Self-organizing processes in strategic interaction

Implications on price dynamics of investors' decisions

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Abstract

Starting from the observation of market anomalies in respect to expectations derived from economic theories, behavioral finance put a spin on the basic assumptions of economic models about investors' nature, leading to investigation of processes govern decisions under uncertainty. Following this direction we simulated investors' strategic decisions with a group of students interacting through linked computers. We provided as feedback for each decision only the effects on the aggregate market values, hypothesizing that the dynamic of individual decisions based on reciprocal expectations would generate deterministic patterns in the aggregate time series. We expected that self-organizing processes would make each observation on the aggregate predictable in the short run. Technical concepts assuming predictability such as trends, support, or resistance, are in the ordinary financial language and conceptual instruments of most traders and recent studies also supported the hypothesis of chaotic motions of financial prices. Our results suggest that intuitive decisions made as a result of observing price dynamics might be not irrational, but rather a reasonable reliance on shot-term predictability.

Self-organizing processes in the strategic interaction:

Implications on price dynamics of investors' decisions

Financial markets and people

By definition people move stock prices, that is stock market prices are ruled by the ask and bid law. To the extent that people act as rational and efficient information processors, their choices will guarantee that prices will reflect perfectly and timely all the relevant information about intrinsic value of assets.

As long as the notion of perfectly "rational investor" was accepted, economists didn't need to take interest in the "black box" of psychological processes between information and prices because "rational investors" simply re-codify the new information under exactly defined rules, thus recovering the equilibrium price. By the end of the eighties, especially with the "markets' overreaction hypothesis" sustained by De Bondt and Thaler (1985, 1987) and successively reinforced by Chopra, Lakonishok and Ritter (1992), academics began to shake off the notion that stock prices are always right. The assumption that investor is a "homo economicus" conflict with the observation of his real behavior:

Future dividends or interest rates can't explain market volatility (Mankiw, Romer & Shapiro, 1985; Shiller, 1981; West 1988), small firms and cheap stocks, as gauged by their book values (i.e. price earnings or cash flow), often perform over any "rational" expectation (Alpert, 1997). Fast and wide price's changes often occur without any new relevant information (Leland 1987) and markets also show surprising seasonal effects (De Bondt & Thaler, 1987). In the face of such evidences, analytical and normative approaches, equilibrium models in which asset prices are related to exogenous data like the “Capital Asset Price Model” (Lintner 1965, Sharpe 1964, 1977) or the “Arbitrage Pricing Theory” (Connor 1984, Ross 1976), began losing the full support of empirical facts. The presence of investors who don't behave "rationally" because of their lack of knowledge or access to information, don't offer an valid explanation of such anomalies because market efficiency would still be saved by "rational" agents which can take advantage arbitraging on errors of "noise traders". Market anomalies necessarily imply that even the most expert and successful traders have to behave differently from what the notion of economic rationality require.

As finance theory couldn't offer an explanation for anomalies (DeBondt, 1995), and because the psychological assumptions about rational investors as Bayesian forecasters and expected-utility maximizers (Von Neumann and Morgenstern, 1947) began staggering, attention moved trying to understand behavior of people. But arguing about the investor's irrationality, theorists still assume the economic point of view about what a rational behavior is. According to Simon (1976) the lack of reciprocal contributions between economics and psychology just depended on a different notion of rationality. Simon (1976) and March (1991) consider economic theories of formal decisions to be a cultural artifact which produces a concept of rationality founded on the gathering, elaboration and optimum handling of the largest possible amount of information.

Simon (1976) observes that the model of objective rationality is unable to describe the behavior of decision - makers for at least three reasons:

a) It necessitates a list of all possible strategies whereas in real behavior only some alternatives spring to mind. b) It necessitates a list of all the consequences of such strategies is required whereas knowledge of the consequence is always fragmented. c) It necessitates that values associated with consequences are known whereas the anticipation of such values is always imperfect.

A model of decision making as the rational calculation of advantages and disadvantages of various possible courses of action is represented by “prudential algebra” which Benjamin Franklin teaches his friend Joseph Priestley (Dawes, 1988). Prudential algebra is a linear model of decision that requires: a) Listing of all possible pros and cons of a given course of action, or of all relevant predictors. b) Calculating the relative “expected utility”, hence of the products of values of every possible outcome for the probability associated with it. c) Weighing of such utilities. d) Calculating the mean of such weighted values from which a decision emerges as a choice of the higher average.

Such normative models which guarantee optimum performance and which describe the behavior of the ideal decision-maker, do not correspond to the way in which an expert manager really makes decisions. Mitchell and Beach (1990) point out that formal, analytical strategies are not usually used even by those who are familiar with them, and that results which do not coincide with their intuition, are rarely accepted. March (1991) notes that as a consequence of the cultural artifact related to the way a decision should be make in order to be considered rational, managers are considered adequate according to their ability to gather and elaborate information. Actually, even though they require more and more information, they rarely use it. Shon (1983), Wagner (1987) and Isenberg (1988), have shown that while young managers are more analytic, using with rigor their decisional instruments, expert managers’ decisions match less and less the criteria of rational problem solving.

