Complexity economics as an early-warning system: a proposal.

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Abstract: Economics has largely failed to predict global financial crises. In an increasingly globalized world, the consequences of that failure are likely to become more severe. The present article attributes much of economics' malaise to the traditional and continuing use of equilibrium models. The unifying assumption of the equilibrium viewpoint has been that the components of an economy will persist in a state of balance unless perturbed by external factors. This article challenges that assumption, proposing instead that economies are typically out of balance, and that equilibrium is transitory. That single changed assumption, central to complexity economics, entails additional changed assumptions regarding policymaking. Global economic growth will be most effectively managed, and crises most effectively avoided, when economists deploy dynamic models which address the immediate future. As a programmatic example, Boolean Network (BN) modeling of global economic criticality utilizing the Lempel-Ziv (LZ) complexity metric is proposed as an Early Warning System (EWS) useful in decision-making and forecasting economic crises. The new viewpoint, if adopted, would likely present political challenges, which are evaluated at some length.

Keywords: economic models; complexity economics; computational modeling; Boolean networks; LZ complexity

Abbreviations: BN: Boolean Network; CM: Continuous models; DM: Discrete models; EWS: Early Warning System; LP: Link prediction; LZ: Lempel-Ziv; RBN: Random Boolean Network

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Is economics a static subject? Do economists, accordingly, seek and find eternal verities as, say, chemists or physicists do? Or are the institutions with which economics deals in a constant process of transformation to which the subject, and more particularly the policies it urges, must be in a similarly constant process of accommodation?

John Kenneth Galbraith (1987)

1. Introduction.

"What went wrong?" asked Alan Greenspan, former Chairman of the Federal Reserve, five years after the onset of the 2008 Great Recession (Greenspan, 2013). "Why was virtually every economist and policymaker of note so blind to the coming calamity? How did so many experts, including me, fail to see it approaching?" But Greenspan was far from the first. Difficulty in predicting international economic crises has challenged economists and policymakers since the Panic of 1857, arguably the first global economic collapse. One possible basis for the problem is that economic slumps have been conducive to tunnel vision. Tularam and Subramaniam (2013) note that "each model was adapted to specific situations to explain the financial crises faced rather than being visionary or systematic in approach." Similarly, *The Economist* (April 12, 2014) observes that economic models motivated by emergencies were "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." Economics' current self-critical mood extends to the scientific status of the discipline itself. Thus a recent book-length study addressed the "financial crisis and the failure of economic theory" (Rodriguez et al., 2014), and a February 9, 2015 *New York Times* colloquium of American economists critiqued "the profession's poor track record in forecasting and planning, and the continued struggles of many Americans."

This review article evaluates the historically-demonstrated weakness of traditional economic models in anticipating global crises from the standpoint of complexity theory. This approach, although presently lacking a consensus definition, may be provisionally construed as a set of mathematical and computational strategies for describing the degree of order within a dynamic system. Widely used in biology and medicine, complexity theory has also been extensively applied to economics, giving rise to a new sub-discipline, "complexity economics". Viewed from that emerging theoretical perspective, economics' historic malaise may be explained in a different way: While the haste in formulating models under emergency conditions may have indeed played a significant role, considerable damage could also have resulted from fundamental misconceptions intrinsic to the science (But see Schumpeter, [1942] 2010 and Robinson, 1962). Foremost among these is the concept of equilibrium, i.e., an idealized condition (mathematically modeled by Arrow and Debreu, 1954) in which economic variables persist in a state of balance unless perturbed by exogenous factors. This article questions that assumption. Here it is proposed, based on growing evidence, that economies are typically out-of-balance, and that equilibrium is episodic. As Joan Robinson once put it: "A model applicable to actual history must be capable of getting out of equilibrium; indeed it must normally not be in it (Robinson, 1962)." From this single changed assumption derive significant implications for prediction and policymaking. Accurate forecasting can likely be achieved only in the short run. Long-range, interacting waves of systemic change, often initiated by small events, and operating "in parallel across the economy and at all scales" (Arthur, 2013), i.e., chaotic systems, make distant forecasting difficult, resembling the problems evaluated in computability theory (Reiter and Johnson, 2012). Accordingly, global economic policy will most effectively manage growth---and avoid politically and socially destabilizing crises---when based on non-equilibrium models which address the immediate future.

