Complexity Theory and the Financial Crisis: A Critical Review

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Abstract

We present a critical review of the impact of complexity theory on the analysis of financial markets, concentrating on the differences between Econophysics and Econobiology. Both approaches show that there are limitations in our current understanding of the banking system, which can lead to regulatory problems, and in turn may have contributed to the inability of most academics and economic agents (including the FED) in predicting the crisis.

Introduction

The effects of the Financial Crisis are still being felt, and speculations on the predictability of the crisis and what measures should be taken to prevent another one are hot topics in financial circles. The purpose of this article is to analyze the financial crisis through the lens of complexity theory and to ponder which explanations can be given and which path should be open if one considers the world through the complexity theory lens.

The main advantage of using a complexity-based approach is that it meets head-on a common discontent of many researchers after the crisis: that current financial models

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were incapable of signaling the crisis. But there are no easy answers, because one of the main characteristics of complexity theory is incompressibility (for more, see Richardson (2008) and Ciliers (2005)), which puts a limit on the information that can be extracted from complex systems, and which also necessarily leads to theoretical pluralism. If we take the reasonable assumption that financial systems are complex in nature, there is no single theory that could explain every feature of each system, which makes a simple, decisive explanation for the crisis impossible. However, that does not mean that we cannot extract predictions, lessons, policies, or insights from thinking complexly about financial systems. In fact, it is just the opposite; thinking deeply on the impacts of complexity into financial system can lead to different kind of analyses that should bring testable implications for financial research. Here we focus on one possible explanation for the crisis, that the true nature of systemic risk is ignored by the Central Bank, due to an incomplete understanding of the true nature of financial markets and thus its available actions will be inherently curbed until it properly models the banking system.

1. Complexity in Financial Markets: A Primer

Richardson (2008) divides the approaches of how complexity thinking can impact management studies into three broad schools: the neo-reductionist school, the metaphorical school, and the critical pluralist school. Although the impact of complexity research on management studies is still in its infancy, the complexity school in financial market is much more developed. There is no question that complexity matters in financial markets, and the literature is developing in such a way that even investor strategies are now being designed based on complexity concepts (for instance, Brunnermeier and Oehmke (2009) point out three different ways in which boundedly rational investors can deal with complexity).

In fact, there are two main general approaches to complexity in economics and finance, that of Econophysics and Econobiology. Both are bottom-up, population-based approaches (Rickles, 2010), but differ sharply in their methods to deal with complexity.

Econophysics is a term coined by Stanley et al (1996) and is preoccupied with the application of the physics of complex system into financial and economics markets [see, for instance, Mantegna and Stanley (1999) and Rickle (2010)], while Econobiology takes its lessons from biological complexity models (e.g. Arthur, 1995)). Because both approaches have its origins clearly defined, the implications for complexity studies in finance are finely traceable.

First a caveat: while in the realm of Finance complexity models are much more common than in management studies, the confusion that Richardson (2008) observed between complexity and complicatedeness still persists, as can be seen in the examples of Caballero and Simsek (2009) and Bushman et al (2004), both of which use complexity in the common usage of the word. There is nothing wrong with either works, but here we analyze complexity in its technical form.

Using Richardson's classification, we can easily put the majority of Econophysics in the neo-reductionist school and much of Econobiology in the metaphorical school. This classification is so straightforward that it is uninteresting at first sight. However, when applied to a broader perspective of financial systems, this classification allows for some interesting insights, as will be shown later.

Rickle (2010) summarizes the Econophysics literature and the relationship with complexity, arguing that: ”according to the econophysicist’s conception of financial markets the prices (of assets) are viewed as fluctuating macroscopic variables that are determined by the interactions of vast numbers of agents”, and presents some important findings regarding asset returns that can be explained by econophysics, but not necessarily by regular financial models, such as fat tails, volatility clustering, and volatility persistence as examples. The methods of Econophysics are based on the tools of dynamical physics, like statistical mechanics and chaos theory, for instance. Since those tools are numerous, there are a multitude of different Econophysics models that try to deal with particular questions in financial markets, but all share the same epistemology – i.e. are based on data analysis first and hypothesis formulation second.

The idea of a paradigm shift brought by Econophysics to financial and economic modelling is strong: “Econophysics is viewed (by most of its practitioners) as a revolutionary reaction to standard economic theory that threatens to enforce a paradigm shift in thinking about economic systems and phenomena” (Rickles, 2010, p.13).