Therefore, in order to define the rational behavior, we must take into account:

1) The economizing of the adopted procedures, given the cognitive systems' limitations. 2) The explanatory categories of actors on which basis their actions become reasonable and coherent within the horizons of meaning and rules in which they move. 3) The environment, which is understood by means of socially-organized interpretative constructs dynamically evolving. 4) The intrinsic complexity of such environment.

1) Limits of cognitive systems.

According to Simon (1976) even the most expert decision-makers, even in situations when they are able to calculate all possible future states of the system, select a group of strategies which help to arrive at a satisfying solution rather than aiming at an optimum one. Simon observes that such behavior is linked to limitations of individual cognitive processes, to incomplete information regarding different alternatives, and to the uncertainty regarding the environment.

Tversky and Kahneman (1974) showed that people selectively gather and elaborate only a small portion of potentially relevant information. They also demonstrated that predictions are often wrong in a systematic ways (1973) and that even people with statistical training are vulnerable to errors (1971). Such evidence suggests that the roots of such biases could lie in adaptive mechanisms in the natural environment for which strategies that could have had survival value in the far past could still be appropriate facing complexity of everyday situations. Metzger (1995) verified such hypothesis studying 3-5 age children’s prediction of successive values of chaotic series. Children used the “anchoring heuristic”, which consisted in an estimation starting from the last value, as a behavioral medium to reach the goal. Metzger and Theisz (1994), Metzger

(1995), Smithson (1995), demonstrated that people are able to intuitively predict chaotic sequences using the same strategies that often fail in simple tasks of probability judgment. They experimentally showed that such strategies, clearly useful on facing environment uncertainty, could have been naturally selected in order to deal with the dynamic nature of natural processes.

The linkage between inherent biases in decision-making and market overreactions has been strongly pointed out by De Bondt and Thaler (1990) who have found in the predictions of stock market professionals the same pattern overreaction found in the predictions of naïve undergraduate. They verified that "generalized overreaction can pervade even the most professional of predictions" (p. 57). Makridakis, Wheelwright and McGee (1983), Camereer (1992), Czaczkes and Ganzach (1996), Tassoni (1996) verified that investors and gamblers actually use heuristics like "anchoring" or "representativeness" in making decisions.

The "representativeness heuristic", through which people "evaluate the probability of an uncertain event, or sample, by the degree to which it's similar to the essential properties to its parent population…" (Tversky & Kahneman, 1972, p. 431) has been pointed out by Andreassen (1988) as a strategy responsible for feedback loops. Following his argument, trend formation or price escalations could be explained as a consequence of the use of such heuristic when market volatility drives the focus of attention from price to price change or vice versa.

Biases, like "hindsight phenomenon" (Fischhoff, 1975), "desiderability bias" (McGregor, 1938) or "wishful thinking" (Hogart, 1987), "misconceptions of regression" (Tversky & Kahneman, 1974), have been observed in financial agents with high professionalism and experience, respectively by Andreassen (1987), Olsen (1997), Bolger and Harvey (1995).

All these studies show systematic and persistent deviations of investor's decision-making from the "rational" model. But if we consider such deviance to be cognitive biases leading to irrational behavior, we risk stating that "rational" traders are expelled from the market by a natural selection process because they are unable to maintain equilibrium. Moreover if using heuristics is successful in forecasting dynamical processes and if they have been developed in order to face the natural dynamical environment why must the concept of rationality to be shaped on a static notion of equilibrium?

If markets show any regular formation and past prices contain any information theoretically useful to predict the future, prices can be caused neither by economic models nor by irrational behaviors. They must reflect the "rational" investors' decisions, which are interpretations, skills developed through experience, predictions of dynamic systems through appropriate strategies. If we just consider that every local market is influenced by whatever happens in all foreign markets, as Murphy has shown (1991), rational investors are supposed to quickly check, select and elaborate potentially infinite amount of relevant information. That's why instead than "optimize", they select only a piece of information that they consider useful to reach a "satisfactory" goal. Isn't that rational?

2) The actors' reasons.

Rational epistemology - at the roots of which lies an optimum, unique, decision which can be arrived at by a process of analytic calculation - is founded on dualistic ontology which distinguishes the objective world of physical reality from the mental world. Decisions in this cultural context are considered rational only if they are able to conform to a given reality since rational laws transcend individuals and their cognitive acts.

Galileo’s conviction that there exist objective facts independent of interpretation is rejected by modern epistemology; according to Prigogine (1979): “Every description of nature is produced by man and he who produces it is himself a product of nature.” Agree (1993), too, is convinced that “the system of metaphors founded on ‘inside’ and ‘outside’ is unable to make concrete sense of concepts that do not reside within agent or surroundings but rather in the relationship and interaction between the two.” (p. 67).

