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Paradigm shifts

Pierre-André Guy Maugis

Abstract

The author studies the evolution of the number of coexisting beliefs in a financial market in a framework where the paradigm driving the agents' behavior is left unspecified. The overreaching aim is to gain insights regarding the dynamic of the variety of beliefs in an auction based financial market independently of any assumptions on agents' behaviors. The resulting framework may be seen as an abstract agent based model. In a computer experiment he exhibits a cycle between two states, so that either all agents act according to the same belief, or there is no leading belief; i.e., there is one dominating belief, or none. Further, he finds that the frequency of this cycle is positively linked to the quality of the information available to the agents.

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1 Introduction

We provide an assumption free framework to study the fundamental dynamic of the heterogeneity of beliefs in financial market. We do so by building upon the agent based modeling framework.

From a general abstract perspective, the heuristic of agent based modeling is to first create a copy of a financial market, and then to use this copy as proxy to infer properties of a real financial market. The copy is built on two main components: a set of agents and a market structure. Then, as in a real financial market, agents are allowed to interact with each other and the market structure, allowing for experiments can be performed, and phenomenon of interest observed. The finality of this process is that, assuming that the constructed copy is a satisfying replicate of a real financial market, we can draw inference on how events occur in real markets. See for instance [Arthur et al. \(1996\)](#) and [Huang et al. \(2005\)](#), and [LeBaron \(2006\)](#) for a review.

The market structure component of an agent based model usually replicates a structure commonly found in financial markets, and as such does not raise modeling issues; we will here work on a batch auction market. The agent component and especially how and why agents act and interact is on the other hand a modeling issue. Our view is that as few assumptions or parametric restrictions should be made on this regard as they might be violated by unforeseen behavior and motivations on the part of the agents ([Shiller, 1999](#)).

2 Framework Elicitation

To make minimal assumption regarding agents behavior, we make the following reasoning. We deconstruct the expression of a behavior as a three step process: first information is perceived, then this information is processed, and finally a behavior is expressed. The transformation at the center of this process, that goes from information to behavior, is what could be loosely referred as an agent's belief, but that we define here as an agent's *paradigm*.

Within this deconstruction, there exists an infinite number of possible paradigms. In its broadest sense, a paradigm may encompass the agent belief in one economic or financial model, his experience of financial markets, his risk appetite, and so on. However, since there exists only a finite number of agents at a given time, we can approximate all currently used paradigms arbitrarily well by n paradigms.

Likewise, this approach allows for an infinite number of different kind of information to be perceived; especially since here the perceived information also contains information that might have been obtained by interacting with other agents. However, for the same reason as above, we can approximate all currently perceived information by l bits of information.

Hence there exists in our framework only nl possible behaviors at a given time. Then, as in an agent based model, each of these behaviors will translate into placing an order at a specific price, or by abstaining to do so. Thus, if we order the nl behaviors, say through a random permutation, we can match the orders in any order book in our framework, and simulate auctions between our agents.

As such auctions take place, agent might change of paradigm. This may be random, or triggered by the model failing to produce a good price. Thus, if an agent's order is far from the auction closing price, and he had satisfactory information (to this end we will organize the information bits as satisfactory ones and dissatisfactory ones), he will have a probability p_1 of changing paradigm, he otherwise has a probability $p_2 < p_1$ of doing so.

We now explore using a computer experiment how the proportion of agents using each paradigm evolves as more auctions take place. Note that since our approach is based on an approximation we will in the following only report qualitative results.

3 Experiment Design

We now formalize the process described above. To do so we will have to distinguish both: between the n different paradigms, and between the l different information bits considered. To this end, we assign to each a number, respectively from 1 to n and from 1 to l , and refer to these numbers as paradigm index and information index. The simulation will require a few artifacts parameters, which we will find to have small or no effect on our results, as long as they take reasonable value, as in (Kirman, 1993; Alfarano et al., 2005).

Initialization: To each N agents (this number is static through time, and all N agents remain actors in the market throughout the process), we assign randomly a paradigm index and an information index. The paradigm index is drawn uniformly over $\{1, \dots, n\}$, while the information index is drawn

over $\{1, \dots, l\}$ using the probabilities $\{p_1^i, \dots, p_l^i\}$. These last values are parameters of the simulation. We then decide randomly which agents will take part in the next auction, each agent having the same probability p of participating (p is also a parameter of the simulation).

