

END-OF-DEGREE PAPER

Universitat Pompeu Fabra

APPLICATION OF THEORETICAL MODELS TO FINANCIAL INNOVATION

Gerbert Garcia i Bassa



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Abstract

This paper is aimed at providing a general strategic overview of the potential synergic interactions between science, finance and economics in the context of the emergent econosciences, and presenting some of the existing theoretical models in science that have applications in the field of financial innovation. Thermodynamics, swarm intelligence, and chaos theory are explored, and some of their main applications in finance presented. Financial innovation, along with information, is considered as the centerpiece of the global financial and economic system, and a core strategic and geostrategic asset for corporations and societies throughout the globe. Financial R&D+i centers are briefly described as the main infrastructure to generate, control, defend, and capitalize information and knowledge in today's technology-based, integrated financial markets. An analytical framework is subsequently suggested as a tool for financial analysis: according to it, the financial system may be modeled as a vector field of forces in an informational space in which subunits (i.e. particles, economic entities) interact according to the laws of thermodynamics and classical mechanics, and constitute a complex system. Finally, an analysis of the effects of financial innovation, along with a proposal to enhance the strategic synergies between science and economics and finance, concludes the paper.

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To my dad, thank you whole-heartedly for helping to build the foundations of a solid conceptual structure. Your wisdom, energy and genius have acted as a permanent inspirational guide in the vast and complex realms of knowledge.

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1. INTRODUCTION

1.1. PRESENTATION

The present project constitutes the End-of-Degree Paper (EDP) for the academic year 2012-13 that Gerbert Garcia i Bassa, senior student of the degree in International Business Economics at the Facultat de Ciències Econòmiques i Empresariales at Universitat Pompeu Fabra (Barcelona), executed during the third academic term and submitted electronically on June 13, 2013. As part of the academic requirements set forth by the institution, the project complies with the criteria, structure, schedule, and limitations determined by the syllabus governing it. The realization of the paper was tutored by Pr. Pelegrí Viader i Canals, associate professor of Mathematics and secretary general at Universitat Pompeu Fabra.

1.2. CENTRAL THEME OF THE PROJECT

The present paper is aimed at providing a general strategic overview of the existing theoretical models that have applications in the field of financial innovation. Whereas most financial developments have relied upon traditional economic tools, a new stream of research is defining a novel paradigm in which mathematical models from diverse scientific disciplines are being applied to conceptualize and explain economic and financial behavior. Indeed, terms such as ‘econophysics’ or ‘quantum finance’ have recently appeared to embrace efforts in this direction. As a first contact with such research, the project will present a brief description of some of the main theoretical models that have applications in finance and economics, and will try to present, if possible, potential new applications to particular areas in financial analysis, or new applicable models. As a result, emphasis will be put on the implications of this research for the financial sector and its future dynamics.

1.3. OBJECTIVES

The content of this paper has been devised to achieve a set of purposes derived from the motivations (which may be called ‘preoperational antecedents’) mentioned in *Section 1.4*. In accordance with the overall approach of the project, the completion of each section implies the achievement of a specific objective. As long as each section relates to the previous one and refers to the next one, the structure of the project allows for a gradual, constant, and consistent development aimed at maintaining a solid transition between theoretical frameworks and applied knowledge. In essence, the objectives (both internal and external) for the paper can be summarized as follows (global objectives set by the syllabus for all EDPs will not be mentioned here):

<p><i>1. INTRODUCTION</i></p>	<ul style="list-style-type: none"> ▪ Introduce readers (and the author himself) to the central theme of the project and the approach it is going to adopt given the scope and limitations of the EDP. ▪ State the objectives of the project so that a proper structure of contents can be derived and a suitable research method chosen. ▪ Formulate an execution plan for the project so that a schedule is devised that meets the deadlines and is aligned with the overall structure of the paper.
<p><i>2. CONCEPTUAL FRAMEWORK</i></p>	<ul style="list-style-type: none"> ▪ Present an emerging field in economics and finance, which may be viewed as strategic given the current financial context. ▪ Study the synergies between science and economics and finance, and explore their implications and mutual impact. ▪ Describe various applications of scientific models in finance.
<p><i>3. APPLIED RESEARCH</i></p>	<ul style="list-style-type: none"> ▪ Develop potential applications of existing theoretical models in the area of financial innovation, or propose potential applicable models.

<i>4. CONCLUSIONS</i>	<ul style="list-style-type: none"> ▪ Analyze the potential effects of financial innovation on the current dynamics of the financial sector. ▪ Defend the case for a complete and dynamic alignment between science and economics / finance.
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1.4. MOTIVATION

Undoubtedly, academic research projects can be associated with a set of factors that ultimately make some curious mind(s) undertake cognitive enterprises to fulfill personal goals, inquire about the nature of things, and/or propose novel approaches to existing models. As such, the critic researcher will set some goals to be achieved, or at least define some target levels she will try to approach as much as possible. There is indeed a fine line between motivations and objectives, cause and effect. I have already defined my desired goals, now it's time for the factors that caused such goals to emerge to be explicitly stated:

<i>ACADEMIC MOTIVATION</i>	<ul style="list-style-type: none"> ▪ Realization of the End-of-Degree Paper as required to all senior students of the degree in International Business Economics at UPF. ▪ Review contents from previous courses in the degree, in order to consolidate my knowledge and gain a cross-sectional perspective on the paper's main theme.
<i>SOCIAL MOTIVATION</i>	<ul style="list-style-type: none"> ▪ Study the financial sector, which has been at the center of an intense debate among different actors in the public sphere due to the current context of crisis. ▪ Try to investigate potential game changers. ▪ Develop a project from a set of unequivocal values, like commitment to excellence (both personally and towards the academic institution).
<i>INTELLECTUAL MOTIVATION</i>	<ul style="list-style-type: none"> ▪ Satisfy intellectual inquietudes formulated ex ante. ▪ Study some of the most important theories in natural sciences, which will likely have a major impact on future developments in both science and economics. ▪ Inquire about the links between science and economics.

1.5. METHODOLOGY

This section will be devoted to present, very briefly, the key procedural methods used in the execution of the paper.

1.5.1. General Theme

As described in the syllabus cited above, EDPs may be classified into one or more broad categories that ultimately define the scope and limitations of the work. In this respect, the present paper will pivot around three main themes and be complemented by a fourth one: The first half of the project, devoted to build a solid conceptual background, will transition from T3 (Review of bibliographical research) to T1 (Theoretical); the other part, devoted to research on potential applications of the abovementioned theoretical framework, will clearly be included in T2 (Empirical); and finally, as a result of any high-value-added contribution which could potentially be derived from the work, this paper may be considered ready to be potentially included in T6 (Published or accepted for publication papers or reports).

1.5.2. *Research Method*

As stated in *Subsection 1.1*, the execution of the project will be consistent with the requirements and methodological requisites set by the syllabus of the EDP. This project has been designed, on the one hand, as an intellectual research (based on bibliographical and theoretical research) and, on the other hand, as applied research (through the consolidation of previous knowledge and the investigation of potential links to reality). As such, a systematic research method will be used to find appropriate (and multiple) sources of information, comprehend and analyze their contents, extract relevant knowledge from them, interrelate and integrate them with existing pieces of knowledge already contained in the conceptual development of the paper, and create a consistent framework from which explore possible modeling applications (i.e. innovation in the financial sector) and infer meaningful conclusions and projections. In any case, the basic methodological procedure has been the following:

1. Definition of objectives
2. Development of a working plan according to them
3. Analysis of its feasibility
4. Execution

1.5.3. *Sources of Information*

Information search will be mainly based on journals, articles, papers, books, and reports from multiple disciplines (chiefly physics, biology, economics, finance, and geometry) allowing the reader to obtain a cross-sectional perspective on the issue being analyzed in the project. The vast majority of the sources of information used in this paper will be assumed to be relevant and reliable insofar as scientific, economic and finance materials will be extracted from the databases, subject guides, and catalogues UPF manages and students have access to. In this respect, information will be accessed and examined for the most part in digital support. The main sources of information are presented below:

- Electronic databases:
 - EconLit
 - JSTOR
 - Elsevier
 - SCIRUS
- Search engines:
 - UPF's Catalogue
 - RePEc
 - Google Scholar

1.6. LIMITATIONS OF THE PROJECT

As already mentioned in previous subsections, the scope of the EDP and its time and space constraints definitely set some limitations worth considering now. On the one hand, time constraints severely limit the conceptual depth of the descriptions and analyses of theoretical models and their applications; given the relatively large number of analytical models studied but not all presented in this paper (with the objective of providing a global view of some of the most important potential tools in financial innovation), the project will present a general overview of each of the models, cover the most relevant components, and include some of its applications in the field of finance. Moreover, the development of new applications or the suggestion of new applicable models will of course be limited by the degree of theoretical development achieved in the previous section. On the other hand, space limitations in terms of extension add another restricting element affecting the overall scope and reach of the paper. Above all, it should be noted that the syllabus regulating the EDP is the ultimately contextual element defining the scope, academic justification, and global objectives of the paper. Hence, it should be made clear that the present document is meant to provide a first introductory, strategic glimpse of financial innovation, its potential implications, and some novel proposals derived from the theory developed previously.

1.7. STRUCTURE OF THE PROJECT

The overall structure of the project is made explicit in the index preceding *Section 1* of this paper. As commented above, the general structure of the project is intended to provide a consistent transition from theoretical frameworks (*Section 2*) to applied research (*Section 3*); in addition, some final remarks and projections will be completed at the end of the paper (*Section 4*). Each section and subsection will have two clearly identifiable parts: At the beginning of each section or subsection, a paragraph will introduce the specific topic to be analyzed and the goals to be achieved; a final paragraph will provide a summary of what was done, which goals were accomplished, and how it interrelates with the next section. With such an internal structure, the interplay between sections will become evident and consistent throughout the development of the paper.

2. CONCEPTUAL FRAMEWORK

As explained in the introductory part of the present paper, this section is devoted to developing a solid theoretical base in which financial innovation will be defined and contextualized, potential synergies between science and economics will be presented, and diverse analytical models that have applications in finance will be briefly explored.

2.1. FINANCIAL INNOVATION

Financial innovation, besides other considerations, constitutes the core of the present paper. But before characterizing financial innovation, it would be worth defining the term *innovation*. After that, brief analyses of the current financial crisis, traditional applicable models, active research areas in finance, and financial R&D centers will be performed.

There exists extensive literature on innovation; each definition emphasizes different dimensions and explores different effects on invention, technological change, organizational structure, and economic growth. Indeed, terms such as «organizational innovation», «technological innovation», «scientific innovation», «entrepreneurial innovation», or «process innovation» evidence the multitude of applications of the same basic concept to diverse fields. In fact, most definitions and models of innovation have been proposed by actors as different as consultants, economists, engineers, scientists, psychologists, and business schools.

In any case, innovation may be defined as «the generation, acceptance, and implementation of new ideas, processes, products, or services» (Thompson, 1970). Mansfield (1968) makes a clear distinction between invention and innovation, and defines the latter as the effective application of an invention. Innovation has been widely described as a process rather than a concept in itself; Myers and Marquis (1969) develop on the idea of innovation as a process which consists of five sequential stages: recognition, idea formulation, problem solving, solution, utilization, and diffusion. Kimberly (1981) states that innovation can be understood as a process; as a discrete item including programs, products, and services; and as an attribute of organizations. Considering external factors, Scherer (1965) completes the picture by identifying key additional elements in the process (chiefly, entrepreneurship and investment), and Schmookler (1966) recognizes the role of market forces in innovation activities. Whatever the case may be, the same basic structural elements (i.e. research, development, production and diffusion) can be identified in nearly all definitions of the process. Some causal relationships, however, remain unclear in light of the different perspectives formulated on the issue (market-driven vs. science-originated, exogenous vs. endogenous innovation); context-specific factors, or the scope and goals of the process, should be considered when analyzing the causes and nature of particular types of innovation activities. Alternative interactive models (see Kline, 1985, and Rothwell, 1992), as opposed to conventional linear models, may shed light on the interrelation of the abovementioned elements—though little statistical evidence has been provided so far (Godin, 2006).

A quick look at historical developments may provide a proper tool to understand the characterization of innovation; according to Godin (2006), the concept of innovation was developed during three sequential stages: a discussion about *basic* and *applied research* (from the beginning of the 20th century to circa 1945), the addition of *development* into the equation (from 1934 to circa 1960), and the introduction of non-R&D activities such as *production* and *diffusion* into the model (starting in the 1950s). This last component—that is, the extension of the model to include the effective translation of research findings into products and processes adopted by the market, the ‘capitalization on the discoveries of science’ (Brozen, 1951)—constitutes the very basis of the discussion about the economic impact of research.

Diffusion is a particularly interesting component of the ‘innovation chain belt.’ Concepts such as *product adoption*, *product life cycle*, *network externality*, *learning curve* or the Schumpeterian *creative destruction* refer to some of the elements and processes that have an effect on new products’ adoption and growth rates in the market. Rogers (1962) associated the concept of diffusion with *communication* and included the effects of innovation on the social system and through time as key elements of the overall process. The fundamental relationship of innovation with science, technology,

and economics has been made clear since the first theoretical frameworks were developed to understand and model this apparent connection. Bush (1945) was one of the first authors to establish causal links between science and socioeconomic progress: «Without scientific progress, no amount of achievement in other directions can insure our health, prosperity, and security as a nation in the modern world». Indeed, he was considered to be one of the early proponents of the lineal model of innovation, which postulates that innovation starts with basic research, it is followed by applied research and development, and finally ends with production and diffusion (i.e. the economic components to it). The model has been very influential in the past decades and has attracted both supporters and detractors, but despite its regular criticisms, it has a strong statistical foundation that rival models lack. In fact, many academic organizations acting as a lobby for research funds and economists as expert advisors to policy makers have strongly disseminated the model, and have justified government support to science using it (Godin, 2006). In spite of the Solow's Paradox (by which empirical evidence seems to reduce the potential effect of technological innovation on economic growth and productivity), there is widespread consensus that innovation has a positive, long-term effect on economic systems.

As already mentioned, external factors have a clear incidence on the origination and impact of innovations. The 'national system of innovation' is a clear environmental determinant for organizations and research centers in their innovation activities; by providing incentive and pressures, competences available for production and research, and proper institutional settings, the national system of innovation imparts the rate and direction of technological change. Indeed, Frame and White (2004) acknowledge that the stream of innovations does not appear to be uniform across firms, industries, or even time. As such, environmental conditions seem to prevail over other factors. Levin and Cohen (1989) and Cohen (1995) help determine structural conditions that have an effect on innovation intensity: the market power of enterprises; the size of enterprises; technological opportunity; appropriability; and product demand conditions.

After having explored the general characterization of innovation, a definition of financial innovation should be made before proceeding with the rest of the section. When considering financial innovation, all the aforementioned elements will be present in the discussion and acquire relevancy later on when anticipating the potential impact of novel tools on the financial system and its dynamics.

2.1.1. What Is Financial Innovation?

What is financial innovation? The answer to this question remains partly unanswered. Despite the importance the financial sector and, more specifically, financial innovation have on the global economies of the 21st century, the latter does not count on a solid and consistent consensus about its nature. Miller (1986) put it this way: «The word revolution is entirely appropriate for describing the changes in financial institutions and instruments that have occurred in the past twenty years». Yet, «everybody talks about financial innovation, but (almost) anybody empirically test hypotheses about it» (Frame and White, 2004). According to Lerner and Tufano (2009), the economics literature on financial innovation tends to concentrate on «the diffusion of these innovations, the characteristics of adopters, and the consequences of innovation for firm profitability and social welfare»; the external, rather than the internal, aspect of financial innovation seems to be emphasized in this type of literature. «A striking feature of this literature, however, is the relative dearth of empirical studies that specifically test hypotheses or otherwise provide a quantitative analysis of financial innovation. This is surprising given the importance of the financial sector, the widespread recognition of the rapid and broad proliferation of financial innovation, and the relative abundance of similar papers for other sectors of the economy, especially manufacturing and agriculture» (Frame and White, 2004). Law literature has also dealt with financial innovation, but it tends to focus on financial products and how market actors might misunderstand the risks created by them (Hu, 1991).

Despite this seemingly inconsistency between relative importance and empirical studies (one may consider at this point that public disclosure from financial corporations, and research centers, constitutes the reason why), some authors have tackled the problem and proposed some definitions and novel theoretical frameworks approaching the issue. Gubler (2011) defines financial innovation as a «process of change, a change in the type and variety of available financial products to be sure, but

also a change in financial intermediaries and markets themselves». In Gubler's characterization, which the author dubs the 'financial innovation framework,' important insights from the 'New Institutional Economics' are used to assume that organizations and markets act as both substitutes and complements for organizing and governing economic transactions. As such, markets may act as substitutes for financial intermediaries (which are meant to provide financial products to firms and individuals, and manage their inherent risk) and so the latter may experience strong incentives to remove assets from their balance sheets, transfer them to the market, and concentrate on new, more complex, and often more profitable risks. Banks can also become complements to markets, and so the effective transfer of assets from banks to markets may indeed create new business opportunities for them. Thus, risk origination and management, and the interplay between financial instruments, intermediaries and markets seem to be a crucial cause of financial innovation.