According to Salvini and Pirritano (1984) “there are no ontologically given facts but only interpretative constructs (p.174) and Suchman (1993) observes that the “complexity or simplicity of situations is a distinction which does not belong to situations themselves but to the characteristics that we ourselves attribute to them” (p. 74-75). Peters’ (1994) assertion that “the importance of information may be considered as being greatly dependent on the investment horizons of investors” (p. 42), shows the multiple and contradictory nature of investor’s goals who use different information selected and processed according to different purposes or risk propensity. Different investment horizons lead to different interpretations of the market’s behavior, thus what one investor may consider a price at which to cautiously close non-beneficial bull positions, another investor may consider a good purchase price for short strategies or even an opportunity to give rise to new bull positions.

Peters criticizes efficient market theories and believe that just because not all information has the same impact on investors, market stability is insured and Hammond (1996), note that such goal is reached because investors use satisfying strategies instead of optimizing ones that, when they fail, create greater variance in outcomes.

According to Mantovani (1995): “An overload of information does not constitute the root of complexity of daily situations, since humans select and process the information they require on different levels. The actual complexity of daily situations, the fact that they cannot be addressed by means of analytical tools, and the fact that they cannot be reduced to formal ad pre-determined models, derives from different cognitive and motivational resources which they are able to set in motion in a given moment” (p. 29). The curve of values described by Kahneman and Tversky (1979, 1992) in the “prospect theory” offer an explanation of why the environment perception is also related to such different cognitive and motivational resources that evolve within investors. “The nature of actors” and their dynamical changing through interaction, is another aspect of the environmental complexity when their acts and choices have a role in its definition.

Hence the interests of actors and their instability determine different environmental scenarios which, in relation to their aims, bring threats or opportunities and contribute to a re-definition of their interests (Frijda, 1986 and 1987, Frijda and Swagerman, 1987, Lazarus, 1991). Different strategies depend on differences among investors concerning their risk propensity and aims (Peters, 1991, 1994, Reichlin, 1997) and, as Payne (1993) noted, investor’s decisions are adaptive to the perceive nature of the problem and the environment in which the problem is framed.

2) <u>Socially-organized interpretative constructs, dynamically evolving</u>.

When investors try to make sense of what happens in the markets and try to understand the meaning of such events in the course of future events, they formulate hypotheses and build possible scenarios through the search for reasons, which explain why the market might move in certain directions. Investors refer to theories, explanatory and predictive models that have a historical and cultural basis and are only temporarily held. According to Granger (1992) " Once knowledge of an apparently trading rule becomes wide enough, one would expect behaviour of speculators to remove its profitability, unless there exists another trading rule the speculators think is superior and thus concentrate on it (p. 12).

Hunter and Coggin (1988) for example showed that investors don't process all potentially relevant information but only what is considered relevant by their theories. Moreover, information could be elaborated by means of both formal and informal models, in a way that forecasts present warps or "errors" when still compared to the formally correct application of the theoretical model they refer to. Hence it follows that the judgment of analysts arises from the consideration of limited information gathered on the basis of a specific theoretical model but elaborated in an imperfect manner, that is, different from what the model itself proposes.

The actions of investors do not converge by means of social influence in the sense of a social pressure that annuls individual rationality, but neither because of precise rules shared in the analytic elaboration of information. Sometimes traders focus their attention on information sources with informative power not better than chance. Even so, they improve their value just because traders think that, although it's rationally wrong, everybody will pay attention to that or everybody will think in the same way. In this way prices will move in a predictable way based on an invalid predictor.

So in order to explain the dynamic of decisional processes based on reciprocal expectations, such as those manifested in financial markets, we have to find out a dynamical model. When individual choices and actions are based on the others' choice and actions, we could consider group decisions as a self-organization process where the aggregate variable (the market) behave *as if* the components (investors) come to some consensual agreement (Haken, 1983). The resulting effect will be different from the sum of initial individual preferences neither could be considered to originate by the influence of an external source. Examples are the "aggregate attributional effects" described by Andreassen (1987), as a consequence of which not only news determine prices but "also price motion could determine news" (pag. 491). Financial analysts and journalists have in fact the goal to regularly communicate information and offer explanations, but this claim modifies the way they process information. They select facts and make causal attributions that could offer a coherent scenario. Moreover Abolafia (1996) demonstrated how positive feedback might also be the result of the action of professional investment managers when their beliefs and practices are part of a common institutional culture.

4) The intrinsic complexity of environment.

Making decisions in financial market is a, so called, "Complex, ill-structured task". Such tasks are characterized ex ante by lack of a unique set of characteristics that clearly define the method and information needed to arrive at a single, well defined goal" (Olsen, 1998, p.8). Olsen, citing Forgas (1991), Epstein (1994), Hammond (1996), Busemeyer (1995), writes that "complex ill-structured tasks or decisions give rise to great variability in decision outcomes because they tend to lie more towards the experiential or intuitive end of the decision spectrum than the objective end and make greater use of idiosyncratic information and procedures that are personal, concrete, holistic, affective "(p.8).

