Analysis of Financial Markets with the Artificial Agent-based Model — NNCP*

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Abstract. The study of financial markets using agent-based computer simulations has grown considerably in the last few years. Artificial intelligence paradigms such as Neural networks, Genetic Algorithms and Classifier systems have played an important role in these developments. Here, a new artificial financial market (AFM) is presented — the NNCP — which can easily be configured to study different models of market organization and the role of various types of market participant. We use the model to study liquidity and volatility in a double auction market and a market order driven model with and without *market makers*. We also study the effect of heterogeneous use of information by informed traders in these different organizational models and the role of adaptation as a means of enhancing profits.

1 Introduction

Financial Markets (FMs) are complex, adaptive, dynamic systems; both at the level of their constituents and their interactions, as well as at the global level. Their study has recently attracted researchers from disciplines other than the traditional ones of economics and finance, such as artificial intelligence, statistical physics and complex systems. In particular, viewing FMs as an ecology of competing strategies (see for example [1]) provides natural bridges to other disciplines. Due to the difficulty of carrying out controlled experiments on real FMs agent-based AFMs have become a powerful tool in examining the processes and interactions that govern their dynamics. The most well known of these models is the Santa Fe AFM [2–5].

The AFM – NNCP – was motivated by the desire to include relatively neglected elements, such as the effect of organizational structure on market dynamics and the role of *market makers* and information. All of these elements are crucial in the formation of market microstructure [6]. Currently the NNCP can be used to study three different organizational models: double auction (with

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different variants for the auction rules); market orders without *market makers* and market orders with *market makers*. The market participants can be of various types: value or growth investors, informed or uninformed traders, *market makers* or *specialists*, and can dynamically evolve their strategies.

Here, we outline the basics of the NNCP model and present briefly some of the principal results derived so far. More details can be found in [7].

2 Description of the NNCP

A simulation is carried out for a prescribed number of *ticks* on a single risky asset. At each *tick* an agent takes a position (buy/sell/neutral) or a double auction is carried out. After each *tick* price is updated either exogenously, such as via a supply/demand type law as in (1), or endogenously as in the case of a market with *market makers*.

$$p(t+1) = p(t)(1+r_t)[1+\eta(B(t)-O(t))] \tag{1}$$

In this equation, which is common to many AFMs, $p(t)$ is price at *tick* t and $B(t)$ and $O(t)$ are the demand and supply at t. r_t is a bias in the price series which can be thought of as a continuous (reinvested) dividend stream or compensation for risk, while η is a tuning parameter.

2.1 Double Auction

In the double auction, at every *tick* each agent takes a position with an associated volume and at a given price, each agent being able to value the asset independently but with prices that are not too different. In this model price changes are induced only via the disequilibrium between supply and demand. Specifically:

1. At time t one lists all the positions taken by the agents and the associated volume and price. The agents bids and offers are obtained at time t via a Gaussian distribution with mean $\bar{p} = p(t-1)$.
2. A bid and an offer are matched only if they overlap, i.e. $p_b(t) > p_o(t)$. To realize a transaction two variants have been used: i) "*best bid/offer*" where the highest bid and the lowest offer are matched at their midpoint successively until there are no overlapping bids and offers. ii) "*equal bid/offer*" where only bids and offers at the same price are crossed, where equal price is considered up to cents, e.g. 17.1175 and 17.1235 are considered the same price.
3. Price is updated via (1) using only those bids and offers that are not matched and that have overlap, i.e. $p_b > p(t)$ and $p_o < p(t)$.

2.2 Market Order model

In this model an agent makes a bid/offer and waits until a matching order appears. If there are *market makers* in the market then they match the market order (at least up to a given volume) thus providing liquidity. In the contrary case the agent waits until another agent places a complementary order. In this case price is not only affected by supply and demand but also by the time the agent has to wait until the order is matched. The actual mechanics of this model in the case where there are no *market makers* consist of:

1. At each *tick* an agent is randomly chosen and his/her position noted.
2. Price is updated according to (1) where $B(t)$ and $O(t)$ are calculated taking into account all existing positions and their corresponding volumes.
3. To calculate the difference between supply and demand one uses a queue that contains the agents whose bid/offer has not been matched. This queue is time prioritized such that the first agent to take a position has the right to be matched first.