Miller (1986) and Merton (1992) considered financial innovation as an 'engine of growth.' It may in fact be considered as a 'general purpose technology,' as Lerner and Tufano (2011) establish from the work of other authors, which has the potential to change the entire economic system. In a new model of economic growth, Michalopoulos, Laeven, and Levine (2010) argue that growth is not only a consequence of profit-maximizing entrepreneurs willing to introduce new technologies, but of financial entrepreneurs who find novel ways to finance the technologists. Not all outcomes are necessarily positive in the short term; Gubler (2011) argues the result of the modern financial innovation process is increased product and institutional complexity, and increased market fragility. Though the lack of empirical evidence on the impact of financial innovation on the economy should make one cautious about the potential consequences of it, it is nonetheless acknowledged that financial innovation has a clear incidence on highly-financially-dependent economies.

As will be discussed in subsequent sections, information has acquired an essential role in today's knowledge economies and financial systems, where it represents one of the most valuable strategic assets. The financial sector has seen many products emerging that redefine risks, cash flows, time horizons, underlying assets, and information schemes. Merton (1992) stated that «the primary function of the financial system is to facilitate the allocation and deployment of economic resources, both spatially and across time, in an uncertain environment». As such, concepts like time transformation, intertemporal consumption, investment decisions, asymmetric information, or risk reduction are indispensable to understand the nature of financial systems and their dynamics. Frame and White (2004) define financial innovation as «something new that reduces costs, reduces risks, or provides an improved product/service/instrument that better satisfies participants' demands». In addition, financial innovations, according to the authors, may be grouped into four different categories: new products, new services, new 'production' processes, and new organizational forms. Unquestionably, financial products have evolved to enhance certain characteristics, meet specific risk profiles, adapt to changes in regulatory environments, or accommodate particular macroeconomic conditions; credit default swaps (CDSs), mortgage-backed securities (MBSs), collateralized debt obligations (CDOs) or exotic options are some of the products that the financial sector has been trading during the past decade.

2.1.2. Antecedents: The Current Financial Crisis

The current financial crisis has undoubtedly put financial innovation at the center of the debate. The role that novel financial products played in the origination of the financial crisis has opened a vigorous debate about the nature of financial innovation, its value, and the proper regulatory response to it. Policy makers have been recently urged to develop new regulations dealing with financial innovation, and institutional supervisors (such as the Securities and Exchange Commission, SEC) have created special divisions overseeing it (Gubler, 2011). Amid the growing complexity of financial products (due to securitization, alternative risk schemes, and new market structures), information asymmetry has been reported as one of the main determinants of the origination of the financial crisis of 2008-2013 (we may trace back the start of the crisis in 2006, when clear signs started to emerge). Yet, it would be naïve to think that information asymmetry, the complexity of financial products, (intentionally?) flawed credit ratings, and the nature of the underlying assets alone are the sole causes of the sudden lack of liquidity that followed the bankruptcy of Lehman Brothers in October 2008 and paralyzed most Western economies; indeed, the system presented

strong incentives for all the main actors in the market to follow inertia and continue trading toxic assets or adopting overleveraged capital structures before the external shock occurred (i.e. the collapse of subprime mortgages). One could use models from game theory to argue that most financial intermediaries and institutional investors had clear dominant strategies. It may be too early to provide a comprehensive analysis of the factors that caused the current financial crisis; Posner (2009) points at regulatory failures, monetary policy, budget deficits, banking deregulation, or even ‘collective madness.’ Nonetheless, its consequences are well known.

Exogenous shocks, however, have a much more devastating power on interconnected, globalized, information-based, deregulated markets. According to Gubler (2011), the creation of new markets as a result of the abovementioned process of securitization and increased innovation in financial institutions makes markets expand but become even more fragile: they are relatively inefficient (and consequently subject to severe realignments in the wake of exogenous shocks), and untested in dealing with the stress that results from such shocks. In effect, the ongoing process of worldwide interconnection of financial markets has made them truly interdependent and reliant upon updated, constant informational inputs (e.g. statistics, news, rumors, or high-frequency data); as such, the consequences of external shocks are amplified, and the system presents immediate reactions that modify its internal dynamics and create global systemic changes. In such circumstances, one could argue that financial markets have become hyper-symbolic in the sense that information is the true centerpiece of the system (that may indeed be one of the reasons for the apparent disconnection between the so-called productive or real economy and the financial system). Though it will be covered later on, it could already be argued that the global financial system parallels a *neural network*, a *human brain*: a network of interconnected neurons (i.e. financial centers and IT platforms) that receive informational inputs (stimuli) and coordinate (ir)rational, specialized responses according to them. Neuroscience, or artificial intelligence, may become the next-generation models to conceptualize international financial flows and information impacts.

2.1.3. *Financial R&D Centers*

Research and development (R&D, or R&D+i) is the denomination of organizational structures within corporations, academic institutions, and public organisms that devote human, financial, and technological resources to innovation and basic and applied research. Innovation, as mentioned in previous sections, has emerged as a strategic asset for corporations and societies throughout the globe—who acknowledge the importance of generating, controlling, defending, and capitalizing information and knowledge in today’s integrated, globalized, knowledge economies. Indeed, we may characterize innovation as the generation of knowledge. The geostrategic implications of innovation and knowledge are obvious: from strategic control over energy and resources to military dominance and financial capacity, knowledge stands up as the focal point for long-term success.

De Gerbert d’Orlhac a la recerca d’Omega (Gerbert Garcia Bassa, 2009): Knowledge may be defined as the set of data, concepts, and practices around a specific subject matter, or the appreciation of the possession of multiple, interrelated inputs, which ultimately translate into the definition of a model of reality. Scientific, technological, philosophical, humanist, theoretical, applied... knowledge takes multiple forms and feeds itself in a synergic, interdependent manner. Humankind has always felt the necessity to comprehend and know the world surrounding it. Questions like who we are, where we come from, where we are heading to, which is the origin of the universe... obey to our ingrained eagerness to deal with fundamental questions linked to our existence and consciousness. The human species occupies a relatively insignificant portion of the cosmos (a cosmos which is in constant conceptual transformation); it may be argued that this is in fact the main reason for one of the features that better define human beings: the permanent search for knowledge [of reality]. Be it because of our inherent dissatisfaction or the need to better adapt to the environment, human beings have produced knowledge in an exponential dynamics. Population growth, energy control, and knowledge feedback are key factors. (The conceptual development of space, time, and energy constitutes one of the key success factors for the progress of the human species.)

The financial system is no exception. Finances represent a crucial component of today’s economic system, which is the model (i.e. organizational structure) human societies have developed to survive, manage resources, and progress as a civilization. As such, financial innovation is crucial. And

it is definitely exercised through financial R&D+i centers. Some academic institutions, primarily universities and business schools, have put in place some financial research units to conduct research on a variety of topics (e.g. simulation techniques and financial optimization), promote high-level exchanges among different players, organize workshops and conferences, and diffuse knowledge to society. Examples may be found in the United States or Australia in well-known, reputed institutions. Research need not necessarily be reduced to specifically designed centers though; most universities count on their own research departments, and journals such as the *Journal of Financial Research* generate synergies between researchers and institutions around the globe.

Corporations may be hosting the most powerful and high-impact-potential financial R&D+i centers though. As said, financial innovation essentially represents a core asset for financial corporations that affects its performance and long-term profitability. As such, the main global players tend to devote resources to it and create efficient internal structures to develop new products, create and test new financial high-tech and intelligence, support their global services, and generate robust financial modeling. But not only do global companies undertake innovation activities, but smaller financial institutions also innovate using different strategies (such as the creation of foundations dedicated to research and funded by a grouping of companies).

The geostrategic component of financial research has not escaped the analyses of countries which do not host important financial corporations with their own financial R&D+i units. The government of Israel has been one of the most active players in creating government support aimed at inducing foreign financial corporations set R&D+i centers within its borders, use local infrastructure, and take advantage of local human capital. «This plan [Relative Advantages Plan] is designed to meet the world's need for sophisticated analytical solutions that support the financial industry. Israel has quality manpower with advanced technological infrastructures and good-quality higher education» (Sharon Kedmi, director general of the Ministry of Industry, Trade and Labor of Israel) (Israel Trade Commission, 2010). The Irish government is also granting assistance to promote technology-based financial R&D.

2.2. SCIENCE AND ECONOMICS AND FINANCE: INTERDEPENDENT KNOWLEDGE

Science and economics; economics and finance; ergo science and finance. This conceptual triangle constitutes the basic theoretical motivation behind the application of theoretical models to financial innovation. Paradoxically, this trinomial has been long ignored by both scientists and economists; in fact, both sides seem to be reluctant to acknowledge the potential synergies a strategic cooperation could provide. The term 'social science' has created some problems to orthodox scientists, who base their arguments against utilizing the term 'science' on the grounds that economics does not effectively implement the long accepted, consistent, systematic, and empirically verified scientific method. Even if it did, they argue, the very nature of economic variables makes any *a priori* similarities disappear. On the other hand, economists seem to forgo the potentiality stemming from the strong analytical apparatuses that describe reality at a microscopic and macroscopic level. In fact, most financial models rely on very specific tools that prove effective on a limited set of strong assumptions. It seems clear, though, that both disciplines have a shared goal: to understand reality, its underlying laws and dynamics, and be able to predict it. The way to achieve such a goal is to develop systematic models: be it quantum mechanics or the IS-LM model, both conceptual constructions present an internal structure, are based on axioms (empirically inferred or conceptually derived?), and are empirically contrasted (or at least provide a framework to analyze reality). As such, there is no justification to make both sciences mutually exclusive. One may argue that their methods are effectively different, or that the degree of development between the two differs considerably (notice economics is a really young science); there is an enormous potential then. In fact, social sciences are a notable field test for natural sciences, providing them with really complex systems with agent-based, interdependent decisions. «The main force behind this outflow [econophysics] is not so much that physicists have lost interest in physics, but the realization that there are incredibly interesting complex phenomena taking place in other disciplines which seem now within the reach of the powerful theoretical tools which have been successful in physics» (Chatterjee, Yarlagadda, et al., 2005).

Not only conceptual, but historical links seem to point out in the same direction. Ray (2011) provides an interesting historical perspective about how economics as a science was developed and benefitted from the crucial contributions of some prominent physicists. In 1801, Nicholas-François Canard theorized that supply and demand were opposing forces in a physical sense (and so economic equilibrium was considered as a clone of mechanical equilibrium). Leon Walras (1874), the father of the general economic equilibrium, cited and subsequently utilized methodologies used by the physicist Louis Poincaré (1803). In 1930, Irving Fisher was a student of the physicist Willard Gibbs (the founder of statistical mechanics, which is one of the most heavily utilized models in econophysics); some years earlier, Albert Einstein (1905) had become the first person in all history to quantify random behavior after quantifying the stochastic process of the Brownian motion (as it will become evident, this is an important development for the agent-based models used in econophysics). More strikingly, Alfred Marshall (1920) admitted that he had borrowed heavily from physics to formulate his seminal *Principles of Economics*, and interpreted economics as a «branch of biology, broadly interpreted». Finally, Paul Samuelson (1947) acknowledged that physics had also been crucial in developing his *Foundations of Economic Analysis*. All in all, connections are evident between physics, economics, and finance. Some more evidence: the Black-Scholes-Merton option pricing model (1973) is essentially an application of the heat-transfer equations from physics; and one of the most used equations in finance, the time value of money, derives from the constant growth rate formula $X_t = X_0(1 + g)^t$ used by physicists for centuries (Ray, 2011). Certain events, in addition, propelled the exploration of economic and financial systems by non-economists; since the 1970s, when currencies began floating the Black-Scholes-Merton option pricing model was first introduced, and the 1980s, when electronic trading in the foreign exchange market started to produce high-frequency data, researchers were able to obtain complete data to which apply physical models and new statistical tools. It was when the financial markets started to be continuously monitored at very small scales of time (i.e. seconds) that enough information was produced to be analyzed with robust analytical models (Stanley and Mantegna, 2000). But that's not the complete picture.

Aren't in fact both disciplines inextricably interconnected today? Resources are costly, and basic and applied research depend significantly on public support and private initiatives trying to capitalize on it. In the wake of economic downturns, resources devoted to research tend to diminish considerably (as an extreme example, consider the case of Spain, where short-term economic needs are not aligned with longer-term goals). Economic incentives are two-edged swords, but whenever there is a strong, dynamic private sector (consider the case of the United States of America) economic incentives end up boosting science and technology and creating synergic poles of attraction (e.g. clusters) in the medium and long term. Science depends on the economy, it forms part of the economic system, and it certainly has immense potential to modify it. As such, an alignment between both should really become the next strategic alliance our societies develop during the 21st century.

The next subsections will be devoted to present some disciplines that are emerging and explore the consequences of an interesting and powerful relationship between science and economics and finance. Though these disciplines are based for the most part on the application of scientific models on economic and financial systems (that is, a one-way flow of knowledge from natural sciences to economics), future developments are likely to reverse this trend (so that econosciences contribute to natural sciences by shedding light on the dynamics of complex systems).

2.2.1. *Econophysics*

Econophysics has emerged as the most notable response to such knowledge gap. Constructed out of 'economy' and 'physics,' the term 'econophysics' first appeared on 1995 at an economics conference (titled *Dynamics of Complex Systems*) in Calcutta (India) performed by the physicist H. Eugene Stanley. Jovanovic and Schinckus (2012) show that the term econophysics, as a specific label and conceptual practice, was first used in a paper published by the same Stanley and Afanasyev in 1996. Other authors, though, trace back the origins of the discipline back to 1991 when Mantegna published a paper about the use of stable Lévy processes in finance (Kutner and Grech, 2008). Jovanovic and Schinckus (2012) identify the basic ideas of econophysics in finance on Benoît Mandelbrot's work analyzing the analogy between the evolution of financial markets and the phenomenon of turbulence. Whenever the origins might be, econophysics has become a rapidly growing science that has increased

its influence exponentially over the past years. Economists and physicists have been co-authoring numerous papers published in specialized journals (e.g. *Nature* or *Quantitative Finance*), many conferences have emerged, PhD programs have been created (consider the pioneering efforts of the University of Houston), and journals specialized on econophysics have been produced (Cornell University maintains an online econophysics journal at arXiv.org). Common topics include income and wealth distributions, stock prices, GDP growth rates, city sizes, firm sizes, wealth concentration, foreign exchange returns, money characteristics, and various other economic and financial subjects (Ray, 2011).

But, what is exactly econophysics? According Ray (2011), econophysics is a scientific discipline within econosciences that utilizes mathematical models from physics to explain economic and financial behavior. Jovanovic and Schinckus (2012) define it in methodological terms as «a quantitative approach using ideas, models, conceptual, and computational methods of statistical physics» applied to economic phenomena (especially financial phenomena). In essence, econophysics is the exchange of methods between natural and socioeconomic sciences (Mimkes, 2011). For Schinckus (2011), econophysics «presents itself as a new paradigm and a new specialty (or even a discipline) using various models and concepts imported from condensed matter and statistical physics to analyze financial phenomena». Going even further, the same author argues that it effectively attempts to replace the theoretical framework that currently dominates financial economics with a new framework derived directly from statistical physics. In any case, the aim of econophysics is to understand the universal behavior of a market (Alessio Farhadi). Theories like the theory of turbulence, scaling laws, random matrix theory, chaos theory, neuroscience, pattern recognition, or fractals are some of the theoretical frameworks explored by econophysicists and applied to some relevant issues in economics (such as data analysis, risk management, artificial markets, or macroeconomics) (Săvoiu and Simăn, 2008). Complementary, as opposed to mutually exclusive, may be the proper adjective to describe the binomial financial economics–econophysics. Originally, econophysics was created by physicists trying to explore complex systems (i.e. economic and financial systems) with their analytical tools; their effect on economists, though, has proved powerful. Schinckus (2011) argues that econophysics could be a source of inspiration for financial economists to broaden their theories, while Săvoiu and Simăn (2008) state that econophysics means either a new domain for physicists or new methods and ways of thinking for economists in the modern world.

Schinckus (2011) provides an excellent depiction of what econophysics is, which concepts and models uses, and how it can add value to the overall analysis of financial and economic systems. (The following three paragraphs rely very much on his work.) This new discipline was created within the context of the development of the so-called ‘complexity science’ that emerged during the 1990s, a new approach to science that studies how relationships between parts give rise to collective behaviors of a system and how it interacts and forms relationships with its environment. As such, the study of complex systems constitutes, by definition, the core of complexity science and econophysics. How are complex systems characterized? Complex systems are composed of a large number of interdependent subunits that basically interact non-linearly between them. Adaptive complex systems, in turn, imply that microstructural units modify their behavior with respect to a changing environment, resulting in the generation of new systemic properties. There is even another level of complexity: organizing adaptive complex systems. In them, individual subunits modify their own properties and behavior with respect to the properties and behavior of the unit system they jointly determine (Latora and Marchiori, 2004).

