Towards A Physics Of Economics

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Over the past couple of decades, a large number of physicists have started exploring problems which fall in the domain of economic science. The common themes that are addressed by the research of most of these groups have resulted in coining a new term "Econophysics" as a collective name for this venture. Bringing together the techniques of statistical physics and nonlinear dynamics to study complex systems with the ability to analyze large volumes of data using sophisticated statistical techniques, the discoveries made in this field have already attracted the attention of mainstream physicists and economists. While still somewhat controversial, it provides a promising alternative to (and a more empirically-based foundation for the study of economic phenomena than) the mainstream axiom-based mathematical economic theory.

Introduction

Physicists have long had a tradition of moving to other fields of scientific enquiry and have helped bring about paradigm shifts in the way research is carried out in those areas. Possibly the most well-known example in recent times is that of the birth of molecular biology in the 1950s and 60s, when pioneers such as Schrödinger (through his book *What is Life?*) inspired physicists such as Max Delbruck and Francis Crick to move into biology with spectacularly successful results. However, one can argue that physicists are often successful in areas outside physics, because of the broad-based general nature of a physicist's training rather than the applicability of physical principles as such in those areas. The large influx of physicists since the late 1990s into topics which had traditionally been the domain of economists and sociologists have raised the question: does physics really have some significant insights for these areas? Or, is it a mere fad, driven by the availability of large quantities of economic data which are amenable to the kind of analytical techniques that physicists are familiar with? The coining of new terms such as *econophysics* and *sociophysics* (along the lines of *biophysics* and *geophysics*) have hinted that many physicists do believe that physics has a novel perspective to contribute to the traditional way of doing economics. Others, including the majority of mainstream economists have been dismissive until very recently of the claim that physics can have something significant to contribute to the field, which is seen by them to be primarily a study of interactions between rational agents able to formulate complex strategies to maximize their individual utilities (or welfare).

However, even before the current worldwide crisis revealed the inadequacies of mainstream economic theory, economists had realized that this new approach of looking at economics problems cannot be simply ignored, as evidenced, e.g., by the entry of the terms "econophysics" and "economy as a complex system" in the new Palgrave dictionary of economics (Macmillan, 2008). The failure of economists, by and large, to anticipate the collapse of markets worldwide in 2008 over such a short space of time has now led to some voices from within the field of economics itself declaring that new foundations for the discipline are required. The economists Lux and Westerhoff in an article published in *Nature Physics* (Jan 2009) have suggested that econophysics may provide such an alternative theoretical framework for rebuilding economics. As Lux has pointed out elsewhere, the systemic failure of the standard model of economics arises from its "implicit view …that markets and economies are inherently stable". However, worldwide financial crises (and the accompanying economic turmoil) are neither new nor as infrequent as economists would like to believe. It is therefore surprising that mainstream economics has ignored, and sometimes actively suppressed, the study of crisis situations. The famous economist Kenneth Arrow even tried to establish the stability of economic equilibria as a mathematical theorem; however, what is often forgotten is that such conclusions are crucially dependent on the underlying simplifying assumptions, such as, perfectly competitive markets and the absence of any delays in response. It is obvious that the real world hardly conforms to such ideal conditions. Moreover, the study of a wide variety of complex systems (e.g., from cellular networks to the internet and ecosystems) over the past few decades using the tools of statistical physics and nonlinear dynamics has led to the understanding that inherent instabilities in dynamics often accompanies increasing complexity.

Figure 1: The economy machine.

A reconstruction of the Moniac (at the University of Melbourne), a hydraulic simulator of a national economy built in 1949 by A. W. H. Phillips of the London School of Economics, that used the flow of colored water to represent the flow of money. It is currently again being used at Cambridge University for demonstrating the dynamic behavior of an economic system in economics first-year lectures. (Source: http://airminded. org, Photo: Brett Holman)

The obsession of mainstream economics with the ideal world of hyper-rational agents and almost perfect competitive markets has gone hand in hand with a formal divorce between theory and empirical observations. Indeed, the analysis of empirical data has ceased to be a part of economics itself, and has become a separate subject called *econometrics*. Since the 1950s, economics has modeled itself more on mathematics than any of the natural sciences. It has been reduced to the study of self-consistent theorems arising out of a set of axioms to such an extent that it is probably more appropriate to term mainstream economics as *econo-mathematics*, i.e., mathematics inspired by economics and that too having little connection to reality. This is strange for a subject that claims to have insights and remedies for one of the most important spheres of human activity. It is a sobering thought that decisions made by the IMF and World Bank which affect millions of lives are made on the basis of theoretical models that have never been subjected to empirical verification. In view of this, some scientists (including a few economists) have begun to think that maybe economics is too important to be left to economists alone. While a few have suggested that econophysics may provide an alternative theoretical framework for a new economic science, we think that the field as it stands is certainly an exciting development in this direction, and intend to give an introduction to it here.

Before we go on to describe how physicists have recently brought fresh perspectives in understanding economic phenomena, let us point out that despite the present state of economics, there has been a long and fruitful association between physics and economics. Philip Mirowski, in his book, *More Heat Than Light* (1989) has pointed out that the pioneers of neoclassical economics had indeed borrowed almost term by term the physics of 1870s to set up their theoretical framework. This legacy can still be seen in the attention paid by economists to maximization principles (e.g., of utility) that mirrors the framing of classical physics in terms of minimization principles (e.g., the principle of least action). Later, Paul Samuelson, the second Nobel laureate in economics and the author of possibly the most influential textbook of economics, tried to reformulate economics as an empirically grounded science modeled on physics in his book *Foundations of Economic Analysis* (1947). While the use of classical dynamical concepts such as stability and equilibrium has also been used in the context of economics earlier (e.g., by Vilfredo Pareto), Samuelson's approach was marked by the assertion that economics should be concerned with "the derivation of *operationally meaningful* theorems", i.e., those which can be empirically tested. Such a theorem is "simply a hypothesis about empirical data which could conceivably be refuted, if only under ideal conditions". Given the spirit of those times, it is probably unsurprising that this is also when the engineer-turned-economist Bill Philips (who later became famous for the Philips curve, a relation between inflation and employment) constructed the Moniac, a hydraulic simulator for the national economy (Fig. 1), that modeled the flow of money in society through the flow of colored water. The mapping of macroeconomic concepts to the movement of fluids was a direct demonstration that the economy was as much a subject of physical inquiry as other more traditional subjects in physics.

This was however the last time that physics would significantly affect economics until very recently, as the 1950s saw a complete shift in the focus of economists towards proving existence and uniqueness of equilibrium solutions in the spirit of mathematics. A parallel development was the rise of mathematical game theory, pioneered by John von Neumann. To mathematically inclined economists, the language of game theory seemed ideal for studying how selfish individuals constantly devise strategies to get the better of other individuals in their continuing endeavor to maximize individual utilities. The fact that this ideal world of paranoid, calculating hyper-rational agents could never be reproduced in actual experiments carried out with human subjects where "irrational" cooperative action was seen to be the norm, could not counter the enthusiasm with which economists embraced the idea that society converges to an equilibrium where it is impossible to make someone better off without making someone else worse off. Further developments of rational models for interactions between economic agents became so mathematically abstract, that an economist recently commented that it seems (from an economic theorist's point of view) even the most trivial economic transaction is like a complicated chess game between Kenneth Arrow and Paul Samuelson (the two most famous American economists of the post-war period). The absurdity of such a situation is clear when we realize that people rarely solve complicated maximization equations in their head in order to buy groceries from the corner store. The concept of *bounded rationality* has recently been developed to take into account practical constraints (such as the computational effort required) that may prevent the system from reaching the optimal equilibrium even when it exists.