When *market makers* are present the mechanisms are different. A *market maker* quotes simultaneously a *bid* and an *ask* price, representing the prices at which he/she is prepared to buy and sell the asset. The *bid* price is higher than the *ask* in order to compensate the *market maker* for offering liquidity. The *montage* is the set of *bids* and *asks* of all the *market makers*. All transactions are carried out at the best quotes for a given volume. Specifically in the NNCP:

1. At each *tick* an agent is randomly chosen and the position and volume noted.
2. One searches the *montage* for the *market maker* offering the best complementary price at that volume.
3. Contrary to previous cases price is not updated exogenenously using an equations such as (1), but rather price corresponds to that of the last transaction. The *market makers* update their quotes after covering a transaction and the price in the next *tick* is that of the best *bid/offer* in the new *montage*.
4. The *market maker* pays for covering the transaction a fixed amount which represents in the real world the operational and administrative costs that a *market maker* faces.

Each *market maker* after realizing a transaction updates his quotes. Whether or not the other *market makers* update their quotes at the same time depends on their strategies. The latter consist of two types: "nervous" *market makers* are unsure of their quotes and update them every "tick" while "confident" *market makers* only update their quotes after realizing a transaction.

3 Market Participants and Information

NNCP agents are currently classified according to four different strategy types: technical strategies, fundamental strategies, random strategies and *market maker* strategies. The first two types use simple technical or fundamental analysis based rules to arrive at a position. Their strategies can be adapted using a classifier system. Random agents take a position randomly. *Market maker* strategies will be discussed in section 4.

The information that the agents possess is a crucial determinant of market behavior. Here we analyze the effect of information and, in particular, the effects of a non-homogeneous response to the *same* information by different agents. An explicit realization of this is to give to the random agents information about the bias r_t in the price evolution. Specifically, we define three types of informed trader:

- Short term speculators — where the position probabilities are:

$$P(c) = 1/3(1 + r_d D), \qquad P(v) = 1/3(1 - r_d D), \qquad P(n) = 1/3, \qquad (2)$$

  where r_d is the expected price increase per day and D is the time horizon of the agent in days. These agents are aware of the market bias r_d but in analogy with speculators in a real market these agents are not risk averse and try to obtain quick profits by exploiting short term price movements.
- Risk averse agents — where the position probabilities are:

$$P(c) = \frac{1}{2}(1-x)(1+r_d D), \qquad P(v) = \frac{1}{2}(1-x)(1-r_d D), \qquad P(n) = x. \quad (3)$$

  where x is a measure of the risk adversity in the sense that agents with x close to one make very few transactions. These agents are aware of the price bias but due to their passivity prefer to maintain their portfolios.
- Buy and Hold agents — where the position probabilities are:

$$P(c) = 1 \text{ if } S_i < S_t, \qquad P(c) = 0 \text{ if } S_i \geq S_t, \qquad P(v) = 0,$$
$$P(n) = 0 \text{ if } S_i < S_t, \qquad P(n) = 1 \text{ if } S_i \geq S_t, \qquad (4)$$

  where S_i and S_t are the actual and required number of units of the risky asset by the agent and $S_t = (1 + r_d)^x$, where x is once again proportional to the agent's horizon. These agents are aware of the price bias and choose to exploit it by buying as quickly as possible until their inventory requirement is satisfied and then maintaining their portfolio constant.

It is important to emphasize here the diversity that these different types of informed trader bring to the market. Even though they all receive the same information their response to it, as in a real market, is markedly different. In other words, once again as in a real market, they are not perfectly rational.[1]

4 Market Maker Strategies

One of the novel elements of the NNCP is the emphasis placed on *market makers*. One of our principal goals is to understand the role of market making within

[1] Such agents are known as *boundedly rational agents* [3] in the sense of rational expectations models.

the context of an AFM. In order to have *market makers* as active participants it is necessary to have them implement a strategy. Here, we introduce some elementary "toy" strategies with the same goal in mind as the other market participants — to maximize profits. We consider simple "toy" strategies in extremal situations in order to be able to identify the main characteristics and tendencies that will enter in the makeup of a more realistic strategy. We assume that each *market maker* places quotes according to a a *bid* and *ask* price (*pb* and *pa* respectively).

Monopoly : Given that the principle source of profit for *market makers* is the *spread* it's natural to suppose that a good strategy would be to increase the *spread* as much as possible. This strategy can be represented algorithmically as

$$pb(t+1) = \alpha pb(t), \qquad pa(t+1) = \beta pa(t), \tag{5}$$

with $\alpha < 1$ and $\beta > 1$. This strategy results in large short term gains for the *market makers* but is parasitic in nature leading to a collapse in the market when the investors exhaust their resources through excessive friction.