According to econophysics, economic and financial systems should be analyzed as complex systems in which multiple components (agents) interact in such a way as to generate the macroproperties of systems and subsystems (Rickle, 2008). This is a revolutionary concept. Macroproperties emerge as statistical regularities that are best described by power laws (chiefly Lévy processes), which characterize the macroresult of the behavior of a large number of interacting components at lower levels. Econophysics adopts a macro perspective then, whereas standard financial economics focuses on the individual characteristics of agents (notably rationality) and tends to forgo the synergies and complementarities emerging from the interactions between them (that is, it ‘disembeds’ agents from the system they form part of). No real ‘microeconophysics’ exists; the conceptual framework econophysics uses effectively removes the traditional macro-micro distinction by adopting a model in which micro properties are dynamic, interactive, and are embedded in the

macro state of the system (micro properties in fact depend on the same macro state). Interacting parts are found to obey macro laws (laws independent of each microscopic detail and dependent on some macro parameters), and may be understood as reactive individual subunits that modify their own properties and behavior with respect to the properties and behavior of the unit system they jointly determine. That sharply contrasts with traditional economics, in which individual agents have defined characteristics that configure specific macro equilibriums (that is, the simple addition of individual behaviors determines equilibrium). The notion of equilibrium need not play a key role in econophysics though: whereas there are a lot of similarities between economic and physical equilibrium (in both cases the same mathematical apparatus is used), equilibrium is characterized in econophysics as a potential state of the system rather than a foundational aspect of economic theory. Structure and evolution, as compared to stability, are the main elements characterizing complex economic systems (where downward causality prevails over the traditional bottom-up approach of financial economics). In effect, all markets are characterized by non-stationarity, a general feature of adaptive complex systems (Săvoiu and Simăn, 2008).

Econophysics takes an interactive atomistic approach. (Let's now use the word 'particles' in a physical sense to refer to economic agents such as traders, speculators, or hedgers, for example.) Not only do particles interact between them and form complex systems, but their interactions depend on specific variables (e.g. distance): particles will interact and create different structures as a function of their positions in the system (consider molecular structures and crystals, which may be a realistic representation of economic systems). There is some degree of heterogeneity in interactions too (in a physical sense: weak, strong, gravitational, and electromagnetic interactions) which configures the structure and internal dynamics of such self-evolving, adaptive complex systems.

Uncertainty constitutes another important dimension in econophysics. Econophysicists usually use the term 'entropy' to characterize the idea of uncertainty in economics and finance (Schinckus, 2011). Dionisio et al. (2005) argue that «entropy is a measure of dispersion, uncertainty, disorder, and diversification used in dynamic process, statistics, and information theory, and has been increasingly adopted in financial theory. [...] The use of entropy as a measure of uncertainty in neoclassical finance appears to have many potentialities and a vast field of development both in theoretical and empirical work». The application of this concept in finance is very recent, yet models such as the Gibbs entropy, Tsallis entropy, Shannon entropy, or Rényi entropy are being explored by econophysicists (Schinckus, 2011). Uncertainty is inevitably related to risk, and hence further developments in this field are likely to have an impact on the notion of risk, risk calculations, risk management, and financial innovation. (The section devoted to thermodynamics will further explore the implications of entropy and the thermodynamic principles in economic and financial systems.)

After characterizing econophysics, and depicted some its most relevant aspects, it would be worth discussing it methodologically. Two different methodologies are used in econophysics: strictly mechanical, and agent-based (Jovanovic and Schinckus, 2012). The first refers to the provision of analytical tools to describe and characterize macroeconomic regularities in the evolution of complex systems; the latter, to the provision of a framework to reproduce these statistical regularities by giving them micro-foundations, that is, reproducing observed data in real economic systems (Farmer and Foley, 2009, and Schinckus, 2011). Hence, econophysics is composed of a descriptive component trying to observe regular patterns in economic systems mostly using the advanced tools of statistical physics, and an integrative component incorporating statistical regularities into a consistent model of the evolution of complex economic systems. In any case, data-driven methodologies are essential in econophysics: «We recommend a more data-driven methodology. Instead of starting out with *ad hoc* specifications and questionable *ceteris paribus* assumptions, the key features of the data should be explored via data-analytical tools and specification tests» (Colander et al., 2008). Stanley and Amaral (2000) state that, in contrast to standard economics, econophysicists begin empirically with real data that one can analyze in some detail but without prior models.

The main tools of econophysics are presented next. The traditional models applied to financial economics are mostly based on linear models and Gaussian distributions; econophysics, however, establishes a new paradigm by changing some of the deep-rooted assumptions of standard finance. Non-linearity, as compared to linearity, is the main conceptual innovation. In *The Death of Economics*, Ormerod (1994) already argued that non-linearity would replace linearity in classical economics. In fact, most physical models and theories assume non-linearity (consider genetic

algorithms, chaos theory, complexity theory, or fractal geometry). Complex systems are better characterized by non-linearity (linearity just applies under a set of specific conditions). Just to put a clarifying example, consider the two paradigms of the nature of space and time: Newton vs. Einstein. Whereas Newtonian mechanics assumes that space and time are linear, absolute and separate entities, Einstein's general relativity proves that space and time constitute a single entity (the 4-dimensional space-time) which is non-linear and relative (Ray, 2011). (This example, though, may lead to an important conclusion: microscopic and macroscopic complexity may be correctly simplified at certain scales, just as quantum and relativistic effects can be neglected at the human scale and low speeds; in this respect, relatively simple models may provide an efficient synthesis of a more complex reality.) Linearity is defined as the mathematical property by which linear functions such as $f(x)$ are additive ($f(x + y) = f(x) + f(y)$) and homogeneous ($f(ax) = af(x)$).

Apart from non-linearity, econophysics is defined by:

- **Scaling laws**

The scaling properties of economic and financial systems are another key element in econophysics. Defined as the property by which the same statistical features (patterns) are found at different levels of observation, scaling laws open up the possibility of studying regularities using some statistical and geometric tools such as power-law distributions and fractal geometry (in fact, fractality can occur along the spatial and temporal dimensions; consider the case of financial markets, whose fractality with respect to time has long been studied). Pareto had already established a first scaling law in 1897 (if Ω is defined as any number of observations of a variable that exceeds X observations of that variable from its population, and μ and ψ are positive constants, then $\Omega = \mu X^{-\psi}$ exhibits the scaling property $\ln(\Omega) = \ln(\mu) - \psi \ln(X)$). In fact, this scaling model seems to better describe income and wealth distributions with fat tails (Ray, 2011).

- **Statistical mechanics**

Statistical mechanics is a branch of physics that largely applies probability theory to the study of physical systems (mostly thermodynamic) composed of a large number of particles (i.e. complex). In fact, it provides a framework for relating microscopic properties with the macroscopic behavior and properties of such systems. According to Ray (2011), statistical mechanics applied to econophysics uses probability theory to analyze large populations whose variables are continually subjected to a random force (e.g. stock prices). By analyzing and aggregating the behaviors of the individual variables in the population, statistical mechanics can deduce population properties. Stochastic dynamics, short- and long-range correlations, unpredictable time series or self-similarity are some of the new concepts from statistical physics used in econophysics (Mantegna and Stanley, 2000).

- **Entire family of stable distributions**

Standard financial economics relies mostly on linear models and Gaussian distributions to analyze large populations (e.g. stock prices). Though Ray (2011) explains the propensity to use such distributions as a consequence of Samuelson's demonstration that the lognormals of the variables of large populations closely approximate a Gaussian distribution, other stable distributions are more robust in explaining empirical data (especially those distributions that present 'fat tails', i.e. probable high values relative to the mean). As such, the Cauchy and Lévy distributions better model fat-tail distributions like income, or price changes (though diverging in terms of moments and variance, both distributions are special cases of stable distributions). The Cauchy distribution has a probability density function

$$f(x; x_0, \gamma) = \frac{1}{\pi\gamma \left[1 + \left(\frac{x - x_0}{\gamma} \right)^2 \right]} = \frac{1}{\pi} \left[\frac{\gamma}{(x - x_0)^2 + \gamma^2} \right]$$

where x_0 is the location parameter, and γ the scale parameter of the distribution. Its moments are undefined and its variance is infinite. The Lévy distribution has a probability density function over the domain $x \geq \mu$

$$f(x; \mu, c) = \sqrt{\frac{c}{2\pi}} \frac{e^{-\frac{c}{2(x-\mu)}}}{(x-\mu)^{3/2}}$$

where μ is the location parameter, and c the scale parameter. (It should be noted here that its variance is infinite.) Indeed, there is a close relationship between stochastic processes and the Lévy distribution; Lévy stable processes are stochastic processes obeying a generalized Central Limit Theory. The sum of independent and identically distributed stochastic processes $S_n = \sum_{i=1}^n x_i$ characterized by a probability density function with power-tails $P(x) \sim x^{-(1+\alpha)}$ will converge in probability to a Lévy stable stochastic process of index α when n tends to infinity (Mantegna and Stanley, 2008). The importance of Lévy distributions is well acknowledged; according to the same authors, Mandelbrot's hypothesis that price changes follow a Lévy stable distribution was «a revolutionary development» in econophysics.

To conclude the discussion about econophysics, it would be worth considering its relationship with financial economics. Contrary to the historical developments in economics already mentioned (in which economists constantly borrowed from physical sciences), econophysics has been mainly developed by physicists that go beyond the boundaries of their discipline to study various problems of social sciences with their models (Jovanovic and Schinckus, 2012). In fact, «the main force behind this outflow is not so much that physicists have lost interest in physics, but the realization that there are incredibly interesting complex phenomena taking place in other disciplines which seem now within the reach of the powerful theoretical tools which have been successful in physics» (Chatterjee, Yarlagadda, et al., 2005). As such, there is a potential problem of cohesion between econophysicists and economists. As argued, both natural and social sciences share many elements, goals and tools, and econosciences have the potential to build strong, synergic relationships between the two. The human factor is really important in this process though. If econophysics continues to be developed mostly by physicists within their traditional fields of study, economic theorists and financial economists are not likely to adopt econophysic models, which use a mathematical apparatus they are not familiar with and do not master. Without the potent tools of natural sciences, economics will hardly develop into an empirical, consistent, and systematic science. The opposite is true of natural scientists; without the insights and meaningful interpretations of economics and finance, and the existence of the complex systems they are analyzing, they forgo an opportunity to study and interpret complex dynamics. Jovanovic and Schinckus (2013) put it this way: «econophysicists do not attempt to develop common models or theories by making a synthesis with models or theories from economics». This is a real mistake. Econophysics, as its name evidences, should constitute an open dialogue between natural and social sciences where strategic synergies are enhanced. Some barriers will have to be eliminated though; Jovanovic and Schinckus (2012) identify both theoretical and sociological difficulties that may jeopardize any potential collaboration. The first difficulty lies in the fact that most of the models used by econophysicists are not used by financial economists because they are incompatible with financial economics' theoretical framework; a clear example of that is the interpretation of the variance of certain distributions: the variance of stable Lévy processes is infinite, and so it creates theoretical problems (the expected mean and variance are essential elements of risk and return in standard financial economics). Indeed, one could even argue that some econophysic models are apparently incompatible with the well-known portfolio theory, CAPM, or the Black-Scholes-Merton option pricing model. Sociological barriers are also present: some econophysicists seem to be opposed to a potential collaboration with economists; they criticize financial economics by emphasizing, for instance, the “superficially appealing” nature of its concepts or by describing the field as a “tapestry of beliefs” (Jovanovic and Schinckus, 2012). The econophysicist McCauley even stated that «econophysicists are safer to ignore the lessons taught in standard economics texts».

Whatever the case may be, Jovanovic and Schinckus (2012) argue that, in spite of the fact that some collaboration exists between scientists and economists, econophysics remains an autonomous field which cannot be defined as integrative and collaborative. The same authors, though, provide readers with some future guidelines (i.e. hope): «To be an interdisciplinary field, econophysics should provide integration and a synthesis of economics and physics by developing a common methodology, models and theories. However, up to now, all models developed by econophysicists have

stayed within the boundaries of statistical physics. Indeed, econophysicists try to explain economic phenomena only with theoretical tools, models and methods derived from physics. [...] A transdisciplinary econophysics would imply a more integrative approach in which econophysicists and financial economists would share a common conceptual scheme that transcends both disciplines. This “integrative dimension” refers to two kinds of integration: on the one hand, a methodological integration to produce a common conceptual framework and, on the other hand, a sociological integration—meaning that theorists from the disciplines involved go beyond their cultural differences in order to work together in a common project».

2.2.2. *Econochemistry*

Apart from econophysics, there are other disciplines applying scientific models to economics and finance. Econochemistry stands up as a less developed yet potentially powerful discipline applying models from chemistry to the modeling of economic systems; the lack of literature makes any further analysis unfeasible at this point.

2.2.3. *Econobiology*

Econobiology, as its name indicates, consists of the application of biology models to economic and financial systems. As in the case of econochemistry, there is little literature on econobiology; nonetheless, it uses a powerful tool that has proven extremely successful in modeling agent-based complex systems: the swarm theory (also known as swarm intelligence) which will be explored in greater detail in *Subsection 2.3.2*.

2.3. NEW APPLICABLE MODELS

2.3.1. *Thermodynamics*

2.3.1.1. DEFINITION

Thermodynamics (from the Greek words *therme* (θερμη), «heat», and *dynamis* (δυναμις), «power») is the branch of natural science that studies the effects of changes in temperature, pressure, and volume on physical systems at a macroscopic level and, most importantly, the relation of heat with energy and work. Lord Kelvin, one of the fathers of thermodynamics, defined it in 1854 as «the subject of the relation of heat to forces acting between contiguous parts of bodies, and the relation of heat to electrical agency». Alternatively, thermodynamics defines macroscopic variables (such as temperature, internal energy, entropy, and pressure) which are interrelated and characterize materials, but change over time as a result of thermodynamic processes; indeed, this discipline analyzes and classifies the interactions between thermodynamic systems, which are characterized by equations of state (or characteristic equations) when they are in thermodynamic equilibrium. The concept of thermodynamic equilibrium (i.e. when no macroscopic change is occurring or can be triggered) is one of the most important concepts of thermodynamics, along with the conceptual distinctions between *system* vs. *surroundings* (i.e. other thermodynamic systems that can interact with it) and *process* vs. *state* (i.e. the macroscopic physical and chemical variables that describe the macroproperties of a system).

The results of thermodynamics have been largely used in fields as diverse as physics, chemistry, aerospace engineering, or material science. Economics is no exception.

The keystones of thermodynamics are its four universal laws:

- **Zeroth Law of Thermodynamics**

Developed during the first third of the 20th century when the other three laws had already been defined and widely used, the Zeroth Law of Thermodynamics states that

If two systems (A and B) are each in thermal equilibrium with a third one (C), they are also in thermal equilibrium with each other.

Thermal equilibrium is defined as the situation in which the empirical state variables or thermodynamic coordinates of a system (such as volume, pressure, or temperature) are constant over time, i.e. spontaneous molecular thermal energy exchanges between systems do not lead to a net exchange of energy ($\Delta T = 0$). Mathematically, the law relates systems A, B, and C as follows

$$\begin{aligned} &\text{if } T(A) = T(B), \text{ and} \\ &\text{if } T(B) = T(C), \text{ then} \\ &T(A) = T(C) \end{aligned}$$

where T is the temperature of the systems. In essence, this law provides an empirical definition of temperature.

- **First Law of Thermodynamics**

This law represents an application of the principle of conservation of energy to thermodynamic systems. It states that

The increase in internal energy (ΔU) of a closed system is equal to the difference of the heat (Q) supplied to the system and the work (W) done by it:

$$\Delta U = Q - W$$

Heat may be absorbed by the system from a source at a higher temperature or transferred to a system at a lower temperature; conversely, work may be performed by the system or its surroundings. The differential expression

$$dU = \delta Q - \delta W$$

(where d and δ denote infinitesimal changes in the variables) is also used to distinguish between state variables (U) and processes or changes of the state of systems (Q and W). In open systems, with mass and energy fluctuations, the law can be restated as

$$\Delta U = Q - W + \sum_{\text{in}} m_{\text{in}} \left(h + \frac{1}{2} v^2 + gz \right)_{\text{in}} - \sum_{\text{out}} m_{\text{out}} \left(h + \frac{1}{2} v^2 + gz \right)_{\text{out}}$$

where $\sum_{\text{in}} m_{\text{in}}$ and $\sum_{\text{out}} m_{\text{out}}$ are mass variations, and $h + 1/2 \cdot v^2 + gz$ is the addition of enthalpy (h), kinetic energy ($1/2 \cdot v^2$, where v is mass velocity), and potential energy (gz , where g is gravity and z mass height) which account for the energy of each unit of mass transferred from or to the system.