As a programmatic example, computational modeling of criticality---a poised systemic state between dynamic order and chaos---is presented as an Early Warning System (EWS) potentially useful in forecasting economic crises. Importantly, no claim is made---*contra* Bak et al. (1992)---that criticality is an optimized state, analogous to those encountered in nature (Schmulevich et al., 2005; Wallace, 2015), toward which an economy will self-organize. Rather, in view of the equivocal results of attempts to demonstrate criticality in economic systems (reviewed in Terán, 2001), as well as the controversies surrounding many putative examples of SOC in nature (Hesse and Gross, 2014; Botcharova et al., 2012), the present analysis views economic criticality as a managed state, i.e., requiring exogenous tuning. The article begins by examining the relative strengths of discrete and continuous economic models (Medio, 1991). Although both strategies have their advantages, and hybrid models are also possible (Khan et al., 2014) it is suggested that Boolean networks (BNs), a discrete approach in which interactions among binary-state components (nodes) are governed by algebraic rules (Kauffman, 1969), are particularly well-suited for modeling economic criticality, thus functioning as an EWS. Lempel-Ziv (LZ) complexity (Lempel and Ziv, 1976), a data-compression algorithm widely used in biology and medicine (e.g.,Orlov and Potapov, 2004; Gulati and Wallace, 2014)), and which is compatible with BN modeling, is then presented as a candidate metric to evaluate the degree of order within the system. Finally, the EWS is situated in a larger context of digital economic diplomacy (Sandre, 2013, 2015).

2. Continuous and discrete-time models in economics.

For many years there has been a vigorous debate in economics---which can only be treated summarily here---regarding the relative strengths and weaknesses of continuous (CM) and discrete-time modeling (DM). It should be emphasized that both approaches are used in the analysis of dynamic, "out-of-equilibrium" economic systems (Robinson, 1962) in which "accurate forecasting is impossible except in the very short run" (Medio, 1991). CM, which normally utilizes differential equations, construes time as a continuous variable during which the economic transactions of interest also take place continuously. Against the critique that economic data generally occur in discrete form---i.e., one in which the economic variables have values that remain constant throughout some unit of time (e.g., annual GDP)---CM proponents respond that aggregate economic transactions typically overlap in time in a random manner compatible with the use of such models. On this point, Wymer (2009) has noted: "As macro-economic behavior is the result of the action and interaction of individual economic agents, aggregation of the micro-variables across sectors or markets will produce macro-variables which will tend to be continuous, so that the macro-economic process can be treated as continuous or as if it were continuous."

Nonetheless, certain variants of DM modeling have their unique advantages. The type of DM utilized here, known as Boolean Networks (BN), is mathematically simpler than most CM approaches, largely employing algebraic rules governing the interactions of binary units, a property that has facilitated considerable versatility (Bornholdt, 2008). Recent BN applications include molecular genetics (Quiñones-Valles et al., 2014), biology (Wang et al., 2012), medicine (Gulati and Wallace, 2014), and foreign policy (Corbetta, 2010). In addition, BNs are well-suited for qualitative modeling of systems for which quantitative information is inadequate. At first glance, this would not seem relevant to economic analyses in which, as noted above, most variables are usually quantified. But, as will be discussed below, economic modeling, if it is to yield accurate forecasts, and anticipate crises, as a basis for policymaking, must be able to represent multi-level, densely connected---and often highly volatile---networks of ecological, demographic, cultural, and political variables. For this "inclusive" economics (Rosefielde and Pfouts, 2014), BNs may be ideally suited. Finally, BNs are appropriate, and have been effectively used (e.g., Schmulevich et al., 2005), to evaluate systemic complexity via the Lempel-Ziv (LZ) metric (Lempel and Ziv, 1976). This measure, "originally developed for use in information-theoretic problems of coding and data compression" (Wallace, 2015), is presented here as a candidate Early Warning System (EWS) through which global economic criticality---construed as a managed, optimized state---may be recognized and sustained.

A BN model is comprised of a set of components or nodes $\{\sigma_1, \sigma_2, . . . \sigma_n\}$ which can assume only two values, ON (1) or OFF (0) corresponding, respectively, to the active or inactive state of the variable, or to its above- or below-threshold value (Fig. 1). Nodes are linked by a wiring diagram in a first approximation which may be somewhat speculative, especially if the variables are not yet well-understood (Davidich and Bornholdt, 2008; Helikar et al., 2011; Wallace, 2015). In economic modeling, BN nodes may represent variables at many different levels. For example, in "bottom-up" approaches such as agent-based computational economics (ACE) or, its close relative, game-theoretic modeling---in which agents, or actors, are computational objects interacting via simplified rules relating to incentives or information---BN nodes and wires can model these units and their interactions (Galstyan and Lerman, 2002). But higher-level modeling is also possible. A recent---and provocative---BN study by Caetano and Yoneyama (2015) examined hypothetical international financial contagion, i.e., the propagation of market disturbances, in BRIC countries (Brazil, Russia, India, and China) and Argentina, each of which was represented by a BN node; the model predicted herd-like behavior in the wake of a financial crisis. Finally, the binary output of each node $\{\sigma_1, \sigma_2, . . . \sigma_n\}$ is specified by logical operations utilizing AND, OR, and NOT; the input-output relations, or Boolean functions $\{B_1, B_2, . . . B_{\mathrm{n}}\}$, are represented in a "truth table". Under the best of conditions---i.e., when educated guesswork is minimal---the BN approach may be regarded as an approximation technique in which successive applications of updated model variants frequently yield a result with high predictive power.

