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Addressing the malaise in neoclassical economics: a call for partial models

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Abstract
Economics is currently experiencing a climate of uncertainty regarding the soundness of its theoretical framework and even its status as a science. Much of the criticism is within the discipline, and emphasizes the alleged failure of the neoclassical viewpoint. This article proposes the deployment of partial modeling, utilizing Boolean networks (BNs), as an inductive discovery procedure for the development of economic theory. The method is presented in detail and then linked to the Semantic View of Theories (SVT), closely identified with Bas van Fraassen and Patrick Suppes, in which models are construed as mediators creatively negotiating between theory and reality. It is suggested that this approach may be appropriate for economics and, by implication, for any science in which there is no consensus theory, and a wide range of viewpoints compete for acceptance.

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Keywords Economic models; history of economic theory; complexity economics; computational modeling; Boolean networks; semantic view of theories

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Abbreviations: BN: Boolean Network; CNA: CellNetAnalyzer; GET: General Equilibrium Theory; HFT: High-frequency trading; ODE: ordinary differential equation; SQUAD: Standard Qualitative Dynamical System; SVT: Semantic View of Theories

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1. Introduction.

Joseph Stiglitz, recalling his chairmanship of the Council of Economic Advisers (1995-1997), noted that one of his major problems was hiring a macroeconomist. As he recalled it: "The prevailing models taught in most graduate schools were based on neoclassical economics. I wondered how the president, who had been elected on a platform of 'Jobs! Jobs! Jobs!' would respond to one of our brightest and best young economists as he or she explained that there was no such thing as unemployment" (Stiglitz, 2010, p. 350, note 14). Like most satirical observations, this one contains (at least) a grain of truth. Of course neoclassical economists are aware that unemployment is real. But the target of Stiglitz' barb is the idealized neoclassical assumption of full employment of labor and other resources. This stipulation, together with other similarly unrealistic assumptions---e.g., perfect competition, fixed consumer income, perfect mobility of factors of production, as well as several others---comprise the foundation of Léon Walras' (1834-1910) General Equilibrium Theory (GET): a critical component of the neoclassical framework and of mainstream economics (Turk, 2012). While any scientific theory is to some extent an abstraction, critics of GET maintain that the present form of this model is a purely mathematical achievement with remarkable internal consistency but total irrelevance to economic life (Ackerman, 2002). Criticism of GET, of its larger neoclassical context, and indeed of the entire science, has dramatically escalated---helped by a strong assist from the blogosphere (*The Economist*, December 28, 2011)---following the 2008 market collapse. Failure to predict the crisis, or to expeditiously cure it, has suggested that GET---and, in the bargain---all of economics, was hopelessly out of touch with reality. "The economist has no clothes," as one critic observed (Nadeau, 2008). (Yet, and importantly, it was probably never that simple. Historically, as *The Economist* (April 12, 2014) noted, economic slumps have generated emergency models "cobbled together at the bottom of financial cliffs. Often what starts out as a post-crisis sticking plaster becomes a permanent feature of the system. If history is any guide, decisions taken now will reverberate for decades.") Perhaps most emblematic of the deepening self-critical mood was a February 9, 2015 New York Times colloquium of American economists which addressed "the profession's poor track record in forecasting and planning, and the continued struggles of many Americans."

This article is not the addition of one more voice---that of an anthropologist---to the growing heterodox chorus calling for an end to the neoclassical view. Nor is it a retrenched attempt to defend that orthodoxy in the face of its historical record. Instead, the article proposes an inductive, exploratory approach in which partial models of an economic system---i.e., “models that are at the same level of abstraction and represent different ‘views’ of a phenomenon” (Amigoni and Schiaffonati, 2008)---are deployed in a computational strategy in which components of the models are combined in unpredictable ways. A theory is thus a synthesis of input models, and should be tested for its ability to predict an actual economy. Models, in this approach, are thus exploratory devices and clearly differ from theories. In accordance with the Semantic View of Theories (SVT) pioneered by Bas van Fraassen and Patrick Suppes, and subsequently developed by Margaret Morrison, Mary S. Morgan, Francesco Amigoni and Viola Schiaffonati, we would designate models as cognitive tools or, equivalently, as conceptual instruments, that “mediate” between the referent (reality) and the synthetic interpretation, or theory. The strategy is illustrated through a Boolean Networks (BN) model originally utilized in cell biology. BNs are a class of computational models primarily distinguished by discretized variables (nodes) for which input-output relations are governed by Boolean functions (Helikar et al., 2011). (Alternative strategies, including hybridization with agent-based models or ABNs, are certainly possible. New approaches are being developed all the time. The BN method was chosen because of its relative simplicity and demonstrated accuracy in partial modeling of complex systems). In the following section, each major step of BN partial modeling is explained in (mostly) nonmathematical detail, and sample economic implications are embedded within the discussion. Emphasis is placed on two key properties: the use of modeling conventions or standards when partial models are combined; the ability of the method to incorporate externalities, such as cultural or religious variables, for which quantitative data are frequently inadequate or lacking. The BN method is then examined in the larger context of SVT. Here, the autonomy of the partial modeling procedure, in which the modeler cannot predict what the results will be, is construed as a computational variant of Morrison and Morgan’s approach. As a programmatic example, partial modeling is proposed for recent theoretical controversies related to high-frequency trading (HFT). It is concluded that partial modeling is appropriate for economics---and by extension, for any science---in which the traditional framework has failed, there is no consensus theory, and an array of alternative viewpoints compete for recognition.