Extreme Competition: It is logical to think that a single *market maker* in the presence of monopolists could increase his/her order flow by placing quotes inside the *spread* of the other *market makers.* This strategy can be modeled by (5) with $\alpha > 1$ and $\beta < 1$. The success of this strategy depends on those of other market makers. Against monopolists the "competitor" wins. However, in the presence of another competitor the *spread* diminishes until it is not enough to cover costs and the competitors exhaust their resources. These two extreme strategies show that successful market making involves at the least an adaptive, time-dependent mix of monopolist and competitor strategies.

Random: Here the *market maker* makes quotes randomly within a maximum allowed *spread*. In some sense this strategy is a mix of the previous extreme strategies with variable values of α and β. Specifically,

$$pb(t+1) = p(t)[1 + (|\alpha|/100)], \qquad pa(t+1) = p(t)[1 - (|\beta|/100)] \tag{6}$$

where $p(t)$ is the price of the last transaction and α, β are random numbers. These *market makers* can only make profits when the "random" *spread* is greater than the transaction cost. The resultant price evolution from this strategy looks very similar to that of a real market.

Inventory Management: One of the principal concerns of a *market maker* is to dynamically maintain an inventory which permits him/her to remain in the market. With this in mind a reasonable strategy is to make quotes randomly when the inventory is within certain bounds and in the contrary case to make aggressive quotes, as in the case of a "competitor", until the inventory becomes

Table 1. Noinfo=20 uninformed agents. Spec, RiskAv and B& H=20 speculators, risk averse or Buy & Hold agents respectively. HetInfo=Mix of informed agents (of the three different types). HetNoinf=Mix of informed and uninformed agents.

Exp	r	Equal			Best			Morders		
		VT	V	V/VT	VT	V	V/VT	VT	V	V/VT
Noinfo	100	164.00	0.005	29.11	22407.20	0.002	0.07	13546.00	0.0002	0.02
Noinfo	7	179.00	0.008	46.27	22632.60	0.002	0.10	13673.80	0.0002	0.02
Spec	100	182.40	0.004	21.78	22492.60	0.002	0.07	13455.60	0.0002	0.02
Spec	7	174.20	0.005	31.18	22575.20	0.002	0.09	13667.40	0.0002	0.02
RiskAv	100	0.00	0.000	0.00	1.20	0.0002	203.33	0.00	0.000	0.00
RiskAv	7	0.00	0.000	0.00	0.20	0.0003	1865.00	0.00	0.000	0.00
B& H	100	0.00	0.002	0.00	0.00	0.002	0.00	0.00	0.0003	0.00
B& H	7	0.00	0.002	0.00	0.00	0.002	0.00	0.00	0.0003	0.00
HetInf	100	39.00	0.001	30.10	9053.20	0.001	0.13	5371.80	0.0002	0.04
HetInf	7	39.40	0.001	37.77	9170.40	0.003	0.28	5518.80	0.0002	0.03
HetNoinf	100	117.60	0.002	16.48	17548.80	0.002	0.09	10534.20	0.0002	0.02
HetNoinf	7	111.60	0.004	36.94	17734.20	0.002	0.12	10649.40	0.0002	0.02

rebalanced. Intuitively, this is a good strategy. However, the results strongly depend on the reactions of the investors to the quotes. The *market maker* has to make an effort to balance his/her inventory and this must be compensated by profits made when the inventory is within the required bounds.

5 Principal Results

The objective of the first set of experiments is to compare the relative efficiency of four different organizational models for the market and to investigate the effect of information and its use. The first experiments are for a market without *market makers*. In each experiment 20 agents were used with a mix of informed and uninformed strategies as outlined in section 3. Simulations were over 250 days. In the auction models (Equal and Best) 30 auctions/day were carried out and the value of η chosen was 0.05. In the market order simulations (Morders) there were 200 *ticks*/day giving rise to an average of 10 operations/day/agent. η was chosen in this case to be 0.0001. For each model two sets of experiments were carried out with values of r_t corresponding to annual increases of 100% and 7%. The first, extreme, value serves to identify if there is an effect or not, by working in a high signal to noise regime, while the second corresponds to annual returns in a typical real FM.

In Table 1 we see an average over five simulations for the volatility (V), transaction volume (VT) and their ratio (V/VT). Note that volume is larger in the auction associated with the "best", followed by the market orders model. In the case of an auction between "equals" volume is small. Volatility is of the same order of magnitude in the two auctions while it is an order less in the mar-

Table 2. HetInfo=Mix of informed agents (of the three different types), HetNoinf=Mix of informed and uninformed agents, SpecNoinf=Mix of speculators and uninformed agents. LPNoinf= Mix of long term B & H and uninformed agents.