- **Second Law of Thermodynamics**

This law states that

*Heat cannot spontaneously flow from a colder location to a hotter location.
Alternatively, it is not possible to change heat completely into work.*

This principle concerns two of the most important magnitudes in thermodynamics: temperature and entropy; it is an observation that over time differences in temperature, pressure, and chemical potential to even out in an isolated physical system. Entropy constitutes an indicator of this process; expressed as the measure of the disorder of a system or the amount of non-usable energy in a system (i.e. irrecoverable heat), entropy (from the Greek *εντροπια*, «evolution») defines the limitations on the amount of thermodynamic work that can be delivered to an external system by a thermodynamic process. In reversible processes, entropy is analytically expressed as

$$dS = \frac{\delta Q}{T}$$

where S is entropy, Q heat exchanged between the system and its surroundings, and T absolute temperature. When the process is irreversible (that is, what occurs in reality), entropy may be defined as

$$dS = \delta\sigma_p + \sum_{i=1}^n \frac{\delta Q_{TF_i}}{T_{FT_i}}$$

where σ_p stands for *entropy production* (in reversible processes, $\delta\sigma_p = 0$). Entropy thus defines irreversibility in nature (e.g. the arrow of time, asymmetry, or causality). A thermodynamic process can only occur in an isolated system whenever total entropy increases (entropy in the universe tends to increase over time); at thermal equilibrium, entropy reaches the maximum value. In any case, variations in entropy (ΔS) may be expressed as

$$\Delta S_{\text{universe}} = \Delta S_{\text{system}} + \Delta S_{\text{surroundings}}$$

or

$$\Delta S_{\text{isolated system}} = \Delta S_{\text{subsystem}} + \Delta S_{\text{subsurroundings}}$$

- **Third Law of Thermodynamics**

The last principle states that

As a system approaches absolute zero, the entropy of the system approaches a minimum value.

This law states that it is impossible to reduce the temperature of any system to absolute zero (i.e. 0 K, or -273.15°C) with any procedure consisting of a finite number of operations. At absolute zero, the entropy of a system would reach a minimum, constant value known as absolute entropy ($dS/dt = 0$). At absolute zero, systems would present their fundamental state; any changes in its thermodynamic state would be associated with increases in overall entropy levels, and so entropy may be considered as a measure of the degradation of the primordial system.

2.3.1.2. APPLICATION

Von Neumann believed that thermodynamic formalism could potentially be useful in computer theory, for formulating a description of intelligence, and was interested in the possibility of a thermodynamics of economics (McCauley, 2007). There is extensive literature on the application of thermodynamics on economic systems; in fact, principles and concepts such as entropy have been used to explain economic behavior and provide alternative economic structures. «The interest of applying thermodynamics in a systematic manner to describe the behavior of economic and financial systems has a long history» (Quevedo and Quevedo, 2011). «There is some uniformity in views among economists as well as physicists that a functional correspondence exists between the formalisms of economic theory and classical thermodynamics» (Bhattacharya and Kumar, 2006). There has been controversy though; the notion of equilibrium, which is central to both disciplines, has led some authors to deny the potential thermodynamic nature of economic and financial markets (instead, deterministic or stochastic processes within complex systems are considered to better describe actual dynamics). Indeed, some thermodynamic variables are hard to define and quantify in economic systems (e.g. internal energy), and so the effective application of this discipline remains doubtful. What is more, the discussion about the role played by some economic variables can jeopardize any thermodynamic analogy (consider the case of money, which may be defined and used as a thermodynamic variable but some suggest is an irrelevant economic parameter) (Quevedo and Quevedo, 2011). In addition, financial applications remain poor: whereas some authors are able to associate thermodynamic variables such as heat and work with stock markets (or construct trading strategies based on the laws of thermodynamics), most research has focused on economics. In fact, econophysics has largely used models from thermodynamics and statistical mechanics, which deal with the evolution of the macro properties exhibited by systems (nonequilibrium states cannot be treated within the standard approach of statistical mechanics though). (The entropy theory of information is another conceptual framework derived from thermodynamics and applied to the study of financial markets; it provides alternatives to the usual theories in behavioral finance. See Chen

(2005) for a study of the heterogeneity in information processing by investors which offers a simple understanding of the price and volume patterns identified in empirical studies.)

Before proceeding with the rest of the section, it would be worth considering the work of McCauley (2007), who denies any potential analogy between thermodynamics and finance. Using a standard strategy from trading theory, the author argues that thermodynamic analogies fail to describe financial markets (even in the presence of liquidity, the underlying basis for market entropy). (It was von Neumann who first associated market entropy with liquidity, a source of potential disorder.) Indeed, he claims that financial markets are the very best place to test both old and new ideas about economic theory; in this respect, McCauley states that statistical equilibrium is impossible in financial markets, as empirical data suggests (another argument against any analogy). Existing analogies with option pricing models may be flawed too (though the author acknowledges the possibility of an analogy between option pricing and Caratheorodý's formulation of thermodynamics).

McCauley's standpoint is not shared by all researchers; there are those who seem to prove the existence of strong, useful analogies between thermodynamic concepts and laws and economics. Samuelson in 1970 acknowledged that the relationships between pressure and volume in a thermodynamic system bear a striking similarity in terms of differentials to price and volume in an economic system. Earlier, Pikler (1954) had highlighted the connections between temperature and the velocity of money; even Georgescu-Roegen (1979) noted that economic systems exchange both energy and matter with their environment and are thus best represented as open thermodynamic systems. The notions of equilibrium and conservation of certain magnitudes are also crucial for any analogy; Quevedo and Quevedo (2011) state that «there is a reasonable number of arguments which show that certain current economies can be considered as systems in equilibrium and some quantities, like the total amount of money in the system, are conserved during certain periods of time (like money distributions)». Indeed, Meneses (2004) argues that wealth is conserved in transactions, so it could potentially be considered as a measure of internal energy.

Gündüz (2012) develops on the behavior of systems to introduce thermodynamic concepts in economics and social systems; according to the author, systems may react rigidly (i.e. elastically) or viscously (i.e. softly) to external shocks. Therefore, relation-based systems are defined by their degree of viscoelasticity; thermodynamic 'work' (W) is associated with their elastic component, whereas 'heat' (Q) is linked with their viscous component. As long as the stock market represents a good example of a relation-based system (possibly a chaotic system), and may be described by spin dynamics and autocatalytic reactions (e.g. a stock becoming an attractor for investors), the author analyzes the changes of the NASDAQ-100 index between January and June 2011 to determine its thermodynamic properties: the index presented highly dissipative behavior where work terms were very small but heat terms were of large magnitude. Small heat would then denote high fluidity and thus more random motion (in thermodynamics, dissipative energy corresponds to heat). In any case, increases in the value of a stock index may be considered a result of absorption of energy from the environment leading to an increase in the work component of the system. (The author goes beyond this analysis and argues that human behavior, which displays viscoelastic properties, can be characterized quantitatively by thermodynamic terms). Gündüz makes another interesting analysis: «However we are somehow lucky with the second law, which can be applied to all systems whether its energy can or cannot be defined. In simple diffusive mixing where there is no energy involved the entropy of mixing can be easily calculated using the basic equations. This is because, it is sufficient to know or define phase space to calculate entropy. Degradation of phase increases entropy; meanwhile it also drives the system into chaos. Besides entropy 'fractal dimension' is also a powerful tool to analyze an evolving system; the former is a measure of increase of randomness whereas the second is a measure of nonlinearity. The increase of nonlinearity naturally decreases the correlations between the components or variables of a system. So the increase of nonlinearity can both increase entropy and fractal dimension. The increase of randomness in a system increases the heat term in the first law at the expense of the work term».

As seen, structure is an important dimension of economic systems. Quevedo and Quevedo (2011) argue that thermodynamic interaction is an important concept which can completely modify the interior and exterior structures of the system; indeed, the theory of geometrothermodynamics was

formulated with the aim of describing thermodynamics in terms of geometric concepts (one of its results expresses thermodynamic interaction as a curvature of the equilibrium space).

Piotrowski (2000) also explores financial markets; according to the author, the latter can be explained using such notions as gauge symmetry or ultrametricity (to describe the distance between stocks). Portfolio theory, however, provides an interesting field to which apply thermodynamics in finance (in particular, valuation of portfolios and investment strategies): the author defines temperature-like parameters that measure the quality and professionalism of investors, characterizes entropy as the 'temperature' of portfolios, and presents the formula $\delta Q + TdS = 0$ (where Q is investors' knowledge, T temperature, and S entropy). In the same line of thought, Hirai (2008) develops what he calls 'Entropy-Oriented Trading': a finance trading strategy in which state variables are chosen so that the strategy satisfies the second law of thermodynamics.

Entropy, just as in thermodynamics, is a central concept which has offered many analogies in economics and finance. In most applications, Shannon entropy (a measure of the uncertainty in a random variable in information theory) is used more frequently than the standard Carnot entropy (by which $dS = \delta Q / T$, where S is the entropy measure, Q the thermal energy of the state transformation, and T absolute temperature). Smith and Foley defined 'entropy' as a quantity constructed as a Legendre transform on utility, with utility maximization being interpreted as analogous to entropy maximization for a closed mechanical system in thermodynamic equilibrium (McCauley, 2007). Jenkins (2005) argues that the maximization of the production of classical thermodynamic entropy, via the consumption of available energy and other resources, may play a dominant role in economic systems (in fact, the author associates higher levels of economic activity and development with a higher production of entropy, and money itself with entropy; in the same line, Meneses (2004) associates economic temperature with economic development). Human activity would thus act to produce entropy at a maximum rate, subject to practical constraints such as the availability of resources and other raw materials, and the energy which must be diverted in order to extract them (Jenkins, 2005). The term 'maximum entropy production' (MEP) has been widely used as an axiom for most analogies. Indeed, entropy has been widely compared to utility and utility maximization. Jenkins (2005) proposes that, instead of individuals trying to maximize their own 'utility,' individual and political pressures in a society tend to maximize entropy production. Bhattacharya and Kumar (2006) propose an entropic model of extrinsic utility arising out of the element of choice regarding portfolio re-balancing strategies. «The laws of thermodynamics can be intuitively interpreted in an economic context, and the correspondences show that thermodynamic entropy and economic utility are related concepts sharing comparable formal framework» (Bhattacharya and Kumar, 2006). Utility is said to arise from that component of thermodynamic entropy whose change in value is due to irreversible transformations (Foley, 1994). (McCauley (2007) refuses the idea to look for entropy in utility; instead, disorder should be the key.) Jenkins (2005) goes one step further and analyzes certain economic events in terms of entropy: the 'dotcom bubble,' for instance, generated considerable entropy (consider the amount of bits of information produced in the information technology industry). But, the author continues, the entropy generated by it palely compares with the production of entropy of other industries like transportation or industrial production.

Not only partial, but complete analogies have been produced between thermodynamics and economics. Most remarkably, the laws of thermodynamics have been applied to economics so as to generate a set of *economic laws*. Bryant (2007) and Mimkes (2006) provide clear examples of that. Using the First Law of Thermodynamics, Bryant formulates the First Law of Economics with the same formulation but defining δQ as the value being put or taken out of the system not represented by real output (e.g. scarcity or abundance, write-off of an asset, or an investor putting new money into an existing market that is not represented by the underlying productive value) and dW as a volume change. Mimkes calls it the Capital Balance of Production and interprets surpluses (dE) as a result of increases in capital (δQ) and the input of work - dW (understood as the effort and knowhow applied to a job). The Second Law of Economics is characterized by Bryant by entropy changes, which are defined as a measure of the amount of value per index of trading value that is not available in a particular economic process for conversion into real productive content and work done. Mimkes acknowledges the existence of a system function $dS = 1/T \cdot \delta Q$ and the fact that, in stochastic systems,

entropy replaces the Cobb-Douglas function of standard economics as a production function (positive changes in entropy are associated with distribution, and negative ones with collection).

2.3.2. *Swarm Intelligence*

2.3.2.1. DEFINITION

First used in 1998 in the context of cellular robotic systems, the term swarm intelligence (SI) refers to the collective behavior of decentralized, self-organizing complex systems composed of simple agents (also known as boids) interacting locally with one another and their environment. Swarm intelligence emerged as the conceptualization of collective behavior observed in nature and especially recognized in ant colonies, bird flocking, animal herding, bacterial growth, and fish schooling. Ants, bees, and pigeons have been especially studied in terms of path optimization (signaling), collective decision-making mechanisms, and coordinated movements, respectively; James Surowiecki, author of *The Wisdom of Crowds*, put it this way: «The analogy is really quite powerful. The bees are predicting which nest site will be best, and humans can do the same thing, even in the face of exceptionally complex situations. Investors in the stock market, scientists on a research project, even kids at a county fair guessing the number of beans in a jar can be smart groups if their members are diverse, independent minded, and use a mechanism such as voting, auctioning, or averaging to reach collective decision» (Miller, 2007). SI, which is heavily utilized in artificial intelligence (AI), provides an analytical framework dealing with the emergence of collective intelligence as a result of the collaboration and competition of multiple components in a system. Most importantly, complex collective behavior in swarms is said to arise from agents following simple rules (i.e. simple rules of thumb) acting on local information. «Even complex behavior may be coordinated by relatively simple interactions» (Ian Couzin, biologist at Oxford and Princeton Universities). A fundamental question in nature may be formulated at this point: How do simple actions of individuals add up to the complex behavior of a group? (Miller, 2007) Kendall and Su (2006) provide an answer to that: swarm intelligence research argues against the view that individuals are isolated information-processing entities and stresses the fact that intelligence arises from the interaction of intelligent entities.

Swarm systems display a characteristic set of features; apart from relying on relatively simple interactions, swarms do not have centralized control structures (i.e. decision-making processes are decentralized among agents), rely on numerous interactions between individual components, exhibit increased information gathering abilities, offer quick and effective responses to local information and perturbations in the environment, and present intelligent global behavior associated with significant advantages over other complex (biological) systems (Miller, 2007). According to Ahmed and Glasgow (2012), swarm intelligence principles have been successfully applied in a variety of problem domains including function optimization problems, finding optimal routes, scheduling, structural optimization, and image and data analysis.

As a proxy for the simple rules of thumb executed by agents, algorithms have been developed to model and simulate swarms, and use swarm behavior to solve specific optimization problems and settings. Examples include ant colony optimization (ACO; useful in path optimization), artificial bee colony algorithms (ABC), differential search algorithms (DSA; using the concept of Brownian motion to solve numerical optimization problems), backtracking optimization search algorithms (BSA; useful for solving real-valued numerical optimization problems), intelligent water drops algorithm (IWD), multi-swarm optimization (using sub-swarms), and particle swarm optimization (PSO). (Some of them have been successfully applied in finance, as will be evident in the next subsection.)

2.3.2.2. APPLICATION

There are countless applications of swarm theory in science, business and economics. Marco Dorigo, a computer scientist at the Université Libre in Brussels, developed in 1991 a mathematical procedure for solving particularly complex human problems using knowledge of ant behavior (Miller, 2007). In the past decade, the development of robust algorithms and simulations has allowed the implementation of specific swarm-based solutions to complex optimization problems; some applications include the routing of trucks, scheduling for airlines, traffic management, control of

unmanned vehicles (DARPA, the American Defense Advanced Research Projects Agency), management of telecommunication networks, planetary mapping (NASA), or orbital swarms for self-assembly and interferometry (ESA). Air Liquide (a company producing industrial and medical gases at several locations in the U.S. and delivering them using a network of pipelines, railcars, and trucks) used an ant-based strategy and AI techniques to develop a computer model on algorithms to reduce costs and increase the efficiency of its logistics network (Miller, 2007). Southwest Airlines (an American medium-cost airline) also used ant-based models to manage traffic at one of its airports, and considered applying similar models in ticket counter areas (Miller, 2007).