Some Econophysics models are by now mainstream in the financial literature, especially those dealing with volatility clustering and persistence, and with fat tails in asset returns – in this area statistical mechanics modelling thrives, due to the inherent characteristics of probabilistic function in asset pricing and returns.

However, important critiques of econophysics have surfaced, even when the discipline was in its infancy. One particular relevant critique comes from Mirowski (1989), where the author argues that much of Econophysics is problematic due to epistemological considerations (specifically, that there is no theory behind the transposition of physics models to economics), even though it can be argued that financial systems are much more akin to physical systems than most economics models. Econophysics then helps in a better understanding of the statistical properties of financial systems. Econobiology, on the other hand, has a different approach to the complexity of financial systems.

Arthur (1995) offers a paradigmatic view of Econobiology processes. In Econobiology models, the complex systems develop bottom-up through agent-based interactions, as in Econophysics models, but the difference is that while in the former the locus of analysis is agent interactions and the processes of emergence, in the latter the goal is to determine the statistical properties of the results of the agents' interactions. The difference is not only on the mechanics of both approaches, but also in their epistemology – Arthur (1995, p.20) expresses the view that one should look into economics and financial markets in "psychological terms: as a collection of beliefs, anticipations, expectations, and interpretations; with decision-making and strategizing and action-taking predicated upon these beliefs and expectations".

The bottom-up approach of Econobiology models is preoccupied with emergent properties from agent interactions. It is very useful to analyze innovation activity, for instance, because this kind of activity fits nicely as an emergent property of agents searching for innovation (since Nelson and Winter's (1982) seminal work, evolutionary economics modelling of innovative activity has become mainstream in the industrial organization literature). For financial models, Arthur et al (1995) show how a simple model of stock valuation can be radically transformed by changing a simple assumption on the behavior of rational investors, now assuming that investors are heterogeneous in their expectations. The result is that (p.24) “Under heterogeneity, deductive logic leads not just to indeterminate expectations but also to unstable ones. (…) Given differences in agent expectations, deductive expectation formation becomes indeterminate, and so even perfectly rational investors cannot form expectations in a determinate way”.

The main avenue of research of Econobiology models in finance is then the inductive approach through the use of simulation. The idea is to populate the simulator with heterogeneous agents and identify the properties of the emergent features of the interactions. Arthur et al (1996) studied asset pricing under inductive reasoning using a simulation with 100 artificial investors each with 60 expectational models. The main results are that, if agents believe in the standard model of finance, their beliefs and the standard model is evolutionary stable and thus upheld; and that the market possesses a non-trivial *psychology*, with evolving strategies and different periods of volatility in the price series (sometimes consistent with GARCH processes). The advantage of this kind of models is that regular stylized facts of financial models (such as stocks cross-correlations) can be generated instead of being simply observed. More recent models have stretched the use of simulation (Ponzi and Aizawa, 2000) and evolutionary models to refine the analyses of emergent properties in financial markets, with the use of neural networks (Azzini and Tettamanzi, 2006), biological algorithms (Brabazon and O’Neil, 2006), and grammatical evolution (Adamu and Phelps, 2009). The main problems with evolutionary finance models are that there is still a reliance on simulations, with many results still exploratory; and that the models offer a different way to look at financial markets but are too scant in terms of definite predictions.

Here we concentrate on network topology and other models to analyze some of the possible dynamics of financial systems. Which is the best approach to analyze this important feature of the crisis? In the next section we review some works in each approach to complexity in finance, and try to extract some insights to help explain the building of the crisis.

2. Complexity Models, Risk Creation and the Financial Crisis.

There are many proposed explanations for the crisis: lack of regulation; cheap money; irrational exuberance; “creative” exotic financial instruments; and excessive risk-taking. Here we want to concentrate on the fact that the problem of banking regulation is more fundamental than simply choosing the level of regulation – we may not understand important features of the banking system dynamics.

Take risk, for instance. Regular financial micro models divide risk in idiosyncratic and systemic components. For regulation purposes the focus is usually on systemic risk, the component that can affect the whole financial system. The proponents of financial deregulation usually claim that markets are efficient – i.e. that it operates on the basis of a “Law of Conservation of Risk”, in which banks are efficient in allocating risk throughout the system, and risk is neither created nor destroyed, merely shuffled around efficiently.