‘ Exp	r	Equal			Best			Morders		
		S	B & H	U	S	B & H	U	S	B & H	U
HetInf	100	-313.26	939.782	0.00	-321.86	977.570	0.00	-341.13	1027.47	0.00
HetInf	7	-26.01	78.023	0.00	-1.40	0.413	0.00	-0.18	-0.06	0.00
HetNoinf	100	-137.80	772.348	-27.61	234.31	518.172	-94.23	71.65	309.60	-40.35
HetNoinf	7	-3.71	10.773	0.03	42.65	8.720	-10.50	38.78	2.29	-9.26
SpecNoinf	100	12.69	0.000	-4.23	-24.47	0.000	8.16	37.47	0.00	-12.49
SpecNoinf	7	7.00	0.000	-2.33	-0.50	0.000	0.17	15.14	0.00	-5.05
LPNoinf	100	0.00	911.218	-101.25	0.00	432.292	-48.03	0.00	336.83	-37.43
LPNoinf	7	0.00	20.422	-2.27	0.00	1.023	-0.11	0.00	9.26	-1.03

ket orders model. However, the more relevant measure, volatility/transaction, is similar in the market orders and “best” auction models while in the double auction between “equals” it is three orders of magnitude higher.

In all three models the results observed with speculators are essentially the same as with uninformed agents. This shows that the extra information in the hands of the speculators is not being put to good use. Markets with only risk averse or long term Buy & Hold agents lack liquidity. In the first case because nobody wants to trade while in the second case everybody wants to trade but nobody wants to take the counterpart. In the experiments with heterogeneous groups of agents we can see that the more informed agents there are the less liquidity there is and the higher the volatility. In table 2 we present the averaged results for profit/agent for the different strategies: Speculators (S), Buy & Hold (B & H) and uninformed (U). Risk averse agents are excluded as their profits in general are close to zero. Observe that long term Buy & Hold agents on average always have the highest gains. These are similar in the case of an auction between “equals” while in other models they diminish in accordance with the number of informed traders. Note that Speculators, on average, do not make profits relative to uninformed traders.

5.1 Adaptation

Adaptation of the agents is implemented using a simple Genetic Algorithm [8] the objective of which is to apply a selective pressure in order to select the strategy which best utilizes the information in the market at a given moment. Proportional selection is used where the fitness function is the wealth increase obtained during the evaluation period. Two variants were used: a) *copycat* — where the strategy search space for selection at time t is restricted to that of the agents that participate in the market at time t; and b) *analyst* — where the strategy search space for selection is the set of all possible strategies considered. Thus, in the first case the adapting agent looks to copy the most successful strategy currently in use while in the second the most successful possible strategy is searched for among all possibilities. Two type of experiment were carried out. In the first, two of the twenty agents were *copycat* agents while in the second one of the agents was an *analyst*. The parameters used – number of ticks, number of agents and η – are the same as in previous sections. Adaptation was carried out periodically at a frequency τ^{-1} with $\tau = 1$ day, 1 month and 6 months.

In general the success of an adapting agent depends on a combination of three parameters: the liquidity in the market model, the adaptation rate and the composition of the market. The latter influences heavily the information use of the rest of the market participants. The *copycats* lose when there is little liquidity as this prevents the clear statistical identification of a winning strategy. i.e. the *copycat* gets confused and follows "noise" rather than "signal". Additionally, even if the *copycat* identifies a winning strategy the low volume means that it is not easy to exploit it. In more liquid markets the *copycats* make profits when the adaptation period is less than 6 months and there exists in the market a good strategy to copy, such as buy & Hold. Even in this case however, the "noise" from other strategies can confuse the agent if there is no strong signal, such as is the case with $r_t = 100\%$ which gives a clear and recognizable advantage to the Buy & Hold strategy.

The *analyst* is not as affected by the liquidity of the market given that his/her analysis of strategies is not affected by it[2] and can determine which is the correct strategy to follow, at least in the sense that it is the strategy that leads to optimized profits in a given period. Interestingly, contrary to the *copycat*, this agent suffers if there exist Buy & Hold agents given that it is difficult to recover from the losses made during the period where he/she was determining what was the best strategy. In other words the Buy & Hold agents *started* with a strategy that used information optimally whereas the *analyst* had to learn it. The presence of speculators or uniformed agents benefits the *analyst* as he/she can make profits from their inferior strategies.

