deprived some of the actors of information in the process. The seeds of the explanation can be found in the probabilistic rule, the "logit rule" (equation 7), used to determine the probability of a buyer visiting a seller on the basis of past profits. This rule can be derived (see Weisbuch et al. 1998) from the maximization of a convex combination of the information gain, "exploration" from visiting new sellers, measured by entropy and the benefit from using past experience, "exploitation." Individuals who, in the market, have a low critical value β of the key parameter β_c i.e., who attach considerable importance to previous experience, will rapidly converge to visiting a single seller, and thus give up the benefits of exploring new opportunities.

Proceeding in this way, by examining the evolution of the structure of relationships in the market, provides a very different picture from the standard one of anonymous individuals trading at equilibrium prices.

One further point is worth mentioning. When we simulated the model with, for example, 3 sellers and 30 buyers, where the latter all had β values below their critical value, β_c individuals continued to "shop around," as in Figure 2.2a, where each buyer is a dot in the 3 simplex, his vector of probabilities of visiting the various sellers. However when the buyers had values of β higher than the critical value β_c they rapidly became loyal to particular sellers, as in Figure 2.2b. Now a natural question arises. What if the population of buyers is mixed with differing critical values β_c. The answer might be expected to be that the structure of the graph would be at least partially demolished,

FIGURE 2.3 Source: Kirman (2010).



since sellers would no longer be able to predict accurately the number of buyers they would receive and this might undermine the loyalty links. However, simulating the model in this case showed that the presence of low, below the critical β_c buyers did not prevent the higher value buyers from becoming loyal, as can be seen in Figure 2.3 (Kirman 2010).

In that figure there are two groups of buyers—those with a low threshold β_c and those with a high threshold β_c. Even after over 2000 iterations, the separation between the loyalists and the shoppers persists. The empirical evidence from the Marseille fish market is clear, as shown in Weisbuch et al. (2000). There is a clear bimodal distribution of loyalty, by which I mean the number of sellers visited by a buyer in a month. There is a concentration of buyers on one, that is, who only visit one seller, and then a distribution of other buyers with a mean of 5. This reflects precisely the prediction of the theoretical model.

However, when trying to build a more realistic model of a market, at each step there is some important feature of the market that has been omitted but which could safely be ignored in a more conventional model. In the case of the Marseille fish market, as soon as one understands that networks will evolve at least partially into clusters of buyers around different sellers, and that there is inertia in the system, the question naturally arises as to why the sellers do not exploit this structure by charging higher prices to their loyal customers.

To examine this question, we built an "agent-based model" (ABM), in Kirman and Vriend (2001), to see what would happen if buyers, using simple rules, not only decided which sellers to visit but also which prices to accept, and sellers decided which prices to charge to which buyers at each point in time. Such a model is not analytically tractable but can be simulated and robustness checks made on the relevant parameters. In the model in question, each individual agent uses a Classifier System (an approach to learning developed by John Holland 1976), for each decision and this means that each agent has four such systems "in his head." A classifier system consists of a set of rules. Each rule has a condition "if . . . " and an action "then . . . " and in addition each rule is assigned a certain strength. The classifier system decides which of the rules will be active at a given point in time. It checks the conditional part of the rule and decides among all of those rules for which the condition is satisfied which to choose. This is done by a simple auction procedure. Each rule makes a "bid" to be the current rule and this bid = current strength $+\varepsilon$ where ε is white noise, a normal random variable with mean 0 and fixed variance. The rule with the highest "bid" in this auction becomes the active rule. The white noise means that there was always some experimenting going on, and there was always some probability that a rule, however bad, will be chosen.

The classifier system updates the strength s of a rule that has been active and has generated a reward s_{t-1} at time $t-1$ as follows. $s_t = s_{t-1} - cs_{t-1} + creward_{t-1}$ where $0 < c < 1$. Hence, as long as the reward generated by the rule on day $t-1$ is greater than its strength at $t-1$ the strength will increase. The strength of each rule converges to the weighted average of the rewards generated by that rule. What the reward is will depend on the rule in question. Supposing that in our market example the rule for the buyer is of the form, *"if the price proposed by the seller for one unit of fish in the morning is 10 euros then accept."* The reward for using this rule would then be the profit that is generated by using it. In this case that would be the price at which the unit of fish is sold on the retail market minus the price paid. When the model is started, the strengths of all rules are equal.

The question now is how does the market structure itself? Do the networks of buyers linked to sellers persist? Will price discrimination occur or will buyers move on to cheaper suppliers? The answers are interesting. The networks do indeed persist, and loyal buyers pay higher prices than their less loyal counterparts, but paradoxically make higher profits. This is because sellers learn to serve their loyal customers first but to charge them higher prices. The advantage of better service more than offsets the higher prices paid. The market self-organizes into a stable situation in which the networks become well established and change very little. The empirical evidence confirms these findings. Buyers who visit several sellers pay lower prices than those who concentrate all their purchases on one seller but are, in general, less profitable.

The picture that emerges from all this is far from that of the perfectly competitive market but the importance of the network of buyer-seller relations is clear. This is still a simplified model, and there are a number of other features that one might want to take account of, such as family ties or homophily considerations. Graddy (1995) in her investigation of the Fulton Fish Market, for example, found that ethnic considerations played a role in determining how much buyers paid. Geertz (1978), in his famous studies of North African bazaars, studied the impact of the relationship between buyers and sellers, and Mclean and Padgett (1997) emphasized the role of family relations in the textile markets in Rennaissance Florence. The latter is particularly striking with regard to what we observed on the Marseille fish market. As they say:

> . . . Both from their perspective as buyers and from their perspective as sellers, banking and wool firms engaged in significantly more repeat-business and "relational trading" than perfect competition theory permits. This was true not only internal to the banking and wool sectors themselves, but, more importantly, between the banking and wool firms

and a majority of all other sectors. Thus, for a two hundred year period between 1300 and 1500 the structure of the Florentine markets bore many of the hallmarks we still observe in modern markets. Networks of relations are omnipresent and the anonymous competitive market is a rare exception.

2.2 Networks in the Financial Sector

Let me now turn to another example, that of the financial sector, which has too often been described as one in which most of the action takes place between numerous relatively anonymous actors and where the structure of the links between these actors is of little importance. It is in fact clear from recent events that this is far from the case.

Consider for a moment the crisis of confidence in the world economy after 2008. Here we see the role of networks. Bad risks from the American mortgage market had been bundled with good risks into derivatives, and these had diffused through the international banking system. Up to that point the financial system, thought of as a network of banks, had become larger and more connected and it was argued that the resultant diversification of risk was a stabilizing influence. Yet there was little analysis of the effect of the increasing connectivity of the network on the probability of an epidemic of negative impacts. The problem is that as risk is diversified into different instruments, those who buy these instruments lose track of the underlying assets. Thus, while the risk is diversified, the information is not. When this happens, an epidemic of mistrust can develop as each bank in the network is wary of lending to another which may have inherited risks that turned out to be bad. Worse, not only may banks find themselves with assets which may turn out to be toxic but the market may also revise its valuation of these assets so that the prices of even those derivatives that do not contain toxic elements may fall. Thus, the fact that banks are highly interdependent through, in part, the exchange of these assets, is crucial to our understanding of how a market or an economy functions or may fail to function.