In financial decisions the choice of investment involves predicting possible results, hence hypotheses regarding expected results, to which values of subjective probability may be assigned, are formulated. It would be impossible to calculate objective probabilities due to unique and unpredictable events that influence prices. Investors who have to make rapid decisions in uncertain conditions, within a constantly changing environment containing infinite available information, would tend to refer to their experience, to a method of gathering and handling information which is not analytical but mostly related to their "implicit knowledge" (Polany 1967, Berry and Broadbent, 1988, Nonaka 1991), “direct comprehension”(Weber, 1949), "pre-reflexive activity” (Heidegger, 1967), “practical understanding” (Wittgenstein, 1953).

Theories of action guided by predetermined plans do not correspond to continuous and flexible adaptation of that plan to unpredictable and changing situations, hence although we consider them as plans (Argyris, 1995), actions are more often improvised according to the situation (Suchman, 1987). So, when decision makers must withstand a complex environments, like markets, they shift towards non compensatory procedures which are open to the continually changing environment, less expensive and more efficient, more reversible and hence adaptive.

According to Broadbent and Aston (1978), individuals could improve their decision-making skills without improving their ability to provide adequate verbal descriptions of their behavior. Nevertheless non-selective (implicit) learning is suitable for the acquisition of skill in making accurate business decisions (Hayes and Broadbent 1988).

Chaos theory and people

As long as it was argued that "rational" investors act according to linear economic models, simply transforming unpredictable information as soon as it is available, we have to expect that markets behavior will equally be stochastic. In that case past prices don't contain any information useful to predict the future.

If instead, as it was developed in the previous sections, psychological processes cause investors' errors in intuitive probabilistic judgments to be biased in a specific directions, then they will aggregate into predictable market motions (Camerer 1992, Czaczkes and Ganzach. 1996). Investors face the complex environment according to a "dynamic comprehension" (Kellert 1993, West and Ward 1994) which is "holistic, historical, qualitative, avoiding deductive systems, mechanisms and causal laws" (Kellert 1993, pag. 114). The use of strategies which lead to errors in simple probabilistic problems, often ensure correct solutions dealing with complex ones (Nisbett and Ross, 1980). Therefore prices that investors try to predict could be shaped by such efforts as a collective result of the self-organizational process. If it is so, we have to expect that, besides a great deal of noise due to the economic theories investors refer to and to the randomness of the related information, there must be some trace of a deterministic process.

Sterman (1989) showed that expert managers making decisions in dynamic situations make use of the anchoring heuristic and Jensen (1987), Mosekilde, Larsen and Sterman (1991) showed that the results of decisions in complex environments have a deterministic nonlinear behavior.

Signs of nonlinear behavior of financial markets time series have been found among others by Sayers (1987), Blank (1990), Brock and Sayers (1988), Barnett and Chen (1988), Frank and Stengos (1988, 1989), Le Baron (1988) Brock (1988), Sheinkman and LeBaron (1986, 1989), Hsieh (1989) Shaffer (1995), Peters (1991).

Most of the authors emphasize that results are not conclusive because, as DeCoster, Labys, Mitchell (1995) note, "if chaos is present is probably accompained by noise" (p. 193) and noise in the time series make hard to ditinguish chaos from randomness (Brock, 1986).

Many authors have often underlined the importance of reciprocal expectations involved in decision-making tasks focusing especially on economics decisions (Keynes, 1921, Von Neumann and Morgenstern, 1947, Shelling, 1980, Shaw 1990). Their observations can be extended to many other social contexts in which strategic decisions depend from inferred anticipations of preferred choices, based on a shared symbolic universe and from the feedback of previous decisions.

In order to explain financial investment Keynes offers a good metaphor:

> -…professional investment may be likened to those newspaper competitions in which the competitors have to pick out the six prettiest faces from a hundred photographs, the prize being awarded to the competitor whose choice most nearly corresponds to the average preferences of the competitors as a whole; so that each

> competitor has to pick, not those which he himself finds prettiest, but those which he thinks likeliest to catch the fancy of the other competitors, all of whom are looking at the problem from the same point of view. It's not a case of choosing those which, to the best of one's judgment, are really the prettiest, nor even those which average opinion genuinely thinks the prettiest. We have reached the third degree where we devote our intelligence to anticipating what average opinion to be. And there are some, I believe, who practice the fourth, fifth and higher degrees. - (p. 156).

The norms of the competitors, that is the modal average of the distribution of choices, is not the average of individual aesthetic judgments. The Keynesian description would be paradoxical if the expectations recurrence couldn't find its place in a shared system of meanings, that is the social representation of beauty which evolve through its exteriorization.