It is in the background of such increasing divergence between economic theory and reality that the present resumption of the interrupted dialogue between physics and economics took place in the late 1980s. The condensed matter physicist Philip Anderson jointly organized with Kenneth Arrow a meeting between physicists and economists at the Santa Fe Institute that resulted in several early attempts by physicists to apply the recently developed tools in non-equilibrium statistical mechanics and nonlinear dynamics to the economic arena (some examples can be seen in the proceedings of this meeting, *The Economy as an Evolving Complex System*, 1988). It also stimulated the entry of other physicists into this inter-disciplinary research area, which, along with slightly later developments in the statistical physics group of H. Eugene Stanley at Boston University finally gave rise to *econophysics* as a distinct field, the term being coined by Stanley in 1995 at Kolkata. Currently there are groups in physics departments around the world who are working on problems related to economics, ranging from Japan to Brazil, and from Ireland to Israel. While the problems they work on are diverse, ranging from questions about the nature of the distribution of price fluctuations in the stock market to models for explaining the observed economic inequality in society to issues connected with dynamical fluctuations of prices as a consequence of delays in the propagation of information, a common theme has been the observation and explanation for scaling relations (or power laws). Historically, scaling relations have fascinated physicists because of their connection to critical phenomena; but more generally, they indicate the presence of universal behavior. Indeed, the quest for invariant patterns that occur in many different contexts may be said to be the novel perspective that this recent incursion of physicists have brought to the field of economics, and that may well prove to be the most enduring legacy of econophysics (Fig. 2).

Given that the term econophysics was coined in India, it is perhaps not surprising that several Indian groups have been very active in this area. Physicists at the Universities of Delhi and Pune, Physical Research Laboratory (PRL) at Ahmedabad, Saha Institute of Nuclear Physics (SINP) at Kolkata and the Institute of Mathematical Sciences (IMSc) at Chennai, to name a few, have made pioneering contributions in the area, e.g., modeling inequality distribution in society and the analysis of financial markets as complex networks of stocks and agents. The annual series of *Econophys-Kolkata* conferences organized by SINP (2005 onward) and the meeting on *The Economy as a Complex System* (2005) at IMSc have increased the visibility of this area to physicists as well as economists in India.

Figure 2: **Are there universalities in economic phenomena?** Whether it is the interaction between buyers and sellers at a fish market in Kolkata (left) or the frenzied trading among brokers in the Bombay Stock Exchange (right), econophysics detects invariant patterns in strikingly different varieties of economic activity. (Photos: Sayan Mitra (Left), Husain Stephane(Right).

Why are so few rich and so many poor?

We shall now focus on a few of the problems that have fascinated physicists entering economics. The first one we shall deal with has to do with the question: why is neither wealth nor income uniformly distributed throughout society? If we perform a *gedankensperiment* where the total wealth of a society was brought together by the government and re-distributed to every citizen evenly, would the dynamics of exchange subsequently result in the same inequality (as before) being restored rapidly? While such unequal distributions may to an extent be ascribed to the distribution of abilities among individuals which is biologically determined, this cannot be a satisfying explanation as the biological distribution is Gaussian and therefore, has less variability than either income or wealth, which typically have extremely long tails that follow a power law decay. Indeed, econophysicists would like to find out whether inequality can arise even when individuals are indistinguishable in terms of their abilities.

Before turning to the physics-based models that have been developed to address this question, let us consider the empirical facts on the distribution of inequality. Investigations over more than a century and the recent availability of electronic databases of income and wealth distribution (ranging from national sample survey of household assets to the income tax return data available from government agencies) have revealed some remarkable and universal features. Irrespective of many differences in culture, history, social structure, indicators of relative prosperity (such as gross domestic product or infant mortality) and, to some extent, the economic policies followed in different countries, income distribution seems to follow an invariant pattern, as does wealth distribution: After an initial increase, the number density of people at a particular income bracket rapidly decays with their income. The bulk of the income distribution is well-described by a Gibbs or log-normal distribution, but at the very high income range (corresponding to the top 5–10% of the population) it is fit better by a power law with an exponent, between 1 and 3 (Fig. 3). This seems to be an universal feature: from ancient Egyptian society through 19th century Europe to modern Japan. The same is true across the globe today: from the advanced capitalist economy of USA to the developing economy of India.

The power-law tail, indicating a much higher frequency of occurrence of very rich individuals (or households) than would be expected by extrapolating the properties of the bulk of the distribution, had been first observed by the Italian economist-sociologist Vilfredo Pareto in the 1890s (Fig. 4). Pareto had analyzed the cumulative income distribution of several societies at very different stages of economic development, and had conjectured that in all societies the distribution will follow a power law decay with an exponent (later termed the Pareto exponent) of 1.5. Later, the distribution of wealth was also seen to exhibit a similar form. Subsequently, there have been several attempts starting around the 1950s, mostly by economists, to explain the genesis of the power-law tail. However, most of these models involved a large number of factors that made understanding the essential reason behind the occurrence of inequality difficult. Following this period of activity, a relative lull followed in the 1970s and 1980s when the field lay dormant, although accurate and extensive data were accumulated that would eventually make possible precise empirical determination of the distribution properties. This availability of large quantity of electronic data and their computational analysis has led to a recent resurgence of interest in the problem, specifically over the last one and half decades.

Although Pareto and Gini had respectively, identified the power-law tail and the log-normal bulk of income distribution, demonstration of both features in the same distribution was possibly done for the first time by Montroll and Shlesinger, in an analysis of fine-scale income data obtained from the US Internal Revenue Service (IRS) for the year 1935–36. They observed that while the top 2–3% of the population (in terms of income) followed a power law with Pareto exponent ν~ 1.63, the rest followed a log-normal distribution. Later work on Japanese personal income data based on detailed records obtained from the Japanese National Tax Administration indicated that the tail of the distribution followed a power law with a ν value that fluctuated from year to year around the mean value of 2.

Further work showed that the power law region described the top 10% or less of the population (in terms of income), while the remaining income

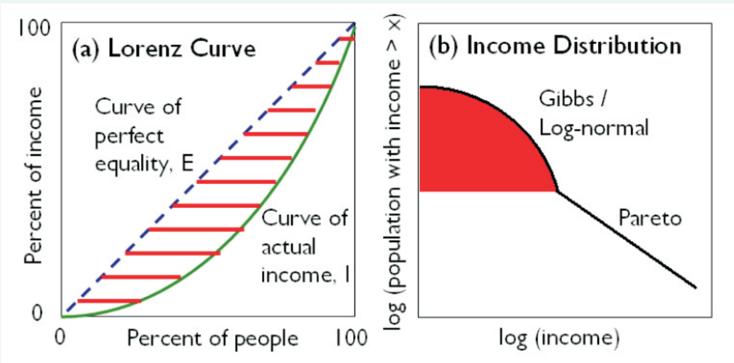


Figure 3: Measures of inequality: Gini coefficient and Pareto exponent. (a) The Gini coefficient, G, is proportional to the hatched area between the Lorenz curve (I), which indicates the percentage of people in society earning a specific percent of the total income, and the curve corresponding to a perfect egalitarian society where everyone has the same income (E). G is defined to be the area between the two curves divided by the total area below the perfect equality curve E, so that when G=0 everybody has the same income while when only one person receives the entire income, G=1. (b) The cumulative income distribution (the population fraction having an income greater than a value x plotted against x) shown on a double logarithmic scale. For about 90-95% of the population, the distribution matches a Gibbs or Log-normal form (indicated by the shaded region), while the income for the top 5-10% of the population decays much more slowly, following a power law as originally suggested by Pareto. The exponent of the Pareto tail is given by the slope of the line in the double-log scale, and was conjectured to be 1.5 for all societies by Pareto. If the entire distribution followed a power law with exponent 1.5, then the corresponding Lorenz curve will have a Gini coefficient of 0.5, which is empirically observed for most developed European nations.