2. Addressing the climate of uncertainty in economic theory: partial modeling with Boolean networks.

Boolean networks (BNs) began as the almost inevitable outgrowth of the Digital Revolution which swept the behavioral, social and biological sciences in the late Fifties and early Sixties. Computational analogies abounded, ultimately reaching their limit when Vladimir Brix announced that "you are a computer" (Brix, 1970). The initial approaches were homeostatic: The new discipline of cybernetics, as described by mathematician Norbert Wiener (1894-1964) and psychiatrist W. Ross Ashby (1903-1972) comprised living and mechanical systems in which output was sensed, compared with a goal, and the discrepancy was reduced, generating a stable state. In a major theoretical shift, the approach was extended by Magoroh Maruyama (1963) who proclaimed a "second cybernetics": Deviations need not result in correction and continued stability, but may in fact "amplify" and generate widespread systemic change. Influenced by these currents, economist Herbert Simon anticipated BNs in his "satisficing" concept of the economic actor (Simon, 1947). Contrasting sharply with the optimizing agents of neoclassical theory---firms which maximize profits from production and distribution, households which maximize utility, or satisfaction, from consumption---satisficing (*satisfy* and *suffice*) posited an "aspiration level" or acceptability threshold as a tractable heuristic for decision-making behavior.

Herbert Simon's two seminal concepts---binary variables and thresholds---were later incorporated into a fully realized BN model by theoretical biologist Stuart A. Kauffman (1969). Its basic properties were, and are, comparatively simple. Following Helikar et al. (2011), a BN is a discrete model comprised of a set of components or nodes $\{\sigma_1, \sigma_2, . . . \sigma_n\}$ which can typically assume only two values, ON (1) or OFF (0); these correspond, respectively, to the active or inactive state of the variable, or to its above- or below-threshold value. Nodes are linked by a "wiring diagram" formulated by the investigator in a first approximation. The diagram may be---and often is---somewhat speculative, especially if the variables are not yet well-understood (Davidich and Bornholdt, 2008; Helikar et al., 2011). Finally, the binary output of each node is specified by logical operations utilizing AND, OR, and NOT; the input-output relations, or Boolean functions $\{B_1, B_2, . . . B_n\}$, are represented in a "truth table". The model is thus algebraic (although its discrete values, 0 and 1, may be regarded as the limits of continuous functions, and in fact, hybrid variants utilizing ordinary differential equations, or ODEs, continue to be developed). In Kauffman's summary (1991, p. 77): "The dynamic behavior of each variable---that is, whether it will be on or off at the next moment---is governed by a logical switching rule called a Boolean function. The function specifies the activity of a variable in response to all the possible combinations of activities in the input variables. One such rule is the Boolean OR function, which says that a variable will be active if any of its input variables is active. Alternatively, the AND function declares that a variable will become active only if all its inputs are currently active." Under the best of conditions---i.e., when educated guesswork is minimal---the BN approach has proven to be a valuable approximation technique. BNs, and their many variants, have been used in a wide, and expanding, range of modeling applications, "including gene regulatory systems, spin glasses, evolution, social sciences, the stock market, circuit theory and computer science" (Richardson, 2005, p. 365), frequently yielding results with high predictive power.