Risk, instead of being a static feature of financial systems, is part of a dynamic process where it is destroyed and created in the course of trading activity. Shifting risk may allow for more efficiency in terms of costs to market agents, but what may be lacking in regular economic models is the notion that systemic risk is more than the sum of its parts. Recent models are specifically looking into general equilibrium banking models, because as Acharya (2009, p.2) observes: "The standard theoretical approach to the design of bank regulation considers a "representative" bank and its response to particular regulatory mechanisms such as taxes, closure policy, capital requirements, etc." Such partial equilibrium approach has a serious shortcoming from the standpoint of understanding sources of, and addressing, inefficient systemic risk. In particular, it ignores that in general equilibrium, each bank's investment choice has an externality on the payoffs of other banks and thus on their investment choices".

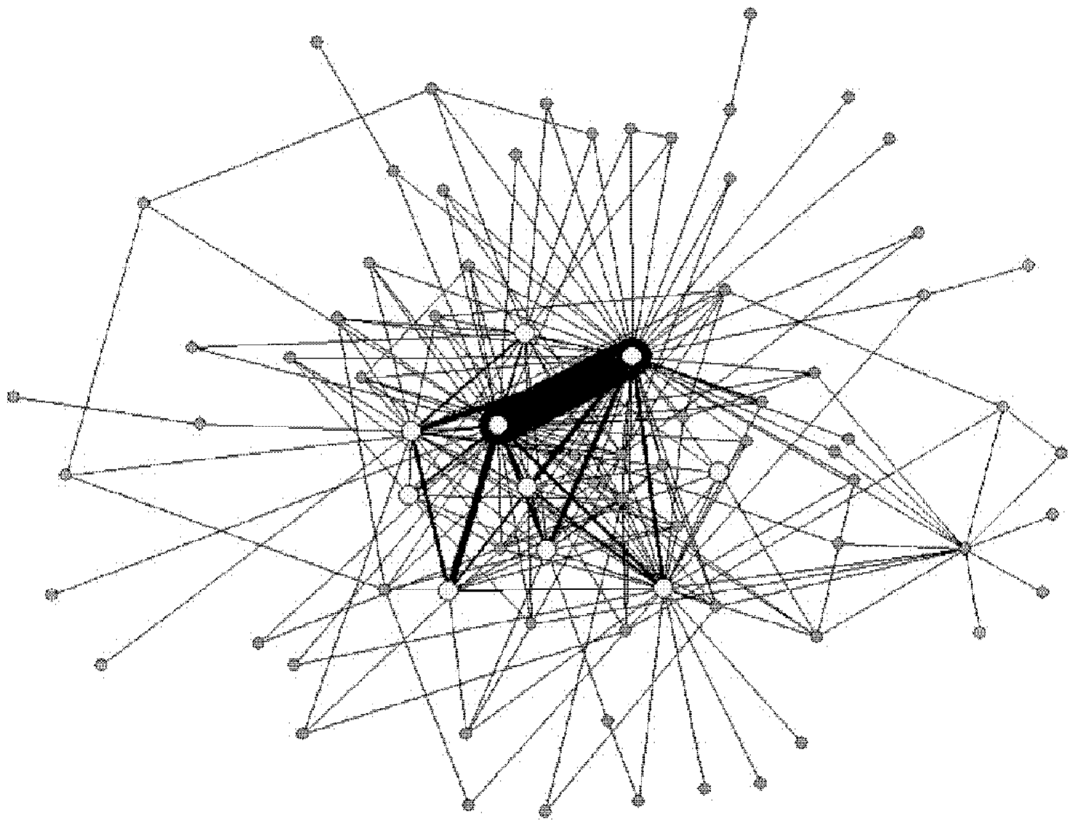
Acharya's model shows that "optimal regulation should be "collective" in nature and should involve the joint failure risk of banks as well as their individual failure risk". For that, he simply defines systemic risk as "the joint failure risk arising from the correlation of returns on asset-side of bank balance-sheets". Both definition and conclusion are the jumpstart for our complexity-based analysis of financial markets. The idea that systemic risk is based on a joint-failure is simple enough, as is the idea that regulation should be collective. Another interesting network banking model is that of Caballero and Simsek (2009), where the authors propose a model of a financial crisis based on the costs of gathering information on the soundness of their trading activity. Financial crises happen when, after an emergence of acute financial distress in a part of the system, the cost of information gathering becomes too unmanageable for banks, and they have no option but to withdraw from loan commitments and illiquid positions. All these models would be considerably enhanced by looking into the world through a complexity lens.

