The Evolution of Imitation

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Abstract

The model developed in this paper considers a population in which a proportion m is consituted of pure imitators and a proportion $(1 - m)$ is constituted of informed agents who take their decision on the sole basis of their private but noisy signal. We study the evolution of this population. We show that m follows a cyclical dynamics. In a first phase, imitative agents obtain better payoffs than informed agents and m increases. But when m reaches a certain threshold, imitation gives rise to a "bubble": the collective opinion does not reflect anymore the economic fundamentals; it reflects others' opinion. When this situation is revealed, m rapidly decreases: the bubble bursts out and a new cycle begins. In this model herd behavior is analyzed as the consequence of informational influences.

KEY WORDS: Imitation, Informational Influences, Bubble, Evolutionary Dynamics, Diffusion Process.

1. Introduction

A lot of recent work has been devoted to informational influences and informational cascades. They have demonstrated that imitation can be a rational behavior: in certain circumstances, it is preferable to conform to the behavior of preceding individuals than to act in accordance with your own private information.

Such a situation leads to "informational cascades" (Banerjee (1992), Bikhchandani, Hirshleifer & Welch (1992)): "An informational cascade occurs when it is optimal for an individual, having observed the actions of those ahead of him, to follow the behavior of preceding individuals without regard to his own information" (Bikhchandani *et al.*, p. 994). This result has been obtained within a sequential model where individuals enter the market one by one, observe their predecessors and take a unique and irreversible action. The order of entering is exogeneous and is known to all.

In preceding works (Orléan (1995, 1998a, 1998b)), I have tried to enlarge these results. I have studied the role of imitation in non-sequential situations where agents are interacting simultaneaoulsy and modifying their decision at each period of time. Such a decision structure is better suited for the modelling of market situations. On financial markets, in particular, all the agents are always present and they revise their opinion in a continuous mode, and not once for all. It has been shown that, in such a framework, imitation is ambivalent (Orléan (1998a, 1998b)): it is rational to imitate as long as the proportion of imitators is smaller than a certain threshold. This result is quite intuitive: it is efficient for me to imitate the others as long as they are better informed than I am; it becomes inefficient if they are also imitators. Section 2 recalls this result. In previous works, I have considered models in which all the agents follow a given mixed strategy: they imitate the group with probability μ and follow their own private information with probability $(1-\mu)$. In the present chapter, I consider a polymorphic population in which a proportion m of the population is constituted of pure imitators and a proportion $(1-m)$ is constituted of "informed agents", acting on the sole basis of their own private information. We note $[M]$, the "mimetic" strategy, and $[I]$, the "informed" strategy. Section 2 shows that there exists an optimal level of imitation, called m^*. If $m < m^*$, an increase in the proportion of imitators will improve the individual and collective efficiency of the group. But, if $m > m^*$, imitation is no longer efficient. It can lead to situations where the group average opinion is far from the true state of the world. Because m is a given parameter, only comparative statics can be made in the frame of section 2.

In section 3, m is no longer a given parameter because agents can modify their strategy. To model this process, we introduce a rule akin to the replicator dynamics used in evolutionary economics. Agents learn from past experience: they compare the observed performances of the two strategies $[I]$ and $[M]$ and select the best one. Does this evolutionary process converge to m^*? We show that this process does not converge to such a situation. It converges towards a cyclical dynamics. This is the main result of the present article: m does not reach an equilibrium value. Why? The argument can be sketched the following way. When the state of the world, named θ, remains constant, m will increase because, in a stable environment, being an imitator gives better results than deciding on the basis of a private but noisy signal. m can even reach the level of 100% if θ is staying constant during a sufficient long period of time. But when the state of the world is changing, being an imitator is no longer efficient as soon as the majority of the population is also constituted of imitators. It follows that m will rapidly decrease. When m has reached a sufficiently low level, the collective opinion of the group is again determined by the informed agents. Then we are back to the initial situation and m will increase. This cyclical pattern is a direct consequence of the ambivalent nature of imitation: "To be an imitator when the others are not and to rely on his private information when others are imitators" is a rule that cannot be generalized without contradiction. It leads to wide swings in the market opinion. This behavioral assumption seems specially well suited to financial situations.

