Strategy Adaptation and the Role of Information in an Artificial Financial Market

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Abstract

An agent-based artificial financial market (AFM) is used to study the role of information and adaptation in the dynamics of trading profits, volatility and volume. We consider the heterogeneous response of non-adaptive informed traders to the same information showing how such information can lower liquidity. We then consider different types of adaptive trading strategies. We find that the success of an adaptive strategy depends on the balance between "exploration" and "exploitation" in the adaptive search and that this sensitively depends on the adaptation rate, the ratio of "signal to noise" in the fitness landscape, market liquidity and the actual composition of the agent population.

1 Introduction

In recent years it has become ever more popular to consider financial markets (FMs) from an evolutionary, rather than the traditional *rational expectations*, point of view. In particular, there has been a substantial increase in studies using agent-based computer simulations. Such AFMs almost inevitably use Artificial Intelligence paradigms, such as Neural networks, Artificial Life, Genetic Algorithms and Classifier systems, in their construction and hence they are natural topics of study for researchers from these disciplines (as well as others, such as statistical physics and complex systems, and, of course, the more traditional ones of finance and economics).

The most well known AFM is the Santa Fe model [1, 2, 3, 4]. In this paper we use an alternative model — the NNCP [5] — whose design was motivated by the desire to study 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 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*, adaptive or non-adaptive.

In this paper, in line with the theme of the conference, we will emphasize the results of experiments carried out to study the effect of learning and adaptation for a group of agents trading a single risky asset. The most intuitive paradigm for this is that of an ecology of competing strategies (see for example [7]). Each agent uses a particular strategy at a given moment in time to try and maximize profits. We will restrict ourselves to a small strategy space; though, as we will see, a surprisingly rich behavior emerges.

We will divide traders into two classes — informed and uninformed. The latter make random decisions while the former base their's on information available in the market. The informed agents, however, have different trading "personalities". Hence, there arises an heterogeneous response to the *same* information. This is of course a phenomenon common in real FMs; not every investor is rational in the sense of responding to information in the same way.

We also introduce adaptive agent strategies wherein an adapting agent may copy the strategy of the most successful agent currently in the market (the *copycat* strategy) or may analyze all possible strategies in the search space and use the optimum at that moment in time (the *analyst* strategy). We will show that whether or not adaptive strategies can beat non-adaptive strategies sensitively depends on market liquidity, the population composition, the adaptation rate and the ratio of "signal to noise" in the fitness landscape.

In section 2 we briefly describe the NNCP model while in section 3 we introduce the different type of market participant and their characteristics. In section 4 we discuss the principal results and in section 5 draw some conclusions.

2 Description of the NNCP

A simulation is carried out for a prescribed number of *ticks* on a single risky asset. An agent can divide his/her wealth between this risky asset and a riskless asset ("cash"). At each *tick* an agent takes a position (buy/sell/neutral) and emits a corresponding market order, 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*.

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

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. Large values of η lead to large price oscillations while small values lead to slow price adjustments. Note that $D(t) = (B(t) - O(t))$ depends not only on the positions taken by the agents but also on the mechanism used to match their trades, e.g. at what price two contrary trades will be matched. In this sense one may think of a "bare" $D(t)$, $D_B(t)$, that represents the imbalance in supply and demand associated purely with the desired trades of the agents while $D(t)$ represents the residual imbalance after matching those orders that can be matched under a given clearing mechanism.

The wealth of an agent i at time t is given by $W_i(t) = (E(t)+H(t)p(t))$ where $E(t)$ and $H(t)$ are the amount of cash and number of shares that the agent possesses at time t. A useful benchmark for measuring profits is that of Buy & Hold where the corresponding agent preserves his portfolio composition throughout the experiment, i.e. $W_i^0(t) = (E(0) + H(0)p(t))$. $P_i(t) = W_i(t) - W_i^0(t)$ measures the profitability of the agent's trading strategy, or asset allocation, relative to an initial asset allocation.