Both types of adaptive agent make profits relative to any agents other than Buy & Hold which is the optimal strategy. These profits increase as a function of the adaptation frequency. This reflects the canonical dilemma of exploration versus exploitation. An adaptation period of 1 day emphasizes more an exploration phase which leads to large profits when the market bias is high (100%), as the exploration in this case is very likely to find the optimal strategy. However, in the case of a low bias (7%) the exploration phase is very easily misled at high adaptation frequencies due to the low signal to noise ratio. An adaptation period of 1 month allows for a reasonable balance between exploration and exploitation. With a low adaptation frequency, such as 6 months, the adapting agents spend too much time checking what is a good strategy. Additionally, proportional selection introduce an extra "noise" element thus potentially confusing further the recognition of signal versus noise.

[2] He/she is in fact considering a type of virtual market within a virtual market!

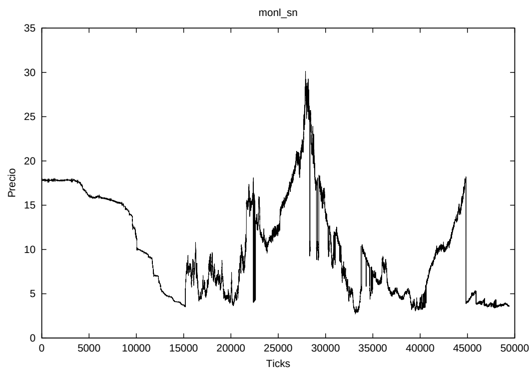

Fig. 1. Graph of price for market with *market makers.*

5.2 Markets with Market Makers

In the experiments with *market makers* 20 uninformed agents were included along with 5 *market makers* employing a range of strategies. In this case, as mentioned, price evolution is autonomous as price is that of the last transaction and this is governed by the *market maker* strategies. In Fig. 1 one sees a typical price series. One can clearly see the market passing through distinct phases. Initially, the "competitors" dominate the market trying to attract the order flow at the expense of the others. Meanwhile, the *spread* decreases until the "competitors" exhaust their resources. At this point the "random" *market makers* take over the order flow by providing the best quotes. Eventually, essentially by a process of "neutral drift", they too exhaust their resources and the monopolists are the sole survivors.

Except for the monopolists all the other *market maker* strategies lose. These losses have two sources: transaction costs and price decreases. The monopolists, given time, always make a profit due to the fact that their *spread* is always greater than the transaction cost. Interestingly, the inventory *market makers* lose more money than the random ones due to the fact that they pay more to maintain their inventory. This is due also to the fact that the investors are uninformed. In this sense there is no realistic feedback mechanism between investors and *market makers.* i.e. given that the investors use a random strategy *market maker* quotes do not affect their behavior and therefore do not affect supply and demand.

The total volume is higher than in the case of the market order model, which of course is the goal of the *market makers.* In spite of the higher liquidity, volatility is very high relative to the other models studied. One surmises that the volatility is due to the *spread*, principally of the random and inventory *market makers.* Repeating the experiment with a reduced transaction cost (which in turn permits a reduced *spread*) the volatility/transaction becomes less than in the case of the market order model. This clearly indicates that operational costs are a very important factor that influences market volatility given that *market makers* to remain viable must maintain a *spread* sufficient to cover the transaction cost.

6 Conclusions

It is quite surprising the relative complexity of the results obtained given the small diversity of strategies used in the experiments. Restrictions associated with different market organization models were seen to clearly directly affect both liquidity and volatility. Lack of liquidity and or volatility were seen to adversely affect profits for informed traders. We saw that the higher the number of informed traders the smaller the volume and the bigger the volatility. This is natural, in that if there are no uninformed traders or traders with adverse information then nobody is willing to take the counterpart of a trade. We also saw that heterogeneous response to market information led to very different trading performances.

Market maker strategies are of particular interest. We saw that the only successful strategy of those studied was the monopolist. However, for obvious reasons, the latter cannot exist in a real market. We also saw how agent adaptation was guided by the usual dilemma of exploration versus exploitation. If one over exploits a strategy the resultant profits are reduced. On the other hand, if one makes an insufficient analysis of which is the best strategy then the risk is high that a bad one will be chosen. Additionally, if one makes an excessively long analysis it will be too late to recover the losses made in this exploration phase. The organizational model plays a role in the results of the adaptive agents in that it determines the rate at which a particular strategy yields profits.

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