One form of BN modeling useful in determining the information---here understood intuitively as the degree of unpredictability or "uncertainty about the actual alternative among a collection of alternatives" (Caves and Schack, 1997)---within a complex, dynamic system, is the Random Boolean Network (RBN) (Kauffman, 1969). Through the use of RBNs it is possible to determine whether the given system is orderly (low uncertainty regarding the actual alternative, and hence, low information), chaotic (high uncertainty, and thus, high information) or critical (delicately poised between the two regimes). In an RBN model, inputs to each node at time t are randomly chosen along with one of the possible Boolean functions $\{B_1, B_2, \ldots B_n\}$. The state of the network at $t + 1$ is then computed by applying the function associated with each node to the state of that node at t. RBNs have been successfully used to generate mock networks in ordered, critical, and chaotic states for comparison with a BN which models an actual system. This type of comparison, which will be examined in some detail below in relation to LZ complexity, is proposed as a possible method for evaluating the dynamic state of a global economic system.

A note on noise: differing from chaos, but in practice not always readily distinguishable from it, noise is found in natural systems (e.g., Eldar and Elowitz, 2010) and has been proposed as a key component of economic and financial activities, e.g., "noise trading" (Black, 1986; Gemmill and Thomas, 2002). Noise is somewhat elusive, both semantically and methodologically. In principle, noise differs from chaos in that the former is stochastic, and hence, unpredictable, while chaos, a dynamical system highly sensitive to initial conditions (though often apparently lacking order) is actually predictable from deterministic equations. But problems abound: noise can induce chaos, and Brownian (stochastic) processes can have a deterministic origin (Gao et al., 2006). This difficulty has spawned a cottage industry of algorithms, but as yet no consensus method, for reliably distinguishing chaotic from stochastic processes (e.g., Rosso et al., 2007). Moreover, there is a tendency, perhaps especially in economics, to write of noise in an everyday, almost colloquial, sense of the term. Thus Fischer Black in his pioneering article (1986), admittedly used the word in several different but equally casual senses, observing that "noise is what makes our observations imperfect. It keeps us from knowing the expected return on a stock or portfolio. It keeps from knowing whether monetary policy affects inflation or unemployment. It keeps us from knowing what, if anything, we can do to make things better." It is worth noting that in each context, there is an underlying theme of negativity, such that noise, as Black construed it, can cause markets to be inefficient, and generate business cycles, for which---contra

Keynesianism (Keynes, 1936; Wapshott, 2011)---government remedies would be unworkable. But the difficulty with Black's view may be less economic than conceptual, or possibly even linguistic: The term "noise", in its everyday sense, is frequently a pejorative. Such usage may be conducive to overlooking systemic effects of adaptive or "good" noise, already documented for living systems (To and Maheshri, 2010; Levens and Gupta, 2010). Alert to this conceptual snare, Franke (2001) has proposed, following Schumpeter's classic account (1912), that a stochastic burst of innovations can yield long, and deterministic, growth in average productivity. BNs are highly useful in representing the effects of noise---both damaging and constructive---in multi-level dynamic systems (Cozzo et al., 2012); accordingly, stochastic change should arguably be incorporated into criticality models, a prospect to which we now turn.