There is by now a considerable literature on networks and contagion in financial networks and an excellent survey is given by Cabralles et al. (2015), in their chapter of this book. They give an account of both the theoretical developments and of some of the more empirical work which is the focus here. However, the theoretical models that they discuss are still very highly simplified and stylized. For the banking sector, for example, almost all theoretical models take, as the primary function of banks, that of direct financial intermediation. That is, banks simply match those with funds available with those who need those funds to invest in economic projects (see, e.g., Gertler and Kyotaki 2011). Yet it is known that such activities are a small proportion of the total activites of banks. Funds transit through a multitude of operations and transformations as they are packaged and repackaged and this trade in derivatives is now the principal activity of the sector. Figure 2.4 illustrates this.

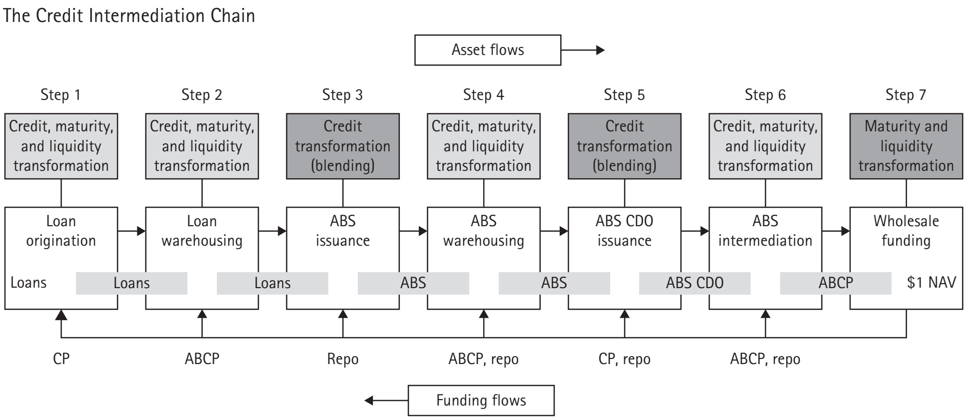


FIGURE 2.4 Source: Pozsar (2010).

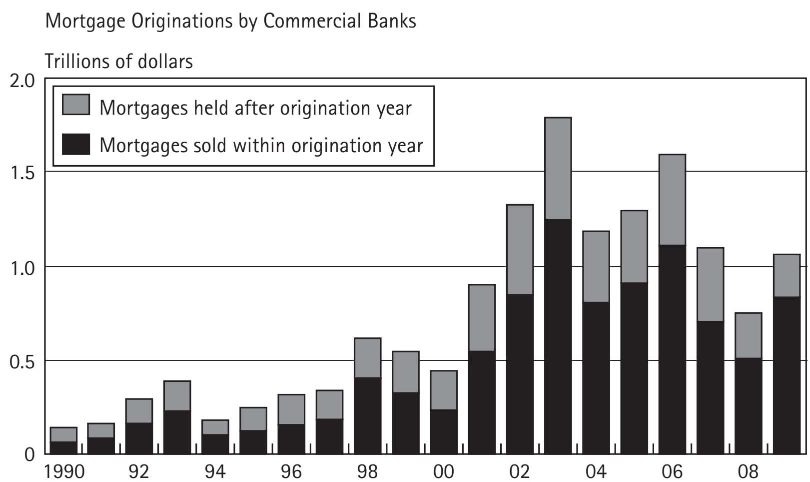


FIGURE 2.5 Source: Cetorelli et al. (2012).

To see how far we have moved from a system where banks issued loans to their clients and then received the associated interest and capital payments, it suffices to examine how many mortgages remain on the books of the institution that issued them. This is illustrated in Figure 2.5. As is clear the majority of mortgages were sold to other institutions.

The transformation of the banking sector and of financial intermediation was far from specific to the United States. An indication of this is given by the expansion of the derivatives market in the United Kingdom, as illustrated in Figure 2.6.

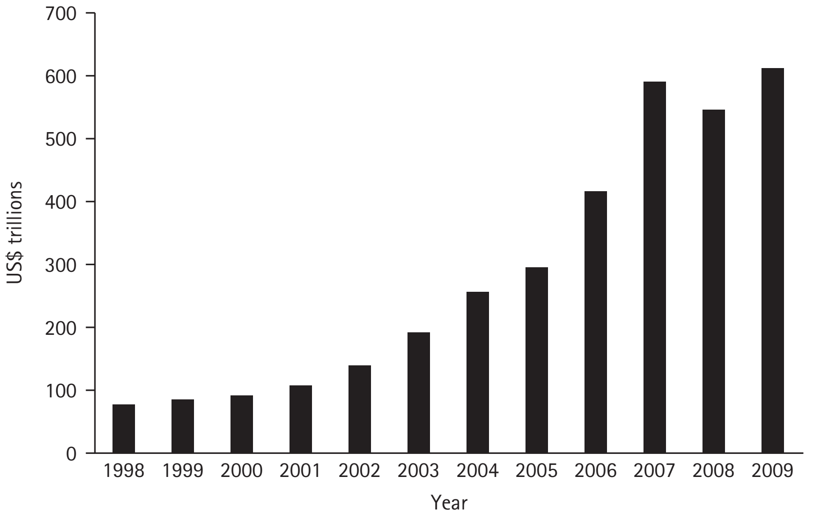


FIGURE 2.6 Notional principal value of outstanding derivative contracts, recorded at year end. These include foreign exchange, interest rates, equities, commodities, and credit derivatives. Data from UK Department for Business, Innovation and Skills, International Monetary Fund and Bank of England calculations (Source: Haldane and May 2011).

This reflects the fact that the linkages between banks were rapidly expanding. What happened subsequently was that various banks were obliged to reassess their losses as a result of the subprime episode and its consequences. These losses were due not only to their discovering the true nature of their assets, but also to the revaluation of these downward by the market. The resultant losses of the banks enhanced the epidemic of mistrust. It is possible that it is simply the increased connectivity of the network that favored the development of such an epidemic. But, in fact, the problem is more subtle than this. Propagation of information or of shocks may be more likely, and the effect may be bigger in networks that are much less than fully connected.

This problem has already been discussed by Allen and Gale (2000). Using a network structure involving four banks, they showed that the spread of contagion depends crucially on the pattern of interconnectedness between banks; that is, on their exposure to each other. When the network is completely connected, with all banks having exposures to each other, such that the amount of interbank deposits held by any bank is evenly spread over all other banks, the impact of a shock is easily absorbed. Every bank suffers a small loss and there is no contagion.

By contrast, when the connectivity of the network is lower, with banks only having exposures to a few counterparties, the system is more fragile. The initial impact of a shock is concentrated among neighboring banks. Once these succumb, the premature liquidation of long-term assets and the associated loss of value bring previously unaffected banks into the front line of contagion. Thus, the structure of the network heightens rather than dampens the effect of a shock. Indeed, there is evidence that even in large, apparently anonymous markets, participants trade or interact with a rather small group of other traders. Hence, the fact that the participants are clustered into limited groups may cause the propagation of a shock which was not particularly large at the outset.[5] In general, what we want to know is whether it is true that a network that emerges from a particular evolution of trading relationships which are mutually advantageous can become fragile without those who participate in it realizing what is going on. Haldane (2009) of the Bank of England, when talking about the evolution of the banking network, stated, "This evolution in the topology of the network meant that sharp discontinuities in the financial system were an accident waiting to happen. The present crisis is the materialisation of that accident" (p. 4).