2. The Basic Model

We consider an economy composed of N agents, named $i \epsilon \{1, 2, ..., N\}$. The state of the world is a random variable named θ: θ can be equal either to $\{H\}$ or to $\{L\}$ with equal prior probabilities. Individuals have to discover the right value of θ. Their action will be noted either (H) or (L). In order to determine their action, agents can follow two different strategies, namely $[I]$ and $[M]$. They are defined as follows.

The first one, called $[I]$, consists in observing a random signal σ whose values, either $\{+\}$ or $\{-\}$, are linked to θ through the following conditional probabilities:

$$\begin{cases} \mathrm{P}(\sigma = + \mid \theta = H) = \mathrm{P}(\sigma = - \mid \theta = L) = p > 0.5 \\ \\ \mathrm{P}(\sigma = - \mid \theta = H) = \mathrm{P}(\sigma = + \mid \theta = L) = 1 - p < 0.5 \end{cases} \tag{2.1}$$

The closer p is to one, the more precise is the signal. Agent i's private information σ_i is defined as an independent observation of the signal σ. It is easy to show that, according to Bayes' rule, the probability that $\{\theta = H\}$ when the agent observes $\{+\}$ is equal to:

$$\mathrm{P}(H \mid \sigma_i = +) = \mathrm{P}(H \mid +) = \frac{\mathrm{P}(+ \mid H) \cdot \mathrm{P}(H)}{\mathrm{P}(+)} \tag{2.2}$$

with:

$$\mathrm{P}(+) = \mathrm{P}(+ \mid H) \cdot \mathrm{P}(H) + \mathrm{P}(+ \mid L) \cdot \mathrm{P}(L)$$

Knowing that each state is equiprobable, agent i obtains:

$$\mathrm{P}(H \mid +) = p_i \qquad \text{et} \qquad \mathrm{P}(H \mid -) = 1 - p_i \tag{2.3}$$

with p_i, the evaluation made by agent i of $p = P(+ \mid H)$. We will suppose that each agent knows the right value of p. It follows that the I-player chooses (H) when he observes $\{+\}$ and (L) when $\{-\}$ is observed.

The second strategy, called $[M]$, consists in following the majority: the M-player chooses (H) when the proportion of agents having chosen (H) is greater than 1/2. If we note by n the number of individuals having chosen (H), and $f = n/N$ the proportion of such choices, M-agent's choice is then equal to (H) when $\{n > N/2\}$, is equal to (L) when $\{n < N/2\}$ and is equal either to (H) or to (L) with probability 0.5 if $\{n = N/2\}$.

Let us consider a "polymorphic" population formed of I agents making their choices according to the strategy $[I]$ and M agents following the strategy $[M]$. We have $N = I + M$. We note m the proportion of imitative agents: $m = M/N$. We call nih, the number of I-agents who have chosen (H) and nmh, the number of M-agents who have chosen (H). It follows that the global number of agents having chosen (H) is $n = nih + nmh$.

To understand how these variables evolve through time, we have to precise the dynamical process of interaction. At each date (t), the population is determined by 3 numbers: m, nih, nmh. In this section we will suppose that m is held constant. It follows that the state variable is $s(t) = [nih(t), nmh(t)]$. At time $(t = 1)$, the value of s is given by: $s(1) = [nih(1), nmh(1)]$. At each time $(t + 1)$, an individual is randomly drawn within the population. If he is from I-type, he observes σ_i and makes his choice according to the strategy $[I]$. If he is from M-type, he observes $n(t)$ and then makes his choice according to the strategy $[M]$. If follows that the variable $s(t) = [nih(t), nmh(t)]$ follows a Markovian process defined by the following transition probabilities:

$$\begin{cases} P[(nih, nmh) \to (nih+1, nmh)] = \dfrac{I - nih}{N} P(\theta) \\ \\ P[(nih, nmh) \to (nih-1, nmh)] = \dfrac{nih}{N}[1 - P(\theta)] \\ \\ P[(nih, nmh) \to (nih, nmh+1)] = \dfrac{M - nmh}{N} P(n) \\ \\ P[(nih, nmh) \to (nih, nmh-1)] = \dfrac{nmh}{N}[1 - P(n)] \end{cases} \quad (2.4)$$