3. The economics of criticality: between order and chaos.

In its broadest sense, criticality is a dynamical fixed point, which may be thought of as a tipping point, at which a system is neither ordered nor chaotic (Bak, 1996; Mora and Bialek, 2011; Phillips, 2009; Wallace, 2015). Originating in condensed-matter physics and the chemistry of phase transitions, both of which examine many-particle systems, the criticality concept has subsequently been extended to collective biological phenomena (i.e., flocks and herds) and, most recently, to economics The latter models have frequently emphasized self-organized criticality (SOC), in which some sector of an economy will "spontaneously evolve" (Scheinkman and Woodford, 1994) toward the tipping point i.e., without tuning by external parameters. For example, da Cruz and Lind (2011) present a physics-inspired model in which two fundamental assumptions---"humans are attracted to each other to exchange labor" and "the amount of labor exchanged…is ruled by the law of supply and demand"---are initially framed as a two-body problem, and then extended to a many-body problem. In the latter, preferential attachments among transacting agents generate relatively stabilized exchange networks which are vulnerable to random crashes. Aggregate activity in the system can evolve into an SOC, which in turn may further cascade into a global economic crisis. The approach has good empirical fit with stock market performances on the New York, Frankfurt, Paris, Hong Kong, Tokyo, and Chicago exchanges. Thus the model is valuable and provocative, and not least because its minimal assumptions, traditionally found in equilibrium models, can theoretically generate an economic crisis. But do living systems, including economies, really behave in this way? Are SOC economic models motivated by a disanalogy? Sandpiles and earthquakes notwithstanding, some forms of collective phenomena referenced in the models may not display SOC dynamics. Phase transitions, for example, may not occur at a critical point, but appear to be "smoothed out over a small parameter range" (Hesse and Gross, 2014). Claims that SOC is displayed in neuron synchronization patterns have been difficult to replicate (Botcharova et al., 2012). Models of SOC in neurologically complex animals, as Detrain and Deneubourg (2006) point out, are compromised by the fact that "social differentiation coupled with a relatively high autonomy of each living unit may enhance or counteract the impact of self-organizing processes on the group structure." Most analogically significant, however, to the viewpoint of the present article, is the proposal by Torres-Sosa et al. (2012), based on a BN model of gene regulatory networks, that two fundamental assumptions---"(i) the existing phenotypes must be resilient to random mutations, and (ii) new phenotypes must emerge for the organisms to adapt to new environmental challenges"---is sufficient to generate criticality. This finding suggests that criticality may be an optimized state (c.f., Atmar, 1994)---resilient to internal change, but adaptive to external "challenges"---which is arrived at not spontaneously, but by sustained external tuning, either by natural selection in the case of biosystems or, in complex economies, by policymakers or agents.

There are several complexity metrics actually or potentially useful for evaluating criticality. The state of the art is fluid, and new methods are emerging all the time (Lloyd, 2001). For a recent example that utilizes degree-entropy and betweeness-centrality metrics in a study of cancer molecular networks, see Breitkreutz et al., 2012). The approach presented here, Lempel-Ziv (LZ) complexity--- developed by Abraham Lempel and Jacob Ziv in 1976---was first used in the informational sciences as a data-compression algorithm. Variations in LZ were subsequently developed, including one by Terry Welch (1984) for use in high-performance computing. Compatible with BN modeling, LZ has been applied in molecular biology (Schmulevich et al., 2005), medicine (Zhou et al., 2011; Gulati and Wallace, 2014), evolution (Huang et al., 2011), psychology (Katerndahl et al., 2015) and a variety of other sciences. In economics, Taufemback et al. (2011), applied LZ to "tick-by-tick" return data, detecting a decline in stock market relative efficiency (Fama, 1965)---i.e., the degree to which market performance departs from random December 2008.

The mathematical basis of LZ is given in Lempel and Ziv (1976), which those wishing a formal presentation are urged to consult. This article offers instead an illustration of the algorithm by means of an example (Schmulevich et al., 2005; Wallace, 2015). Consider a finite and binary alphabet in which complexity is defined as the number of unique substrings, with the possible exception of the last one (which may not be unique), as the sequence evolves from left to right. Importantly, in the version of LZ presented here, the search for previous occurrences of a substring may bridge previously seen substring boundaries. Thus, in the sequence 01100101101100100110, the first digit, 0, is new; it has not been encountered before. The (evolving) LZ value is therefore 1. Proceeding to the next digit, 1, it is clear that this digit is also new. Thus the LZ value increases to 2. Continuing from left to right, the next (third) digit is 1, which has been previously encountered. Therefore, the length of the substring is increased by one digit (i.e., the fourth digit, 0), yielding a new substring 10, and an evolving LZ value of 3. Next, beginning with the fifth digit, 0, and continuing to move from left to right, the next new substring is 010, yielding an evolving LZ value of 4. The process is continued until the sequence is parsed as follows: 0-1-10-010-1101-100100-110, where dashes indicate the boundaries between substrings. The LZ complexity of this sequence is thus 7. It should be noted that in this LZ variant, the final substring 110, although it was counted, was not new (the reader should bridge the second hyphen).

In applying this method to the global economy, it is proposed that the LZ complexity obtained from a BN model incorporating not only market-performance data (e.g., "tick-by-tick" read-outs), but in addition binarized variables representing cultural, political, and even ideological processes, e.g., increasing (1) or diminishing (0) nationalist sentiment in an ethnic group should be compared with LZ values obtained from RBN models of ordered, critical, and chaotic regimes. In this approach, LZ values are calculated for binarized time-series readouts at clocked moments as the network is running. The LZ values of the network realizations are then displayed as a probability distribution. The latter is then compared with the probability distributions of LZ values obtained from the time-series readouts, again at clocked moments, of RBN mock regimes in ordered, critical, and chaotic states. Although simple visual examination of superposed distributions can itself be highly informative (Fig. 2), several mathematical approaches exist for evaluating the similarity between the LZ probability distribution corresponding to actual data, represented as $P = [p_1, \ldots, p_m]$ and each of the RBN mock-data probability distributions, represented as $Q = [q_1, \ldots, q_m]$. For example, the Euclidean distance given by $E(P,Q) = (\sum_{i=1}^{m}(p_i - q_i)^2)^{½}$, and the Kullback-Leibler (KL) divergence or relative entropy, given by $D\ (P,Q) = \sum_{i=1}^{m} p_i \log(p_i / q_i)$ may both be used for this purpose. In a comparison, the more different the distributions of P and Q, the larger will be the values of the Euclidean and KL measures. (It follows that if the P and Q probability distributions are identical, $E(P,Q) = D(P,Q) = 0$). Schmulevich et al. (2005) recommend that more than one metric be applied to insure that "the results do not depend on the particular measure used."