distribution was well described by the log-normal form. While the value of ν fluctuated significantly from year to year, it was observed that the parameter describing the log-normal bulk, the Gibrat index, remained relatively unchanged. The change of income from year to year, i.e. the growth rate as measured by the log ratio of the income tax paid in successive years, was observed to be also a heavy-tailed distribution, although skewed, and centered about zero.

Later work on the US income distribution based on data from IRS for the period 1997–98, while still indicating a power-law tail (with ν~ 1.7), has suggested that the lower 95% of the population has income whose distribution may be better described by an exponential form. Similar observation has been made for the income distribution in UK for the period 1994–99. It is interesting to note that when one shifts attention from the income of individuals to the income of companies, one still observes the power-law tail. A study of the income distribution of Japanese firms concluded that it follows a power law with ν~1 (often referred to as *Zipf's law*). Similar observation has been reported for the income distribution of US companies.

Figure 4: Vilfredo Pareto and the power-law description of income distribution. Pareto had graduated in mathematics and physics from the Polytechnic Institute in Turin and became Professor of Political Economy at the University of Lausanne in 1893. His main work in economics is the *Course of Political Economy* (1896-7, trans. 1906) in which he gave a rigorous mathematical foundation to economic theory. This was part of a wider program to make the laws of society as close as possible to the laws of physics, in terms of general applicability and predictive power. Most importantly, the *Course* incorporates the results of Pareto's detailed research into the distribution of income. He had found that the relationship between an income level x and the number of taxpayers (N) with income greater than or equal to x can be reasonably well-represented by the equation $N(x) = A/x^{\nu}$, where A, ν > 1 (usually referred to as the Pareto curve or distribution). On examining income data for a range of countries and cities (England, Prussia, Saxony, Peru, Italy, and some European cities, e.g., Paris, Florence and Perugia) using the double log transformation of the Pareto curve, i.e., log N (x) = log A + ν log x,Pareto reported that the exponent ν tends to a constant value of about 1.5. This constancy is also sometimes referred to as Pareto Law. Pareto believed this to be an universal feature of economics and stated that if a society is left to its own devices, the distribution curve will take its original (Paretian) form.

Vilfredo Pareto (1848-1923)

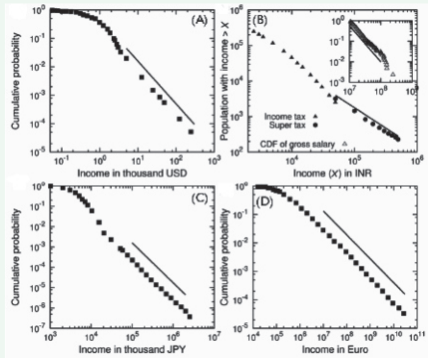


Figure 5: Cumulative probability distributions of income showing the Pareto tail. (A) Annual personal income in USA from 2001 IRS data with Pareto exponent ν ~1.5, (B) Annual personal income in India during 1929-30 calculated from income tax and super tax data with ν~ 1.15 (the inset shows the employment income for the top 422 salaried Indians from the 2006 Business Standard Survey with ν ~ 1.75), (C) Annual personal income in Japan for 2000 with ν ~ 1.96 (D) Firm size in terms of total assets in France for 2001 with ν ~ 0.84 .[Source: A. Chatterjee, S. Sinha and B.K. Chakrabarty, Current Science 92(May 2007) 1383-1389]

Compared to the empirical work done on income distribution, relatively few studies have looked at the distribution of wealth, which consists of the net value of assets (financial holdings and/ or tangible items) owned at a given point in time. Lack of an easily available data source for measuring wealth, analogous to income tax returns for measuring income, means that one has to resort to indirect methods. Levy & Solomon used a published list of wealthiest people to infer the Pareto exponent for wealth distribution in USA. An alternative technique was used based on adjusted data reported for the purpose of inheritance tax to obtain the Pareto exponent for the UK. Another study used tangible asset (namely house area) as a measure of wealth to obtain the wealth distribution exponent in ancient Egyptian society during the reign of Akhenaten (14th century BC).

More recently, wealth distribution in India at present has also been observed to follow a power-law tail with the exponent varying around 0.9. The general feature observed in the limited empirical study of wealth distribution is that wealthiest 5–10% of the population follows a power law while an exponential or log-normal distribution describes the rest of the population. The Pareto exponent as measured from the wealth distribution is found to be always lower than the exponent for income distribution, which is consistent with the general observation that, in market economies, wealth is much more unequally distributed than income.

The striking regularities (Fig. 5) observed in income distribution for different countries, have led to several new attempts at explaining them on theoretical grounds. Much of the current impetus is from physicists' modeling of economic behavior in analogy with large systems of interacting particles, as treated, e.g., in the kinetic theory of gases (Fig. 6). According to physicists working on this problem, the regular patterns observed in the income (and wealth) distribution may be indicative of a natural law for the statistical properties of a many-body dynamical system representing the entire set of economic interactions in a society, analogous to those previously derived for gases and liquids.

By viewing the economy as a thermodynamic system, one can identify income distribution with the distribution of energy among particles in a gas. In particular, a class of kinetic exchange models have provided a simple mechanism for understanding the unequal accumulation of assets. Many of these models, while simple from the perspective of economics, have the benefit of coming to grips with the key factor in socio-economic interactions that results in different societies converging to similar forms of unequal distribution of resources.

Meghnad Saha

B. N. Srivastava

Simple ideal gas-like models of asset distribution

To introduce the simplest class of physics models that reproduce the distribution of assets as seen in reality let us think of economic activity to be composed of a large number of pair-wise exchanges between agents. Unlike in the real economy, we do not consider actual commodities, but rather their value in terms of a uniform asset (e.g., money). In an asset exchange game, there are N players, each of whom has an initial capital of 1 unit. N is considered to be very large, and the total asset $M = N$ remains fixed over the duration of the game as is the number of players.