with $P(\theta)$ being the probability of chosing (H) when the agent follows the strategy $[I]$, i.e. of observing $\{+\}$:

$$P(\theta) = \begin{cases} p & \text{if} \quad \theta = \{H\} \\ \\ 1-p & \text{if} \quad \theta = \{L\} \end{cases} \quad (2.5)$$

and $P(n)$ being the probability of chosing (H) when the agent follows the strategy $[M]$:

$$P(n) = \begin{cases} 1 & \text{if} \quad n > \frac{N}{2} \\ \\ 1/2 & \text{if} \quad n = \frac{N}{2} \\ \\ 0 & \text{if} \quad n < \frac{N}{2} \end{cases} \quad (2.6)$$

What is the asymptotic behavior of this Markov chain? Because the transition matrix is given by equations (2.4), it is possible to determine exactly the stationary distribution when the process is ergodic. In (Orléan, 1998a), such a way is followed in a similar but easier situation. Here we will present our results in a more intuitive manner. Firstly, let us remark that, within the sub-population of I-agents, the probability to choose (H) is a constant, either p or $(1-p)$, depending on the state of the world θ. Then it is easy to determine the stationary distribution followed by $fih = nih/I$. It is a binomial law of parameter $P(\theta)$:

$$\begin{cases} E(fih|\theta) = P(\theta) \\ \\ Var(fih|\theta) = \dfrac{P(\theta) \cdot [1 - P(\theta)]}{I} \end{cases} \quad (2.7)$$

From now on, we will suppose that $\theta = \{H\}$. The properties of the system when $\theta = \{L\}$ can be infered easily from this analysis. It follows from equation (2.7) that $E(nih|H) = (1-m)pN$ with $p > 0.5$.

Secondly, let us consider the M-population. How will the group of imitators behave? If the proportion of informed agents having chosen (H) is greater than $1/2$, all the imitative agents will choose (H). If we consider that nih/N is close to $(1-m)p$, it follows that, when $(1-m)p$ is greater than $1/2$, all the M-agents will choose (H). Then the proportion of agents having chosen (H) will be equal to $(1-m)p + m$. This intuition can be rigorously demonstrated. When $(1-m)p$ is strictly greater than 0.5, i.e $m < m^* = 1 - \frac{0.5}{p}$, the Markovian process is ergodic: it tends towards an unique stationary distribution. This stationary distribution has a unique mode in $s_I = [(1-m)pN, mN]$. The proportion of agents having chosen (H) in s_I is equal to f_I:

$$f_I = (1-m)p + m = p + m(1-p) \tag{2.8}$$

When θ is evolving, this peak will be noted $f_I(\theta)$ to avoid any confusion. It follows that $f_I(H) = (1-m)p + m$ and $f_I(L) = (1-m)(1-p)$.

Because the variance of the stationary distribution is very small when N is great, the asymptotic values of f will stay in the neighborood of f_I. It follows that, when $\theta = \{H\}$, an adequate evaluation of the collective performance of the group is given by f_I. The more f_I is close to 1, the greater is the efficiency of the group because, in such a situation, almost every agent has done the right choice (H). When $\theta = \{L\}$, an adequate measure of the efficiency of the group evaluation is given by $(1 - f_I)$, i.e. the proportion of agents having chosen (L). It should be noted that $f_I(H) = 1 - f_I(L)$: the performance of the group does not depend on the state θ.

Equation (2.8) shows that the collective performance of the group increases when the proportion of imitators m grows. It is easy to understand. When m is smaller than m^* and f is close to f_I, the collective opinion given by f is a more accurate signal than σ because it aggregates all the private information. Thus choosing on the ground of f leads to better results than collecting information: in such a situation, when you are an imitator, the probability to make the right choice is equal to 1 but when you are an I-agent, the probability to make a right answer is only equal to p. Hence the collective performance is improving when the proportion of imitators grows. But what happens when the proportion of imitators is getting too large? Is the collective opinion remaining a better signal than the private information?