How does this approach translate into economic policy? BNs can be readily manipulated, which permits hypothesis-testing regarding the specific elements of the network responsible for a departure from criticality. As with other applications of complexity theory, the method does not involve the Procrustean grafting of a preconceived model (e.g., the variant interpretations, throughout much of the 20th century, of Keynesian and Hayekian policies) to an economic crisis (Wapshott, 2011)---the failed approach thus far---but rather the inductive derivation, through iterated attempts, of adjustments deemed necessary for the individual case (Arthur, 1994). Through the use of simulation software such as Boolnet for R (Müssel et al., 2010), or BooleanNet for Python (Albert et al., 2008), BNs can be simulated and analyzed in this way. These packages, however, require downloading, installation, and some degree of programming knowledge (Bock et al., 2014). To address this limitation, Matthias Bock's team has recently written a simulator, BooleSim, that "supports the import of common model file formats, model simulations, easy manipulation through on-click functionality and visualization of a network's dynamical properties as well as export of the Boolean model, graphical network view and the time series." As with complexity metrics, it is likely that interactive strategies for analyzing economic systems will continue to be developed. The major challenges to the present approach are thus not mathematical---which may soon suffer from an embarrassment of riches---but conceptual and political issues, which we will now examine.

4. Discussion: Conceptual and political challenges.

Calamity is chronic. "We should be surprised," remarked the Duc de La Rochefoucauld, "that we can still be surprised." Were the great seventeenth-century aphorist alive today, he would likely be incredulous that we can still be astonished by anything. Viewing his observation through the lens of economic history mentioned briefly in the Introduction, the 2008 Great Recession is only the most recent in a long train of financial surprises. Accordingly, this article has proposed a computational Early Warning System (EWS) for helping to regulate the global economy, motivated by the need for more accurate short-term predictions and more informed systemic adjustments to reduce the economic crises that have frequented modern history. Economic criticality---a poised system situated between the opposed perils of stalled and overheated economies---was designated as an optimized state. In this section we will consider the conceptual and political challenges that this proposal must inevitably face. We will consider three major issues: 1) The demonstrated limitations of equilibrium models, and the current quest for alternatives; 2) The problematic structure of current economic policymaking, viewed in terms of computational approaches and the criticality model; 3) The conflict between idealistic transparency in computational economic diplomacy, and realistic vigilance regarding national security.

In a critique of the equilibrium models which have dominated economic thinking since the era of Léon Walras (1834-1910) and John Stuart Mill (1806-1873), David Colander's policy group endorsed "early warning schemes that indicate the formation of bubbles. Combinations of indicators with time series techniques could be helpful in detecting deviations of financial or other prices from their long-run averages. Indication of structural change (particularly towards non-stationary trajectories) would be a signature of changes of the behavior of market participants of a bubble-type nature" (Colander et al., 2008). The present article concurs with this view, and echoes its cautionary note: The development of effective EWS models for managing the global economy will be contingent on a changed understanding of economics itself. Construed for well over a century through a largely unsuccessful framework in which rational individuals seek maximum utility, and rational firms seek maximum profits (both acting independently on the basis of full information), economics must now embrace a cultural and ideological diversity of agents. These latter must surely include socially marginalized and ideologically passionate peoples who seek political change, and the often equally passionate "market-dominant" groups who seek their continued suppression or, at a greater extreme, their expulsion (Chua, 2002). The economic effect of these tensions is significant and global in scope.

Consider Greece: At the time of writing (December, 2015), the Greek parliament has approved a bill which will allow banks to sell non-performing loans to the private sector. The measure was passed in response to pressure from international creditors to lighten Greece's burden of bad loans, a condition for disbursing over one billion euros ($1.1 billion). The creation of a secondary market for non-performing loans, however, is itself the outgrowth of earlier financial stresses resulting in the near-collapse of the Greek economy. (BBC Country Profiles at http://www.bbc.com/news/world-europe-17373216 and other major media sources). Escalating national debt following the passage of a controversial 2008 pension reform bill resulted in a 2009 downgrading of Greece's credit rating, motivating austerity measures enacted by the George Papandreou government. Nonetheless, the crisis deepened. Accordingly, a series of rescue packages (including a $145 bn (110 bn euros) Eurozone bailout in 2010, a 109 euro infusion channeled through the European Financial Stability Facility in 2011, a 130 bn euro bailout from the Eurozone in 2012, and several debt swap deals with private-sector lenders in 2012) were enacted, but failed to revive the economy. Finally, in 2015, Greece accepted a three-year 86-billion euro ($93-billion) EU bailout, which prevented it from leaving the eurozone. Exacerbating the economic struggle is Greece's unemployment---currently 24%---the highest rate in the EU---while youth unemployment, often socially destabilizing, stands at around 52%.