Yet, this would seem to contradict the results of Allen and Gale (2000), for in their model as the network becomes more connected it becomes more robust, while what we have witnessed might suggest the contrary. However, it is important to realize that it is not only the connectivity of the network, but other characteristics also that come into play when considering systemic risk. It is worth examining the relation between these two phenomena when the scope of the model is enlarged. For example, Iori et al. (2006) find that when the network of banks is heterogenous, an inter-bank market can have ambiguous consequences for systemic risk. As usual, the benefits of mutual insurance need to be contrasted with the possibility of contagion. They also show, however, that as the connectivity increases the system becomes more stable, echoing the finding of Allen and Gale (1998). Similar conclusions in relation to the degree of network connectivity are reached by Gai and Kapadia (2010), Montagna and Lux (2013), and Nier et al. (2007). However the fact that it is not enough to consider just connectivity is also shown by Gai and Kapadia (2010). They introduce idiosyncratic and aggregate shocks and compare the impacts of the two. They show that when banks have relatively high capital to total asset ratios, the system can survive the former type of shock but, with aggregate shocks, contagion risk significantly increases. Efforts such as these to model the financial system using complex networks analysis have been promoted by ecologist Robert May (see Haldane and May 2011), who sees clear analogies between the collapse of ecosystems and that of the banking network.

Over the last 10 years, many researchers have followed this promising line of research by using these analytical tools to improve our understanding of the financial sector in general and banking systems in particular. Yet the literature has often had to focus on simple models to obtain analytic results. Allen and Gale (2000) use a very simple four-bank structure, for example, and Cabralles et al. in this handbook compare a ring structure for the network of institutions with a completely connected graph. However, the banking network tends to have a more "core-periphery" structure, and it would be interesting to extend their analysis to such a case.

[5] See Allen and Babus (2009) for a review of various applications of network theory to the study of financial issues.

In parallel to the literature in economics is econophysics, which has used complex systems to analyze various economic systems, including the behavior of asset prices (for a review, see Varela et al. 2013). This field has not focused on analytical results and often uses simulations.

Battiston et al. (2012) characterize the evolution over time of a network of credit relations among financial agents as a system of coupled stochastic processes. Each process describes the dynamics of individual financial robustness, while the coupling results from a network of liabilities among agents. Here again the role of the network of interdependencies between entitities is crucial. The average level of risk diversification of the agents coincides with the density of links in the network. In addition to a process of diffusion of financial distress, they also consider a discrete process of default cascade due to the re-evaluation of agents' assets. They then investigate the probability of individual defaults as well as the probability of systemic default as a function of the network density. They underline the reasons for doubting the idea that diversification of risk always leads to a more stable financial system, since in their model, as in other network models, a tension emerges between individual risk and systemic risk. As the number of counterparties in the credit network increases beyond a certain value, the default probability, both individual and systemic, starts to increase. They explain that this tension originates from the fact that agents are subject to a financial accelerator mechanism. In other words, individual financial fragility feeding back on itself may amplify the effect of an initial shock and lead to a full-fledged systemic crisis. Once one accepts the crucial role that the network of linkages between agents or entities plays, their results offer a simple possible explanation for the endogenous emergence of systemic risk in a credit network.

Again, the network structure as it transmits information and shocks can generate sudden large and endogenous changes in the overall performance of the system. Understanding the dynamics of this complex system depends on the recognition of a certain number of factors. Among the most important is the heterogeneity of the actors involved. This in turn involves several considerations, the size of the entitities, their different scope, and the geographical extent of their operations. These aspects are well illustrated in the graph of Australian banking interdependencies (large exposures) in Figure 2.7. Casual visual inspection reveals that this particular network is far from the simple forms such as rings or complete networks often used for analytical tractability.

What we observe is that this network has a number of rather special features. The big Australian banks are connected both to foreign banks and the smaller credit institutions, but the latter have few connections with banks outside Australia while the foreign banks are linked to each other and to the major Australian banks. Analyzing the consequences of a difficulty in some part of this system is not possible without understanding the structure of the network. In other words, both the nature of the nodes and the structure of the graph in which they are embedded play an important role.

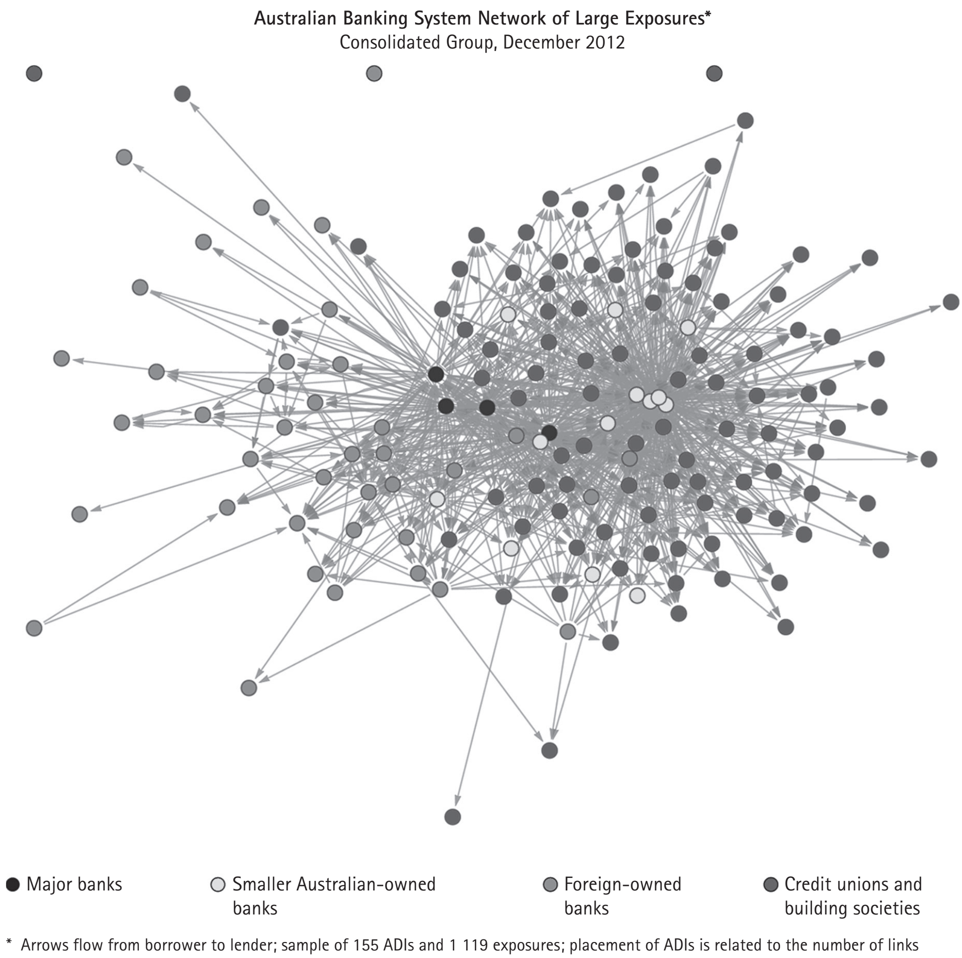


FIGURE 2.7

2.2.1 Derivatives

As mentioned earlier, an important part of the financial puzzle is the role of derivatives. These instruments package tranches of assets held by one financial institution into new assets, which are then sold to other institutions. The resultant instruments can be repackaged and resold. This, it was thought, would diminish risk, since the risk in the instruments in question was diversified. The opposite turned out to be true. As Warren Buffett (2002) stated even before the crisis:

> The derivatives genie is now well out of the bottle, and these instruments will almost certainly multiply in variety and number until some event makes their toxicity clear.