If m is getting greater then m^*, $E(nih) = (1-m)pN$ is no more greater than $N/2$. The I-agents having chosen (H) do not constitute anymore a majority. They need some individuals of the M-group to form a majority. But M-agents will choose (H) only if (H) has already been chosen by a majority! Here we face a vicious circle. It can be shown that two states can be obtained. If the M-group chooses (H), the opinion (H) will be majoritary and the M-agents' choice is validated. The proportion of (H) will then be equal to f_I as in the preceding situation. But the M-group can also choose opinion (L). In such a situation, this opinion will be majoritary and the M-agents' choice is again validated. The proportion of (H) will be equal to $(1-m)p$. In others terms, when m is greater than m^*, imitation can give rise to a self-validating process. It is the imitators' choice which determine the majoritary opinion that they will follow!

Another difficulty appears when m is getting greater than 0.5. In that case, once a unanimity is obtained within the M-population, it can not be destroyed anymore. The Markovian process is no longer ergodic. The probability to go from f_I to f_M (or from f_M to f_I) is equal to 0 and there are two stationary distributions.

These intuitions can be rigorously demonstrated. When $m^* < m < 0.5$, it can be shown that the process remains ergodic but the stationary distribution has become bimodal. The first mode is $s_I = [(1-m)pN, mN]$, the same as the one obtained when $m < m^*$. But a second mode appears: $s_M = [(1-m)pN, 0]$. The proportion of agents having chosen (H) is respectively equal to:

$$\begin{cases} f_I(H) = (1-m)p + m & \text{when } s = s_I \\ \\ f_M(H) = (1-m)p & \text{when } s = s_M \end{cases} \tag{2.9}$$

When $\theta = \{L\}$, we obtained the following values:

$$\begin{cases} f_I(L) = (1-m)(1-p) \\ \\ f_M(L) = (1-m)(1-p) + m \end{cases} \tag{2.10}$$

When $m > 0.5$, the Markovian process is no longer ergodic. There are two stationary distributions. Each of them is unimodal. The two modes are the same as in equation (2.9).

These results show that imitation is ambivalent. It can lead to two different kinds of dynamics: a first one is efficency-improving. Through imitation agents have access to the global information. But as soon as imitation reaches a certain threshold, a new dynamics appears. In this dynamics, imitation gives rise to a self-validating process. Imitation is no more efficient. It leads to what can be called a "bubble" because the average collective opinion is deconnected from the fundamental information σ.

To illustrate this result, let us consider a situation where m is smaller than m^*; for example $p = 0.7$, $m = 0.2$ and $N = 100$. Figure 1.1 shows the way f is evolving when θ is changing every 1000 periods. Here imitation is efficient. f converges towards $f_I(\theta)$. $f_I(\theta)$ is such that always more than $p\%$ of the population makes the right answer. When θ is changing from $\{H\}$ to $\{L\}$, the side of the majority of the population is evolving conformly to the state of the world, from $f_I(H) = 0.76$ to $f_I(L) = 0.24$. Without imitators, the proportions would have been respectively 0.7 and 0.3. Imitation allows better performances. If we look at figure 1.2, we can see how the M-agents form their choice. After a certain time, a unanimity on the right choice always emerges. We have supposed $nmh(1) = 0$.

When m is getting greater than m^*, the situation is quite different because the stationary distributions are bimodal. Figures 2.1 and 2.2 show what happens when $m = 0.80$, $p = 0.7$, $N = 100$. Two situations can be obtained depending upon the initial value. When $nmh(1) = 80$ and $\theta = \{H\}$, f converges to the neighborood of $f_I(H) = 0.94$ (figure 2.1). This situation is better than the one obtained in the preceding case (0.76): a greater number of agents have chosen the right answer. But they are acting this way for a bad reason: because they are conforming mostly to the group opinion. This appears when θ changes from $\{H\}$ to $\{L\}$. In this situation f is moving from $f_I(H)$ to $f_M(L) = 0.86$, the bad mode of the stationary distribution. The collective performance is then very low: only 14% of the population has found the right answer (L). If $nmh(1) = 0$ and $\theta = \{H\}$, f converges to the neighborood of the other mode, $f_M(H) = 0.14$ (figure 2.2). When θ is changing, f is oscillating between $f_M(H) = 0.14$ and $f_I(L) = 0.06$. The population is locked in a situation where opinion (H) is minoritary.