2.1. Econophysics Modelling of the Banking System

There is no single econophysics model of the banking system, but recent work can enlighten some of the important features of financial markets.

The main avenue of research considers the banking system as a network of payment flows, and studies its topology, with the underlying risk determining the stability of the network. One simple illustration of this is presented in graph 1, with an example of the the topology of the Danish network payment system, from Rørdam and Bech (2009).

Graph 1 – The Network Topology of the Danish Payment System (Rørdam and Bech, 2009)



(Rørdam and Bech, 2009)

In the figure the white nodes are the biggest banks. This topology highlights one of the most discussed aspects of the banking crisis,- that some banks are too big to fail. This is measured through the systemic impact of each node on the network stability – a network is more stable if nodes can disappear without loss of payment flows.

Inaoka et al (2004) develop a network banking model based which measures the network stability and is based on power laws and cumulative distributions. The result is that the banking network shows a power-law degree distribution. Also, the main characteristic of the network, in this case, is that it is much more efficient than stable – i.e. there is a trade-off between banks searching for efficiency and the whole stability of the network. Becher et al (2008) don't observe this trade-off in their analysis of the topology of the UK payment system, concluding that "liquidity is able to flow efficiently around the network and that the network is quite resilient to shocks (p.1)" – even taking a node off the network doesn't undermine the ability of banks to have payments flow freely. Pröper et al (2008), in another topological analysis, this time on the Dutch payment system, find some indication of a lack of efficiency – the network is small, compact and sparse, using a mere 12% of possible connections in the long run, and also of stability, stating that the network is subject to possible serious instability.

Another issue of network topology is the network connectivity, which is related to the problem of collective bankruptcy. Aleksiejuk et al (2001) present a model of a banking network, with the goal of relating collective bankruptcies to self-organized criticality. In their model the main parameter is the mean number of interbank connections, q. Two competing processes increase (A) or decrease (B) q (p.5):

A. Due to the random character of the stochastic variable i(t) and the random selection of a financial partners from the nearest neighbors.

B. Due to collective bankruptcies, because new banks that replace bankrupts are not involved in the interbank market at the beginning of their activity.

The authors conclude that (p.6) "if the value of q is below the percolation threshold then the mean size of contagion cluster is small and the process A overcomes the process B. It follows that in the course of time the number of interbank connections q is growing up driving the system to the critical state. If the value of q exceeds a critical value (the percolation threshold) then a large contagion cluster spreading all over the system can appear."

There are other works concerning banking system network topology, but the ones presented here show the relevance of this kind of analysis to the stability analysis of banking systems. There are, of course, still many unresolved issues regarding which features are relevant to regulatory policy, and, more importantly, what should be done once different network characteristics are identified.

Network topology is hardly the only way to analyze financial markets with Econophysics models. For instance, the analysis of entropy in financial markets yields important information on risk creation (Michael and Johnson, 2004), while Bartolozzi and Thomas (2004) analyze a stochastic cellular automata model and conclude that crashes or bubbles are triggered by a phase transition in the state of the bigger clusters present in the network system.

2.2 Econobiology Modelling of the Banking System

Econobiology research in our present context begins with agent-based modelling of the banking system. The main advantage is that the models treat banks as agents in a biological population and analyze their process of evolution – in this sense, risk is one of the determinants of a bank "evolution". Because in a population agents are always entering and leaving, the models have a clear parallel with financial markets. The main problem is that it is difficult to get out of the metaphorical level towards a working agent-based banking model, even though modelling risk is increasingly promising as an avenue of research. However, some frontier research is now breaching the metaphorical level into workable models. Here we present three classes of models which are surprisingly effective in determining banking failures through the lens of evolutionary biology.

The first kind of models use neural networks [beginning with Tam (1991) and Tam and Kyiang (1992), and surveyed by Atiya (2001)]. "An artificial neural network (NN) is a computational structure modelled loosely on biological processes. NNs explore many competing hypotheses simultaneously using a massively parallel network composed of non-linear relatively computational elements interconnected by links with variable weights. It is this interconnected set of weights that contains the knowledge generated by the NN" (Adya and Collopy, 1996, p. 481). The linkage to financial markets is direct, because it is easy to think of banks being interconnected and generating information in the process of transactions between them. Again, as in Econophysics modelling, we arrive at networks as basis of the analysis, but the method of analysis is quite different. The evolution of the neural network yield information on banking failures through decaying processes due to loss of information.