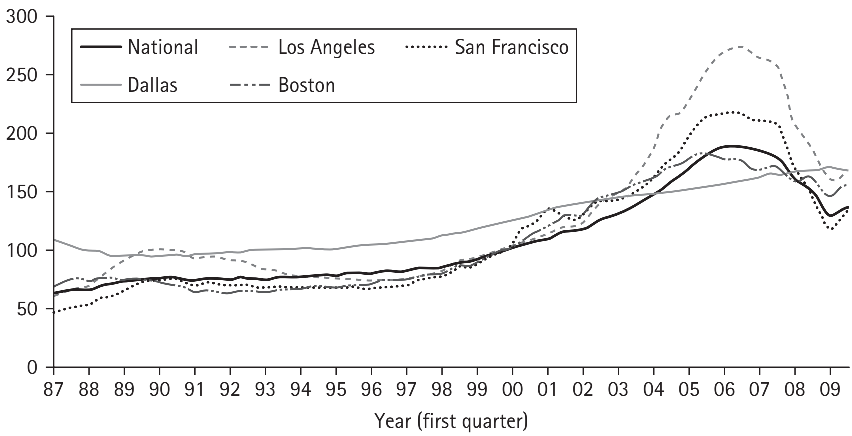


FIGURE 2.8 The evolution of house price indices in different cities in the United States, 1987–2009 (Source: Case Shiller).

> Central banks and governments have so far found no effective way to control, or even monitor, the risks posed by these contracts. In my view, derivatives are financial weapons of mass destruction, carrying dangers that, while now latent, are potentially lethal.

What is the relation between these assets and the network of banks that issue and sell them? A first point is that the actors in the financial sector network have a tendency to adopt the rules or norms that currently prevail in that network. To illustrate this approach, I will now give an example of a model that portrays a market crash and in which individuals have local and limited knowledge, but whose actions are governed by the choices made by those with whom they are in contact.

2.2.2 An Example

To see how the interactions of entities or individuals with whom they are linked can produce an endogenously generated catastrophic change in a market, it is worth considering an empirical example. The dramatic collapse of the prices of MBS (mortgage-backed securities) at the beginning of the current crisis is such an example and had profound ramifications for the economy as a whole (Anand et al. 2013). This collapse occurred rapidly despite the fact that the weakness of the assets underlying the derivatives had increased progressively over time. Each of the instruments in question had a single overall rating but, in fact, consisted of tranches of mortgages with different ratings. Figure 2.8 shows the evolution of housing prices over 20 years. The developments from 2006 onward should have been a first indication that defaults on the mortgages involved in the MBS were likely to rise.

The principal reason for this was that the percentage of loans that represented "positive equity"—that is, where the value of the house was greater than the outstanding amount of the house loan—diminished as the increase in house prices slowed down and was reversed.[6]

In Figure 2.9 the default rate on mortgages in the United States for various years is shown. The increase that occurred in that rate for mortgages issued in 2006 and 2007 can be explained by two factors. First, house prices increased more slowly than previously, and the gain from defaulting offset any capital gain. Second, more mortgages were issued on easier terms. To see this in retrospect, of mortgages issued in 2004, 10% were delinquent after 30 months, whereas for those issued in 2007, 10% were delinquent after only 8 months. The evidence was public and available. Yet the evolution of the prices of MBS did not reflect this steady increase, as can be seen in Figure 2.10.

Prices of similarly rated assets remained stable and then suddenly collapsed. There was a different date of collapse for each asset class, and one could argue that at each of these dates some relevant news was revealed and that this caused the downturn. This is hardly convincing as there was a whole chain of actors from the mortgager to the investor in MBS that would have simultaneously received the news and reacted similarly. However, many have argued that the constancy of the prices before the collapse reflected the rational expectations of all these actors and that their interaction then had no influence over the prices of these assets. Yet at the onset of the crisis, Ashcraft and Schuermann (2008) had already pointed out a number of important informational frictions arising in links in these chains of actors, each of which could potentially lead to a breakdown in the system. These frictions ranged from problems of moral hazard involving the payment of the credit rating agencies by asset managers, to principal agent difficulties between the investor and the asset manager, to moral hazard problems between the issuers of mortgages and the arranger who set up a special vehicle to hold the mortgages and securitize them for eventual purchase by investors. What the authors observed is that the presence of all these frictions led to the initial breakdown of this market. The market was a network of interacting agents and was very far from transparent.

What is particularly important to observe is that despite the fact that the delinquency of differently rated assets was evolving similarly, as seen in Figure 2.9, it is clear that the collapse of the better-rated assets came later. This suggests that the estimates of the probability of default on these instruments were influenced by the ratings, whether or not this was justified by the underlying fundamentals. Thus there were other actors, the rating agencies, in the network who influenced the evolution of prices. Pozsar et al. (2010) show that prices were strongly correlated with ratings but that ratings were very poorly correlated with default rates, indicating clearly that the information provided was far from perfect. The essential question is, why did the behavior of the actors in the

[6] In a number of states in the United States (where loans are "non-recourse") the owners of a property on which they have a loan can simply turn the house over to the bank that issued the loan without having any further financial contribution to make.