Thus, when m is greater than m^*, the population is no more sensitive to the variation of the fundamental information: we observe a self-sustaining dynamics, i.e. a "bubble". In such a situation the number of imitators which has chosen (H) (figure 2.1) or (L) (figure 2.2) does not change: it is always equal to 80 because the number of I-agents changing their choices in accordance with their private information is too small to influence them.

3. Imitation as an evolutionary dynamics

In this section the number of M-agents is not held constant anymore. We introduce a learning process: agents have the possibility to modify their strategy in accordance with the observed relative performances. This process of selection is modelled as a dynamics akin to the replicator dynamics used in evolutionary economics. We consider a succession of rounds. A round is defined as a succession of D periods. The jth round lasts from $\{t = (j-1)D + 1\}$ to $\{t = jD\}$. During the $(D-1)$ first periods of this round, the number M is held constant and will be noted $M[j]$, i.e. the number of M-agents during the jth round. During these $(D-1)$ first periods, the evolution follows the Markovian process determined in (2.4). We can then calculate the relative performance of the two strategies. In order to do that we compare the proportion of right answers allowed by both strategies. If DI and DM are, respectively, the number of I-agents and the number of M-agents which have been drawn, with $(D-1) = DI + DM$, then the performance of the strategy $[M]$ relatively to $[I]$ can be defined by the following variable:

$$X[j] = \frac{UM}{DM} - \frac{UI}{DI} \tag{3.1}$$

where UM and UI are respectively the number of M-agents and the number of I-agents having made the right choice[1]. Because of our definitions, it is easy to see that, in average, UI/DI is equal to p whatever the value of θ. UM/DM equals 1 when the majority is on the right side and equals 0 when the majority is on the wrong side. $X[j]$ will oscillate approximatively between 0.3 and -0.7. Its exact value will depend upon the random draws which have been made. The selection process takes place in the last period of the jth round. Then agents observe the value of $X(j)$ and modify their strategy according to the following equation:

$$\begin{cases} M[j] = M[j-1] + kX[j] & \text{if} \quad 0 < \underline{M} \leq M[j] \leq \overline{M} < N \\ M[j] = \underline{M} & \text{if} \quad M[j-1] + kX[j] < \underline{M} \\ M[j] = \overline{M} & \text{if} \quad M[j-1] + kX[j] > \overline{M} \end{cases} \tag{3.2}$$

[1] $X[j]$ is only defined when DI and DM are both different from 0. If DI or DM is equal to 0, $X(j)$ is assumed to be equal to 0.

If $X[j]$ is positive (resp. negative), the number of the M-agents increases (resp. decreases)[2]. k specifies the strength of the selection process. When k is great, many agents are modifying their strategy. The values $\underline{M}$ and $\overline{M}$ are introduced in order to avoid absorbing states. We want the number of each group being greater than a certain minimum ($\underline{M} = N - \overline{M}$). The probability of drawing each strategy is always strictly positive at each period (t).

The stochastic dynamics defined by equations (2.4), (3.1) and (3.2) is too complex to be solved analytically. It is thus studied by way of numerical simulations. The central question is to what asymptotic value does M converge? The optimal value is equal to $M^* = m^* N$: for smaller values, the efficiency of the group will be smaller because f_I (equation (2.8)) is an increasing function of m; for greater values, "bubbles" occur. Does M converge towards M^*? In order to calculate the asymptotic value, we have to consider a process in which θ is changing. It is then possible to study the adaptation of the group. We assume that θ is following a cyclical dynamics: it is changing every T periods[3]. The way the population adapts itself is depending upon the value of T, as we shall see now.