In the case of financial markets the external referents are mostly economic models but financial markets behavior and group decisions in general, are built through a process which imply a simple feedback after each step, the new price. We can consider as analog referents for the dynamical self-organizing of human group phenomena, like crowd behaviors or norm development, the magnetization of an iron-magnetic material or the capsule of Rayleigh-Benard. Examples are the dynamical evolution of embarrassment described by Goffman (1967), or the euphoric evolution of financial markets described by Galbraith (1990). Physical, biological, economic and social systems, when they reach a <u>critical point</u> are subject to sudden structural modifications or dynamic instabilities that are authentic revolutions which demonstrate radical simplification in their way of behaving.

According to the "efficient markets hypothesis" (Fama, 1970) only rationally relevant information is able to influence price dynamics. On analyzing international data, however, one may observe that speculators hesitate to go beyond certain levels, for example those made up of round figures, over or under which prices could stabilize. When such critical points or "psychological barriers" are eventually broken, a rapid acceleration of price dynamic would ensue and this would be greater than what efficient market theory can predict. This shows that even “rationally” irrelevant information such as proximity to a point of reference is absorbed by the market (Donaldson, 1990). An example of such behavior, which has been object of particular interest on behalf of entrepreneurs, was the dynamic of the Mark/Lira rate exchange from 1993 - 1995. The value of 1000 DM/LIT was resistant to price-increasing during April 1993 and August 1994, but following a break-out of such a round level an escalation ensued which led to 1275 DM/LIT in just 7 months. Evidence of "psychological barriers" in the exchange rate market, analyzing about 10 years (average) of daily data of 37 currency cross rates, has been found by Campello (1998).

Simulating investor's behavior

If market behavior shows any kind of regular formation the reasons could be found in pattern in the social-psychological process in which people are involved making decisions. Investors seem focused in understanding expectations and other investors’ behavioral schema mostly through the observation of price motion because, “ In any trading room, virtually all of the tools of the day trader are technical” **(**Peters, 1994, p. 43) or otherwise, by the relation between information and price. In both cases, as

Andreassen (1987, 1988) noted, cognitive or socio-psychological processes could be responsible for self-organizing decisions and, as a direct consequence, of feedback loops in price motion. Leland (1987) and Bhatt (1987) for example explained the break of the stock market in 1987 as partially due to the previous increase of volatility. Shaffer (1995) asks "what caused this increase in volatility? Standard financial theory is of little help here, as it treats volatility as exogenous and, typically fixed" (p. 88). According with Shaffer (1995)"it's formally incorrect to model the stock market as purely random. Each transaction, along with its price, is the result of conscious decisions by a buyer and a seller" (p. 89).

We suppose that nonlinear dynamics in prices motion could be due to nonlinear strategic interaction among investors. Reciprocal expectations could evolve in a self-organizing process in a way that, as soon some investors reach a certain amount of cooperation, the macroscopic phenomenon drives other investors in the same direction creating price patterns and overshooting. Because in financial markets information adds a lot of noise to the process we have tried a simulation of such phenomenon in controlled situation. In our game subjects can form their expectations about behavior of others, and so make their new decision, reading a numerical feedback about the effects of their own and the collective choices. Individual choices can be influenced by the macroscopic phenomenon in which formation each subject is involved. As in the real process they must "beat the market" but at the same time they must cooperate in order to have a bull market because they can win money only if this condition is satisfied. The game could be described as a simulation of such hypothetical situation: Suppose that a group of financial companies, just like many other gamblers, took a great potential advantage by buying a certain stock which have had a great rise during an “euphoric phase”. For some reason they together realize that it’s time to take profit, and that it must be done right now just before that a shared consciousness that the bull market is finished will make prices fall headlong. Because they reached the same conclusion together and they are all strong investors who have in their hand a great amount of stocks, they are aware that if they sell most of their stocks together the small demand in the market can not support prices.

They can’t all have good result so they have to compete but an excess of competition would only make to collapse the prices with common and immediate negative consequences. If they are not able of partially cooperate in keeping the prices high they will jointly cause a prices crash, loosing immediately all the potential profits.

The goal of such experiment is therefore to establish whether, when subjects strategically interact without any other information except the effects of their own choices, a self-organizing process would arise. If such complex but deterministic process exists we expect to find evidence of nonlinear dynamics in the resulting time series. At the same time we are aware that we could only find some piece of evidence of chaos because, as we are dealing with human decisions, a certain amount of noise will still be present even though the exogenous causes of noise have been cut off.

Method

Participants

Subjects, 4 males and 5 females, were recruited in class of introductory psychology conducted by Robert Warren Anderson in the University of Maryland Baltimore County. We briefly presented the experiment as a "competitive vs cooperative" game, underlining that being cooperative as a group they could reach the conditions under which some money would be available and allowed to the most competitive players. We said that the experiment would have been an amusing game with computer interaction, and we offered a research credit to every participant plus $8 to the best player, $6 to the second, $4 to the third and $ 2 to the last classified. After the presentation we distributed a paper where 15 subjects signed their names and phone number. The day of the experiment 9 subjects came.