Partial modeling utilizing BNs has recently been applied to a sample problem in computational biology (Schlatter et al., 2012). Alternative BN models of liver-cell (hepatocyte) interaction were combined into a larger network representation. As a prerequisite for smooth model integration, the investigators proposed a set of standards or conventions, some of which were highly unrealistic: the ON (1) state of a network molecule may be discretized as multi-valued logic to represent varying concentrations, e.g. high, low, very low, but only if the variations have a functional effect; quantitative experimental data are to be utilized in configuring node interactions; the treatment of time is made somewhat artificial in that the value assigned to a node is based on the peak concentration of the referent molecule at any time point in the signaling process; artificial nodes which do not correspond to any molecular species sum up the network response to selected input nodes with regard to a cellular function of interest (e.g., the effect of the inputs on apoptosis, or cell death), thus constituting a form of early automated analysis; certain input nodes corresponding to molecules which are constitutively active (i.e., operative in the cell under all physiological conditions) are initialized at the ON (1) state; finally, and most importantly for uncertain modeling situations, artificial nodes are used to “model unknown interrelations.” In the liver-cell example, cells switch between two different forms of apoptosis, but the underlying protein mechanism, which has not been identified, was modeled by an artificial node.

Using those conventions, the study demonstrated the coupling of two BN models in two different biological examples: In the first example, BN models of two different cell types were combined; the second example combined partial models of a single cell type. The accuracy of the first example was experimentally verified, and then used as a basis for evaluating the second (partial) modeling approach. In the first example, SQUAD (Standard Qualitative Dynamical Systems) was utilized: This is a hybrid modeling approach---i.e., one which synthesizes discrete and continuous methods---which initially configures a target network as discrete dynamical system (e.g., a BN), and then applies a binary decision algorithm to identify all of its steady states (DiCara et al., 2007). SQUAD simulation essentially consists of three main stages. First, the network is described by a graph or wiring diagram which is then converted into a BN. Through the use of a BN algorithm, all the steady states of the system are identified. Second, through the application of a toolbox it is possible to convert a BN into a continuous dynamical system configured as ordinary differential equations (ODEs); this transform permits the modeler to identify the steady states of the newly-developed continuous model via reference to the preceding BN. Metaphorically, one might think of the steady states of the initial BN as mathematically “visible beneath” the continuous model. Finally, dynamic simulation methods, especially perturbation techniques, reveal the overall behavior of the network and the roles of specific nodes. (The perturbations can be sensitively configured; for example, *singlepulse* can modify a node at a single time point; *rangepulse* can sustain a perturbation for some specified time interval.) In this manner, SQUAD makes possible the simulation of large signaling or regulatory networks through identification and perturbation of multiple stable states. Importantly, SQUAD does not provide information regarding the states that can arrive at any given stable state; i.e., it is uninformative regarding basins of attraction.

For comparison with the experimentally-supported SQUAD results, partial BN models of the molecular network of a single cell type were combined using CellNetAnalyzer (CNA), a Matlab toolbox for BN analysis. A key property of this approach is the simplification of the partial models to avoid an intractable result when they are combined. Thus CNA, given the standards described above, computes node values that approach a unique steady state. This is done by excluding node values that will produce multiple steady states. In addition, feedback loops are excluded because they can frequently yield oscillations. Through the use of these, and additional, simplifying procedures, the partial BNs were then combined. Initially, the partial models were pooled in common model files, and modeler decisions were made regarding the interactions of common nodes; an automated "quality assurance method" evaluated all possible input node values consistent with the modeling standards. Results of the two approaches were very similar, and the combination of partial models "was achieved without fundamental adjustments and the complexity was only moderately increased" (Schlatter et al., 2012).

The study has possible direct implications for partial modeling in economics. Two aspects deserve closer attention: the use of simplifying assumptions, i.e. modeling conventions or standards, when combining partial models; the ability of BNs to include system components (e.g. cultural or religious variables) for which quantitative data are minimal or lacking, without significant loss of predictive power**.** As an example of the first property, in BN models of the global economy, initialization of nodes in the ON (1) state could apply to "anti-monopoly" laws enforced by China against US firms doing business in that country which require "merger reviews and investigations of alleged anti-competitive behavior related to pricing and monopolistic conduct" (Ong and Huber, 2014). Because these regulations, for many modeling purposes, may be considered as "always" present, they are systemically analogous to constitutive enzymes in the Schlatter et al. study which remain active without regard to physiological conditions. Similarly, the use of artificial nodes in the study to "model unknown interrelations" would be directly applicable to unknown components of command economies such as that of North Korea, where economic statistics are regarded as state secrets (Noland, 2012). Often, the best that one can do is utilize "mirror statistics"---e.g. "adding up what other countries say they import from North Korea" to estimate its exports; the results, which are almost always highly questionable, would be configured as an output from an artificial node representing unknown variables.