In a first simulation (figures 3.1 and 3.2), parameters' values are set as follows: $p = 0.7$, $N = 100$, $M(1) = 20$, $nih(1) = 56$, $nmh(1) = 0$, $D = 20$, $k = 2$ and $T = 1000$. Our main result is that the process does not converge towards an equilibrium. The proportion of the M-agents measured by the variable $m(t)$ is following a cyclical pattern as can be seen in figure 3.1. When $\theta = \{H\}$, from ($t = 1$) to ($t = 1000$), $X(j)$ is approximately equal to 0.3 because the opinion (H) is majoritary. Strategy [M] is doing better than strategy [I]: $M(t)$ increases from $M(1) = 20$ to $M(1000) = 54$. When θ becomes equal to $\{L\}$ at ($t = 1001$), the situation is profoundly modified. Because the majority believes in (H), the value of $X(j)$ is becoming negative ($\simeq -0.7$) and the proportion of M-agents is decreasing. This decrease will continue as long as (H) is majoritary. But in order for the opinion (L) to become majoritary, it is necessary that the number of the I-agents which have chosen (L), noted nil, becomes greater than $N/2$. Because nil is approximatively equal to $(1 - m)p$ when $\theta = \{L\}$, this is possible only if m decrease until it reachs approximately $m^* = 0.29$. When this value is obtained, m will increase again because $X(j)$ is now positive: the right answer (L)

[2] Of course, we have $I[j] = N - M[j]$. During the last period of the round ($t = jD$), the proportions of (H) and (L) are held constant: $\dfrac{nih(jD)}{I[j]} = \dfrac{nih(jD-1)}{I[j-1]}$.

[3] According to the spirit of the model, θ should follow a stochastic process. But, to study the analytical properties of the system, it is easier to assume a deterministic cyclical dynamics.

is majoritary. The same dynamics is repeating itself when θ is changing again: m decreases until it reaches m^* then it increases until the next change of θ. Figure 3.2 shows the way f evolves. It oscillates between $f_I(H)$ and $f_I(L)$ but these values are themselves evolving (equation (2.8)) because m changes over time. What happens when we consider a process with a greater T? Does a longer period of stability help the population to adapt more efficiently? In order to answer this question, we consider the same process but with $T = 3000$.

The main difference with the preceding case lies in the fact that the phase during which m is increasing is now longer. It follows that m will reach $\overline{m} = \overline{M}/N = 0.99$. Figure 4.1 shows such a dynamics. From ($t = 2000$) until ($t = 3000$), almost every agent chooses strategy $[M]$. But this quasi-unanimity on $[M]$ falls apart when θ changes from $[H]$ to $[L]$, and a pattern such as the one in figure 3.1 appears: m decreases until m^* is (approximately) reached. When this value is obtained, m will increase again until it attains $\overline{m}$. Figure 4.2 illustrates the dynamics followed by f. A comparison with figure 3.2 shows that the process is more efficient when T is greater because unanimity on the right choice is always obtained[4].

The relation between global efficiency and the value of T is confirmed by figures 5.1 and 5.2 which show what happens when $T = 200$. Because the population has not enough time to adapt, the value of m decreases and stays in the vicinity of $\underline{m}$. Then f is oscillating around 50% as can be seen in figure 5.2.

4. Conclusion

Imitation appears as a complex phenomenon. It improves the global efficiency as long as it stays below a certain threshold m^*: relying on imitation is rational only if the collective opinion is well informed enough. Nevertheless, if the environment is stable, the proportion of imitators will grow and go above this threshold. Why? Because imitative agents obtain better payoffs than informed agents as soon as the state of the world is remaining stable for a sufficient long period. But when the proportion of the imitators becomes greater than m^*, the economy is no longer able to adapt efficiently to changes in its environment. In such a situation, the collective opinion does not reflect anymore the actual state of the economic fundamentals: it reflects others' opinion. Mimetic behaviors dominate the market. Such a process gives rise to what has been called a "bubble". As soon as this situation is revealed,

[4] The evaluation of efficiency integrates the time necessary to go from unanimity on one opinion to unanimity on the other one.

the value of m will rapidly decrease until it reaches m^*: the bubble bursts out and a new cycle begins.

This schematic model thus explains alterning phases of efficient or semi-efficient regims (when m is below m^*) and pathological ones (when m is greater than m^*). Herd behavior is here a consequence of informational influences. In our perspective, the spreads of imitation and the emergence of a bubble are not the consequence of some collective irrationality. They are the result of a behavior which would be rational if it is was not generalized.

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