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. 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 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.

Table 1: Description of populations' composition

Population	Description	Populations	Description
Noinfo	20 uninformed	Spec	20 1-day speculators
RA	20 20-day Risk Averse	B&H	20 Buy & Hold
SpecNoinf	2 speculators, 18 uninformed	B&HNoinf	2 Buy & Hold, 18 uninformed
SpecNoinfP	4 speculators, 16 uninformed	RANoinfP	4 Risk Averse, 16 uninformed
B&HNoinfP	4 Buy & Hold, 16 uninformed		
HetInf	3 1-day, 7-day, 14-day speculators 3 20-day, 40-day Risk Averse 2 60-day Risk Averse, 3 Buy & Hold	HetNoinf	13 uninformed agents, 1 Buy & Hold 1 1-day, 7-day, 14-day speculators 1 20-day, 40-day, 60-day Risk Averse
HetP	3 1-day, 7-day speculators. 2 uninformed 2 14-day speculators, 3 20-day Risk Averse 2 40-day, 60-day Risk Averse, 3 Buy & Hold	HetNoinfP	10 uninformed, 3 1-day speculators 2 Buy & Hold, 1 7-day, 14-day speculators 1 20-day, 40-day, 14-day Risk Averse

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.

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 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:

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

  where r_d is the expected price increase per day and D is the time horizon of the agent in days. In the experiments described below we used $D = 1$, 7 and 14 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"/passive agents — where the position probabilities are:

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

  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. For these agents we used $D = 20$, 40 and 60 days.

- Buy and Hold agents — where the position probabilities are:

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

  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. The horizon for these agents is always 120 days.

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.

Table 2: Table of volume and volatility for the three different market types.

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
RA	100	0.00	0.000	0.00	1.20	0.0002	203.33	0.00	0.000	0.00
RA	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

Table 3: Table of averaged profit/agent for different strategies.

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
B&HNoinf	100	0.00	911.218	-101.25	0.00	432.292	-48.03	0.00	336.83	-37.43
B&HNoinf	7	0.00	20.422	-2.27	0.00	1.023	-0.11	0.00	9.26	-1.03

4 Principal Results

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. The different values of η were chosen so as make the average value of $\eta D_B(t)$ about the same so as to be able to make a fair comparison of volatility between different market clearing mechanisms.

Several different types of experiment were run by varying the composition of the population. The different experiment types are explained in Table 1. 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. In each experiment 20 agents were used with a mix of informed and uninformed strategies as outlined in section 3. 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 2 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 market 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

Table 4: Table of absolute and relative profit/agent for *copycat* strategy. The copycat agents initially were uninformed.