In the simplest version,called the Random Exchange (RE) model, the only allowed move at any time is that two of these players are randomly chosen who then divide their pooled resources randomly amongst themselves (Fig. 7, RE). As no debt is allowed, none of the players can end up with a negative amount of assets. As one can easily guess, the initial delta function distribution of money (with every player having the same amount) gets destabilized with such moves and the state of perfect equality, where every player has the same amount, disappears quickly. The eventual steady-state distribution of

Suppose in a country the assessing department is required to find out the average income per head of the population. They will proceed somewhat in the following way. They will find out the number of persons whose income lies within different small ranges. For example, they will find out the number of persons whose income lies between 10s. and 11s., between 11s. and 12s. and so on. Instead of a shilling, they may choose a smaller interval, say 6d. Then it can be easily seen that the number of persons whose income lies between 10s. and 10s.6d. will be approximately half the number found previously for the range 10s. to 11s. We can generalize by saying that the number whose income lies between x and $x+dx$ is $n_x dx$. It should be noted that the number is proportional to the interval chosen (dx). To get the average income they should choose the interval to be as small as possible, say a penny. When this is not possible they will choose a bigger interval but their results will be proportionately inaccurate.

To represent graphically[1] the income of the population they will plot a curve with n_x as ordinate and x as abscissa. The curve will be similar to that given in Fig. 6. This will begin with a minimum at 0, rise to a maximum at some point, and thereafter approach the axis of x, meeting it at a great distance. The curve will have this shape because the number of absolute beggars is very small, and the number of millionaires is also small, while the majority of population have average income.

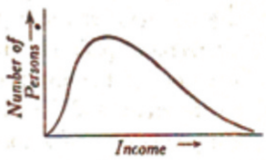


Fig. 6.—Distribution of income among persons.

Figure 6: Saha, Srivastava and the income distribution analogy in kinetic theory of gases. In their textbook *A Treatise on Heat* (1931) Meghnad Saha and B. N. Srivastava used the example of reconstructing a distribution curve for incomes to illustrate the problem of determining the distribution of molecular velocities in kinetic theory. The relevant extract from page 105 of their book (given above) prefigures developments in the first decade of this century showing this indeed the bulk of the income distribution follows a Gibbs-like distribution.

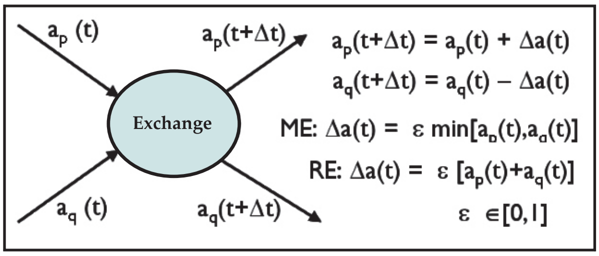


Figure 7: Schematic diagram of the two-body scattering process underlying the kinetic asset exchange models. The asset owned by agent a_p at time t changes due to an exchange (e.g., through trade) with a randomly chosen agent a_q. The scattering process conserves the total amount of assets for the pair but can be of different types, e.g., random exchange (RE) or minimal exchange (ME).

assets among the players after many such moves is well known from the molecular physics of ideal gases develped more than a cetury ago - it is the Gibbs distribution: $P(m)$~exp[$-m/T$], where the parameter $T = M/N$ corresponds to the average asset owned by an agent (see Fig. 8).

We now consider a modified move in this game: each player 'saves' a fraction λ of his/her total assets during every step of the game, from being pooled, and randomly divides the rest with the other (randomly chosen) player. If everybody saves the same fraction λ, what is the steady-state distribution of assets after a large number of such moves? It is Gamma-function like, whose parameters depend on λ:

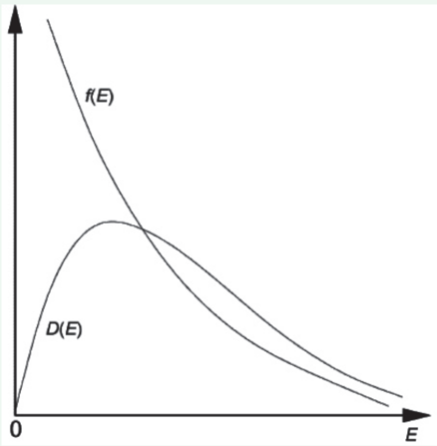
$$P(m) \sim m^{\alpha} \exp[-m/T(\lambda)];\ \alpha=3\lambda(1-\lambda)$$

Although qualitative explanation and limiting results for $\lambda \to 0$ or $\lambda \to 1$ are easy to obtain, no exact treatment of this problem is available so far.

What happens to the steady-state asset distribution among these players if λ is not the same for all players, but is different for different players? Let the distribution ρ(λ) of saving propensity λ among the agents be such that ρ (λ) is non-vanishing when $\lambda \to 1$. The actual asset distribution in such a model will depend on the saving propensity distribution ρ (λ), but the asymptotic form of distribution will become Pareto-like:

$$P(m) \sim m^{-(1+\nu)};\ \nu=1 \text{ for } m \to \infty$$

Figure 8: Gibbs and Maxwell-Boltzmann distributions. In a classical ideal gas in thermodynamic equilibrium, the state variables like pressure (P), volume (V) and the absolute temperature (T) maintain a very simple relationship PV = NkT. Here N is the number of basic constituents (atoms or molecules; N ~ Avogadro number ~ 10^{23}) and k is the Boltzmann constant. Statistical mechanics of ideal gas, also called the kinetic theory of gas, intends to explain the above gas law in terms of the constituents' mechanics or kinetics. According to this picture, for a classical ideal gas, each constituent is a Newtonian particle and they undergo random elastic collisions (which conserve kinetic energy E) among themselves and the walls of the container. These collisions eventually set up a non-uniform (kinetic) energy distribution D(E) among the constituents, called the Maxwell–Boltzmann distribution: D(E) = f (E) g(E), where g(E) is the density of states and comes from mechanics (of free or noninteracting particles of the ideal gas), and f (E) (~exp(– E/ kT)) is called the Gibbs distribution and comes from statistical mechanics (result of averages over random scattering events). Identifying the pressure P as the average (over the distribution D(E)) rate of change of momentum of the gas particles on unit area of the container (where the energy E is proportional to the square of the momentum), and the temperature T as the average (over the distribution D(E)) energy, one immediately gets the above mentioned gas law (relating P, V and T).



This is valid for all such distributions (unless $\rho(\lambda) \propto (1-\lambda)^{\delta}$, when $P(m) \sim m^{-(2+\delta)}$. However, for variation of ρ (λ) such that ρ (λ) → 0 for $\lambda < \lambda_0$, one will get an initial Gamma function form for $P(m)$ for small and intermediate values of m, with parameters determined by $\lambda_0(\neq 0)$, and this distribution will eventually become Pareto-like for $m \to \infty$ with ν = 1 (Fig. 9; left). Analytical understanding is now available and a somewhat rigorous analytical treatment of this problem has been given recently.

It may be mentioned that there are a large number of random multiplicative asset exchange models to explain the Pareto (power-law) tail of wealth or income distribution. The advantage of the kind of model discussed above is that it can accommodate all the essential features of $P(m)$ for the entire range of m, not only the Pareto tail.