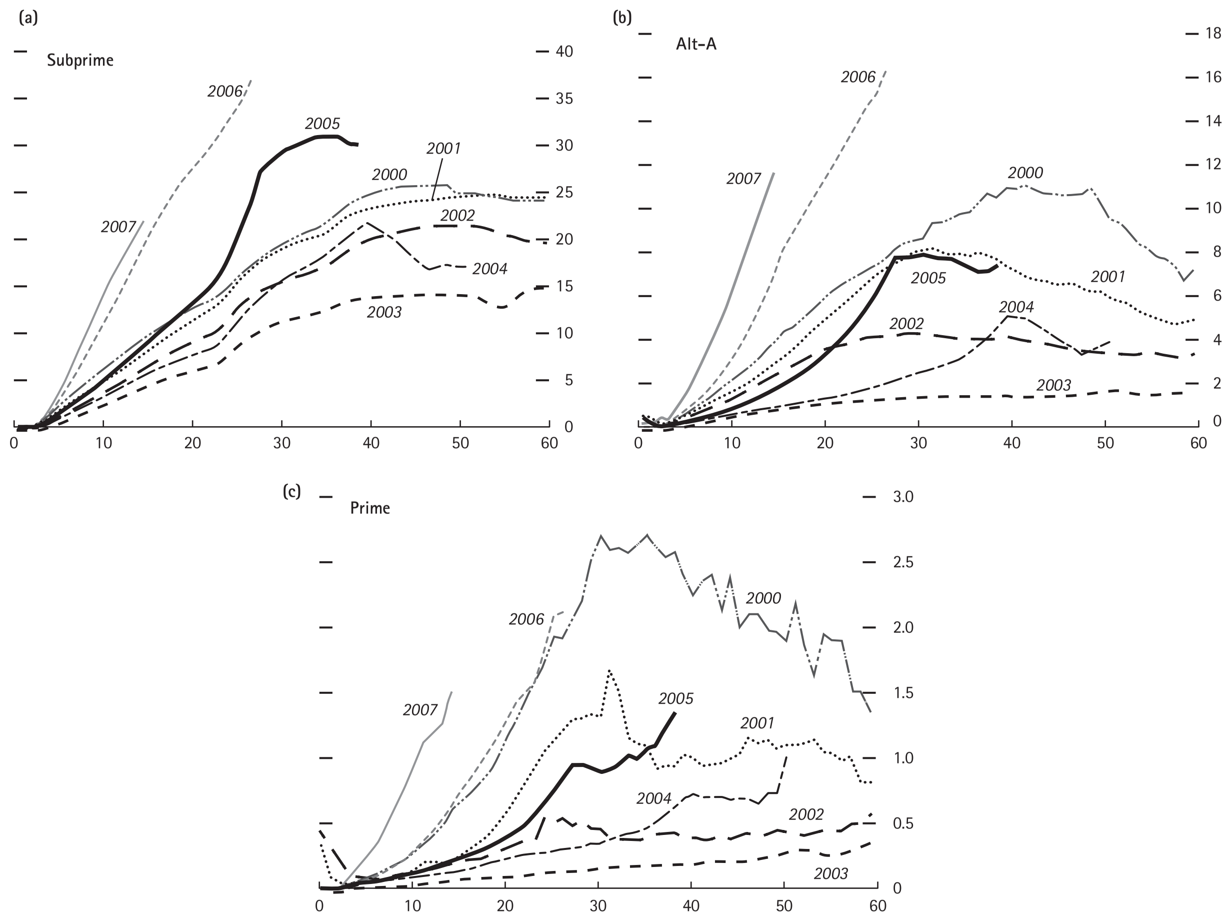


FIGURE 2.9 Delinquency rates on mortgages (months from origin) in the United States originating from 2004 to 2007 (Source: Merrill Lynch and Loan Performance).

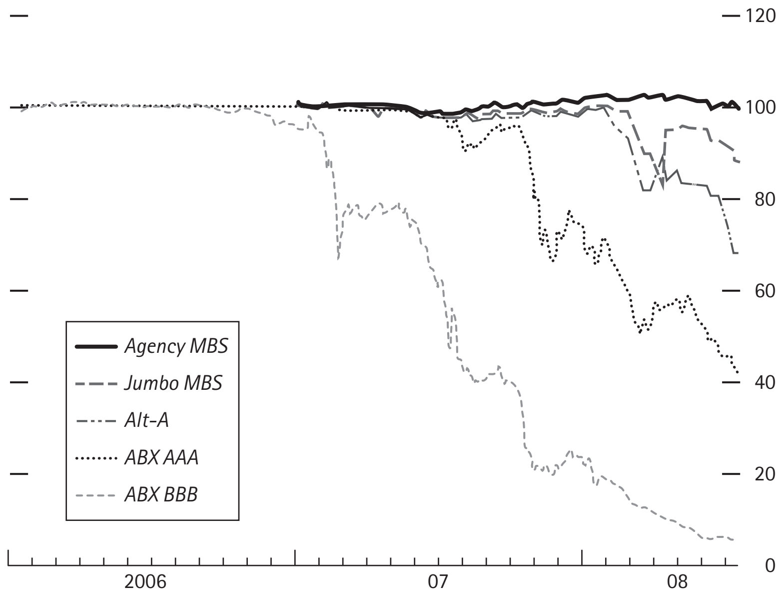


FIGURE 2.10 The prices of MBS with different ratings.

market and their relation to each other prevent the available evidence from translating into a steady decline in the prices of MBS rather than into the sudden collapses that actually occurred?

To understand this, in Anand et al. (2010) we constructed a model of the banking system in which the participants securitize their loans and then sell them via Special Purpose Entities (SPE) to each other. The derivatives thus constructed were made up of bundles of parts of different underlying assets with varying degrees of riskiness. These were frequently rebundled and sold again. It is not obvious why the issuers would have an interest in doing this. The reason lies in the so-called "recourse rule" which puts a risk weight of 50% on individual mortgages but only 20% on highly rated mortgage-backed securities. The amount of capital banks have to hold is conditioned by the risk weighting of their assets. Thus banks bundled their assets to free up capital. Here one sees immediately the role of the network. There is obviously considerable pressure on the rating agencies from those who employ them to overrate derivatives. Worse, even if a rational investor might doubt the rating assigned to a derivative, to reliably estimate the risk entailed checking on the current status of each of the assets in a bundle and involved considerable costs. In other words, the banks were holding derivatives—in particular, MBS—the content of which was extremely costly to evaluate. Not only this, but some of the banks knowingly misrepresented the value of the underlying assets they were selling to their investor clients, as J. P. Morgan admitted in a $13 billion settlement.[7]

[7] November 22, 2013.

These investors had neither the means nor the sophistication to evaluate whether the mortgages in the MBS did, in fact, meet the underwriting standards as was claimed. Finally, the banks when trading among themselves were not doing due diligence. Thus, although these assets were being actively traded, it is difficult to argue that the prices of the associated transactions reflected the decisions of fully informed rational agents. What I have just described is an oversimplified version of a market in which some agents had an interest in hiding or misrepresenting information and others had no incentive to go to the expense of obtaining the full information. Many of the incentives were, contrary to the conventional view of such markets, in the wrong direction. The network structure of the actors and the incentives with which they were faced led to a loss of information as the interlinkages created by securitization developed.

It was worth considering this example in some detail, since it is only by looking at the organization, incentives, and interactions between the actors that one can understand that trying to model such a framework as an anonymous market inhabited by fully informed agents with rational expectations does not capture the essence of what is happening. This market is, to repeat, a complex interactive network, and using a standard model would not have reflected this. The model we proposed focuses on the interaction between the actors in the banking network and provides an explanation as to how a sudden price collapse can occur despite the fact that the underlying fundamentals were gradually changing over a considerable period of time.

Our simple model, which reflects the concerns expressed by Haldane and May (2011), describes the behavior of the participants on the market. This behavior was not irrational in the normal sense of the word but was not fully rational in the sense that that term is understood in economics. The agents in the model have short horizons and condition their evaluation of an ABS not by always examining the fundamentals underlying the instrument, or by analyzing the general evolution of the housing market. Rather, they depended on the ratings of that MBS by the credit rating agencies, and their willingness to buy depended on how much checking was being done by those with whom they traded.

2.2.3 A Simple Model

In this model developed by Anand et al. (2013), the system consists of $i = 1, \ldots, N$ agents, which, in the case of the sub-prime crisis, for simplicity, we can think of as the banks who were both the issuers—via SPEs—and the investors in these ABS. These banks or agents are linked in a network corresponding to the over-the-counter market (OTC), and at each period an agent draws at random another agent among her neighbors. Each agent i is characterized by a variable $z \in \{0, 1\}$which specifies whether she follows ($z = 1$) or not ($z = 0$), the following behavioral rule: purchase an ABS relying on signals from the rating agencies, without independently evaluating the fundamental value of the underlying assets.

Succinctly, we write

$$z_i = \left[\begin{array}{ll} 1 & \textit{if agent } \mathrm{i} \textit{ follows the rule} \\ 0 & \textit{if the agent } \mathrm{i} \textit{ does risk analysis} \end{array}\right. \tag{2.12}$$

The rationale for adopting the rule, as we will see, is not based on the fundamental quality of the asset but rather on the fact that others also follow the rule. If, in fact, enough other participants do so, the agent becomes convinced, not irrationally that the ABS is highly liquid and hence easy to trade.