Exp	τ	r	Equal		Best		Morders	
			Abs	Rel	Abs	Rel	Abs	Rel
HetP	1	100	219.67	471.25	1014.08	1353.64	1337.73	1832.17
HetP	1	7	27.43	67.71	95.60	110.92	58.63	69.58
HetP	20	100	26.73	311.20	589.19	880.27	245.18	527.49
HetP	20	7	17.79	46.49	38.70	44.60	-9.41	-11.22
HetP	120	100	-140.70	75.94	-309.60	-156.59	-547.44	-419.49
HetP	120	7	-16.28	-2.09	38.20	44.84	-23.48	-25.61
HetNoinfP	1	100	152.68	183.62	618.99	652.68	282.81	298.44
HetNoinfP	1	7	9.42	12.10	21.47	22.55	-22.48	-24.27
HetNoinfP	20	100	202.26	276.11	214.37	216.90	335.53	370.30
HetNoinfP	20	7	9.08	13.50	-10.76	-16.51	-36.46	-43.30
HetNoinfP	120	100	-115.25	-109.00	-186.91	-221.47	-138.51	-166.24
HetNoinfP	120	7	18.71	21.89	17.90	18.12	-12.58	-11.73
SpecNoinfP	1	100	-15.09	-25.36	104.64	88.74	77.10	70.63
SpecNoinfP	1	7	1.91	1.74	-0.98	-2.65	17.80	8.65
SpecNoinfP	20	100	-45.55	-51.81	-36.69	-69.68	102.23	119.01
SpecNoinfP	20	7	0.38	2.79	-27.98	-25.31	20.35	20.90
SpecNoinfP	120	100	31.58	30.54	-29.11	-14.11	59.33	53.87
SpecNoinfP	120	7	5.10	5.27	-2.97	-5.53	32.97	16.84
RANoinfP	1	100	-31.94	-33.08	15.79	20.00	-4.15	-5.33
RANoinfP	1	7	6.88	7.29	21.98	22.83	-0.31	-0.28
RANoinfP	20	100	30.57	31.16	26.20	27.75	-2.46	-2.42
RANoinfP	20	7	0.51	0.53	-2.77	-2.83	10.26	10.27
RANoinfP	120	100	-31.52	-32.43	6.68	8.99	-28.58	-29.79
RANoinfP	120	7	1.66	1.63	17.51	17.36	-82.71	-86.41
B&HNoinfP	1	100	48.12	257.12	708.01	856.97	265.59	341.83
B&HNoinfP	1	7	38.45	62.20	-36.13	-38.95	-12.11	-12.71
B&HNoinfP	20	100	-102.39	52.77	394.23	515.09	231.68	324.47
B&HNoinfP	20	7	15.21	31.52	-9.99	-9.88	-55.71	-59.57
B&NoinfP	120	100	-226.95	-112.66	-224.07	-168.54	-40.91	30.36
B&HNoinfP	120	7	-23.73	-13.69	-24.61	-26.22	-2.58	-3.08

informed agents there are the less liquidity there is and the higher the volatility.

In table 3 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.

4.1 Adaptation

Adaptation of the agents is implemented using a simple Genetic Algorithm (GA) the objective of which is to apply a selective pressure in order to select the strategy which best utilizes the information in the market. Given that the search space is small we did not implement mutation and crossover. Proportional selection was used rather than a deterministic selection scheme in order to have at least some stochastic element in the evolution. The fitness function for agent i at time t, was taken to be proportional to the wealth accumulated by that agent up to that time relative to a Buy & Hold strategy, $P_i(t)$ (as described in section 2 and not relative to long term Buy & Hold agents as described in section 3). Note that $P_i(t)$ can be negative hence cannot be used as a legitimate fitness function. The function, $F_i(t) = P_i(t) - P_m(t)$, where $P_m(t) = 0$ if no agent has negative relative wealth and is the value of the worst performing agent in the contrary case.

Two types of adaptive strategy 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 strategy of the most successful agent present, while in the second the most successful possible strategy is searched for among all possibilities. "Successful" here does not simply mean the strategy with the highest gain: each adapting agent selects a strategy, j, with probability $P_j(t) = F_j(t)/\bar{F}(t)$, where $\bar{F}(t)$ is the average population fitness at time t.

Three classes of experiment were carried out. Two to measure the profitability of adapting strategies relative to their non-adapting counterparts and the last to see what happens when every agent adapts in the case of *copycat* strategies. In the first set of experiments, two of the twenty agents were *copycat* agents, in the second set one of the agents was an *analyst* while in the third all the agents were *copycats*. The parameters

Table 5: Table of absolute and relative profit/agent for *analyst* strategy. In HetP y HetNoinfP a copycat was substituted by a speculator. The analyst agent was initially an uninformed agent in heterogeneous markets.