Materials and procedure

The computer programs for the game consisted in a series of files written in “C” and “shell bash” format, which have been realized thanks to the cooperation of Piergiorgio Sartor of University of Padua.

The game, consisting in 200 trials, was performed in a computer classroom at UMBC where, through an IBM 300 GL, subjects entered in a common account of a UNIX system server.

We have used the "prisoner dilemma" model, a game with sum different from zero, that in the classical procedure consists in a choice's matrix in which each of two subjects can choose among two different strategies: one is always dominant because it always offers the best score independently form the other's choice. For this reason subjects will more easily converge in the dominant strategy but in this case they both reach less points than if they would be able to both converge on the non-dominant strategy.

We have used a large matrix so that each subject could chose among 101 strategies, from the most cooperative (0) to the most competitive (100). Individual scores are determined, as in the classical game, by the pattern of two choices that in our game are: the individual and the average of all players' choices. After all players made their decision the program returned four feedback: The subject's score, the team's score (which was the average of all players' scores), a cumulative score for the player and one for the team.

While the individual and the team's scores offered an information about subjects' performance after each trial, each player could check the course of the whole game through the two cumulative scores. If in the end of the game the team cumulative score would be above zero, subjects with the higher individual cumulative score would win.

The scores were computed to 6 digits of accuracy. For feedback to the subject, scores were displayed rounded to the nearest integer. Before the game subjects received the instructions contained in appendix A and after everybody read them a practice game with 100 trials started. Subjects were allowed to put questions and talk each other during the time preceding the real game in order to permit subjects to be as confident as possible with the game. We chose to play a game with 200 trials in order to have a minimum amount of data for the analysis but at the same time keeping in mind that some fatigue might be involved.

Results

Fig. 1 shows respectively: The time series of "team cumulative", the cumulative series obtained summing a random scrambling of "team" data, the dynamic map of "team cumulative" dynamic map and its phase space.

A visual comparison of the time series with the random scrambling of the same data suggests a considerable difference between the process of players' choices and the effects of the same choices in each trial without any process occurring.

An auto-regressive component is confirmed by the results of the auto-regression analysis: $X_t = 1.49^* X_{t-1} - .55^* X_{t-2} + .29^* X_{t-3}$ (order = 3, parameters significant at p < .05). The dynamic map shows the typical elliptical shape of chaotic processes with a trajectory folding back after it gets too far away. In the phase space there are evidently three different regions in which the self-organizing processes arise corresponding in the time series to 2 flat phases and a changing in the process direction.

In order to determine the presence of a structure in the data we investigated on their fractal dimension (FD), that is a measure of the complexity of a geometric object through information about how it fills its space. As a line fills a space whose dimension is 1, a plane fills a two-dimensional space and a cube a three-dimensional one, a pure random process fill each space it is plotted in (which is called embedding dimension, M). Stochastic processes have infinite dimensions that increase with the value of M, because their elements are non-correlated and independent. In deterministic processes not every point of the space is equally likely and therefore we should expect that the FD would stabilize at a certain level as we increase M, while estimating the FD of embedded noise its value should be equal to M. (Grassberger & Procaccia, 1983). In order to realize such test it useful to de-trend time series supposed to have a linear component, like it must be done analyzing stock prices because they rise over time. In that case the test could be realized on the first differences of the data (Elridge, Bernhardt, Mulvey, 1995), and in our case such differences are the "Team" results.

We computed the FD of “Team” using Sarraille and DiFalco’s (1992) FD3 program that have been realized referring to Liebovitch and Toth’s (1989) algorithm providing three measures: Capacity, information and correlation dimension. The authors recommend to use 2^ (4*M) distinct points, and no less than 200 distinct points in order to obtain less than 5% error. For such reason, as we have 200 data, our test has been realized using 2-m.

Because the size of our data is small we could not verify if at a certain point the FD would remain constant for further value of M, therefore we compared the measures of FD on the times series with the random reordering of the same data. Scheinkman and LeBaron (1989), Casti (1992) suggest that random scrambling the order of structured data the values of FD should grow up towards the value of M.

In order to make more meaningful the comparison, we reported in table 1 the measures of FD for the time series, for the average of 3 shuffled series, and for the average of three pure random series.

An auto-regression analysis shows evidence of dependence among data also in the “de-trended” series: $X_t = .50^* X_{t-1} - .06 X_{t-2} + .23^* X_{t-3}$ (order = 3, parameters signed with * are significant at $p < .05$). In order to offer a visualization of the difference between the process under study and a purely random one in the same range, we reported in Fig. 2 both the dynamic maps.