One can of course argue that the random division of pooled assets among players is not a realistic approximation of actual trading carried out in society. E.g.,in

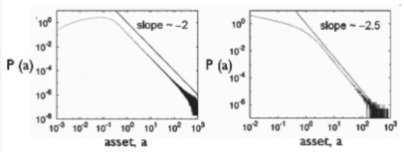


Figure 9: Kinetic asset exchange models can reproduce the observed power law tails in inequality distribution with almost quantitatively accurate exponents. By randomly distributing a "savings" parameter among the population of agents playing a Random Exchange version of the model, a power law with Pareto exponent – 1 is obtained (Left) [Note that, the figure shows the probability distribution function (pdf), while the Pareto exponent is defined for the corresponding complementary cumulative distribution function, whose exponent value is obtained by adding 1 to the pdf exponent.](Right) The Pareto exponent of 1.5 (as originally conjectured by Pareto) can be obtained from an asymmetric asset exchange model where players are randomly assigned strategies interpolated between the two extremes of Random Exchange and Minimal Exchange.

exchanges between an individual and a large company, it is unlikely that the individual will end up with a significant fraction of the latter's assets. Strict enforcement of this condition leads to a new type of game, the Minimum Exchange (ME) model, where the maximum amount that can change hands over a move, is a fraction of the poorer player's assets. Although the change in the rules from the RE game does not seem significant, the outcome is astonishingly different: in the steady state, one player ends up with all the assets. In the language of physics, the system has converged to a condensate corresponding to an asset distribution having two delta-function-like peaks, one at zero and the other at M. If we now relax the condition that the richer player does not completely dictate the terms of exchange, so that the amount exchanged need not be limited by the total asset owned by the poorer player, we arrive at a game which is asymmetric in the sense of generally favoring the player who is richer than the other, but not so much that the richer player dominates totally. Just like the previously defined savings ability of a player to exploit its advantage over a poorer player. For the two extreme cases of minimum ($\tau = 0$) and maximum ($\tau = 1$) thrift, one gets back the random exchange (RE) and minimum exchange (ME) models respectively. However, close to the maximum limit, at the transition between the two very different steady-state distributions given by the two models,(i.e.,the Gibbs distribution and a condensate, respectively) we see a power-law distribution! As in the case of λ, we can now consider the case when instead of having the same τ, different players are endowed with different thrift abilities. For such heterogeneous thrift assignment in the population, where τ for each player is chosen from a random distribution, the steady-state distribution reproduces the entire range of observed distributions of income (as well as wealth) in the society: the tail follows a power law, while the bulk is described by an exponential distribution. The tail exponent depends on the distribution of τ, with the value of $\nu = 1.5$ suggested originally by Pareto, obtained for the simplest case of uniform distribution of τ between [0, 1] (Fig. 9, right). However, even extremely different distributions of τ (e.g. U-shaped) always produce a power-law tailed distribution that is exponentially decaying in the bulk, underlining the robustness of the model in explaining inequality.

All the gas-like models of trading markets discussed above are based on the assumptions of (a) asset conservation (globally in the market; as well as locally in any trading) and (b) stochasticity. Questions on the validity of these points are natural and have been raised. We now forward some arguments in their favor.

If we view trading as a scattering process, one can see the relevance of conservation principles. Of course, in any such 'asset exchange' process, one receives some goods or service from the models. However, if we concentrate only on the 'cash' exchanged, every trade is an asset conserving one (like the elastic scattering process in physics!) In more recent models, conservation of asset has been extended to that of total wealth (including money and commodities) and the introduction of the notion of price which fluctuates in time has effectively allowed slight relaxation of this conservation, but the overall distribution has still remain the same. It is also important to note that the frequency of asset exchange in such models defines a timescale in which total asset in the market does not change. In real economies, total asset changes relatively slowly, so that in the timescale of exchanges, it is quite reasonable to assume the total asset to be conserved in these exchange models.

Is the trading random? Surely not, when looked upon from an individual's point of view. When one maximizes his/her utility by money exchange for the *p*th commodity, he/she may choose to go to the *q*th agent and for the *r*th commodity he/she may go to the *s*th agent. But since $p \neq q \neq r \neq s$ in general, when viewed from a global level, these trading/scattering events will all look random (although for individuals this is a defined choice or utility maximization). It may be noted in this context that in the stochastically formulated ideal gas models in physics (developed in late 19th and early 20th centuries), physicists already knew for more than a century that each of the constituent particles (molecules) follows a precise equation of motion, namely that due to Newton. The assumption of stochasticity in asset-exchange models, even though each agent might follow a utility maximizing strategy (like Newton's equation of motion for molecules), is therefore not unusual in the context. Further, analysis of high-quality income data from the UK and USA shows Gamma distributions for the low- and middle-income ranges, which is strong evidence in favor of models discussed here.

Are Market Movements Universal?

Given that the wealth and income of the highest bracket in the population (which exhibits the Paretian power-law tail) can be attributed mostly to their investment in financial instruments, it is probably expected that scientists would look for power laws in such market movements. Financial markets can be considered as complex systems (Fig. 10) that have many interacting elements and exhibit large fluctuations in their associated observable properties, such as stock price or market index. The state of the market is governed by interactions among its components, which can be either traders or stocks. In addition, market activity is also influenced significantly by the arrival of external information. The importance of interactions among stocks, relative to external information, in governing market behavior has emerged only in recent times. The earliest theories of market activity, e.g., Bachelier's (Fig. 11) random walk model, assumed that price changes are the result of several independent external shocks, and therefore, predicted the resulting distribution to be Gaussian. As an additive random walk may lead to negative stock prices, a better model would be a multiplicative random walk, where the price changes are measured by logarithmic returns. While the log-return distribution calculated from empirical data is indeed seen to be Gaussian at long time scales, at shorter times the data show much larger fluctuations than what we would expect from this distribution. Such deviations were also observed in commodity price returns, e.g., in Mandelbrot's (Fig. 11) analysis of cotton price variation, which was found to follow a Levy-stable distribution. However, it contradicted the observation that the distribution converged to a Gaussian at longer time scales. Later, it was discovered that while the bulk of the return distribution for a market index (the S&P 500) appears to be fit well by a Levy distribution, the asymptotic behavior shows a much faster decay than expected. Hence, a truncated Levy distribution, which has exponentially decaying tails, was proposed as a model for the distribution of returns. Subsequently, it was shown that the tails of the cumulative return distribution for this index actually follow a power law, with an exponent of -3. This is the so-called *inverse cubic law*, where the exponent lies well outside the stable-Levy regime (of exponent value between 0 and 2).

This is consistent with the fact that at longer time scales the distribution converges to a Gaussian. Similar behavior has been reported for the DAX, Nikkei and Hang Seng indices. These observations are somewhat surprising, although not at odds with the "efficient market hypothesis" in economics, which assumes that the movements of financial prices are an immediate and unbiased reflection of incoming news and future earning prospects. To explain these observations various multi-agent models of financial markets have been proposed, where the scaling laws seen in empirical data arise from interactions between agents. Other microscopic models, where the agents (i.e., the traders comprising the market) are represented by mutually interacting spins and the arrival of information by external fields, have also been used to simulate the financial market. Among non-microscopic approaches, multi-fractal processes have been used extensively for modeling such scale-invariant properties. The multi-fractal random walk model has generalized the usual random walk model of financial price changes and accounts for many of the observed empirical properties.