Exp	τ	r	Equal		Best		Morders	
			Abs	Rel	Abs	Rel	Abs	Rel
HetP	1	100	355.83	593.10	940.58	1198.85	986.41	1285.23
HetP	1	7	63.48	93.14	17.45	19.23	31.83	34.64
HetP	20	100	-227.19	-16.71	402.85	651.82	251.94	532.56
HetP	20	7	-28.81	-10.72	51.42	55.70	9.76	10.99
HetP	120	100	-528.65	-353.59	-579.82	-434.75	-162.05	62.21
HetP	120	7	12.97	35.39	-13.71	-15.12	142.77	154.90
HetNoinfP	1	100	306.50	404.88	600.29	615.33	382.33	415.01
HetNoinfP	1	7	-13.43	-15.04	-10.84	-9.20	35.68	35.58
HetNoinfP	20	100	-157.05	-111.50	141.25	149.96	220.32	235.79
HetNoinfP	20	7	-1.61	-1.30	33.22	42.38	42.36	44.27
HetNoinfP	120	100	8.50	59.38	127.42	125.10	-28.61	-13.83
HetNoinfP	120	7	-10.18	-10.87	24.89	26.24	29.46	27.87
Noinf	1	100	165.61	169.97	500.48	513.65	225.10	231.02
Noinf	1	7	1.14	1.17	-30.92	-31.74	65.15	66.87
Noinf	20	100	28.39	29.14	291.40	299.07	94.70	97.19
Noinf	20	7	1.11	1.14	-14.68	-15.06	-73.11	-75.03
Noinf	120	100	24.20	24.83	153.44	157.47	33.87	34.76
Noinf	120	7	-7.38	-7.58	32.51	33.36	-18.43	-18.91
Spec	1	100	46.24	48.67	448.56	472.17	354.25	372.89
Spec	1	7	0.77	0.81	-26.57	-27.97	-24.71	-26.01
Spec	20	100	129.98	136.82	189.22	199.18	203.09	213.78
Spec	20	7	-19.73	-20.77	-30.78	-32.40	6.73	7.09
Spec	120	100	82.66	87.01	267.29	281.36	15.41	16.22
Spec	120	7	-19.73	-20.77	22.17	23.34	-19.62	-20.66
RA	1	100	0.00	0.00	230.05	242.16	44.63	46.98
RA	1	7	0.00	0.00	-12.93	-13.61	4.66	4.90
RA	20	100	0.00	0.00	293.24	308.68	-0.42	-0.45
RA	20	7	0.29	0.30	5.37	5.65	7.43	7.82
RA	120	100	0.00	0.00	267.23	281.29	3.20	3.37
RA	120	7	0.00	0.00	-2.76	-2.91	0.25	0.26
RA	1	100	-3252.07	-3252.07	-45588.52	-45588.50	-15615.79	-15615.80
RA	1	7	-1191.08	-1191.08	-2020.52	-2020.52	-12429.65	-12429.70
RA	20	100	-1805.78	-1805.78	-13493.95	-13493.90	-125.83	-125.83
RA	20	7	-594.65	-594.65	-1076.31	-1076.31	-3245.37	-3245.37
RA	120	100	0.00	0.00	0.00	0.00	0.00	0.00
RA	120	7	0.00	0.00	0.00	0.00	-121.94	-121.94

used – number of ticks, number of agents and η – are as previously mentioned. Adaptation was carried out periodically at a frequency τ^{-1} with $\tau = 1$, 20 and 120 days.

In general the success of an adapting agent depends on a combination of four factors: the liquidity in the market, the adaptation rate, the "signal to noise" ratio (i.e. the market bias and the volatility) and the composition of the market. The latter due to the fact that it is easier for an adapting agent to profit against uninformed traders than informed traders. 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" (see Table 4). Additionally, even if the *copycat* identifies a winning strategy, the low volume means that it is not easy to exploit it, i.e. there may not exist sufficient liquidity in the market to realize the desired operations. In more liquid markets the *copycats* make profits when the adaptation period is less than 120 days 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 $r_t = 100\%$.

In Table 5 we see the results of experiments with one *analyst* in the population. The *analyst*'s ability to follow various "what if?" scenarios implies that he/she is not as affected by the liquidity of the market in terms of an adequate statistical identification of the winning strategy [1], at least in the sense that it is the strategy that leads to optimized profits in a given period. However, as is the case with the *copycat* low liquidity can make the realization of a desirable trade problematic.