Auction: As explained in the introduction, there exists in our approximation nl possible behaviors, which translates into agents having the possibility of putting orders at nl different unknown possible values v_1, \dots, v_{nl} . By drawing a random permutation s over \mathfrak{S}_{nl} , we can order these values. We now assume that if an agent trades, he trades only one unit. Then we can infer the price that maximizes the number of trades and close the auction: $\forall k \leq nl$ we can compute the number o_k of order at the value v_k , so that the closing price is the price $v_{s(k^*)}$ with k^* such that:

$$k^* = \operatorname{argmin}_{1 \leq k \leq nl} \left\{ \left| \frac{N}{2} - \sum_{j=1}^k o_{s(j)} \right| \right\}.$$

Iteration: After the auction, agent are able to determine whether the information they possessed was satisfactory or not, this is made independently of the auction itself. Ignoring the case where the satisfactory bit of information is possibly different for each agent or paradigm, without loss of generality, we will assume that only the bit of information numbered 1 is satisfactory (this is possible since information indices are arbitrary). Then, for each agent we distinguish two cases: either he possessed the satisfactory information that produced $v_{s(k^*)}$, but put an order more than r rank away from it, or not (if an agent placed an order at $v_{s(k)}$, then we say that this order is more than r rank away from $v_{s(k^*)}$ if $|s(k) - s(k^*)| \geq r$; r is also a parameter of the simulation). In the first case the agent will change of paradigm index with probability p_1 , in the other he will change of paradigm index with probability p_2 ($p_2 < p_1$). In both cases the new paradigm index is drawn uniformly over all remaining paradigm indexes. Finally, new information indexes are drawn for all agents using the probabilities $\{p_1^i, \dots, p_l^i\}$ as in the initialization.

4 Experiment Results

We will now present the results obtained. To do so we will begin by presenting a representative example of produced dynamic. Then, using this example,

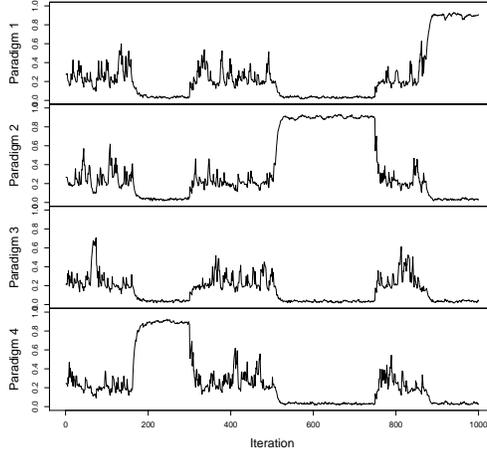


Figure 1: Proportion of agents using each paradigm in an example of 1000 iterations with $n = 4$ models, $l = 5$ bits of information, $N = 500$ agents. The probability of having satisfactory information is $p_1^i = 0.6$, the remaining parameters are $p = 0.9$, $p_1 = 0.9$, $p_2 = 0.05$, and $r = 1$.

we will introduced in more details the two states mentioned above: the homogeneous state where all agents share the same paradigm index and the heterogeneous state where there is no leading paradigm index. Finally, we will compute the probabilities of going from one state to the other for varied values of the parameters.

Representative dynamic example Our focus is the proportion of agents using each of the n paradigms through time. More precisely, using the procedure reported above, we will report the proportion of agent being assigned each paradigm index at each iteration. In Figure 1 we plot these proportions for a simulation of our framework (All computations are done in R (R Development Core Team, 2011).) In this example there are $N = 500$ agents, the number of models n is 4, the number of bits of information l is 5. The remaining parameters are as follows: the probability of having satisfactory information is $p_1^i = 0.6$, the probabilities of having unsatisfactory information (p_2^i to p_5^i) are 0.1, the probability p of entering a trade is 0.9 and finally $p_1 = 0.9$, $p_2 = 0.05$, and $r = 1$.

In this example the proportion of agents being assigned each paradigm

label is behaving differently from iteration 1 to 200 than from iteration 200 to 300. In the first window (1 to 200) there is no leading paradigm label, while in the second window (200 to 300), paradigm label four is consistently concentrating above 80% of the population. We will call the first state the heterogeneous state, and the other the homogeneous state. In this example the system repeatedly changes of state through time: approximately at iterations 200, 300, 500, 750 and 900. This type of dynamic is representative of what we obtained for a large number different parameters. It should be noted that such oscillations between two states corresponds to results found in other agent based models (Huang et al., 2005; Huberman and Glance, 1993; Guesnerie, 2002; Kirman, 1993).