Recently, there had been a debate in the literature concerning the range of applicability of the inverse cubic law for price fluctuation distribution. As most previous reported observations were from developed markets, a question of obvious interest was whether the same distribution holds for developing or emerging financial markets. If the inverse cubic law is a true indicator of self-organization in markets, then observing the price fluctuation distribution as the market evolves gradually over the years will inform us about the process by which this complex system converges to the non-equilibrium steady state characterizing developed markets. Recent analysis of high-frequency trading data from the National Stock Exchange (NSE) of India shows that this emerging market exhibits the same inverse cubic law as all other developed markets (Fig. 12), despite commencing operations only in 1994. In fact, as the data stretches to the present (when it is the third largest financial market in the world in terms of transactions) from its inception, it is possible to study the nature of the return distribution as a function of time. Thus, if markets do show discernible transition in return distribution during their evolution, the Indian market data is best placed to spot evidence for it, not least because of the rapid transformation of the Indian economy in the liberalized environment since the 1990s. However, the results show that the power law nature of the return distribution can be seen even in the earliest days of the market, from which time it has remained essentially unchanged. The convergence of the return distribution to a power law functional form is thus extremely rapid, so that a market is effectively always at the non-equilibrium steady state characterized by the inverse cubic law regardless of its stage of development.

So, if emerging markets do not differ from developed ones in terms of the properties of price fluctuations, are there still other observables which will allow us to distinguish between them? It now appears that the cross-correlation behavior between stock price fluctuations in a market may have very different nature depending on the state of evolution of the market. The observation of correlated movement in stock prices gives us a proxy variable for studying interactions between stocks mediated through the action of agents who are buying/selling different stocks. As the dynamics of individual investors is being only indirectly inferred based on the dynamics of price for the different stocks, this is somewhat akin to a "Brownian motion" picture of the market (Fig. 13), analogous to the process of inferring the dynamics of air molecules by observing the movement of pollen grains with which the molecules are colliding. The existence of collective modes in the movement of stock prices had been earlier inferred from the study of market dynamics, although such studies had almost exclusively focused on developed markets, in particular, the New York Stock Exchange (NYSE). A recent detailed analysis of the cross-correlation between stocks in the Indian market, has demonstrated that an emerging market differs from more developed markets in that, the former lacks clusters of co-moving stocks having distinct sector identities.

To uncover the structure of interactions among the elements in a financial market, physicists primarily focus on the spectral properties of the correlation matrix of stock price movements. Pioneering studies have investigated whether the properties of the empirical correlation matrix differ from those of a random matrix that would have been obtained had the price movements been uncorrelated. Such deviations from the predictions of random matrix theory (RMT) can provide clues about the underlying interactions between various stocks. It was observed that, while the bulk of the eigenvalue distribution for the correlation matrix of NYSE and Tokyo Stock Exchange follow the spectrum predicted by RMT, the few largest eigenvalues deviate significantly from this. The largest eigenvalue has been identified as representing the influence of the entire market, common for all stocks, whereas, the remaining large eigenvalues are associated with the different business sectors, as indicated by the composition of their corresponding eigenvectors. The interaction structure of stocks in a market can be reconstructed by using filtering techniques implementing matrix decomposition or maximum likelihood clustering. Correlation matrix analysis has applications in the area of financial risk management, as mutually correlated price movements may indicate the presence of strong interactions between stocks. Such analyses have been performed using asset trees and asset graphs to obtain the taxonomy of an optimal portfolio of stocks.

While it is generally believed that stock prices in emerging markets tend to be relatively more correlated than the developed ones, there have been very few studies of the former in terms of analyzing the spectral properties of correlation matrices. Most studies of correlated price movements in emerging markets have looked at the *synchronicity* which measures the incidence of similar (i.e., up or down) price movements across stocks. Although related to correlation the two measures are not same, as correlation also gives the relative magnitude of similarity. By analyzing the cross-correlations among stocks in the Indian financial market, over the period 1996–2006, it has been found that, in terms of the properties of its collective modes, the Indian market shows significant deviations from developed markets. As the fluctuation distribution of stocks in the Indian market follows the same "inverse cubic law" seen in developed markets like NYSE, the deviations observed in the correlation properties should be almost entirely due to differences in the nature of interaction structure in the two markets. The higher degree of correlation in the Indian market compared to developed markets is found to be the result of a dominant market mode affecting all the stocks,

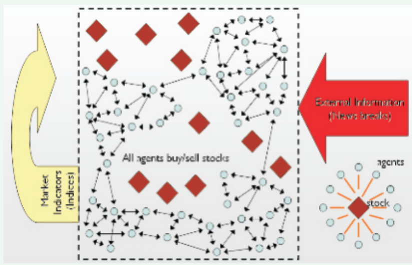


Figure 10: Schematic view of the financial market as a complex system. Agents (indicated by circles) buy and sell stock (indicated by diamonds), based on their perception of the market conditions through interaction with other agents and from external information (news breaks such as announcement of the central government budget, tax rebates, banking collapse etc) and from market indicators such as the Sensex.

Figure 11: Do markets follow Bachelier or Mandelbrot ? Louis Bachelier (1870-1946) in his 1900 thesis *The Theory of Speculation* suggested that stock prices follow a random walk. He derived a rigorous mathematical theory about five years before Einstein's work on the theory of Brownian motion. Bachelier's theory implies that changes in market prices follow a Gaussian distribution. However, Benoit Mandelbrot (1924-) working at IBM in 1961 made a detailed analysis of the movements of cotton prices and realized that market movements do not necessarily follow the Gaussian model. The much higher frequency of bubbles and crashes than what would have been expected from a random walk theory fits, in fact, a distribution with a power law tail.

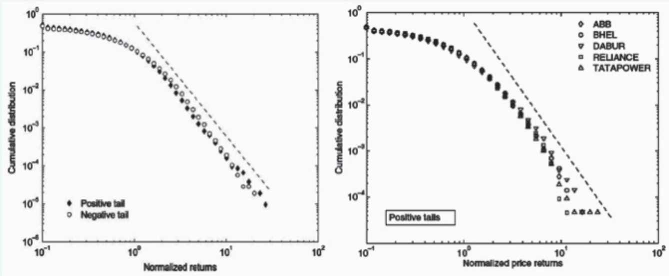


Figure 12: The "inverse-cubic law" for distribution of market fluctuations. A power law tail is observed for the distributions of logarithmic returns calculated for both the NSE India market index (left) as well as individual stock prices (right). [Source: R. K. Pan and S. Sinha, Europhys. Lett. 77 (2007) 58004; Physica A 387 (2008) 2055-2065].

Figure 13: A Brownian motion view of the market. A simplified view of Fig. 10 with the agents not being considered explicitly but rather their collective effects are assumed to result in effective direct interactions between stocks.

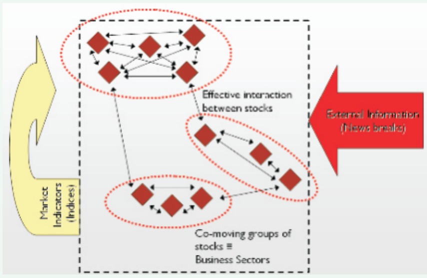


Figure 14: Structure of the interaction network of stocks in the Indian financial market. The left cluster comprises of mostly technology stocks, while the middle cluster is composed almost entirely of healthcare and pharmaceutical stocks. By contrast, the cluster on the right is not dominated by any particular sector. The node labels indicate the business sector to which a stock belongs. In contrast to developed markets such as NYSE, the Indian market does not show significant cross-correlations between stocks within most business sectors, indicating that except for the IT and pharamaceutical sectors, businesses are more affected by general market-wide (i.e., non-sector-specific) information resulting in an overall synchronization of their price movements so that the market responds as a single homogeneous entity to various pieces of information. [Source: R.K.Pan and S.Sinha, Physical Review E 76 (2007) 046116.

which is further accentuated by the relatively very few number of clusters of mutually interacting stocks as compared to, say, NYSE (Fig. 14). These results imply that one of the key features signifying the transition of a market from emerging to developed status is the appearance and consolidation of distinct sector or group identities.