Support vector machines (SVM) can also be used to model risk in financial markets [e.g. Tay and Cao (2001) and Chen and Shih (2006)]. SVM is a type of learning machine based on statistical learning theory. Instead of considering the network structure as in neural networks models, it uses optimization procedures based on learning processes, another important feature of biological processes.

The last class of banking models based on evolutionary biology briefly described here is that of genetic algorithms (GA). A genetic algorithm is an optimization procedure based the idea that evolution happens through changes in genes, hence concepts like inheritance, mutation, and selection. If we think of banks as agents searching for survival, a selection processes based on evolutionary biology can describe what happens on financial markets. Min et al (2006) presents a model that uses GA to improve on their model of SVM to analyze the probability of banking failures. In their model, the authors were able to measure relative performance and conclude that it outperforms regular financial models in detecting the probability of banking failures. In this sense, their model would be complementary on Value-at-Risk internal models.

Table 1 summarizes the main implications and disadvantages of the Econophysics and Econobiology approaches to financial markets. The table below is far from exhaustive, its goal being merely to illustrate some of the research agenda of complexity theory in financial markets.

Table 1 – Econophysics; Econobiology and Financial Markets.

	Underlying foundations	**Methods**	**Financial Markets**	**Disadvantages**
Econophysics	Statistical mechanics, Self-organized criticality; Chaos Theory	Dynamical Modelling; Network Topology; Power-Law Distributions	Network Topology, Volatility Clustering and Persistence; Fat Tails; Extreme Events	Narrow explanations; Theoretically empty.
Econobiology	Evolutionary biology; Bounded rationality; Learning theory	Agent-based models;Genetic Algorithms; SVM;Simulation	Herding, Self-fulfilling behavior, Adaptative Market Hypothesis; Uncertainty emergence; Innovation.	Lack of predictions; Hard to model.

3. Final Comments

The purpose of the paper was to present important contributions of complexity theory to the analysis of financial markets, focusing on the distinction between Econophysics and Econobiology and their possible contribution to the better understanding of financial markets dynamics. It was our intention to bring new issues into the fold, instead of answering decisively questions like why the major crisis of 2007-8 happened.

We followed the reasoning of authors like Mainzer (2009, p.1): "the world-wide crisis of financial markets and economies is a challenge of complexity research. Misleading concepts of linear thinking and mild randomness (e.g. Gaussian distributions of Brownian motion) must be overcome by new approaches of nonlinear mathematics (e.g., non-Gaussian distribution), modelling the wild randomness of turbulence at the stock markets. Systemic crises need systemic answers". Bouchaud (2008) goes beyond it, calling for a scientific revolution for economics based on complexity theory. Here we don't take a strong position against regular financial and economic models, and we don't advocate that complexity theory will answer everything, because there is no simple explanation or easy answers to be given.

However, the models and results here can bring to light some important questions regarding the shaping of financial markets – if the banking system presents characteristics like self-criticality, power law distributions, risk emergence, bounded rationality, and other non-deterministic features, the problem of the regulator is much more difficult than regular economic models allow for. It is just not a question of how stringent to regulate the system or not, but a more fundamental question of what is being regulated.

Further research on the complexity approach should greatly enhance our understanding of financial markets, and a specific line of research could concentrate on developing an encompassing theory to tie all the different approaches together to arrive, at some point, at a complexity-based standard model of finance.

References:

Acharya, V.V. (2009). A theory of systemic risk and design of prudential bank regulation, Journal of Financial Stability, 5: 224-255.

Adya, M., and F. Collopy (1998). How effective are neural vided fine research assistance. Journal of Forecasting 17, 481–495.

Adamu, K. and S. Phelps (2009). Modelling Financial Time Series using Grammatical Evolution. Working Paper, (http://web.mac.com/davidrh/AMLCF09/papers/5.pdf).

Aleksiejuk, A., A.J. Holyst, and G. Kossinets (2001). Self-organized Criticality in a model of collective bank bankruptcies, cond-mat/0111586

Arthur, B. (1995). Complexity in Economic and Financial Markets, Complexity, 1(1): 20-25.