Not only business, but numerous financial applications of swarm intelligence have greatly contributed to the development of computational finance; Mukhopadhyay and Banerjee (2010) state that «computational finance has deeply benefitted from swarm intelligence». One of the main reasons to use swarm intelligence is the emergence of nonlinear complex systems as realistic modelers of financial systems: «It is well known that economy and financial systems are very complicated nonlinear systems which are concerned with real life entities and decision-making containing several complex factors. It is the developmental direction of economics to utilize nonlinear dynamics, especially bifurcation and chaos theory, to study the internal complexity of economic and financial systems» (Mukhopadhyay and Banerjee, 2010). «I think the key lesson is to remind us of the fragility of the equilibrium models that we consider in finance and macroeconomics» (LeBaron, 2002). In such a context, the use of agent-based financial models using both computational and more sophisticated mathematical tools is one of the direction researchers have been taking recently (LeBaron, 2002). As in the case of chaos theory, the increase in computational capacity has resulted in an exponential increase in swarm-based applications and simulations. With computer simulations, in contrast to other methods, it is possible to formalize complex theories about processes, carry out experiments, and observe the occurrence of emergence (Gilbert and Terna, 1999). Neural networks and evolutionary computation have effectively opened new doors in computational finance (Mukhopadhyay and Banerjee, 2010). The development of artificial intelligence (AI) has also had clear effects on computational finance and agent-based simulations: AI tools are able to learn to recognize patterns in the data set, they are flexible in changing environments, and they can build up models when more conventional approaches fail (Nenortaite and Simutis, 2005).

Poli (2008), who analyzes the existing literature on the applications of particle swarm optimization (PSO), found that common finance and economics topics include financial risk early warning, investment decision-making, option pricing, investment portfolio selection, and the electricity market. Chen, Chang and Du (2009) argue that the research area referred to as *agent-based models of financial markets* has grown very rapidly. Indeed, Mukhopadhyay and Banerjee (2010) use a variant of PSO known as Chaotic Multi-Swarm Particle Swarm Optimization (CMS-PSO) that proves successful in estimating and optimizing the unknown parameters of a new hyperchaotic financial system (where the variables are the interest rate, investment demand, price index, and a state feedback controller). Marinakis et al. (2009) show that ant colony optimization (ACO) and PSO assisted in the automated feature selection problem providing decision-makers with a scope to efficiently explore the solution space, and test the results on credit risk assessment and financial classification problems (Mukhopadhyay and Banerjee, 2010). On the same line, O'Neill and Brabazon (2008) use the self-organizing particle swarm algorithm (SOSwarm) for the purposes of credit risk assessment; indeed, the authors apply the SOSwarm to two important credit risk assessment problems: the prediction of corporate bond ratings and of corporate failure (results are highly competitive against those obtained using traditional classification methodologies).

LeBaron (2002) analyzes the creation and development of the Santa Fe Artificial Stock Market, an agent-based stock market simulation which uses genetic algorithms as a learning mechanism for agents; results show that return series present excess kurtosis, very little linear autocorrelation, persistent volatility, small amounts of predictability, and sensibility on the learning speeds of agents (i.e. the frequency with which they run the genetic algorithm; when updates are frequent, the market is likely to generate the patterns common to financial time series). Terna (2000) offers another example of a simulation of a stock market; the author creates the SUM (Surprising (Un)realistic Market) which is composed of simple no-minded agents and does not contain artificial price formation. Agents (which are referred to as myopic by the author) know only the last executed price, choose randomly the buy or sell side, and fix their limit price by multiplying the previously

executed price by a random coefficient; behavior from these agents generates increasing and decreasing price sequences with relevant volatility. Unlike other models, this structure presents bubbles and crashes generated within the market structure, without the need of exogenous explanations. Shu-Ping, Yong, and Chun-Yan (2010) use the support vector regression (SVR) learning algorithm, which has greater generalization ability than traditional neural networks, along with PSO in order to forecast share prices (experimental results demonstrate that this algorithm produces the lowest forecasting errors when compared to traditional share price forecasting algorithms).

Other applications include decision-making models: Nenortaitė and Simutis (2005) develop an intelligent decision-making model which is based on the application of artificial neural networks (ANN) and swarm intelligence algorithms (PSO), which are more suitable for decision-making in stock markets. Using data from a group of 350 stocks with the highest liquidity ratio from the S&P 500 index (stock returns for a 12-year time period from October 1991 to October 2003), the authors developed a one-step forward decision model considering historical data of daily stock returns. Option pricing has been largely modeled by computational finance; Prasain et al. (2010) refers to it as «one of the challenging problems of computational finance». The same authors, who first attempted to use PSO for an American option pricing problem, show that PSO could be effectively used for the option pricing model. Though results do not show special effectiveness when compared to standard classical Black-Scholes-Merton model for simple European options, the authors put an emphasis on the importance of swarm optimization in developing more effective option pricing models.

Portfolio selection has also been a recurrent topic in agent-based models. Kendall and Su (2005) apply PSO to the construction of optimal risky portfolios for financial investments (with the aim of achieving maximum reward-to-variability ratios). Niu, Tan, Xue, Li and Chai (2010) use a complex constrained portfolio selection model using a multi-swarm approach; results appear to be more efficient than PSO-based methods.

2.3.3. *Chaos Theory*

2.3.3.1. DEFINITION

Chaos theory is defined as the mathematical discipline that studies the behavior (evolution) of nonlinear dynamical systems that are highly sensitive to initial conditions. Small perturbations in initial conditions yield widely divergent outcomes for such dynamical systems over time; as a result of such sensitivity, these systems display complex, chaotic behavior even though they are completely deterministic. Systems that display chaotic conditions present complex behavior over time that generally renders long-term predictions impossible. Chaotic behavior may be observed in atmospheric models, the solar system, economic and financial models, plate tectonics, turbulent fluids, or population growth models.

Dynamical systems are defined as physical systems that evolve over time, and can be mathematically characterized by modeling their structure, limits, and dynamics. Such systems are composed of interacting parts that define causal relationships between them and are affected by both endogenous and exogenous variables (recall our definition of complex systems in econophysics). Mathematically, a dynamical system may be defined as a model in which fixed rules describe the time dependence of a point in a geometrical space (deterministic relations are either differential equations, difference equations, or other time scales). The iteration of such rules gives rise to the evolution of the system and the trajectories (or orbits) of its points. In fact, the nature of the rules makes dynamical systems be linear (e.g. $x_{n+1} = 3x_n$) or nonlinear (e.g. $x_{n+1} = rx_n(1 - x_n)$, the logistic map); they may also be discrete or continuous with respect to time (the logistic map is an example of a discrete dynamical system).

There are indeed other types of dynamical systems depending upon their evolution; they can be stable (the system tends to reach a specific point or orbit over time, depending on the dimension of the system and its attractors), unstable (the system escapes from any attractor), or chaotic. For a nonlinear dynamical system to be classified as chaotic, three requirements must be met (under certain conditions some of these requirements might be redundant though):

1. *It must be sensitive to initial conditions.* This condition implies that points in the system that are arbitrarily close will have significantly different future trajectories in the phase space; thus, an arbitrarily small perturbation of the current trajectory may lead to significantly different behavior in the future. Consider the well-known ‘butterfly effect’, by which flapping wings represent a small perturbation in the initial conditions of a deterministic nonlinear dynamical system (i.e. the atmosphere) that ultimately produce a chain of events leading to large-scale phenomena (i.e. a hurricane). Chaotic systems will only behave identically whenever initial conditions are exactly the same. The Lyapunov exponent provides a measure of a system’s sensitivity to initial conditions: the distance between two trajectories in the phase space initially separated by δZ_0 will tend to $|\delta Z(t)| \approx e^{\lambda t} |\delta Z_0|$ (where λ is the Lyapunov exponent). The maximum Lyapunov exponent (MLE) within the entire spectrum of exponents determines the potential chaoticity of the system (positive MLEs are associated with chaos).
2. *It must be topologically mixing (or topologically transitive).* This condition implies that the system will evolve in such a way that any trajectory will move across a specific region of the phase space periodically. Because of the finite nature of the phase space, the different trajectories of the system will eventually overlap after some time.
3. *Its periodic orbits must be dense.* This condition implies that in the phase space between two periodic orbits another periodic orbit will also exist; alternatively, every point in space will be approached arbitrarily closely by periodic orbits.

In fact, chaotic systems present stretching and folding trajectories in the phase space because of exponential divergence and boundedness (due to the first two conditions). Chaotic movements can be visualized by observing the trajectory of the system in the phase space (where points represent the state of the system, time is implicit, and the axes represent a variable or degree of freedom of the system). In such phase spaces, strange attractors may be identified (i.e. a set of orbits the system will tend to adopt through time in a subset of the phase space, which usually has a fractal structure). (See *Figure 1* for a representation of the strange attractor of the Lorenz system). The mathematical characterization of a dynamic system of n dimensions may be described by

$$\dot{x} = f(x, t; \mu)$$

where $f: \mathbb{R}^n \rightarrow \mathbb{R}^n$ is a vector field defined in a subset U of \mathbb{R}^n , x belongs to an n -dimensional phase space, μ belongs to a p -dimensional parameter space, and t is time. The solution of the system is a function $\Phi_x: \mathbb{R}^n \rightarrow \mathbb{R}^n$ defined over an interval I of \mathbb{R} that verifies the above equation and has x as the initial condition (the set of all solutions is called the flow Φ of the dynamical system).

As a final remark, chaos theory offers two important practical implications: long-term predictions under chaotic systems are worthless, and complex behavior can have simple causes (consider the case of simple difference equations with one variable: iterates diverge very rapidly so that the model ends up presenting chaotic behavior) (Williams, 1997). One last observation: a finite amount of information about initial conditions of a system will make it unpredictable beyond a certain time.

2.3.3.2. APPLICATION

Interest in nonlinear dynamics (especially deterministic chaotic systems) has increased in the last decades due to the evolution of financial markets and their unexpected volatility; the attractiveness of chaotic dynamics lies precisely in its ability to generate large movements which appear to be random (and with greater frequency than in linear models) (Hsieh, 1991). In fact, traditional economics literature tends to accept that the economy has a stable equilibrium that is constantly being perturbed by external shocks that determine its dynamic behavior and fluctuations in output; in chaotic growth models, however, the economy follows nonlinear dynamics that are mostly generated internally and do not depend upon exogenous shocks (Guégan, 2009). Grandmont (1992) offers another useful insight: the economic time series that display most volatility (such as investment,

inventories, durable goods, or financial and stock markets) are those for which expectations play an important role in generating learning-induced local dynamic instability; in this case, nonlinear models should be applied to the study of such complex endogenous expectations-driven volatility. Hommes (1991) and Majumdar and Mitra (1992) raise the key issue of the plausibility of chaos as a generating mechanism of fluctuations in the real economy. A report by the U.S. National Academy of Sciences in 1987 made the importance of nonlinear analyses explicit: «As a consequence of its fundamental intellectual appeal and potential technological applications, nonlinear science is currently experiencing a phase of very rapid growth». Such growth, which accelerated during the 1990s, was largely due to an exponential increase in computational capacity (in fact, linearization has been considered as a result of computational constraints in the past). What is more, nonlinear models can generate much richer types of behavior as compared to linear models (Hsieh, 1991). Some evidence for and against the application of chaotic nonlinear models in finance will be presented next; nonetheless, some observations should be made before proceeding. Regarding the differences between physical and social science systems, Levy (1994) argues that the latter may present very complex underlying relationships that include the interaction of several potentially chaotic systems (e.g. crop prices being affected by the economic system and the weather), along with different sources of unpredictability. As such, any direct application of chaotic models should account for these factors. Two approaches have been adopted in the study of chaoticity in financial markets: theoretical efforts have been aimed at ascertaining whether simple nonlinear deterministic models can exhibit the kind of fluctuations typically found in economic data; and an empirical approach testing for the possibility that actual economic and financial time series are characterized by chaotic dynamics (Khilji, 1994).

Despite its intellectual appeal, the application of chaos theory to the social sciences is still in its infancy, and there are those who think that expectations are too high (Baumol and Benhabib, 1989). In fact, the very nature of financial data sets poses serious problems: there is a unique trajectory (no possibility to repeat experiments exists); the presence of measurement noise may hinder any attempts to identify chaotic behavior from nonlinear stochastic processes (indeed, robust deconvolution techniques should be further developed) (Guégan, 2009); and long sampling intervals may not be possible to obtain (so as to avoid micromarket structure dependencies) (Hsieh, 1991). There has been considerable debate in the finance literature about how to test data in order to detect nonlinearity (Hsieh, 1991); nonetheless, no strong evidence has been provided that demonstrates the chaoticity of financial markets (Sewell (2008) provides an interesting review of existing literature). Though systems can effectively transition between chaotic and nonchaotic states (Levy, 1994), the application of the Brock, Dechert and Scheinkman (BDS) method on stock market returns (i.e. weekly stock returns from the Center for Research in Securities Prices (CRSP) at the University of Chicago, beginning in 1963 and ending in 1987) does not contradict the efficient market hypothesis (EMH) but does not provide evidence of low complex chaos in the stock market either (in fact, nonstationarity, low complex chaos, and nonlinear stochasticity are all possible under the test) (Hsieh, 1991). Willey (1992) tested the daily prices of the S&P 100 and NASDAQ 100 indices and rejected deterministic chaos in two out of three empirical tests. Stronger rejection is provided by Sewell et al. (1996): results for the period 1980-1994 do not prove the existence of chaos in six major stock indices (in the U.S., Korea, Taiwan, Japan, Singapore, and Hong Kong) nor do for the exchange rate of the U.S. dollar against the other currencies (the tests do prove chaoticity in some cases though). This result is consistent with Abhyankar, Copeland and Wong (1996), who tested some of the world's most important indices (i.e. S&P 500, DAX, Nikkei 225, and the FTSE 100) and found no evidence of low-dimensional chaotic processes. The direct evidence for deterministic chaos remains thus very weak. All the other studies have found little or no evidence for chaos in any financial and economic time series, but they have turned up a surprising amount of unexplained nonlinear structures (LeBaron, 1994). In addition, Mayfield and Mizrach (1992) provide an interesting finding: high-frequency data from the S&P 500 index are either of low dimension with high entropy, or nonlinear but of high dimension.

There is evidence supporting the chaoticity of financial markets to some extent though. Khilji (2007) found that expected monthly returns (i.e. stock returns for the period July 1986 to June 1992 of the State Bank General Index of Share Prices from Pakistan) are time dependent and nonlinear (though the distinction between nonlinear deterministic systems vs. nonlinear stochastic systems could not be made). Brock and Hommes (1998) show that chaoticity can arise in the traditional

expectations model and the asset pricing model with the introduction of heterogeneous beliefs. Peters (1991) claimed to have found chaos in the financial markets, while Blank (1991) identified necessary conditions for the S&P 500 index and the market of soybeans to have the underlying generating dynamics characterized by deterministic chaos. Decoster, Labys and Mitchell (1992) identified the presence of chaos in commodity futures prices (silver, copper, sugar, and coffee) though further tests should be performed to confirm the validity of the discovery. Panas and Ninni (2000) found strong evidence of chaos in daily oil products for the Rotterdam and Mediterranean petroleum markets. Guégan (2009) presents even more appealing evidence and theory; according to the author, the auto-regulation of financial markets (i.e. the lack of complete knowledge of the market by its participants) can be interpreted in terms of an attractor. The same author proposes a chaotic model of the evolution of exchange rates with the form

$$S_t = X_t S_{t-1}^\alpha S_{t-2}^\beta$$

where S_t represents the exchange rate at time t , X_t some behavioral variable, and α and β parameters of the system. For certain values of the parameters, the evolution of exchange rates presents an attractor (see *Figure 2*). Not only exchange rates, but spot electricity prices may also present chaotic behavior: the evolution of deconvoluted German spot (hourly) prices of electricity from June 16, 2000 to December 16, 2004 seems to define an attractor too (see *Figure 3*) (Guégan and Houmyia, 2005). «In financial markets we are concerned with the amount of price movements and trading activity coming from the flow of new information into the system, versus the system generating that through a dynamic of trading and learning» (Guégan, 2009). Chaotic systems could be one of the answers for that. One last piece of evidence can be presented here: Garliauskas (1999) shows how artificial neural network (chaotic) models can be applied to forecast financial time series. In effect, forecasting using the neural network approach has more advantages than classical statistics (neural networks act dynamically by learning from experience and present more accuracy). With data of the Wood Fibre Ltd. shares trading on the Lithuanian Stock Exchange from March 11, 1997 to December 18, 1997, the author finds out that mean square errors (MSE) are minimized when neural forecasting is used.

«Just because evidence for chaos in time series data is weak does not mean that chaos is not a useful lens through which to view economic activity» (Brock, 1993). As seen, research has been essentially focused on performing tests to financial data to determine its potential chaoticity; however, an active approach has also been taken which provides financial agents with useful insights from chaos theory. From forecasting to movements in foreign exchange and stock markets, to understanding international business cycles, chaos in economics has a broad range of potential applications. Ideas from nonlinear sciences such as genetic algorithms and neural networks have been applied to the design of trading strategies in financial markets (Brock, 1993). Connelly (1996) cites the following implications for financial planners: chaotic systems are unpredictable; the EMH is right; prediction in chaotic systems may be possible over the short run (in futures and options markets with high turnover short-term trading strategies may be affected at relatively low cost); the governing probability distribution of a chaotic time series is leptokurtic; phenomena such as the small-cap and value-stock effects may not be stable; and, finally, two models are proposed out of the chaos theory literature that attempt to describe the behavior of financial markets: the coherent market hypothesis and the fractal market hypothesis. With such implications in mind, financial planners should modify their trading strategies to account for the chaotic dimensions of financial markets. Indeed, the same author acknowledges that most financial institutions all over the world (including Wall Street) are constructing trading and money management tools based on nonlinear techniques. Neural networks (which seek to recognize patterns in the past data and apply that knowledge to the present) and genetic algorithms (useful in unstable systems because they allow for adaptation to their evolution) are the most prominent tools used by them.