Homogeneous & Heterogeneous States As the repartition of agents among paradigms at a given iteration is qualitatively well described by the state—homogeneous or heterogeneous—the system is in, it is of interest to us to evaluate the probabilities of the system moving from one state to the other. We therefore set p_o as the probability of entering the homogeneous state from the heterogeneous state. We likewise define p_e as the probability of entering the heterogeneous state from the homogeneous state.

To estimate p_o and p_e , we will simulate a large number of dynamic and average the estimates produced for each dynamic. More precisely, for a dynamic such as the one presented above, we construct from the series shown in Figure 1 an historic of the visited states (we characterize the homogeneous state by one paradigm gathering more than 80% of the agents for at least two iterations), and then use this historic to estimate of p_o and p_e .

Theoretically p_o and p_e are functions of all the parameters of the model. However, we report no qualitatively significant link between any of the parameters and these probabilities but for p_1^i , the probability of having satisfactory information. In our simulations we exhibit a positive link between p_1^i and p_o and $1 - p_e$. In Figure 2 we plotted p_o and $1 - p_e$ as functions of p_1^i and N . We observe that for all N the probabilities are qualitatively similar, but that they increase with p_1^i , the probability of possessing satisfying information.

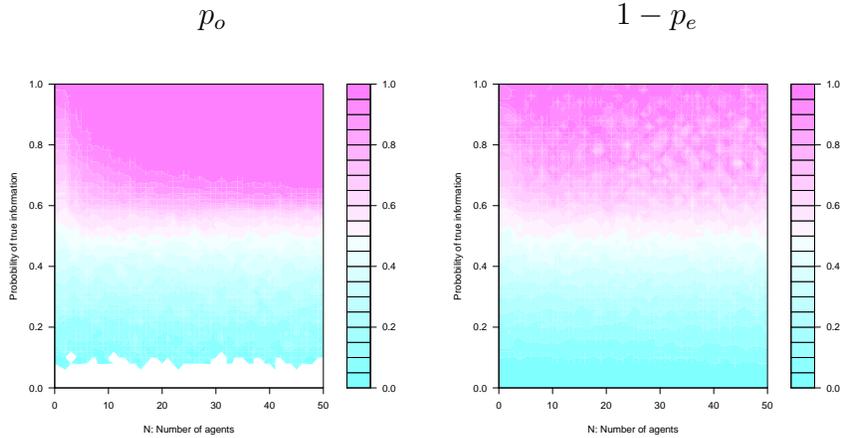


Figure 2: p_o and $1 - p_e$, each point estimated with 500 simulations of 1000 iterations.

5 Discussion

We observed that independently of all parameters, the system oscillates between two states: a homogeneous one, where all agents use similar paradigms; and heterogeneous one, where there is no leading paradigm. By its generality, and the simplicity of the framework it is elicited in, this result provides a deeper perspective to similar results found in different agent based models and in laboratory experiments; see [Huang et al. \(2005\)](#); [Huberman and Glance \(1993\)](#); [Guesnerie \(2002\)](#) and [Heemeijer et al. \(2009\)](#).

Further, we find that the quality of the information available to the agents is a key factor that determines the frequency of the oscillations between the two states. We argue that this is surprising, as it implies that better informed agents (agents having a higher probability of possessing satisfactory information), as a group, converge toward the riskier equilibrium. We say the homogenous state is risky, as then the stability of market is almost solely dependent on the used paradigm. Indeed, the leading paradigm is driving the market: if for instance the leading paradigm was a different one, say the paradigm labeled 1 instead of 3, the price dynamic generated might be completely different. On the other hand the heterogeneous state can be seen as less risky. As the group has a diversified set of used paradigms, heuristically the risk involved in using each paradigm is limited (since it is used by a small portion of the population) and might compensate each other (see [Huberman](#)

and Glance (1993); Easley and O'Hara (2010)).

A possible explanation is that the homogenous state allows to share information efficiently: in the homogeneous state, the system is much simpler (only one paradigm rather than many), and allows agents to communicate more efficiently (as they share the common ground of the having the same paradigm, see Shiller (1995)). Practically, as for instance through the use of implied volatility Dumas et al. (1998), if 'price=paradigm(information)', and paradigm is known, a price communicates information in as much as paradigm is invertible; i.e., writing 'information = paradigm⁻¹(price)'.

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