That the Greek crisis can be, to a significant extent, understood as an array of economic factors coalescing in a perfect storm would appear strongly supported by the evidence. But is economics alone adequate to explain the crisis? Recent studies suggest that the Greek bailout controversy "is not just a story about profligate spending and rigid monetary policies. The European debt crisis is not just an economic crisis: it is an escalating identity conflict---an ethnic conflict" (Sambanis, 2012). Bechtel et al. (2014), in a study conducted in Germany, determined that an individual voter's economic standing has only limited explanatory power "in accounting for their position on the bailouts". Much more significant were "altruism" and "cosmopolitanism": the ability to overcome nationalistic sentiment and view geopolitically or culturally distant groups as fellow Europeans. The cosmopolitan viewpoint, however, is increasingly threatened in Germany and elsewhere in the EU (including Britain, Hungary, France, Denmark, and importantly, Greece itself), by the rise of populist sentiment opposing immigrant groups, the welfare state from which they benefit, and European integration itself (Moschopoulos, 2014). It is precisely these types of forces that must be taken seriously in modeling the Greek crisis, given their implicit consequence of Eurozone collapse, and resulting instability of global markets. BNs, which, as noted above, can represent multi-level systems, are well-suited to analyze this and other economic crises in which cultural, ideological, and even emotional factors may play a significant role. The admission of such variables, however---often not as well documented as "purely" economic data---will likely generate multiple BNs with highly different system architectures. How does one decide between them as a sound basis for policymaking? Lü and Zhou (2011) review several link prediction (LP) algorithms which evaluate the likelihood of a candidate link between two nodes in a complex network "based on observed links and the attributes of nodes." LP algorithms can address inaccurate or incomplete data by identifying spurious links, and can predict the links which may appear in the future of an evolving network. As LP methods continue to be refined, they could play a significant role in evaluating candidate EWS networks, and hence in policy decisions regarding the management of criticality.

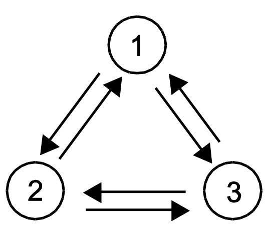
The second major implication of the proposed new approach is a change in the tempo and structure of economic diplomacy. Sustaining criticality in global economic networks would require multilateral tuning by agents on an increasingly frequent basis. The global economy, as noted above, will likely not self-organize. Rather it may be analogized to a nuclear reactor in which criticality---a configuration in which fuel rods produce and lose a constant number of neutrons, resulting in stable power---is sustained by regular adjustments (Scheinkman and Woodford, 1994). It is therefore likely that "fast diplomacy" (Sandre, 2013), in which economic actors, utilizing EWS modeling, routinely generate new agreements and revise existing treaties to sustain a critical state, will become commonplace. But not without resistance: The recent (2015) Senate decision, following intensive controversy, granting Barak Obama fast-track authority (FTA) to expedite negotiations with 11 other countries party to a Trans-Pacific Partnership (TPP), is only the most recent chapter in a 50-year history of US ambivalence to legislation endorsing rapid economic diplomacy. As Brainard and Shapiro (2001) documented (well in advance of TPP), the debate over FTA---which began in 1962 in the Kennedy Round of negotiations under the General Agreement on Tariffs and Trade (GATT)---cannot be adequately explained by the "size, complexity, or importance" of the treaties in question. For example, the bilateral agreement permitting China's 2001 accession to the World Trade Organization, implemented without FTA, affects much more trade than the 1985 US-Israel trade agreement, which utilized FTA. The explanation, they suggest, is the absence or inadequate development of “mechanisms insuring meaningful consultations between the President and key members of Congress during negotiations.” Importantly, they recommend a nonpartisan professional staff which would “provide relevant input as negotiations proceed, reducing the need to legislate detailed negotiating instructions in the abstract.” Consistent with this view, the US and other developed nations must create new agencies in which nonpartisan actors develop EWS models, formulate policy recommendations, and---in close cooperation with heads of state and key economic actors, test policies in the domain of international relations. In the US, the actors would include, but not be limited to, the Council of Economic Advisers, the Office of the United States Trade Representative (USTR), the Department of the Treasury, the Trade and Development Agency (TDA), and the Export-Import Bank (EXIM). The Extractive Industries Transparency Initiative (EITI), which examines transparency “in countries receiving income from extractive industries” (Philpot, 2012), along with similar agencies, could serve as models for an advisory group regarding broader transparency issues in economic diplomacy.