3. APPLIED RESEARCH: DEVELOPMENT OF A NEW ANALYTICAL FRAMEWORK FOR FINANCIAL ANALYSIS

After having explored the potential interrelations between natural sciences and economic and financial systems, described econophysics as an emergent field of study exploiting the obvious synergies between the two, and presented three theoretical models which have been applied to economics and finance, the present section is meant to build a new theoretical model from which analyze economic and financial systems. In fact, the goal of this exercise is to generate a preliminary, systematic, novel approach to economic analysis; it constitutes a first approximation (by a business and economics undergraduate student) to the hard but promising task of effectively using scientific models to formulate a consistent, holistic analytical framework for economic and financial analysis. The model will essentially rely on the materials covered so far in the paper and relatively basic mathematical formulations; other models (consider artificial intelligence or quantum mechanics) are likely to produce useful contributions as well. In any case, it will borrow heavily from thermodynamics and classical mechanics, which are meant to provide a first attempt to conceptualize the dynamics of interactions in complex, evolving systems.

The economic and financial system may be modeled as a vector field of forces in an informational space in which subunits (i.e. components, agents) constitute an energetic system and interact according to the laws of thermodynamics and classical mechanics. In such a context, it is worth recalling the distinction between a force, which is a vector variable (determined by the modulus and direction of a vector in the geometrical space), and energy, which is a scalar variable (that is, it can be expressed by a single number and remains invariable to transformations in the coordinate system). The vector field of forces plays an important role in the model: it defines a region in space where the directionality of the dynamic interactions between forces, energy, and mass is a crucial component when defining energy and work flows (the relationship will become evident in subsequent paragraphs). The vector field of forces operates within a space, a coordinate system; the informational space is defined here as the n -dimensional space where each point represents a unit's specific position ('informational position') with respect to the origin of coordinates.

3.1. DEFINITION OF VARIABLES

Before proceeding, an essential description of the main elements of the model should be made (which borrows from Gerbert Garcia Bassa, 2009).

3.1.1. *Energy*

Energy may be defined as the physical scalar magnitude that defines the state of a system and remains constant over time in closed systems. Alternatively, energy is described as the capacity to work, or as a measure of the capacity of a body to interact with others. Energy constitutes an abstract mathematical tool that allows characterizing the state of a reference system, in other words, it is a magnitude created rationally in order to describe the dynamics of any physical system. The invariance defined by the Noether's theorem (by which a physical system remains constant relative to temporal displacements, so that there is a direct relationship between symmetries and laws of conservation in physics), or the First Law of Thermodynamics explored earlier, may be used to define another important characteristic of energy: the law of conservation of energy (by which the total amount of energy is constant in isolated physical systems). This invariability does not prevent the existence of processes by which a form of energy (i.e. a given state function) is transformed into another one; according to classical mechanics, however, there only exist two fundamental types of energy: kinetic and potential energy. Kinetic energy is related to the movement of a body; potential energy is associated with the position of a body within a field of conservative forces (such as a gravitational field). Whereas other forms of energy exist (such as thermal energy), they can certainly be derived from these two basic energies, which can derive in multiple energetic configurations. (The energy of mass, as defined by Einstein's relativity, can also be considered as a third primordial type of energy.) Then, the total energy of a system can be expressed as

$$E_{\text{total}} = E_p + E_k$$

where E_p stands for potential energy, and E_k for kinetic energy. Classical kinetic energy can be expressed as

$$E_k = \frac{1}{2}mv^2$$

where m is mass, and v is speed (or velocity). (Gravitational) potential energy is expressed as

$$E_p = -G \frac{Mm}{r}$$

where G is the universal gravitational constant, M the mass of a massive body, m the mass of a lighter body, and r the distance between the two bodies. Apart from constituting a scalar state variable of physical systems (with position and movement as key variables), energy represents a measure of potential interaction: a reference system with a high energetic potential has the capacity to alter the state of a system with an inferior energetic configuration (and so modify its properties). Thermodynamic interactions, in which bodies at a higher temperature tend to transfer heat to colder bodies, are a clear example of how energy constitutes an indicator of the propensity of a system to react to external conditions.

3.1.2. Work

Another important element is the relationship between energy and work: the transfer of energy between systems is produced in the form of work. Work can be defined as the productivity that energy provides when applied to a body; mechanically, it is the scalar magnitude defined in its most basic form by

$$W = F \cdot d$$

where W is mechanical work, F the force applied to a body, and d the displacement of the body produced as a result of the application of the force. Hence, work emerges as the result of applying a force to a body during a displacement. Using

$$F = m \cdot a$$

(where m stands for mass, and a for acceleration), and

$$\Delta x = \frac{v_2^2 - v_1^2}{2a}$$

(where Δx is a linear displacement, and v speed), the relationship between energy and work becomes even clearer with the expression

$$W = ma\Delta x = m \frac{a(v_2^2 - v_1^2)}{2a} = \frac{1}{2}m(v_2 - v_1)^2 = \frac{1}{2}mv_2^2 - \frac{1}{2}mv_1^2 = E_{k_2} - E_{k_1} = \Delta E$$

Then, work is defined alternatively as the variation of energy as a result of the application of a force to a body along a spatial (and temporal) displacement. Work and energy are intimately connected; both magnitudes are related to interaction. The First Law of Thermodynamics, by which

$$\Delta U = Q - W$$

(where Q is heat), shows how work is a determinant of the internal energy of a system. (Heat is indeed the macro result of the kinetic energy of the molecules of a material.) In fact, potential energy is defined as the work done against a conservative force; alternatively, as the scalar magnitude associated with a force field which quantifies the potential work that a physical system can do as a result of the position it occupies with respect to a reference system. Analytically, potential energy and work are interrelated as follows

$$W = -\Delta E_p$$

or

$$dE_p = -F \cdot ds$$

(where s denotes displacement) which simply states that a loss of potential energy results in the production of work. In the case of gravitational potential energy, the expression defining it

$$E_p = F \cdot d = ma\Delta x = mgh$$

(where g is the constant acceleration of the gravitational field, and h the height of an object) is identical to the definition of work. Kinetic energy, the other fundamental energy, resembles work as well: it is defined as the work necessary to accelerate a mass from its equilibrium position to a certain velocity. Work relates energy and force (the tri-connection between energy, work, and force will be one of the prominent axioms of the economic model presented below).

3.1.3. Time

Time is another important variable. Characterized as the scalar aggregation of a magnitude, time is defined as the physical concept that quantifies the separation between successive states of the same physical system. Along with space, time constitutes an inherent dimension of the universe and a building block of the space-time continuum. (Energy and force are also intrinsically connected.) Time is an essential element to define evolution, dynamics, and structure; all these concepts, however, are implicitly related to that of directionality (the arrow of time). In fact, it seems there is a unidirectional temporal sequence (i.e. the arrow of time) that defines past, present, and future (as described by the light cone), and formulates causality (as a temporal connection between cause and effect defining a causal arrow of time). In spite of the fact that most physical equations are reversible with respect to time, there is an empirical temporal asymmetry characterizing irreversibility; thermodynamics introduces a concept intimately related to time and its flow: entropy (and the thermodynamic arrow of time). Newtonian vs. relativistic implications are another element defining the nature of time and its relationship with space, energy, and force. In any case, time emerges as an important variable in the economic model presented here.

3.1.4. Informational Space

The informational space constitutes one of the most important elements in the model here presented. But before characterizing the informational space (the spatial variable in which positions are defined), it would be worth defining information. Information is a codification of reality that translates physical realities into processable inputs (i.e. data). As such, information parameterizes multiple dimensions of the space-time continuum (its 'layers') and converts them into operational variables that define the nature, dynamics, and structure of systems. In fact, it could be argued that reality translates into information. Information (be it qualitative or quantitative) is the basic component of physical laws: magnitudes and variables are by definition information. In essence, everything the human being perceives is the result of a cognitive process (i.e. operations) over data (i.e. internal and external stimuli). All decision-making matrices and processes operate over informational inputs. Knowledge, however, represents an upgrade over information: it constitutes assimilation, analysis, conceptualization, model generation, structure, extrapolation, delayering of reality... in one word: consciousness. Knowledge is what translates information into useful, operative inputs. Knowledge is behind all analytical models (which work on raw information and produce results). Anyhow, it is not the scope of this paper to inquire about the vast implications of human consciousness and knowledge (though I'm effectively using them to write these lines). (Gerbert Garcia Bassa (2009) explored these considerations in *De Gerbert d'Orlhac a la recerca d'Omega*.) It can already be said, however, that knowledge gives directionality to information, which exercises a force producing work.

Information has emerged as a strategic asset in today's technified, globalized economies. As argued in *Section 2.1.2*, information is the centerpiece of the financial system, which is constantly creating information, receiving and managing data (chiefly high-frequency data), and being affected by informational inputs and shocks. (Computerized) decision-making functions and algorithms act

upon data to create and execute trading (investment) strategies in the market, and the risk and return schemes defined by standard pricing models can only be implemented upon effective use of information regarding certain variables (such as probability distributions, volatility, or discount rates). Common topics in financial economics such as information asymmetry, data analysis, risk management, artificial markets, financial innovation, or portfolio theory clearly depend on information. The exponential use of technological platforms in the financial sector is another evident consequence of the need to capture, internalize, analyze, compute, and operate an ever-increasing amount of information. In this scenario, entities certifying information (such as audit firms) play and will likely play even a bigger role in today's information economies, which are based on financial information (both private and public) and consistent information systems. Credit rating agencies, news providers, certification companies, central banks, governments, multinationals, or institutional investors are all agents specialized in managing and producing high-impact information affecting the dynamics of the global economic and financial system.

The model presented here develops an informational space: an n -dimensional space where each coordinate represents an informational input. Thus, a point p in the informational space may be expressed as

$$p = (x_1, x_2, \dots, x_n)$$

where x_i are the coordinates (i.e. informational inputs) of the point.

Informational inputs may correspond to any variable which has an effect over the economic position of an entity (from now on particle). The determination of this coordinate system allows the definition of *position*: the position of a particle within the informational space is the set of unique coordinates (variables) that characterize such a particle and determine, as will become evident, its potential energy (recall that potential energy is the capacity to produce work as a direct function of the position of an object with respect to a defined reference system under the effect of a field of conservative forces). The informational space is occupied by particles, economic entities (from individuals to corporations to cities to nations) that interact with each other and determine the internal dynamics and structure of the system. In this respect, the economic and financial systems (which in this case can be treated as a single entity: the economic *and* financial system) can be modeled as a complex system composed of a set of particles that interact nonlinearly and thermodynamically, evolve over time, and generate aggregate behaviors (i.e. macro properties). If such a system, defined by a large number of particles within the n -dimensional informational space consisting of n variables (i.e. informational inputs), can be associated at each point in time by a magnitude called 'state of the system,' then a phase space as defined in previous sections can be used to depict the evolution of the system over time (remember that each point in the phase space represents the state of the system, time is implicit, and the axes represent a degree of freedom of the system). In any case, the informational space represents a conceptual information system from which the position of all particles can be defined so that the concepts of potential energy, kinetic energy, force, and work can be applied.

3.1.5. Force

Force constitutes another fundamental variable characterizing the model. Force is defined as the physical vector quantity (that is, with magnitude and direction) capable of deforming objects (static effect) or modifying their velocity or inertia (dynamic effect). It is a mathematical model of the intensity of interactions, along with energy; alternatively, force can be defined as any action or influence that modifies the state of movement or rest of a body, that is, a perturbation in the quantity of movement (i.e. causing acceleration). Movement and force, then, are intimately connected concepts.

Newton's laws, published by Sir Isaac Newton in 1687 in his *Philosophiæ Naturalis Principia Mathematica*, establish universal principles related to the motion of bodies, and set the basis for the so-called classical mechanics: the first law states that an object remains at rest, or in motion at a constant velocity, unless acted upon by a force; the second one provides a basic analytical definition of force, which is expressed as

$$\vec{F} = m\vec{a}$$

where F stands for force, m for mass, and a for acceleration (interpretation: the application of a force on a body will result in an accelerated spatial displacement; conversely, force is proportional to acceleration and acceleration is inversely proportional to mass); and, finally, the third one states that when a body exerts a force on a second body, the latter will exert a force equal in magnitude but of opposite direction on the first one (the action-reaction principle). Another useful formula is that of the gravitational force, developed by Newton as well, by which

$$F = G \frac{m_1 m_2}{r^2}$$

where G is the gravitational constant (equal to $6.674 \times 10^{-11} \text{ Nm}^2/\text{kg}^2$), m_1 and m_2 the masses of two bodies, and r the distance between them. The presence of gravity, which is an attractive force, creates a field of conservative forces around massive bodies that allow defining the potential energy of lighter bodies as a function of their position with respect to the gravitational center. The development of the theory of relativity by Einstein reformulated the definition of gravitational force, which was reframed as the result of the deformation of the space-time continuum by massive bodies; Newtonian formulation, however, provides good approximations of the effects of gravity when no extreme precision is required or masses are not extremely dense. Along with the gravitational force, three other types of fundamental forces exist in nature: strong, electromagnetic, and weak.

3.1.6. Mass (and wave-particle duality)

Mass is the last fundamental variable defining the model. In it, economic assets (i.e. economic resources) will be associated to the mass of economic particles. The more financial and nonfinancial capital a particle has, the more massive it is within the system (and because of the close relationship of mass with the concepts of density and potential energy, the more volume and weight it has). Both stock and flow variables are included in the model; stock variables will be considered as structural variables constituting the particles, whereas financial flows and capital mobility will be considered as mass [and energy] fluctuations within the system (accelerated masses as a result of the presence of certain directional forces producing mechanical work). Therefore, both static (decelerated) and dynamic (accelerated) masses are defined in the model. Recall Einstein's expression

$$E = mc^2$$

where E is energy, m mass, and c the speed of light; energy and mass are equivalent quantities (and the relational factor is indeed velocity). In our model, energy is considered as a variable defining the state of a system or, conversely, the potential capacity to interact with its environment and generate work; as such, mass has an effect on the particles' potential to produce work, and so it is clearly related with energy. But we may introduce here an equivalent, but more useful analogy: the wave-particle duality established by quantum mechanics. According to it, all mass particles present both wave and particle properties (particles are considered to occupy space and have mass; waves expand through space at a defined velocity and have no mass). Stephen Hawking defined this duality as the «concept in quantum mechanics by which there are no fundamental differences between particles and waves: particles can behave like waves and vice versa». Let's set mass particles as money and waves as information, and a crucial result emerges: the duality money-information. In the informational space described so far, information is the coordinate system by which mass particles have a specific position within the system that determines their potential energy and capacity to produce work through the acceleration of mass flows (i.e. financial flows). As such, information is a crucial magnitude, the reference variable. It can be argued that money has an important informational content, and that information has the potentiality to be converted into money. Consider the financial system: information is constantly being used to create and execute investment strategies. Information is crucial when assessing credit risk and actually determines effective cash flows (and the other way around: a careful analysis of actual financial flows may produce valuable information about the underlying factors). When a company develops strategic information sensitive to originate a sustained competitive advantage, it can capitalize it and convert it into effective financial capacity. Money conveys information, and information has the potential to attract money. In a physical sense, it could

be stated that money has a parallel informational wave. That's the financial wave-particle duality as defined by the model presented here.

3.2. DESCRIPTION OF THE MODEL

As said, this model is meant to provide an overall theoretical framework to analyze the financial system and, by extension, the economic system using some of the elements developed in the previous sections. Far from using elaborated mathematical formulations or defining complex structures, the model exploits some conceptual analogies between physical and financial and economic systems and provides some mathematical foundations when possible. In essence, it constitutes a first attempt to integrate [seemingly distant] disciplines in order to generate a robust model capable of producing meaningful, quantitative results; further developments, probably with the addition of more complex analytical apparatuses and other underlying frameworks, are likely to introduce refinements and mathematical consistency to the model.