A heuristic way to identify chaotic motion is also the visual observation of its power spectrum (Fig.3). In deterministic chaos, but also in a purely random signal, the background level in the power spectrum is broadband while point attractors or limit cycle instead show peaks that are narrower as less noise is present. Sometimes a typical shape that shows an inverse relation between the power spectrum and frequency is present in chaotic motion, thus making a difference with random processes. Our data show a big peak is at 0.015 Hz, corresponding to a period of about 66 steps and a broadband that seems going down as the frequency increase.

We also analyzed a cyclic motion for which the main frequency was about the same as in our data, and to which has been added white noise in a range of 10 times the value of each data point. In the bottom-left panel we graphed the function “Log” to which has been added the same kind of proportional noise, and in the bottom right the power spectrum of random noise in the same range as the data. A background of pure noise had higher value of spectral density compared to our data, while in the other 2 processes noise only added a large but flat band respectively to a single narrow peak and to a flat line at the value zero.

In the end we tried a test of prediction of the de-trended data, that is the “team” series. According to Metzger and Theisz (1994), Metzger (1995), Smithson (1995), people show a surprising ability to predict the next step of even the irregular, unpredictable behavior of deterministic nonlinear systems. Successful prediction of the time series becomes then a sufficient condition to identify the presence of deterministic patterns in empirical data. We tested one subject who could see on the left of his computer screen the first number and on the right side the instructions: “ Starting from the number on your left you must predict the next one and write it below. The range of the series is: (-29, 28). After writing the predicted number press enter. You will see the right one on the left space nearby. Try to make good predictions and good luck!”. On the screen subjects could see the previous choice and the right number, just above the space for the new prediction.

We asked the subject to predict first the time series and then the same series with the observations randomly reordered. The correlation between the "team" series and its prediction was significant ($r = .23$, $p < .05$), the correlation between a randomization of the "team" series and its prediction wasn't significant ($r = .03$, $p > .05$). since the subject was able to predict the "team" series the sufficient condition was satisfied and we conclude that there is a pattern in the series.

Discussion

A visual observation of Fig.1 and Fig.2 suggests that the process generated by the players' choices, has a deterministic structure that can be easily observed comparing its development with a process resulting from random choices in the same range. The dynamic map and the phase space suggest that linear phases could alternate with phases of uncertainty, corresponding to point attractors, where reciprocal expectations re-organize and evolve in nonlinear pattern before stabilizing again in trends. The analysis of the fractal dimension reveals that the time series consists in structured instead than random data, although we don't consider such test useful to distinguish chaos from other formations or a mix of deterministic patterns in the series. The analysis of the spectral density suggests that very unlikely that's just a linear process surrounded by noise.

Limitations of the shortness of time series are obvious, therefore more observations and subjects' experience would be necessary for more conclusive observations. Although Ramsey and Yuan (1989, 1990) noted that with small data set it's not easy to distinguish a deterministic process from a random one, our results show that strategic interactions of individuals evolve in deterministic patterns of the aggregate detectable also under such condition of analysis. This suggests that the phenomenon could be robust**.**

In financial markets exogenous information increases the complexity of price formation adding pure noise. Nevertheless the dynamic of reciprocal expectations exhibit ordered patterns, as choice persistence or unexpected but self-feeding evolutions of the aggregate behaviors, that could offer an explanation for market anomalies. Decisional patterns could really be at the basis of phenomena that each financial trader deals with like trend formation, convergence in point attractors called support and resistance, instability that develop in excess of volatility and overshooting. Sometimes markets seems to have reached a steady state around which prices randomly move, but subsequently prices evolve rapidly, from critical points, in unpredictable directions. Such evolutions seem as sensibly dependent from an irrelevant informational imbalance but positive feedback loops then could drive prices even through euphoric phases or big crashes.

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Table 1

Fractal Dimension

	Team results				
Fractal Dimension	Series	3 random scrambling			Average
Capacity	1.311	1.358	1.371	1.621	1.450
Information	1.459	1.676	1.587	1.724	1.622
Correlation	1.354	1.633	1.608	1.669	1.637
		3 series of random data			Average
Capacity	1.311	1.931	1.883	1.858	1.891
Information	1.459	1.847	1.774	1.731	1.784
Correlation	1.354	1.798	1.685	1.626	1.703

Figure Caption

Figure 1. The top-left panel shows the time series of “team cumulative”, besides the cumulative time series obtained randomizing the order of team. In the bottom-left panel the first return map of “team cumulative” and beside the phase space of the same data.

Figure 2. The left panel shows the dynamic map of “Team”, the right panel shows the dynamic map of purely random numbers.

Figure 3. Power spectrum of 4 times series of 200 data. From the top left: Team, a sine function adding noise proportional to 10 times each value, a Log function adding the same kind of noise, random numbers in the same range of “Team”.

Appendix

Competitive – cooperative game

The experiment consists in 1 game of 200 trials.
In each, players can choose among 101 strategies from the most cooperative (0) to the most competitive (100). Players will then evaluate how much their choice was appropriate, through examination of four numbers, which are provided by the computer:

- YOU = N of points you won or lost on current trial.
- TEAM = Average N of points all players won or lost.
- YOU TOTAL = Your cumulative N of points.
- TEAM TOTAL = Team's cumulative N of points.