Finally, EWS-based policy by the US and other nations would present major security challenges, or as Lewis (2014) has put it, issues of “liberty, equality, and connectivity”. As noted, the internationally-shared BN models of the global economy, to the extent that they will prove effective, must include political, social, and ideological data. But the more levels that these models embrace, including in particular that of private economic actors such as multinational corporations, the greater will be the temptation---especially on the part of authoritarian regimes---to utilize the data unethically. Consider once more “good noise” (Franke, 2001), which in the form of stochastic pulses of technical innovation, can stimulate productivity. Clearly, this feature must be incorporated into any good EWS model. But the greater predictive power that would derive from its inclusion would be severely compromised by intellectual property (IP) theft. Lewis (2014) is frank in his assessment: “Concern over the consequences of irritating China has hobbled transatlantic action to resolve the problems [of cybersecurity], but weak IP protections cost Europe and the United States billions of euros in trade and thousands of jobs every year. While cyber-conflict poses the greatest risk, weak IP protection is the most damaging cybersecurity problem.” Cybersecurity treaties, however, are likely not a workable solution. The primary obstacle is the pronounced divergence between democratic and authoritarian states regarding the definition of information security (Segal and Waxman, 2011). For the US, the United Kingdom, and other democratic nations, information security is the “protection of computer networks from damage and theft.” By contrast, China, Russia, and their authoritarian allies construe it as “controlling content and communication or social networking tools that may threaten regime stability.” Accordingly, Segal and Waxman recommend diplomatic initiatives in Latin America, Africa, and Southeast Asia to develop information technology (IT) partnerships. The objective would be to counter “similar efforts by China to secure their loyalty.” An alternative scenario would be an IT variation of the Cold War Non-Aligned Movement (Westad, 2007) whereby developing countries would accept IT assistance from both power blocs---authoritarian and democratic---but would politically ally with neither. In any event, open societies must engage the developing world as a means of expanding connections among global IT advisers, i.e., “nonpartisan professionals” (Brainard and Shapiro, 2001) needed to develop EWS models. (In addition, greater use of mirror statistics, which reconstruct a nation’s trade through data reported by partner countries, could also be utilized to model the economics of closed societies; this approach has been recently employed by Eberstadt (2015) in a longitudinal portrait of the North Korean economy). Although these strategies are not without risk, the alternative is a future of global financial shocks from which the fallout may extend well beyond the traditional domain of economics.

5. Conclusion.

From the Panic of 1857 to the 2008 Great Recession, economics has failed to predict global financial crises. Because the economies of the world---including, in particular, those of developing nations---are becoming much more densely connected, the consequences of that failure are likely to become more severe. What is to be done with economics? It is becoming increasingly clear that equilibrium models which have dominated economic thought---although, in historic perspective, not without vigorous critiques (Galbraith, 1987)---since the inception of the science must at last be abandoned. The unifying assumption has been that the components of an economy will persist in a state of balance unless perturbed by external factors. This article has challenged that assumption, proposing instead that economies are typically out of balance, and that equilibrium is transitory. That single changed assumption, central to complexity economics, entails additional changed assumptions regarding policymaking. Global economic growth will be most effectively managed, and crises most effectively avoided, when economists deploy dynamic models which address the immediate future. As a programmatic example, Boolean Network (BN) modeling of global economic criticality---a poised systemic state between dynamic order and chaos---was proposed as an Early Warning System (EWS) useful in decision-making and forecasting economic crises. These conceptual and pragmatic shifts will likely present significant challenges. The almost constant communication among international IT specialists---a form of "digital diplomacy" (Sandre, 2015)---required to generate and sustain economic criticality models may confront significant resistance from authoritarian societies. Nonetheless we must ask ourselves if, seeking to avoid this resistance, we wish to continue adhering to antiquated and dangerous fictions.

Figure 1. A simple Boolean network (BN) and its logical connections (OR and AND). The first table indicates the ON/OFF state of each element (node), a 1 or 0, respectively, as a function of the ON/OFF state of the other two elements connecting to it. The second table indicates all possible initial states of the network at time T, while T + 1 indicates the result of applying the logic set to each initial condition. BNs can accurately describe the qualitative behavior of economic systems at many different levels, and can include variables (e.g., social and even ideological factors) for which there is only limited quantitative knowledge. Source: Helikar et al., (2011), *The Open Bioinformatics Journal*.