Assume that the ABS is toxic with probability p. By toxic we mean, for example, that the underlying asset was too favorably rated by a rating agency and either that the original borrower of the loan has already defaulted, or has a higher probability of defaulting, as he is delinquent in his payments. Assume that the cost of purchasing a security is p_0 whereas the payoff from successfully re-selling the security is p_1 where $p_1 - p_0 > 0$. However, if the buyer checks and finds the ABM to be toxic, the price now becomes a "fire sale" price p_2 where $p_2 - p_0 < 0$. The buyer can be sure to avoid this outcome by checking at a cost of X drawn from a p.d.f. $\Phi(X)$ Now one can rescale and reduce the number of parameters by normalizing such that: $p_1 - p_2 = 1$ and $p_0 - p_2 = c$. The agent is then faced with the following problem:

Table 2.1

	Check and toxic	Don't check
$Z(i) = 0$	$-X_i$	$1 - c - X_i$
$Z(i) = 1$	$-c$	$1 - c$

The columns represent the strategy of the buyer and the rows those of the seller. Now consider the expected payoff to the seller of each strategy.

$$u_i(z_i = 1) = E[-p(1 - z_j)c] + [1 - p(1 - z_j)](1 - c) = 1 - p(1 - \bar{z}_i) - c \tag{2.13}$$

where $\bar{z}_i = E(z_j)$ for $j \in N_i$. That is, agent i can correctly estimate the average choice of rule by his neighbors but not the choice of each individual. Thus we have

$$z_i = \frac{1}{k_i} \sum_{j \in N_i} z_j. \tag{2.14}$$

Now the expected payoff from not following the rule and choosing $z_i = 0$—that is, from checking the value of the underlying assets, is:

$$u_i(z_i = 0) = (1 - p)(1 - c) - X_i. \tag{2.15}$$

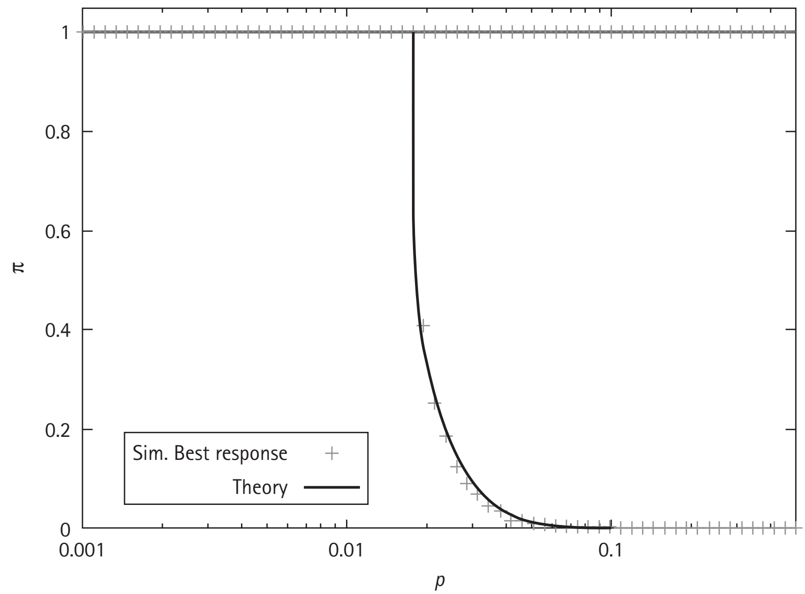


FIGURE 2.11 The coexistence of two equilibria, either all $z_i = 1$ or $z_i = 0$ (Source: Anand et al. 2013).

Thus if the agent checks and finds the assets to be toxic, he simply incurs the cost of checking, while if the asset is not toxic he obtains the difference between the selling and buying price less the checking cost. The strategy, which constitutes the best reply to the strategies of the neighbors, is then given by:

$$z_i = \Theta[u_i(1) - u_i(0)] = \Theta\left[p\left(\frac{1}{k_i}\right)\sum_{j \in N_i} z_j - c\right] \tag{2.16}$$

where the function Θ is defined as $\Theta(x) = 1$ if $x > 0$ and 0 otherwise. Note that the agents are assumed to know the probability of default of the underlying assets. However, in reality, the common perception of p reflected the over-optimistic evaluation of the rating agencies. For low values of p there is one equilibrium in which all agents choose not to check, but once a critical value of the commonly perceived p is passed, another equilibrium emerges in which all agents check. This is illustrated from numerical simulations in Figure 2.11.

When there are two equilibria there is no reason to believe that one or the other will be necessarily realized. However, we can introduce, as in our first example, some noise and assume that the agents only make the best response with a certain probability. What we impose is that, as the superiority of one strategy over the other increases, the probability of choosing that strategy increases. Given this, we can examine whether they coordinate on one equilibrium as p increases. We now use the logit rule, already

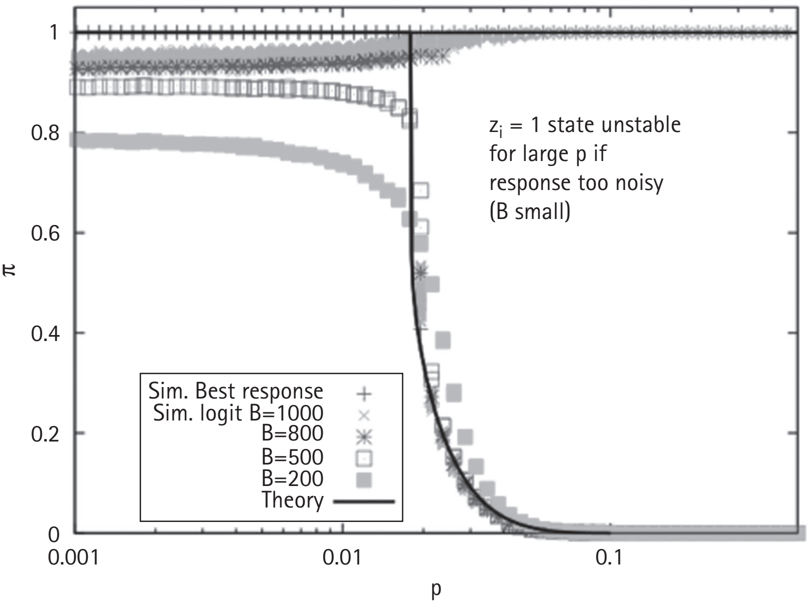


FIGURE 2.12 The evolution of the equilibrium state as p increases (Source: Anand et al. 2010).

discussed earlier, which has the required property. Thus, the probability of choosing $z_i = 1$ is given by:

$$P(z_i - 1) = \frac{e^{\beta u_i(1)}}{e^{\beta u_i(1)} + e^{\beta u_i(0)}} \tag{2.17}$$

where β is a parameter indicating the sensitivity of the agent to the difference between the payoffs from the two strategies. If $\beta = 0$ the agent chooses one of the two strategies at random, whereas if $\beta \to \infty$ then the probability of choosing the best response goes to one.

With the noise in the decisions of the agents, the system switches suddenly from one equilibrium to another. There are two things to observe here. First, a continuous evolution of p, the perceived probability of default or toxicity, leads to a sudden and large change in the equilibrium state. This, in turn, provokes a sharp decline in the prices of the asset-backed security, which is just what was observed and shown in Figure 2.12. The fact that the collapse occurred later for better rated MBS reflects the effect of the ratings on perceived probabilities rather than any real differences in those probabilities across assets. In fact, Pozsar et al. (2010) found that MBS ratings did not fully reflect publicly available data.

The second important observation is that the existence of a certain amount of noise in the decisions of agents leads to the selection of a particular equilibrium. In the context, it is a very partial equilibrium since the evolution of p has been taken as exogenous, and to fully model the process this would also need to be modeled.