With regard to the second property, everyone now realizes---and some have been shocked by events into realizing---that cultural, religious, and ideological forces, especially in the developing world, can impact the world's economies (Chua, 2002; Kaplan, 2012). Accordingly, the institutional economists Greenwod and Holt (2008) vigorously defend the extension of their science, through an interdisciplinary framework, into the realm of "technology and its relationship to cultural habits." Global examples of these "cultural habits" are not difficult to find. Chua (2002) has extensively documented the widespread destructive effects of the adoption by Third World countries of democracy and free-market economies without a supportive institutional context (i.e. an established tradition of nation-state governance, socioeconomic classes, and economic upward mobility). The result has been the enrichment of already-dominant minority groups including, as a major example, Chinese minorities of the Philippines, Burma, Thailand, and Indonesia. Ethnic-based income disparities have culminated in violent clashes in several of these countries resulting, in some cases, social collapse (e.g., Rwanda). Similarly, my student Elaine Chamberlain demonstrated that the success or failure of microfinance organizations in the Middle East and North Africa (MENA) can be significantly shaped by local cultural conditions (Chamberlain, 2015). The examples could be easily multiplied. Yet, for many of these cultural agents, quantitative data are inadequate or lacking. This limitation could be addressed through educated guesswork, as it often is with molecular systems, provided that mirror data or, even better, on-the-ground reports (e.g. from NGOs such as Human Rights Watch, http://www.hrw.org) are available. In those cases, an increase in the cultural activity---for example, the growth of an ethnically-based nationalistic movement---would be represented as 1; decline would be assigned 0. If the available data are somewhat fine-grained---e.g. low, moderate, high---more precise, but still qualitative, models may be developed using multi-valued logic. In this variant, a node may assume more than one value---decimal expressions from 0 to 1---and is typically governed by a threshold rule (Schlatter et al., 2009; Bornholdt, 2008). Finally, we will note that BNs are remarkably flexible: In the event that detailed quantitative information becomes available, either for cultural variables or other features of the model, it is possible to convert selected nodes into ordinary differential equations (ODEs).

Partial models, theories, and the crisis in economic thought.

The Digital Revolution, which as we have seen, exerted a significant influence on theoretical developments in the natural and social sciences some 60 years ago, is now extending that influence into the philosophy of science itself. What is a theory? A model? What do we mean when we speak of a model as having autonomy? How does autonomy affect the concept of scientific representation? Most importantly in the present context, how do these debates escape the confines of philosophy and affect the current state of economic theory? Francesco Amigoni and Viola Schiaffonai (2008) have evaluated these questions. As they note, the great strength of computational models, recognized in the early days of the Digital Revolution, resides in their ability to process quantities of data such as those routinely encountered in molecular cell biology (Amigoni and Schiaffonati, 2008). But the platform had a consequence to some extent unforeseen. The enormous challenge presented by manipulating the ordinary differential equations (ODEs) which describe the kinetic properties of molecular interactions led investigators to question the necessity of such descriptions for many types of problems (For a similar argument see Bornholdt, 2008). In effect, computational modelers were increasingly led to ask that most fundamental of epistemic questions: "What counts as knowledge?" (Amigoni and Scihaffonati, 2008). More exactly: "The adoption of computer programs, namely computational models, is firstly intended to process, manage, and classify huge quantities of data. Moreover, programs serve also to account for the meaning of these data: what counts as knowledge and what we consider as knowledge depends on the data we are able to acquire, on the ways in which these data are collected, and on the form in which they are represented." The historical result, as noted earlier, was the discretization of the continuous processes traditionally represented by ODEs, an innovation pioneered during the 1980s in Stephen Wolfram's cellular automata (CA), and Stuart A. Kauffman's Boolean networks (BNs) utilized here. However, a remarkable feature of these approaches was the inability of the modelers, when presented with simulations of highly complex biomolecular interactions, to predict what the results would be, even when the rules of the simulation were precisely specified. Discrete models thus assumed a new and unexpected identity: they became exploratory constructions, "artificial universes evolving in accordance with local but uniform rules" (Amigoni and Scihaffonati, 2008).