1) If all players choose to cooperate (strategy 0), they each will receive 50 points and the Team will also receive 50.
2) If all players choose to compete (strategy 100), they each will lose 50 points and the team will also lose 50.
3) If one player chooses 0 while the other 8 all choose 100, the one who chose 0 will lose 128 points and the others will lose 28 points.
4) If 8 players choose 0 while only one chooses 100, the 8 will receive 28 and the other one will receive 128 points.

You can see that the most competitive individual always does better, but competitive players gain points only if all others choose cooperative strategies.

Example:

	Player 1	Player 2	Player 3	Player 4	Player 5	Player 6	Player 7	Player 8	Player 9	Team
Chose	0	0	0	0	0	0	0	0	0	
Score	50	50	50	50	50	50	50	50	50	50
Chose	100	100	100	100	100	100	100	100	100	
Score	-50	-50	-50	-50	-50	-50	-50	-50	-50	-50
Chose	0	100	100	100	100	100	100	100	100	
Score	**-128**	-28	-28	-28	-28	-28	-28	-28	-28	-39
Chose	100	0	0	0	0	0	0	0	0	
Score	**128**	28	28	28	28	28	28	28	28	39
Chose	90	80	70	60	50	40	30	20	10	
Score	40	30	20	10	0	-10	-20	-30	-40	0

The bold numbers define the range of the best and worst possible individual result

Aim of the game:

If TEAM TOTAL is above 0 in the end of the game, the 4 top players will win: First:$8
Second:$6 third:$4 Forth:$2

- When you begin the game your PC ask your name first: Pay attention to confirm your name typing "*yes",* not just "*y*".
- After you have typed your number (0-100, your chosen strategy), you will see "wait…"on your screen. When all the other players also finish, you will see the scores.

- Here's how to interpret the scores:

1) *Score at…*(number). This is a count down of the remaining trial (the game finishes with score at 0).
2) The difference between YOU and TEAM gives you an idea of your trial performance compared to others.
3) The difference between YOU TOTAL and TEAM TOTAL gives you an idea of your cumulative game situation compared to others. At the end of the game the 3 players with the higher YOU TOTAL score will win money but during the game the only thing that you can know is your position with respect to the average (TEAM TOTAL).
4) Remember: If the TEAM TOTAL is less than 0 in the end of the game, nobody wins and no money will be awarded - so part of your strategy should be to monitor the TEAM TOTAL and try to keep it above zero.

During the game you can only watch your monitor (you should not look at other's screens, or communicate with other players), but the next page provide you an example of a game with only two players:

- On the left half of the page there is what John sees on his monitor.
- On the right half of the page there is what Jack sees on his monitor.

Before we start the game, we will talk about the example and have a practice game, with 100 trials. During this period you can stop and ask questions, but you can't do that after the game starts.

If you type an invalid entry the program will detect it and allow you to re-enter a number, but if you type a valid number before receiving the feedback the program accept and keep it for the next trial.

JOHN'S MONITOR

```
Enter your name: John
Is it correct? [yes/no] yes
Insert a number from 0 to 100
50
Wait...
Score at 5: You:0 - Team:0 - You total:0 - Team
total:0
Insert a number from 0 to 100
100
Wait..
Score at 4: You:-50 - Team:-50 - You total:-50 -
Team total:-50
Insert a number from 0 to 100
0
Wait...
Score at 3: You:50 - Team:50 - You total:0 - Team
total:0
Insert a number from 0 to 100
100
Wait...
Score at 2: You:50 - Team:0 - You total:50 - Team
total:0
Insert a number from 0 to 100
10
Wait...
Score at 1: You:30 - Team:35 - You total:80 - Team
total:35
Insert a number from 0 to 100
80
Wait..
Score at 0: You:-40 - Team:-35 - You total:40 -
Team total:0
umbc7[2]%
```

JACK'S MONITOR

```
Enter your name: Jack
Is it correct? [yes/no] yes
Insert a number from 0 to 100
50
Wait.
Score at 5: You:0 - Team:0 - You total:0 - Team
total:0
Insert a number from 0 to 100
100
Wait.
Score at 4: You:-50 - Team:-50 - You total:-50 -
Team total:-50
Insert a number from 0 to 100
0
Wait.
Score at 3: You:50 - Team:50 - You total:0 - Team
total:0
Insert a number from 0 to 100
0
Wait..
Score at 2: You:-50 - Team:0 - You total:-50 -
Team total:0
Insert a number from 0 to 100
20
Wait..
Score at 1: You:40 - Team:35 - You total:-10 -
Team total:35
Insert a number from 0 to 100
90
Wait
Score at 0: You:-30 - Team:-35 - You total:-40 -
Team total:0
umbc7[2]%
```