Why Markets Fail: The Genie of Nonlinearity

So far we had been discussing mostly the statistical properties of distributions for meaningful quantities in economics (such as income or price fluctuations). However, the dynamics of economic systems also provides opportunities to physicists in applying their tools of trade to uncover unexpected features. An oft mentioned example showing the importance of nonlinear dynamics in economics is the case of the *beer game* devised by Jay Forrester at MIT which shows how fluctuations can arise in the system purely as a result of delay in the information flow between its components. In this game, various people take on the role of the retail seller, the wholesaler, the supplier and the factory, while an external observer plays the role of the customer, who places an order for a certain number of cases of beer with the retail seller at each turn of the game.The retail seller in turn sends orders to the wholesaler, who places an order with the supplier, and so on in this way, all the way upto the factory. As each order can be filled only once the information reaches the factory and the supply is relayed back to the retail seller, there is an inherent delay in the system between the customer placing an order and that order being filled. The game introduces penalty terms for overstocking (i.e., having inventory larger than demand) and back-orders (i.e., when the inventory is too small compared to the demand). Every person along the chain tries to minimize the penalty by trying to correctly predict the demand downstream. However, Forrester found that even if the customer makes a very small change in his/her pattern of demand (e.g., after ordering 2 cases of beer for the first 10 weeks, the customer orders 4 cases of beer every week from the 11th week on until the end of the game), it sets off a series of perturbations up the chain which never settle down, the system exhibiting periodic or chaotic behavior. Although the change in demand took place only once, the inherent instability of the system, once triggered by a small stimulus, ensures that an equilibrium will never be reached. Based on this study, several scientists have suggested that the puzzle of *trade cycles* (where an economy goes through successive booms and busts, without any apparently significant external causes for either) may possibly be explained by appreciating that markets may possess similar delay-induced instabilities.

If the extrapolation from the *beer game* to real economics seems forced, consider this: every day the markets in major cities around the world,

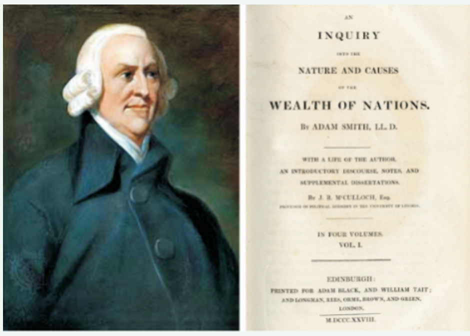


Figure 15: Adam Smith (1723-90) anticipated the principle of self-organization in economic systems when he stated in *The Wealth of Nations* that "Every individual...generally, indeed, neither intends to promote the public interest, nor knows how much he is promoting it. By preferring the support of domestic to that of foreign industry he intends only his own security; and by directing that industry in such a manner as its produce may be of the greatest value, he intends only his own gain, and he is in this, as in many other cases, led by an invisible hand to promote an end which was no part of his intention ... By pursuing his own interest he frequently promotes that of the society more effectually than when he really intends to promote it." (Book IV Chapter II)

including those of Kolkata and Chennai, cater to the demands of millions of their inhabitants. But how do the merchants know how much of goods to order so that they neither end up with a lot of unsold stock nor do they have to turn back shoppers for lack of availability of goods ? How are the demands of the buyers communicated to the producers of goods without there being any direct dialogue between them? In this sense, markets are daily performing amazing feats of information processing, allowing complex coordination, that in a completely planned system would have required gigantic investment in setting up communication between enormous numbers of agents (both manufacturers and consumers). Adam Smith (Fig. 15) had, in fact, in terming it the *invisible hand* of the market, first pointed out one of the standard features of a complex system: the "emergence" of properties at the systems-level that are absent in any of its components.

Economists often cite the correcting power of the market as the ideal negative feedback for allowing an equilibrium state to be stable. It is a very convincing argument that price acts as an efficient signaling system, whereby producers and consumers without actually communicating with each other can nevertheless satisfy each other's requirements. If the demand goes up, the price increases thereby driving supply to increase; however if supply keeps increasing, the demand falls driving the price down thereby signaling a cut-back in production. In principle, such corrections should quickly stabilize the equilibrium at which demand exactly equals supply. Any change in demand results in price corrections and the system quickly settles down to a new equilibrium where the supply is changed to meet the new level of demand (Fig. 16). This is a classical example of self-organization, where a complex system settles down to an equilibrium state without direct interaction between all of its individual components.

Unfortunately, this is only true if the system is correctly described by linear time-evolution equations. As the field of nonlinear dynamics has taught us, if there is delay in the system (as is true for most real-world situations) the assumptions underlying the situation described above break down, making the equilibrium situation unstable, so that oscillations appear (Fig. 17). The classic analogy for the impact that delay can have in a dynamical system is that of taking a shower on a cold day, where the boiler is located sufficiently far away so that it takes a long time (say, a minute) to respond to changes in the turning of the hot and cold taps. The delay in the arrival of information regarding the response makes it very difficult to achieve the optimum temperature. A similar problem arises with timely information arrival but delayed response, as in the building of power plants to meet changing needs for electrical power. As plants take a long time to build and have a finite lifetime, it is rarely possible to have exactly the number of plants needed to meet a changing demand for power. These two examples illustrate that a system cannot respond to changes that occur at a time-scale shorter than that of the delays in the flow of information in it or its response. Thus, oscillations or what is worse, unpredictable chaotic behavior, is the norm in most socio-economic complex systems that we see around us. Planning by forecasting possible future events is one way in which this is sought to be put within bounds, but that cannot eliminate the possibility of a rare large deviation that completely disrupts the system. As delays are often inherent to the system, the only solution to tackle such instabilities may be to deliberately slow down the dynamics of the system. In terms of the overall economy, it suggests suggest that slowing the rate of economic growth can bring more stability, but this is a cost that many mainstream economists are not

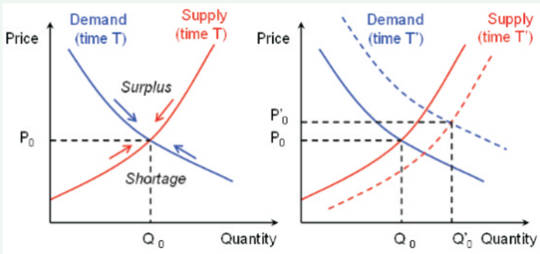


Figure 16: Stable equilibrium between supply and demand achieved by the price mechanism in traditional economic thinking. (Left) The supply (demand) curve indicates how rising supply (demand) results in decreasing (increasing) price. At any given time, if the quantity available in the market (supply) is less than the demand, the shortage causes the price to go up. This stimulates increased production, resulting in larger supply. However, if the supply continues to increase, eventually it will outstrip demand and there will be unsold stock in the market. This will bring down the prices, ultimately resulting in decreasing production. The negative feedback mechanism for price will thus move the system along the supply and demand curves to their point of intersection, where supply exactly equals demand (Q_0) at the equilibrium price P_0. (Right) Over time, as the demand and supply of a product changes due to various factors, the corresponding curves can shift. Thus, the equilibrium can shift to a different price value and quantity, but it is still stable with respect to perturbations.