These methodological developments were, fortuitously, consistent with paralleling transformations in the philosophy of science. From the 1920s to the 1960s, the dominant understanding of scientific investigation---usually designated the "Syntactic View" and most strongly associated with Rudolf Carnap, Carl Hempel, and Herbert Feigl---had placed considerable emphasis on the role of "theoretical sentences". The latter did not deploy natural language but instead contained logical and mathematical symbols, and the symbols of the theory. The theoretical sentences were in turn connected to "observational terms", which referred to the observable properties of a phenomenon, by means of "correspondence rules" (sentences which included both theoretical and observational terms). This "Received View" (Putnam, 1962) prevailed until the 1960s, when it was vigorously challenged by Patrick Suppes (1960) and Bas Van Fraassen (1980), proponents of a "semantic" strategy. One of the key defining features of their Semantic of Theories (SVT) was the replacement of the syntactic edifice linked by correspondence rules with set-theoretic relations based on structural isomorphism. Motivated by mathematics and the empirical sciences, Van Fraassen proposed that "models occupy center stage" (1980), or more exactly, that a scientific theory gives us a family of models to represent phenomena. This major conceptual shift resulted in a view of theory "as determined by the class of its possible realizations" (Amigoni and Schiffonati, 2008). Thus, all possible models of a theory are reduced "to a particular subclass that is more manageable and easier to study, being a subset of the set of all models. The goal, hence, is to consider just a subset, limited and manageable, of the whole set of the models of the theory and to work on it."

Motivated by these foundational changes, Margaret Morrison and Mary Morgan (1999) claimed that models had now acquired an enriched epistemic role. They are not derived from theory; neither are they fully grounded in empirical observations. Instead, they are "semi-autonomous", sharing components with the world and theory, while not being fully connected with either. Žitko (2013, 95-96) compares the semi-autonomy of models to statistical correlation: "With perfect correlation there is little new knowledge to be acquired since th two sets of data will share the same variation, while with zero correlation there is even less to learn since the two sets of data have nothing in common. It is only in between the extreme values that something more can be argued about the two data sets, and a meaningful research can begin." Because of this semi-autonomy, models are remarkably fluid, evolving into novel constructions that challenge traditional theories and (often) illuminate the actual world. Support for this view of science, Morgan and Morrison suggest, is not to be found through formal arguments in the manner of the Syntactical school, but by finding common properties in the actual work of scientists. Accordingly, they consider accounts of model-building in economics, chemistry, and physics, eliciting from their analyses a portrait of the scientist closely resembling that of the artist. (For a similar conclusion based on extensive interviews with scientists and artists see the engagingly-written *Notebooks of the Mind* (1997) by Vera John-Steiner.) In a key passage, they note: "As we have pointed out, there are no rules for model building and so the very activity of construction creates an opportunity to learn: what will fit together and how? Perhaps this is why modeling is considered in many circles an art or craft; it does not necessarily involve the most sophisticated mathematics or require extensive knowledge of every aspect of the system." (Morrison and Morgan's construal of model-building is, of course, to be distinguished from the "cobbling together" of models under emergency conditions discussed in *The Economist* article referenced at the beginning). This perspective is evidenced in a study by Olav Bjerkholt (2007), which documents the early development of business-cycle theory (1920s-1930s), revealing in the process how "bits of the business-cycle theory and evidence could be integrated together into a model" (Morrison and Morgan, 1999). The studies depict in detail how the cognitive "notebooks" (John-Steiner, 1997) of the econometrician Ragnar Frisch were a dynamic amalgam of economic and physical theories (the latter including the famous, and controversial, pendulum analogy), statistics, direct observations and, intriguingly, "heroic guesses, transgressing the observational facts"

(Frisch, 2010, [orig.1930]). The "model world" which emerged from Frisch's mediating approach comprised "those indefinable things in the real world which we might call 'essentials'…with regard to our own ends" (Frisch, 2010, [orig. 1930). R.I.G. Hughes (1997) anticipating the views of Amigoni and Schiaffonati (2008), has shown how Frisch's mediating approach lends itself to simulation. Deploying cellular automata (CA), he discovered "generic cycles which had empirical credibility, and provided a prediction of a new cycle which had not yet been observed in the data" (Morrison and Morgan, 1999).