Before proceeding, it would be worth noting that the model pretends to describe the financial system rather than the overall economic system. There are clear connections between the two though; what could be called 'productive economy' has a symbiotic relationship with a financial system that redirects cash flows, manages risk, provides liquidity, influences intertemporal consumption, and affects investment decisions. In fact, there are multiple strategic interactions between these two subcomponents of the economic system: as a key constituent, the financial system presents some degree of fractality with respect to the overall economic system (its structure has a clear incidence on the macrostructure of the global economy). What is more, the financial system may be characterized as a productive system capable of generating work (i.e. modifying kinetic energy) by means of generating capital flows (i.e. movements of mass) between the components of the system. Hence, the modeling of the financial system may be preliminarily extended to include the overall economic system, which has a fractal structure. In effect, fractality (alternatively scaling laws) is an element to consider in the model: microstructures define macrostructures, and different space scales ('zoom layers') may present the same dynamics and aggregations of particles. Consider, for a visual representation of this last point, a neural network where neurons are aggregations of particles and synapses define interactions among centers and 'intra-actions' between subcomponents (or alternatively, think of a satellite view of the earth at night with bright urban centers configuring interconnected areas of economic activity). As the observer zooms out, the same pattern may be recognized at different scales. Though this analogy may provide a useful representation of the structure of economic activity, this is certainly not the main point of the model, nor does it pretend to be the starting point of the following presentation.

As stated earlier,

The financial system may be modeled as a vector field of forces in an informational space in which subunits (i.e. components, agents, or particles) constitute an energetic system and interact according to the laws of thermodynamics and classical mechanics.

The total energy of the system would be, as described by classical mechanics

$$E_{\text{total}} = E_p + E_k = \sum_{i=1}^m (E_{p_i} + E_{k_i})$$

where E_{p_i} is the potential energy of the i th particle, and E_{k_i} the kinetic energy of the i th particle. Hence, the total energy of the system is equal to the sum of the potential and kinetic energy of the particles constituting it. When considering the thermodynamic dimension of the model, the total energy of the system will be characterized as

$$E_{\text{total}} = U + E_p + E_k = \sum_{i=1}^m (U_i + E_{p_i} + E_{k_i})$$

where U_i is the internal energy of the i th particle in the system. The economic and financial system will be considered as an open thermodynamic system, in which mass inflows and outflows and energy fluctuations characterize its dynamics and internal structure.

With these assumptions, the first result is that the position of the particles with respect to the informational space determines their *potential energy*. Energy is defined as a state variable, and therefore the position a specific particle occupies in the informational space determines its capacity to interact and generate work. Which is the meaning of *position* in the informational space? Recall the informational space is an n -dimensional space in which variables are any informational input that has an effect over the economic position of the particles (be them individuals, companies, governments, cities, or economic areas). Such variables, apart from comprising the typical space-time coordinates, may include, for example (as long as they are quantifiable, standardized, and well defined): mass (as understood by economic size), industrial sector, selected financial ratios, technological capacity, internal and external infrastructure, control over strategic assets and resources, R&D+i efforts, strategic alliances, possession of strategic information, geopolitical connections and influence, information-processing capacity, marketing influence, ability to create shocks, cyber-espionage potential, military capability... in essence, all the elements to define the position of an economic entity within the local, national, and/or global economic systems.

Then, the potential energy of a system is the function

$$E_p = f(m, g, x_1, x_2, x_3, \dots, x_n)$$

where m is the mass of particles, g the constant acceleration of the conservative force field, and x_i the set of informational coordinates. (Recall the classical definition of potential energy

$$E_p = mgh$$

where h stands for height of the particle, that is, the absolute value of the modulus of the shortest vector connecting the particle's position with the surface of a massive object.) In order to define potential energy, a conservative field of forces (like a gravitational field) has been assumed to originate at the origin of coordinates $(0, \dots, 0)$. The acceleration (assumed constant) that it implies should be equal, according to classical mechanics, to

$$g = G \frac{M}{R^2}$$

where G stands for Newton's gravitational constant, M the mass of a massive body (overall mass of the financial and economic system?), and R the radius of the massive body. In the model presented here, however, g may be considered as an exogenous variable (though a refinement of the model could explore the appropriate value of g). A possible specification for the equation of potential energy could be

$$E_p = mg \sum_{i=1}^n x_i$$

which defines the potential energy of a particle as the multiplication of its mass times the constant acceleration of the force field times the summation of the informational coordinates defining its position ($\sum_{i=1}^n x_i$ is used as a proxy for the absolute value of the modulus of the n -dimensional vector connecting the origin of coordinates with the position of the particle $x = (x_1, \dots, x_n)$ in the n -dimensional space). To put an example, consider the case of a 3-dimensional informational space under the effect of a field of conservative forces with acceleration g in which a particle with mass m has a position

$$p = (a, b, c)$$

then, its potential energy would be simply defined as

$$E_p = mg(a + b + c)$$

But, what is the meaning of potential energy in the context of this model? Potential energy represents the potential of an economic entity to attract capital inflows (i.e. mass) as a result of the position it

holds within the industry or market it operates in (the *informational space*). Informational inputs that place a particle defined by $p = (a, b, c)$ at a higher ‘altitude’ as compared to another one defined by $q = (d, e, f)$, that is,

$$(a + b + c) > (d + e + f)$$

are associated with an increased capacity to attract financing. Consider the case of a company which has developed a new technology or has just penetrated into a high-growth-potential market: these developments translate into an increase in the term $\sum_{i=1}^n x_i$ (as a result of a spatial displacement in the informational space) so that it has an increased capability to attract external investment (i.e. financial flows, credit). This interaction with other particles occurs precisely because of information: the informational coordinates of a specific particle generate capital (mass) flows between this particle and the universe of particles surrounding it.

Now, the attraction of financial inflows as a consequence of an improved financial position and a higher potential energy translates into an increase in its mass Δm when the particle pivots from $p \rightarrow q$. If no work is generated by the particle, then

$$\Delta m \rightarrow \Delta E_p \rightarrow \Delta m \rightarrow \dots$$

which simply means that mass increases and potential energy increases enter into an infinite spiral (one may think of this effect as financial bubbles). (Let’s stay away from bubbles at least for the moment.)

Recall kinetic energy (E_k) is defined by

$$E_k = \frac{1}{2}mv^2$$

where v is the velocity of the particle. Work (W) was defined as

$$W = F \cdot d = m \cdot a \cdot d$$

where F is force, d spatial displacement, and a acceleration. Recall also that

$$-\Delta E_p = W = \Delta E_k$$

was another result derived from the law of conservation of energy and the above definitions. When a particle attracts financing (Δm) as a result of its informational position, then it can produce work with this mass/energy inflow and change its position from $q = (d, e, f)$ to $r = (g, h, i)$ (with $(d + e + f) > (g + h + i)$, i.e. r having a lower configuration): a force is acting upon the particle causing it to move from $q \rightarrow r$ and so converting potential energy into kinetic energy. Between these two positions, work has been produced to displace particle i from q to r within the informational space, which has moved because of kinetic energy. In fact

$$-\Delta E_{p_{q \rightarrow r}} = W = \Delta E_{k_{q \rightarrow r}}$$

In the example above,

$$W = -mg(g + h + i - d - e - f)$$

This result can be interpreted as follows: the position of an economic agent determines its capacity to obtain financial resources; once it obtains them, it can effectively use these additional resources to perform work in the financial and economic system, so that its position changes over time. It could be said that financing creates a force by which capital is invested again or used for productive purposes. In fact, financing may be viewed as a consequence of the transformation of information into financial resources, which in turn produces a force mobilizing productive resources. Using Newton’s

$$F = ma$$

the expression could lead to the following interpretation: financing can be defined as a vector quantity related to a force (whose directionality depends on the information in the system) that mobilizes capital (i.e. causes an accelerated spatiotemporal displacement of financial capital toward an attractor). What could be called ‘capitalization’ would in fact be the effect of transforming information into the movement of a monetary base as a result of the generation of an operative force. Because of

that, in an open system (which is the case of the global financial system) the capitalization of information becomes investment (i.e. applied knowledge) and produces work proportional to the attracted monetary mass. Thus, the power of the overall system would be defined as

$$P = \frac{W}{t} = \frac{Fd}{t} = Fv$$

where v is velocity (The power of the system fluctuates over time and is an indicator of the efficiency and growth of it.) The efficiency of the system, that is, the operative transformation of potential energy into work (productive kinetic energy of knowledge), determines the rate of capitalization of the system. The financial and economic system is self-regenerating and always grows due to the transformation of information into work.

The application of the concepts and laws of thermodynamics expands the model and provides additional insights into the real structure and dynamics of the financial and economic system. Why? Thermodynamics analyzes the state of bodies and their interactions through energy transfers. The financial and economic system is basically based upon the complex interactions between agents that configure certain patterns of energy and mass flows, generation of forces, and movement. The useful exercise of extending the model to include thermodynamic implications will likely provide more structure and content to the purely mechanical model developed so far.

At a macroscopic level, the temperature of the system may be defined as the intensity of the aggregate movement of all the particles that constitute it. Paralleling the physical definition of heat and temperature (by which they relate to the kinetic energy of the molecular components of any material), the temperature of the financial and economic system is the degree of work (conversely, kinetic energy) done by the particles in the system. The more work is produced (i.e. larger aggregate spatial displacements within the system), the higher the temperature is. When the financial and economic system experiences long periods of increased activity and thus becomes too 'hot' (after a financial bubble, for instance, when volume and/or pressure also increase), a correction in the form of a 'cooler' period takes place to reach a new, stable thermodynamic equilibrium.

Let's stay away from this straightforward application and concentrate on the subunits that compose the system. If we consider them as open thermodynamic systems, with mass inflows and outflows and energy fluctuations, then the first law of thermodynamics states that

$$\Delta U = Q - W + \sum_{\text{in}} m_{\text{in}} \left(h + \frac{1}{2} v^2 + gz \right)_{\text{in}} - \sum_{\text{out}} m_{\text{out}} \left(h + \frac{1}{2} v^2 + gz \right)_{\text{out}}$$

where U stands for internal energy, Q heat, h enthalpy, and z height (notice how energy related to mass comprises both kinetic and potential energy). When a particle in a specific position within the informational space is able to transform its position into mass inflows (i.e. financial inflows), it is able to produce work and change position. When an economic entity receives financing, however, a productive work has to be done in order for it to be able to generate enough cash flows to service the future principal and interest payments associated to the financing operation. Now, Q may be defined as the present value of the future cash flows associated with the investment produced by an initial work W . If

$$Q > W$$

then the work performed by the economic entity has a positive net present value and, by the first law of thermodynamics, its internal energy increases. (This computation may be realized at different points in time, applying the corresponding changes in environmental conditions; if expected cash flows do not correspond to reality, or expectations are revised so that the net present value becomes negative, then the system's internal energy would decrease.) What is internal energy? The internal energy of an economic entity may be defined as its solvency, its capacity to produce effective work, its credit rating, its risk (systemic and idiosyncratic), its 'global economic position' (as compared to the informational position related to 'financial' potential energy). When the internal energy of a system increases, its position improves: it enjoys an increased capacity to generate potential energy and mass inflows given a set of informational inputs. In addition, the level of entropy associated to the economic entity would be reduced. (The concept of entropy will be further explored below.) As the formula of the first law of thermodynamics shows, the internal energy of a system is not only influenced by the net

present value of a financial operation but also by mass/energy inflows and outflows to the system. A net mass inflow, this is,

$$\sum_{\text{in}} m_{\text{in}} \left(h + \frac{1}{2} v^2 + gz \right)_{\text{in}} - \sum_{\text{out}} m_{\text{out}} \left(h + \frac{1}{2} v^2 + gz \right)_{\text{out}} > 0$$

is associated with an increase in internal energy (due to the same factors mentioned earlier). In fact, there exists a formulation that explicitly relates the total energy of a system with U and potential and kinetic energy

$$E_{\text{total}} = U + E_p + E_k = \sum_{i=1}^m (U_i + E_{p_i} + E_{k_i})$$

The second law of thermodynamics might be applied as well, and a crucial variable is entropy. Defined as the measure of disorder of a system or the amount of non-usable energy in the system, entropy in this model exists when

$$Q < W$$

that is, the net present value of a financing operation (a thermodynamic process) is negative and decreases the internal energy of a system. Conversely, entropy refers to the degree of convertibility of financial flows into productive work. In fact, decreases in the internal energy of a system (by the first law of thermodynamics) are associated with a decrease in value, an increase in disorder, the destruction of value, and/or a negative transfer of resources to another economic entity. When the entropy of the global financial and economic system increases, misalignments in financial flows tend to increase the residual (dissipated) heat of the system and reduce its power and efficiency. In essence, the ability of financial flows to generate work decreases. Consider the definition of thermodynamic efficiency

$$\eta = \frac{W}{Q}$$

by which efficiency is expressed as the percentage of work produced by a given amount of heat. In the model discussed here (where Q is a measure of expected and realized cash flows deriving from an initial investment W), values above 1 are associated with an increase in entropy: the work performed by an economic entity exceeds the returns it generates with it. In such a case, the economic entity has reduced its global economic position, restructured cash flows (in a non-zero-sum operation, it may have effectively eliminated cash flows), and dissipated energy in the form of residual, background radiation. Let's explore the concept of entropy in greater detail. (Differential) entropy is defined as

$$dS = \frac{\delta Q}{T}$$

where T is temperature (defined as a measure of Q). Consider the case of two bodies (1 and 2) at T_1 and T_2 , respectively (where $T_1 < T_2$). Then, the transfer of heat between the two systems (in an isothermal thermodynamic process, in which temperatures remain constant) equal to Q will lead to a positive variation in entropy for the first body of

$$dS_1 = \frac{\delta Q}{T_1}$$

and a decrease in entropy for the second body of

$$dS_2 = \frac{-\delta Q}{T_2}$$

(the negative sign in front of Q refers to the transfer of heat to the first body). Because $T_1 < T_2$, then

$$\left| \frac{\delta Q}{T_1} \right| > \left| \frac{-\delta Q}{T_2} \right|$$

which shows how, in a thermodynamic process, entropy is produced. The economic interpretation of this result is straightforward: a temperature differential between bodies induces an energy transfer, in the form of heat, from the hot body to the colder one (as Q is a measure of the return on

investment, the heat transfer may be interpreted as a reallocation of profitability, productivity among economic entities); any financial operation, by definition, induces a generation of entropy at a greater or lesser extent. The more information can be converted into potential energy and financial inflows, and the greater the return for a given amount of work done, the lower the entropy will be generated in the system during a financial (thermodynamic) operation. In any case, the entropy generated in a system can be expressed in aggregate differential terms as

$$dS_{\text{system}} = dS_{\text{subunit}} + dS_{\text{surrounding}} > 0$$

(in the case of a system composed of a single component) or, more generally,

$$dS_{\text{system}} = \sum_{i=1}^n dS_i > 0$$

where $\sum_{i=1}^n dS_i$ is the aggregate change in entropy of all the components in the system.

When the global system experiences considerable increases in entropy (e.g. in a financial bubble such as a housing boom), the system is effectively undercapitalizing itself, reducing liquidity, destroying value, and reducing the overall temperature of the system. During a bubble, increased work and financial flows may be considered a sign of increased efficiency, power and temperature, but because interactions are based upon non-consistent estimations (though optimal for specific sectors) and hot value structures, a concentration of underlying entropy is being produced: when the system experiences a small change in conditions due to an internal/external shock, the chaoticity of markets will develop into a large-scale correction where previously efficient operations become highly entropic processes.

4. CONCLUSIONS

The present section concludes the conceptual development of the end-of-degree paper. After having developed a theoretical framework in which financial innovation was characterized and the evident strategic links between science and economics explored through an emergent discipline named econophysics, three theoretical models from natural sciences were briefly defined (namely, thermodynamics, swarm intelligence, and chaos theory) and its applications to the financial and economic system presented through a review of existing literature. The conceptual background acquired in *Section 2* constituted the basis for *Section 3*, in which a new analytical framework to study the financial and economic system was derived from the abovementioned theories. According to it,

The financial system may be modeled as a vector field of forces in an informational space in which subunits (i.e. particles, economic entities) constitute an energetic, complex system and interact according to the laws of thermodynamics and classical mechanics.

A definition of the main variables in the system was presented, and a description of the conceptual model was made subsequently by defining the main interactions between them. One of the core results of the analysis was that the financial system acts as a catalytic mechanism by which the informational position of an economic entity configures its potential energy: the capacity to attract financial resources and perform work in the economic system. The role of information and knowledge was thus greatly emphasized in the analytical model, along with the fractality of the financial system and the energy and mass interactions between economic agents. A discussion about the entropy of the financial system was finally made in the context of open thermodynamic systems (the configuration that best describes the global financial system).

The model was considered as a first attempt by the author to using the consistent analytical apparatus of scientific models in order to produce a holistic framework for financial analysis (a process the author considers underdeveloped in light of the strategic synergies between economics and sciences econosciences can effectively provide). As such, there is immense room for developing a more solid econoscientific model: A further refinement of existing mathematical formulations or the introduction of nonlinear, complex dynamics in the analysis (through chaos theory, swarm, quantum mechanics, or artificial intelligence, for instance) are likely to improve and solidify the analytical framework presented in this paper.