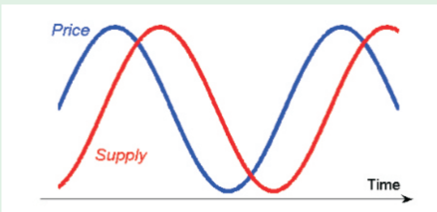


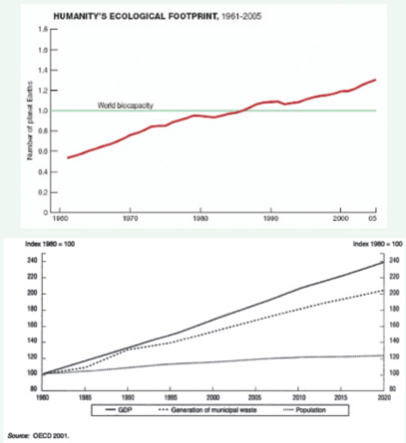
Figure 17. Price oscillations as a result of delay in responding to market movements. In real markets, there is a delay between increasing and reducing production as a result of rising and falling prices, respectively. While the information that the demand for a good is falling may take some time to propagate to the producer, a rise in demand may require some time to be satisfied by inherent delays in the production system. Thus, if the demand fluctuates at a time-scale shorter than the delay involved in adjusting the production to respond to those changes, it will result in oscillations or even chaotic movements in the price.

even willing to consider. While a freer market or rapid technological development can increase the rate of response, there are still delays in the system (as in gradual accumulation of capital stock) that are difficult to change. Thus, instead of solving the problem, these changes can actually end up making the system even more unstable.

The Promise and Perils of Economic Growth

Possibly the biggest impact that econophysics can have on the way traditional economics is done is by making it possible to perform a scientifically rigorous reappraisal of the consequences of economic growth, and even whether growth is desirable under all circumstances (Fig. 18). This will be of immense consequence in view of the current search for sustainable development, i.e., "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland Report, 1987). While there have been fringe voices such as that of E. F. Schumachar (author of *Small Is Beautiful*), calling for smaller economies (and in India, by Gandhian Marxists such as Pannalal Dasgupta), the mainstream economist community considers these views to be heretical. The anarchist utopia of society as a system of self-sufficient villages, where affluence is given up in favor of stability and social justice, has never been considered to be a practical alternative. Indeed the "development at all costs" mindset has permeated to society at large, as reflected by the obsession of the mass media with economic growth and gross domestic product (GDP). Newspapers and television are always worried about whether the rate of growth is slowing down ("an economic downturn") and headlines announce by what percentage the economy has grown in a quarter. However, whether economic growth is a panacea for all social ills, or whether growth itself is the cause for

Figure 18: Is growth sustainable ? (Top) The ecological footprint of humanity measured in terms of the area of biologically productive land and water needed for providing the resources and services to maintain



the human population at the present standard of living, has overshot the biocapacity of the planet (i.e., the amount of biologically productive area available). [Source: WWF, http://www.panda.org].

(Bottom) The ecologically catastrophic consequence of economic growth is underlined by the increase in waste generated by the OECD countries (a group of 30 economically developed nations) along with their GDP, even though the population has not increased significantly. In 1997, OECD countries produced waste corresponding to 500 kg per person in a year and it is estimated that by 2020 this will increase to 640 kg per capita [Source: E. Geyer-Allely, *Towards Sustainable Household Consumption*, OECD 2002].

most problems is not as settled a question as it may seem, in view of its social and ecological consequences. As the linear models of mainstream economics are inadequate for tackling such questions, the systems dynamics approach developed by Jay Forrester at MIT and his students in the 1960s was one of the first scientifically rigorous approaches towards this complex problem.

Jay Forrester's world model

The Club of Rome in the late 1960s had wanted to know how major global problems such as poverty and hunger, unemployment, depletion of natural resources, environmental degradation, etc. are related and if there are ways to solve them. Forrester's computer model suggested that the leverage point (i.e., the factor in a complex system where a small change eventually results in a large overall change in the entire system) was economic growth. The problem was that growth has negative consequences, although traditionally economic development is seen as an unalloyed boon. From a modeling exercise it becomes clear that many problems that are sought to be solved by growth, such as poverty and hunger, can in fact be exacerbated by it. Sometimes the solution might be to slow the growth of the economy, or even to turn it back.

The model developed by Forrester's students, Meadows *et al* (in *The Limits to Growth*) has taken this original work forward by looking at several resource stocks and their flows, and trying to predict resource availability at future times. One of the striking observations of this model was that it is not so much the depletion of resources that is the key problem but the increasing cost of capital (e.g., as a result of environmental pollution, among several reasons). Thus, according to Meadows *et al*, the solution lies not in unconditional economic growth, but in the efficient use of resources. However, the lessons coming out of this study has clearly not permeated beyond a few. From 1985 onwards, we are in fact using more resources than our planet can renewably produce (Fig. 18). In our quest for higher GDP, we have ignored other equally important factors, as reflected in the Genuine Progress Indicator (GPI) which is measured from the GDP by subtracting costs of air and water pollution, loss of farm and wetlands, etc. (Fig. 19)

Thus, sustainable development, if it is to be achieved, has to couple the quest for growth with conservation of nature and the achievement of acceptable social conditions. Sustainability will be achieved when we stop depleting not only economic capital, but also the social and environmental capital bequeathed to us so that they can be carried over to future generations. Econophysics, by being able to view the problem in the light of insights gleaned from looking at other sustainable systems, such as in the biological world, is in an unique position to develop simple models that can suggest possible solutions. If in place of the traditional throughput economy (wasteful of resources) we want a sustainable model that re-uses products in a closed-loop cycle (Fig. 20), would using the concepts learnt from the study of ecological food webs help us ? Can a network economy give a more sustainable alternative to development ? These questions are hard to answer, but possibly the most important that the econophysics community will have to tackle in the near future.

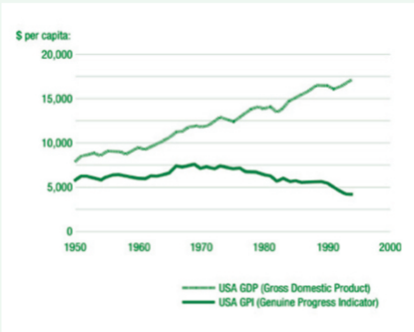


Figure 19: Economic Growth or Decay ? The fall by a factor of half in the Genuine Progress Indicator (GPI), an alternative measure of economic growth suggested by Cobb, Halstead and Rowe in 1995 that takes into account the cost of environmental degradation accom-panying economic activity, even as the Gross Domestic Product of USA has increased three-fold over the latter half of the 20th century. (image source: http://www.sustainabilitydictionary.com)

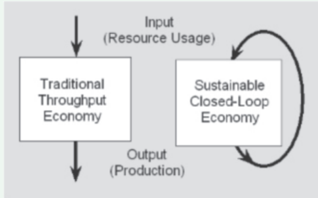


Figure 20: Two models for growth. The traditional non-sustainable economic growth model is contrasted with a closed feedback loop model of sustainable growth that is closer to the way biologically vital resources are maintained in nature (e.g., the carbon-oxygen cycle). The future challenge to econophysics is to come up with details of how such a growth model can be constructed.

For Further Reading

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