2	3	1
0	0	0
0	1	0
1	0	0
1	1	1

AND

1	3	2
0	0	0
0	1	1
1	0	1
1	1	1

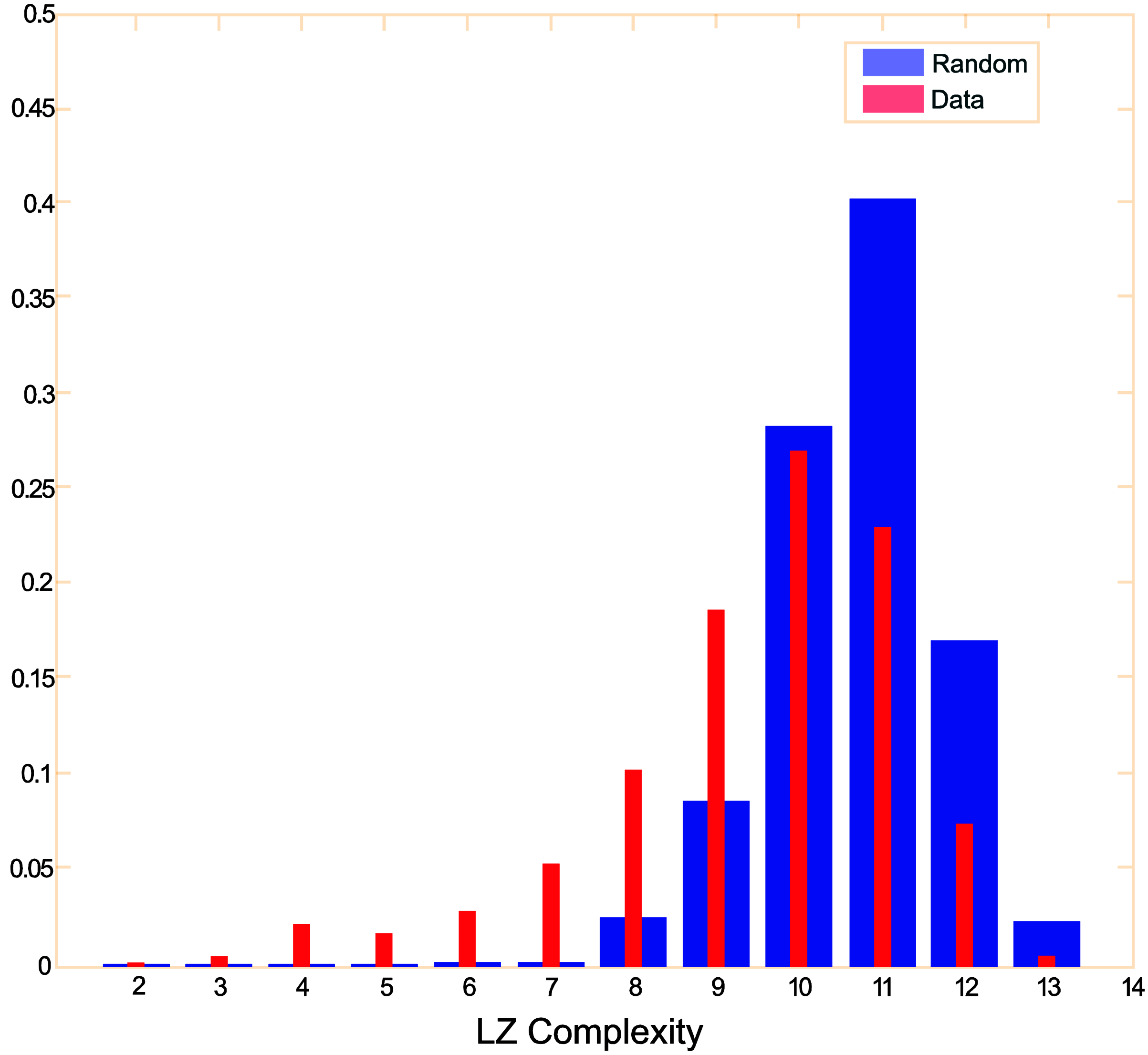
OR

1	2	3
0	0	0
0	1	1
1	0	1
1	1	1

OR

T			T+1		
1	2	3	1	2	3
0	0	0	0	0	0
0	0	1	0	1	0
0	1	0	0	0	1
0	1	1	1	1	1
1	0	0	0	1	1
1	0	1	0	1	1
1	1	0	0	1	1
1	1	1	1	1	1

Figure 2. Hypothetical example of a probability distribution of LZ values for time series based on iterated RBN network realizations utilizing mock data (blue), compared with the probability distribution of LZ values for time series based on a BN model of actual economic data (red). For a detailed discussion of this method, and related mathematical approaches such as Euclidean distance and Kullback-Leibler (KL) divergence (or relative entropy) see Schmulevich et al. (2005), and the present article. Illustration © 2005 by National Academy of Sciences.



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