But Frisch's ideas were developed nearly a century ago. Can partial modeling address today's economic issues and, in particular, the current crisis in economic theory? We would argue that this is indeed the case, and would propose as a sample study that the several competing models of high-frequency trading (HFT) could be simultaneously subjected to a mediating, computational approach. HFT is a relatively recent computer platform, currently expanding throughout much of the developed world, and into the BRICS countries, in which firms use complex, high-speed algorithms to detect supply-and-demand opportunities, and to execute trades. These transactions, fully automated, are typically conducted in milliseconds (thousandths of a second); Johnson et al. (2013) report that a new chip, the iX-eCute, can "prepare trades in 740 nanoseconds" (a nanosecond is a billionth of a second). Although a single HFT trade will often net less than a penny in profit per share, the ultrafast transaction speed permits thousands of transactions a day (Bell, 2013). The practice is spreading rapidly, transforming market culture into "geographies" of competing algorithms (Grindsted, 2016). According to a 2016 estimate by the Congressional Research Service, HFT "accounts for 55% of trading volume in US equity markets and about 40% in European markets" (Miller and Shorter, 2016). High-speed trading is intensely controversial---and hence the object of much model-building---especially since the May 6, 2010 "flash crash", and the later appearance of *Flash Boys*, a critical popular account of HFT (Lewis, 2015). Many recent studies assert that the practice may strongly contribute to national and global market volatility, and should therefore be subjected to stronger government regulation (Adrian, 2016). To explore HFT volatility, Johnson et al. (2013), utilizing NANEX NxCore software, analyzed the millisecond-resolution price stream "across multiple stocks and exchanges" from January 3, 2006 to February 3, 2011. They detected 18, 520 sub-second "extreme events" which, in turn were coupled to "slower global instabilities". A possible key factor underlying this instability, according to Austin Gerig (2012) is price synchronization: If two securities are closely related, a price change in the first will generate, almost instantly, a similar price change in the second. This process, a "gargantuan task" in the traditional stock market, given the more than 1000 transactions per second in US equities alone, can become highly destabilizing in an ultrafast trading environment. Gerig's bio-inspired model proposes that HFT "efficiency"---here, the rapid information transfer between related individual equities---may yield coordinated collective behavior analogous to that of animal groups (herds of ungulates; schools of fish). So, following Levine (2014), we might ask: Is HFT too efficient? Holly Bell (2013) suggests it is not, proffering a defense of HFT as the ultrafast realization of Eugene Fama's "efficient market". Fama (1970) had famously argued that, at any given time, prices were an expression of all the available information on a particular stock market. This property was largely due to the preponderance of rational investors---the neoclassical *Homo economicus*; but a measure of irrational behavior was also consistent with the view (Szyszka, 2007). The latter behavior is generally uncorrelated, and so the investment decisions would likely cancel each other out. Alternatively, a rare (but in principle, possible) coordinated movement would result in a stabilizing counter-movement by rational arbitrageurs. In Bell's model, HFT is a novel micro-world, differing profoundly from the traditional market, where algorithms, as agents, are almost instantly aware of price movements of other agents (Bell, 2013), and adjust their investment behavior (bid-and-ask decisions) accordingly. Volatility does not result, therefore, from irrationality and swarming in the HFT micro-world, but is primarily due to the extraneous over-corrections of individual investors to dramatic economic events (e.g., the subprime mortgage crisis). These HFT models, and many others not considered here, would be appropriate starting-points for a partial-modeling strategy. Thus, the HFT swarming behavior described by Austin Gerig systemically resembles that examined by Caetano and Yoneyama (2015) in a macroeconomic BN model of contagion in BRICS countries. Similarly, the putative efficiency of HFT claimed by Holly Bell would be amenable to BN approaches which model hubs and feedback loops, evaluate their connectivity, and their stabilizing effects (Kwon and Cho, 2007).

4. Conclusion.

Neoclassical economics, the traditional framework of the science, is widely viewed as an obsolete relic of early 20th century thought (Ackerman, 2002; Colander, 2007; Nadeau, 2008) Its obsolescence, it is held, is tellingly reflected in its axiomatized structure, its demonstrated inability to predict financial crises, and in its potential to generate ineffective and dangerous policies. This assessment may be correct. Yet it is also arguable that the neoclassical view will---and should---persist, at least in the short run, in the form of input models that contribute to a synthetic theory. What is required for theoretical advance, as well for informed policy, is the deployment of today's powerful computational platforms to initiate the interactions of semi-autonomous partial models. As an intriguing digital mimicry of the human creative process---with demonstrated successes in medicine and cell biology---partial models are cognitive tools which can generate new theories in a manner no one can anticipate. This property is of signal importance because it impedes the Procrustean habit: The rote imposition of outmoded, but dominant views on non-conforming, recalcitrant data. Economics' self-critical mood may thus have a salutary effect: The emergence of a changed science in which models are not formally derived from a set of governing axioms, but are cognitive instruments in a regime of exploration.

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