However, in a situation where agents are influenced by each others' decisions and where their decision making is not fully "rational," we capture some important empirical facts. The individuals involved are far from the infinitely farsighted optimizers of standard models and are making relatively simple binary decisions, based on the actions of their partners. This can lead to major changes in the aggregate state of the market. Again this is clearly not a comprehensive model of what is, in reality, a very complicated system, but it does capture some of the characteristics that lead to major aggregate shifts without any specific major exogenous shock.

A more ambitious goal would be to build a model in which there are no equilibria and in which the market, its organization, and the behavior of the agents are constantly and simultaneously evolving.

As should be clear by now, analyzing the financial sector makes little sense without taking into account its network structure(s). The very definition of the nodes and the links between them already poses problems. Yet, most theoretical models of the financial network impose a very simple structure on the nodes and their relations. As soon as one tries to define carefully what the nature of a link is, and furthermore one tries to model how these links might be built or broken, and in addition one models the different nature of the financial entities, the situation looks very different from that of the simple but tractable theoretical models which have been built so far. This is why many of the more empirically focused studies of financial networks are often based on simulations.

2.2.4 The Evolution of the System and its Regulation

In looking at the evolution of the banking system, we see why the simple market paradigm, with banks acting as intermediaries between lenders and borrowers is wholly inadequate as a model of the actual transactions system.

> The demonstrated ability of regulated banking institutions to adapt to the changing environment suggests that there may be much to learn about the future evolution of intermediation directly from the observation of banks. Risks are still likely to be concentrated in other parts of the system—that is, outside of banks' balance sheets—but there is a good chance a bank will be involved in new mutations of the intermediation system, either directly or indirectly. This observation thus suggests a new role for bank supervisors: In addition to carrying out their main mandate of monitoring the health of banking firms, supervisors could contribute to dynamic and forward-looking oversight of the whole system of financial intermediation as it continues to evolve.
>
> —Cetorelli et al. 2012, pp. 10–11

What is being argued here is that the system still serves an overall purpose of financial intermediation, but that it is far from being the simple process described in most economic models. As the authors suggest, we ignore the evolution of the structure of the system and all the feedbacks involved and the consequent potential fragility at our peril. When integrating the financial sector into macroeconomic models, account has to be taken of the network structure of that sector, and the way in which contagion can occur between entitities which might seem, at first sight, to be robust to shocks. In fact, the banking sector reflects many of the network features to be found elsewhere in the economy. It is very difficult to find a sector that operates in the way that our basic models describe. As soon as one starts to examine in detail any particular market, firm, or sector, one is forced to admit that the characteristics of the relations within and between different entitities plays a major role in determining the aggregate outcomes.

2.3 Conclusion

The basic message of this chapter is that we should start from networks rather than the standard model of the isolated optimizing individual as our benchmark for economic models. But this does not mean that the sort of network models, particularly the theoretical ones, currently being built will provide easier and simpler answers to economic problems. Copernicus' ideas did not immediately conquer the world of astrophysics, partly because the predictions of his "model" were not demonstrably superior to those of the much-modified Ptolomean construct. Indeed, we see echoes of this in today's discussions in economics, where it is claimed by some that the old model can be recovered if certain limitations are imposed on the underlying interactions. Acemoglu et al., in this handbook, show how important the nature of the interaction and aggregation functions are in this regard. Until the analysis of the cases in which the limitations do not hold progresses further, economists will prefer to work within the more Ptolomean setting. Recall that the Copernican shift had to wait for the underlying theory to be more fully developed. It needed Galileo and Kepler to consolidate the paradigm shift. It would be foolish to put the controversies in economics on that level. Still, it is interesting to see that Goyal, a leading contributor to the development of network theory in economics, in his perspectives chapter in this book, feels that networks in economics have become, in Kuhnian terms, "normal science." For Kuhn, this would mean that all the scientists in the discipline have shifted their perspective and have taken networks as the central focus of attention, or put more bluntly consider networks to be the benchmark model in economics. It is not clear to me that this is the case. As Goyal rightly points out, economics has basically developed along two lines. The first, and still the standard benchmark, is that of a large number of agents interacting through some central mechanism but without much consideration for the structure of individual interactions. The second is the game theory approach, which typically deals with rather small numbers of sophisticated and strategic agents and studies the equilibria in such situations. Goyal believes there is a clear and unresolved tension between the two and perhaps the most empirically relevant situation is one in which there are many individuals who are locally linked but largely unaware of the way in which the system as a whole develops. A full paradigm shift would not endeavor to make progress in either the competitive model or the pure game-theoretic framework but would rather take the more realistic intermediate sort of situation as a starting point. It would not relegate networks and network theory to the status of a tool which has been used to give useful insights into those situations that economics has typically struggled with. Yet, it takes time for a paradigm shift to consolidate and it may be the case that network theory will simply consolidate our previous science. I suspect that the change will be more radical than that as the network approach continues to influence economics. But it is important to understand that it is unlikely to lead to models with the simple causal relationships so sought after by macroeconomists.

In this regard, it is worth noting the caveats expressed by Johnson, a leading expert in complex networks.

> In models of complex systems and networks, tiny changes in the model's assumptions—or changes in what it means to be a node, a link or 'infectious'—can inadvertently invert the emergent dynamics, for example by turning a stable output into an unstable one. Such changes can therefore amplify the inherent risk in any resulting policy suggestions. There is already substantial consensus that policy-makers need to embrace financial market risk within the framework of complex dynamic systems. However, markets contain many heterogeneous objects, the interactions of which may change in any number of ways in the blink of an eye (or the click of a mouse). This new dynamic regime, in which the character of both the links and nodes can change on the same timescale, lies well beyond standard models of ecological food webs, disease spreading and networks. The resulting dynamic interplay can generate unexpectedly large market fluctuations—and it is these that invalidate the financial industry's existing approach to the pricing of financial derivatives and the management of risk.
>
> —Neil Johnson 2011, p. 302

Although he rightly suggests that we should avoid the hubris of thinking that the sort of network models currently being introduced can be immediately and risklessly applied to analyze economic problems and suggest policy measures, two things are worth noting. In the first place his general criticism of the applicability of models applies just as much to standard economic models as to network-based models. Secondly, the fragility he describes is due to the intrinsically dynamic nature of networks and as Jackson observes in his chapter in this book, this is one of the major challenges for the use of networks in economics. Taking this dynamic aspect into account makes prediction more difficult, but it cannot be worse than working with mechanical models in which no such dynamics are present and arriving at totally erroneous conclusions.

References

Abreu, Dilip, and Mihai Manea (2012). "Bargaining and efficiency in networks." *Journal of Economic Theory* 147(1), 43–71.

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2012). "The network origins of aggregate fluctuations." *Econometrica* 80(5), 1977–2016.

Allen, Franklin, and Ana Babus (2009). "Networks in finance." In *The Network Challenge: Strategy, Profit, and Risk in an Interlinked World*, Paul R. Kleindorfer and Yoram Wind, eds., 367–382. Philadelphia: Wharton School.

Allen, Franklin, and Douglas Gale (2000). "Financial contagion." *Journal of Political Economy* 108, 1–33.

Anand, Kartik, Alan Kirman, and Matteo Marsili (2013). "Epidemics of rules, rational negligence and market crashes." *The European Journal of Finance* 19, 438–447.

Ashcraft, A. B., and T. Schuermann (2008). "Understanding the securitization of subprime mortgage credit." *Federal Reserve Bank of New York Staff Report* 318, March.

Battiston, S., D. Delli Gatti, M. Gallegati, B. Greenwald, and M. Gallegati (2012). "Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk." *Journal of Economic Dynamics & Control* 36, 1121–1141.