Arthur, W. B., J. Holland, B. LeBaron, R. Palmer and P. Taylor (1996). Asset Pricing Under Endogenous Expectations in an Artificial Stock Market, in The Economy as An Evolving Complex System II, edited by W. Brian Arthur, Stephen Durlauf and David A. Lane, A Proceedings Volume, Santa Fe Studies in the Sciences of Complexity, 15-44.

Atiya, A. F. (2001). Bankruptcy prediction for credit risk using neural networks: A survey and new results. IEEE Transactions on Neural Networks, 12:, 929–935.

Azzini A. and A. Tettamanzi (2006). A neural evolutionary approach to financial modelling. In Proceedings of the Genetic and Evolutionary Computation Conference, GECCO'06, vol. 2, pp. 1605-1612.

Bartolozzi, M. and A.W. Thomas (2004). Stochastic cellular automata model for stock market dynamics, Phys. Rev. E 69, 046112.

Becher, C., S. Millard and K. Soramäki (2008). *The network topology of CHAPS Sterling*, Bank of England Working Paper No. 355.

Brabazon, A. and M. O'Neill (2006). Biologically Inspired Algorithms for Financial Modelling. Springer, Berlin.

Brunnermeier, M.K. and M. Oehmke (2009). Complexity in Financial Markets, Princeton University Working Paper.

Bushman, R., Q. Chen, E. Engle, A. Smith (2004). Financial accounting information, organizational complexity and corporate governance systems. Journal of Accounting and Economics 37: 167–201.

Caballero, R.J. and A. Simsek (2009). Complexity and Financial Panics, NBER Working Paper #14997.

Chen, W. H. and J.Y Shih (2006). A study of Taiwan's issuer credit rating systems using support vector machines. Expert Systems with Applications, 30:427–435.

Cilliers, P. (2005). Knowing complex systems, in K. A. Richardson (ed.), Managing Organizational Complexity: Philosophy, Theory, and Application, Boston: ISCE, 7-19.

Gordon, D. (1991). A review of More Heat Than Light: Economics as Social Physics, Physics as Nature's Economics. By Philip Mirowski. The Review of Austrian Economics, 5(1): 123-128

Inaoka, H, T. Ninomiya, T. Shimizu, H. Takayasu, and K. Taniguchi (2004). Fractal network derived from banking transaction - an analysis of network structures formed by financial institutions, Bank of Japan Working Paper no. 04-E-04.

Michael, F. and M.D. Johnson, Financial market dynamics, Physica A 320, 525 (2003).

Min, S. H., J. Lee, and I. Han (2006). Hybrid genetic algorithms and support vector machines for bankruptcy prediction. Expert Systems with Applications, 31, 652–660.

Mirowski, P. (1989). More Heat Than Light: Economics as Social Physics, Physics as Nature's Economics. Cambridge: Cambridge University Press.

Mantegna, R.N. and H.E. Stanley. (1999). An Introduction to Econophysics, Cambridge: Cambridge University Press.

Nelson, R. and S. Winter (1982). An Evolutionary Theory of Economic Change. Belknap Press of Harvard University Press: Cambridge, MA.

Ponzi, A. and Y. Aizawa (2000). Evolutionary financial market models, Physica A: Statistical Mechanics and its Applications 287: 507-523.

Pröpper, Marc, I. Lelyveld and R. Heijmans (2008). Towards a Network Description of Interbank Payment Flows, DNB Working Paper No. 177/May 2008, De Nederlandsche Bank

Richardson, K. (2008). Managing Complex Organizations: Complexity Thinking and the Science and Art of Management, Corporate Finance Review, 13: 23-30.

Rickles, D. (2010). Econophysics and the Complexity of Financial Markets, forthcoming in J. Collier and C. Hooker (eds.): Handbook of the Philosophy of Science, Vol.10: Philosophy of Complex Systems. North Holland: Elsevier.

Rørdam, K.B. and M.L. Bech (2009). The Topology of Danish Interbank Money Flows, FRU Working Paper, University of Copenhagen, Working Paper No. 2009/01.

Tam, K.Y. (1991). Neural Network Models and the Prediction of Bank Bankruptcy, Omega, The International Journal of Management Science, 19: 429-445.

Tam, K.Y. and M.Y. Kiang (1992). Managerial Applications of Neural Networks: The Case of Bank Failure Predictions, Management Science, 1992, 38, 926-947.

Tay, F. E. H., and L. Cao (2001). Application of support vector machines in financial time series forecasting. Omega, 29: 309–317.