4.1. EFFECTS OF FINANCIAL INNOVATION

The financial system plays a crucial role in today's globalized, interconnected economies. The analytical framework derived in the present paper provides an appealing reason: fractality. Understood as the property by which certain structures reproduce themselves at larger scales (so that the aggregation of microstructures constitute a macrostructure with the same geometric characteristics), fractality may be identified in the financial system; in fact, it can be argued that the overall economic system is a fractal of the financial system. Both systems are clearly interrelated, and shocks have a much more devastating power on interconnected, globalized, information-based, deregulated markets. Information has acquired an essential role in today's knowledge economies and financial systems, where it represents one of the most valuable strategic assets. The ongoing process of worldwide interconnection of financial markets has made them truly interdependent and reliant upon updated, constant informational inputs (e.g. statistics, news, rumors, or high-frequency data); as such, the consequences of external shocks are amplified, and the system presents immediate reactions that modify its internal dynamics and create global systemic changes. In such circumstances, one could argue that financial markets have become hyper-symbolic in the sense that information is the true centerpiece of the system, which is constantly creating information, receiving and managing data (chiefly high-frequency data), and being affected by informational inputs and shocks. (Computerized) decision-making functions and algorithms act upon data to create and execute trading (investment) strategies in the market, and the risk and return schemes defined by standard pricing models can

only be implemented upon effective use of information regarding certain variables (such as probability distributions, volatility, or discount rates). Common topics in financial economics such as information asymmetry, data analysis, risk management, artificial markets, financial innovation, or portfolio theory clearly depend on information. The exponential use of technological platforms in the financial sector is another evident consequence of the need to capture, internalize, analyze, compute, and operate an ever-increasing amount of information. In this scenario, entities certifying information (such as audit firms) play and will likely play even a bigger role in today's information economies, which are based on financial information (both private and public) and consistent information systems. Credit rating agencies, news providers, certification companies, central banks, governments, multinationals, or institutional investors are all agents specialized in managing and producing high-impact information affecting the dynamics of the global economic and financial system. (Not only information, but knowledge emerges as the effective capitalization of information.)

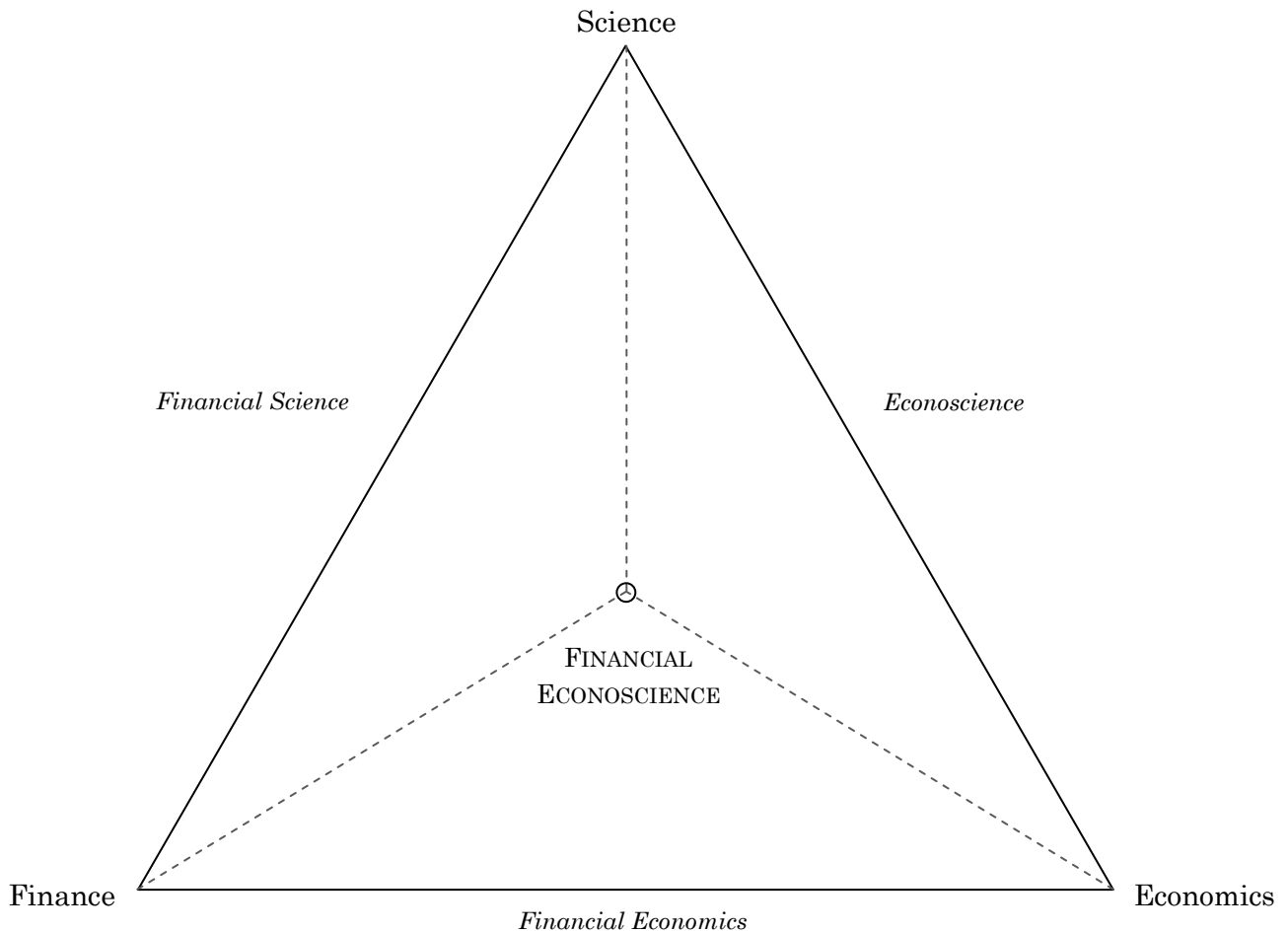
Research and development (R&D, or R&D+i) is the denomination of organizational structures within corporations, academic institutions, and public organisms that devote human, financial, and technological resources to innovation and basic and applied research. Innovation, as mentioned in previous sections, has emerged as a strategic asset for corporations and societies throughout the globe—who acknowledge the importance of generating, controlling, defending, and capitalizing information and knowledge in today's integrated, globalized, knowledge economies. Indeed, we may characterize innovation as the generation of knowledge. The geostrategic implications of innovation and knowledge are obvious: from strategic control over energy and resources to military dominance and financial capacity, knowledge stands up as the focal point for long-term success.

The current financial crisis has undoubtedly put financial innovation at the center of the debate. The role that novel financial products played in the origination of the financial crisis has opened a vigorous debate about the nature of financial innovation, its value, and the proper regulatory response to it. Concepts like time transformation, intertemporal consumption, investment decisions, asymmetric information, or risk reduction are indispensable to understand the nature of financial systems and their dynamics; in fact, the financial sector has seen many products emerging that redefine risks, cash flows, time horizons, underlying assets, and information schemes. Financial innovation essentially represents a core asset for financial corporations that affects its performance and long-term profitability. As such, the main global players tend to devote resources to it and create efficient internal structures to develop new products, create and test new financial high-tech and intelligence, support their global services, and generate robust financial modeling.

The effects of financial innovation are obvious; given the importance of the financial system within the overall economic system and the key role played by technology and information, financial innovation in the form of new products, information models, or technology developments has a clear impact on the dynamics of the global economic structure. Disruptive and incremental innovations may be differentiated at this point, but the truth is that financial innovation may produce fundamental changes in the behavior of economic agents, increase the efficiency of transactions, generate expanded economies of scale and scope, create competitive advantages, induce organizational changes, enhance corporate strategy, and ultimately increase information and financial flows.

The analytical framework developed in the present paper indeed sheds some light on financial innovation and its potential effects on the economic system. Considering the main results derived from mechanics and thermodynamics, financial innovation may be characterized as those innovation processes by which the entropy of financial operations and the system as a whole increases at a decelerate rate (that is, financial flows have more capacity to generate work or, alternatively, a particular informational position is associated with more potential energy and financial flows), accelerates financial flows among economic agents, increases the optimal temperature of the system, reduces the probability of financial perturbations (like bubbles, i.e. generators of underlying entropy) and stabilizes the system, increases the internal energy of economic agents, and increases the power and capitalization of the system.

4.2. SCIENCE AND ECONOMICS AND FINANCE: SYNERGIC INTERACTION



Finance, economics, and science. (The term science is used here to refer to natural sciences.) This conceptual triangle constitutes the basic theoretical motivation behind the topic of this paper: the application of theoretical models to financial innovation. Paradoxically, this trinomial has been long ignored by both scientists and economists; in fact, both sides seem to be reluctant to acknowledge the potential synergies a strategic cooperation could deliver. It seems clear, though, that both disciplines have a shared goal: to understand reality, its underlying laws and dynamics, and be able to predict it. The way to achieve such a goal is to develop systematic models: be it quantum mechanics or the IS-LM model, both conceptual constructions present an internal structure, are based on axioms (both empirically inferred and conceptually derived), and are empirically contrasted (or at least provide a framework to analyze reality). As such, there is no justification to make both sciences mutually exclusive. One may argue that their methods are effectively different, or that the degree of development between the two differs considerably; there is an enormous potential then: in fact, social sciences are a notable field test for natural sciences, providing them with really complex systems composed by multiple agents interacting nonlinearly and developing specific internal dynamics. Finance and economics, in turn, can benefit from adopting the scientific method and utilizing the strong analytical apparatuses from science that describe reality at a microscopic and macroscopic level. The alignment and convergence between the two should really become the next strategic alliance our species develops during the 21st century.

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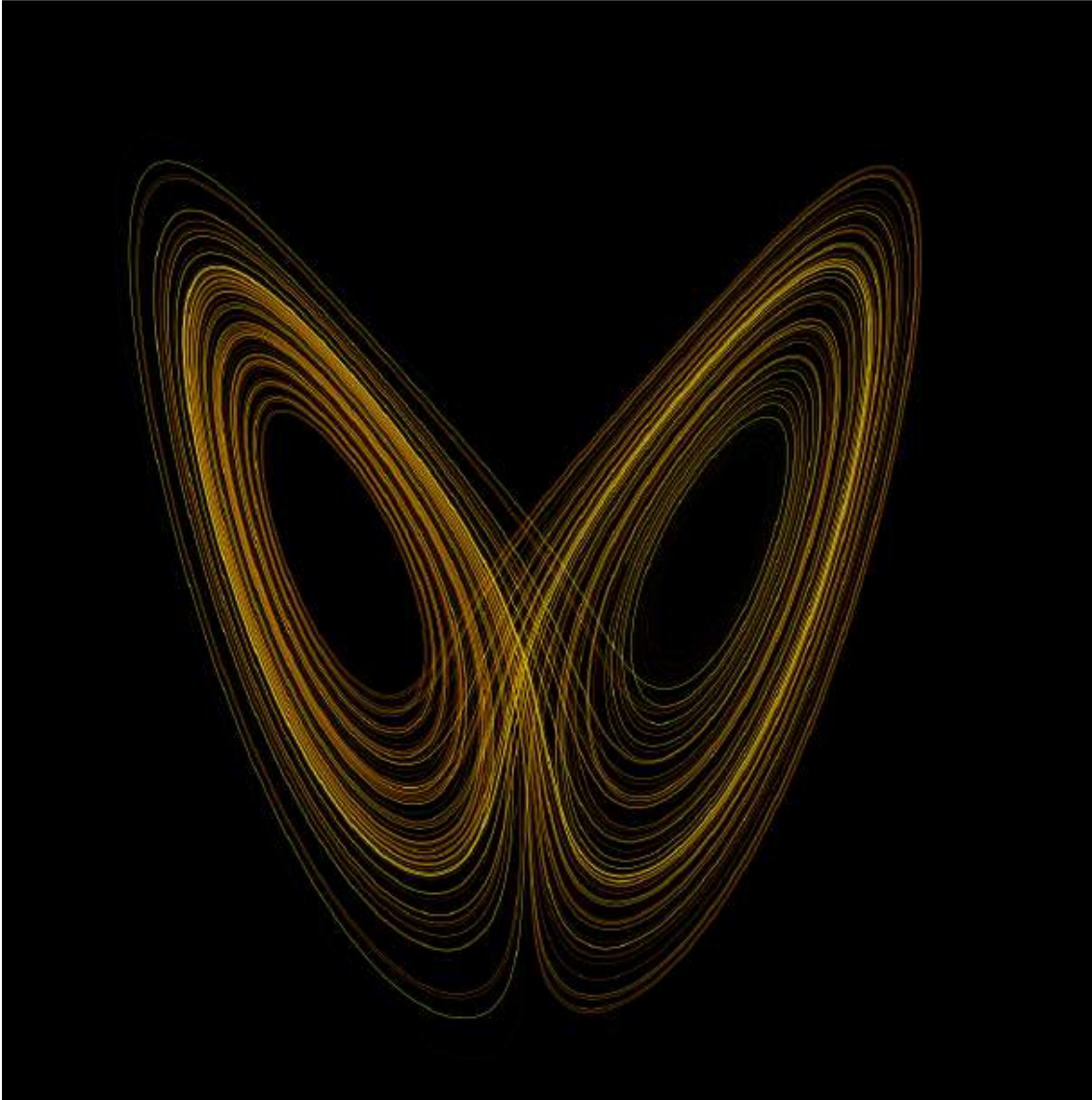
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6. APPENDIX

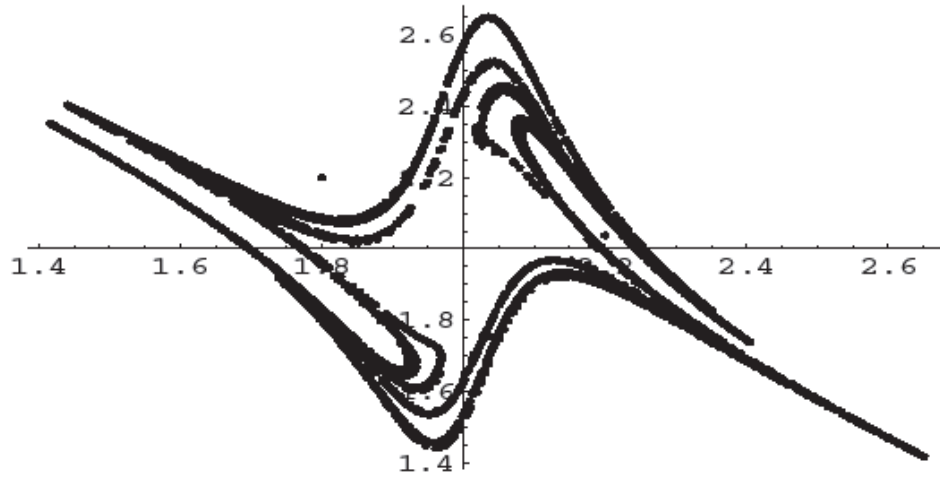
6.1. FIGURES

Figure 1



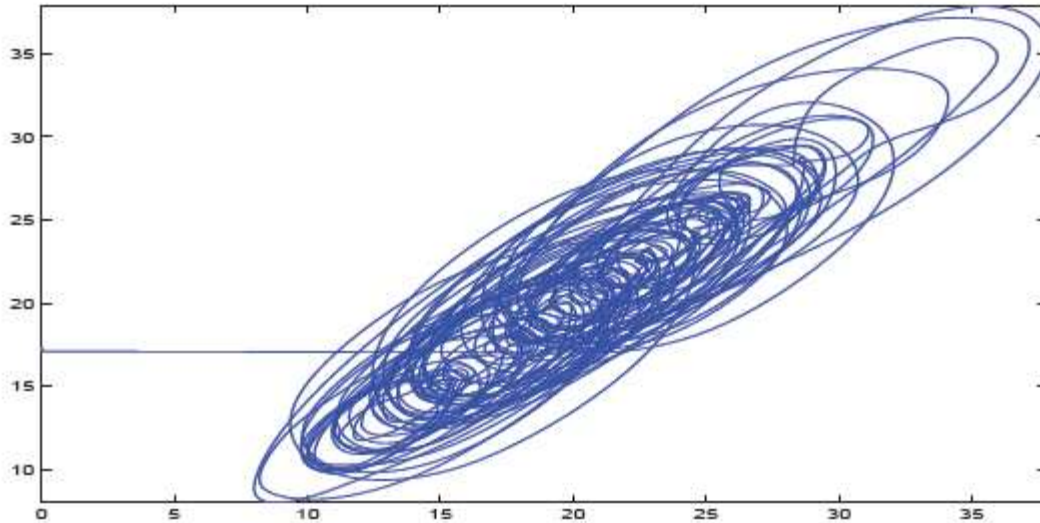
Source: http://es.wikipedia.org/wiki/Teor%C3%ADa_del_caos

Figure 2



Source: Guégan (2009)

Figure 3



Source: Guégan (2009)