Bougheas, Spiros, and Alan Kirman (2014). "Complex financial networks and systemic risk: A review." *CESifo Working Paper Series* No. 4756.

Buffett, Warren (2002). "Berkshire Hathaway annual report."

Bush, R. R. and F. Mosteller (1955). *Stochastic Models for Learning*. New York: Wiley.

Cetorelli, Nicola, Benjamin H. Mandel, and Lindsay Mollineaux (2012). "The evolution of banks and financial intermediation: Framing the analysis." *Federal Reserve Bank of New York Economic Policy Review* 18(2), 1–12.

Coleman, James S. (1986). "Social theory, social research, and a theory of action." *The American Journal of Sociology* 91(6), 1309–1335.

Cournot, A.-A. (1838). *Recherches sur les principes mathématiques de la théorie des richesses*. Paris: L Hachette.

De Vroey, M. (1999). "Transforming Walras into a Marshallian economist: A critical review of Donald Walker's *Walras's Market Models*." *Journal of the History of Economic Thought* 21, 413–435.

Durlauf, Steven N. (2012). "Complexity, economics, and public policy." *Politics, Philosophy & Economics* 11(1), 45–75.

Easley, David, and Jon Kleinberg (2010). *Networks, Crowds, and Markets. Reasoning about a Highly Connected World*. Cambridge: Cambridge University Press.

Edgeworth, F. Y. (1881). *Mathematical Psychics: An Essay on the Application of Mathematics to the Moral Sciences*. London: Kegan.

Elliott, Matthew, Benjamin Golub, and Matthew O. Jackson (2014). "Financial networks and contagion." *American Economic Review* 104(10), 3115–3153.

Feldman, Allan (1973). "Bilateral trading processes, pairwise optimality, and Pareto optimality." *The Review of Economic Studies* 40(4), 463–473.

Feldman, Allan (1974). "Recontracting stability." *Econometrica* 42(1), 35–44.

Gabaix, Xavier (2011). "The granular origins of aggregate fluctuations." *Econometrica* 79, 733–772.

Gai, Prasanna, and Sujit Kapadia (2010). "Contagion in financial networks." *Proceedings of the Royal Society A* 466(2120), 2401–2423.

Geertz, C. (1978). "The bazaar economy: Information and search in peasant marketing." *American Economic Review* 68, 28–32.

Gertler, M. and N. Kyotaki (2011). "Financial intermediation and credit policy in business cycle analysis." In *Handbook of Monetary Economics*, Volume 3, B. Friedman and M. Woodford, eds. Amsterdam: North-Holland.

Goyal, S. (2007). *Connections: An Introduction to the Economics of Networks.* Princeton, NJ: Princeton University Press.

Graddy, K. (1995). "Testing for imperfect competition at the Fulton fish market." *Rand Journal of Economics* 26, 75–92.

Graddy, K., and G. Hall (2010). "A dynamic model of price discrimination and inventory management at the Fulton fish market." *Journal of Economic Behavior and Organization* 80(1), 6–19.

Haldane, A. (2009). "Rethinking the financial network." Speech delivered at the Financial Student Association, Amsterdam.

Haldane, A. G., and R. M. May (2011). "Systemic risk in banking ecosystems." *Nature* 469, 351–355.

Hayek, Friedrich A. (1945). "The use of knowledge in society." *American Economic Review* 35(4), 519–530.

Hobbes, Thomas (1651). *De Cive, or the Citizen*. New York: Appleton-Century-Crofts, 1949.

Holland, J. H. (1976). "Adaptation." In *Progress in Theoretical Biology IV*, R. Rosen and F. M. Snell, eds., 263–293. New York: Academic Press.

Ioannides, Y. (2013). *From Neighborhoods to Nations: The Economics of Social Interactions.* Princeton, NJ: Princeton University Press.

Iori, Giulia, Saqib Jafarey, and Francisco G. Padilla (2006). "Systemic risk on the interbank market." *Journal of Economic Behavior & Organization* 61(4), 525–542.

Jackson, Matthew O. (2008). *Social and Economic Networks.* Princeton, NJ: Princeton University Press.

Johnson, N. (2011). "Proposing policy by analogy is risky." *Nature* 469, 301.

Kuhn, Thomas (1962). *The Structure of Scientific Revolutions*. Chicago, IL: University of Chicago Press.

Latour, B. (2005). *Reassembling the Social: An Introduction to Actor Network Theory.* Oxford: Oxford University Press.

Lux, T. (2011). "Network theory is sorely required." *Nature* 469, 302.

Manea, Mihai (2011). "Bargaining in stationary networks." *American Economic Review* 101(5), 2042–2080.

McClean, P., and J. F. Padgett (1997). "Was Florence a perfectly competitive market? Transactional evidence from the Renaissance." *Theory and Society* 26(2), 209–244.

Montagna, Mattia, and Thomas Lux (2013). "Contagion risk in the Interbank Market: A probabilistic approach to cope with incomplete structural information," FinMaP-Working Papers no. 8.

Morin, Edgar (2007). "Restricted complexity, general complexity." In *Worldviews, Science, and Us: Philosophy and Complexity*, Carlos Gershenson, Diederik Aerts, and Bruce Edmonds, eds. Singapore: World Scientific.

Nier, E., J. Yang, T. Yorulmazer, and A. Alentorn (2007). "Network models and financial stability." *Journal of Economic Dynamics and Control* 31(6), 2033–2060.

Oullier, O., A. P. Kirman, and J. A. S. Kelso (2008). "The coordination dynamics of economic decision-making: A multi-level approach to social neuroeconomics." *IEEE Transactions on Neural and Rehabilitation Systems Engineering* 16(6), 557–571.

Poincaré, H. (1908). *Science et Méthode*. Paris: Flammarion.

Pozsar, Z., T. Adrian, A. Ashcraft, and H. Boesky (2010). "Shadow banking." *Federal Reserve Bank of New York Staff Reports*, no. 458, July.

Roth, A. E., and I. Erev (1995). "Learning from extensive-form games: Experimental data and simple dynamic models in the intermediate term." *Games and Economic Behavior* 8, 164–212.

Rubinstein, A., and A. Wolinsky (1985). "Equilibrium in a market with sequential bargaining." *Econometrica* 5, 1133–1150.

Shiller, Robert (2011). "The neuroeconomics revolution." Project *Syndicate*, November 21.

Varela, L. M., G. Rotondo, M. Ausloos, and J. Carrete (2015). "Complex network analysis in socioeconomic models." In *Complexity and Geographical Economics: Topics and Tools*, Pasquale Commendatore, Saime Suna Kayam, and Ingrid Kubin, eds. Berlin, New York: Springer, Verlag.

Vega-Redondo, F. (2007). *Complex Social Networks*. Econometric Society Monograph Series. Cambridge: Cambridge University Press.

Walker, D. A. (1996). *Walras's Market Models.* Cambridge: Cambridge University Press.

Weisbuch, G., O. Chenevez, A. Kirman, and J.-P. Nadal (1998). "A formal approach to market organization: Choice functions, mean field approximations and maximum entropy principle." In *Advances in Self-Organization and Evolutionary Economics*, J. Lesourne and A. Orlean, eds., 149–159. Paris: Economica.

Weisbuch, G., A. Kirman, and D. Herreiner (2000). "Market organisation and trading relationships." *Economic Journal* 110, 411–436.

Whittle, Andrea, and André Spicer (2008). "Is actor network theory critique?" *Organization Studies* 29, 611.