Interestingly, contrary to the *copycat*, this agent suffers if there exist Buy & Hold agents given that it is difficult to recover from losses made during the period where he/she was determining what was the best strategy. Given that the *analyst* can determine the profitability of the Buy & Hold strategy without having such agents in the market it is preferable not to have to compete against them. 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

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

Table 6: Table of long time population composition with population of 20 *copycats*.

Exp	τ	r	Equal				Best				Morders			
			S	RA	B&H	U	S	RA	B&H	U	S	RA	B&H	U
HetP	1	100	8	8	4	0	0	4	16	0	4	8	4	4
HetP	1	7	0	12	4	4	8	8	4	0	0	16	4	0
HetP	20	100	1	14	2	1	0	1	18	0	3	1	13	2
HetP	20	7	4	4	8	1	6	6	2	4	13	2	3	0
HetP	120	100	5	6	5	1	4	7	5	1	2	7	10	0
HetP	120	7	6	7	4	0	6	5	3	2	6	4	3	2
HetP	1	100	4	4	0	12	0	4	8	8	4	4	4	8
HetNoinfP	1	7	0	0	0	20	8	0	0	12	0	4	0	16
HetNoinfP	20	100	2	3	1	12	1	1	6	10	4	4	4	14
HetNoinfP	20	7	5	0	2	11	6	0	0	11	8	0	0	9
HetNoinfP	120	100	3	3	2	10	3	1	0	13	3	0	3	12
HetNoinfP	120	7	1	1	1	15	1	1	1	14	2	1	0	15
B&HNoinfP	1	100	0	0	4	16	0	0	16	4	0	0	0	20
B&HNoinfP	1	7	0	0	12	8	0	0	20	0	0	0	0	20
B&HNoinfP	20	100	0	0	9	10	0	0	18	1	0	0	14	5
B&HNoinfP	20	7	0	0	8	12	0	0	5	14	0	0	9	10
B&HNoinfP	120	100	0	0	11	9	0	0	7	12	0	0	8	11
B&HNoinfP	120	7	0	0	7	12	0	0	5	14	0	0	5	15

any agents other than Buy & Hold, which is the optimal strategy. These profits increase as a function of the adaptation frequency. This is an important point[2]. This reflects the canonical dilemma of exploration versus exploitation. An important point here is the fitness function used: the latter presently being an *accumulative* measure of the success of a strategy. Additionally, the larger the statistical sample that an adapting agent has to work with the more likely it is that the true winning strategy can be identified. Hence, accumulation of information is an important process here. In this language the adaptation rate has ramifications in terms of opportunity costs. At a certain moment in time a certain amount of information about price has been accumulated. The question is: how can that information be best exploited? With an accumulative fitness function there is no penalty to having a high adaptation rate. Furthermore, this minimizes opportunity costs in that new information is processed as quickly as possible and utilized. For example, accumulated information, updated and processed daily, is more likely to allow an agent to identify a winning strategy and exploit it than when the adaptation rate is lower where there is an opportunity cost associated with the extra time that passes before the information is processed and used.

In an initial phase, a large adaptation rate one might think could be prejudicial, as without enough statistics to identify the best performing strategy it is possible that the adapting agent will be misled into a worse performing strategy than the initial one. However, an agent with a lower adaptation rate has initially, on average no more prior knowledge of the market bias and so is not more or less likely to use a better strategy in this initial transient phase. A low adaptation rate, however, can be prejudicial in terms of identifying signal from noise when the time between strategy changes is longer than the characteristic time needed to identify with some certainty the market bias. Additionally, a lower adaptation rate can badly affect an adapting agent's ability to make a profitable transaction after identifying a winning strategy as liquidity can rapidly disappear, as is the case with markets with many Buy & Hold or Passive agents.

The objective of the last experiment with 20 *copycats* is to show the tendency towards homogeneization that may occur in a market. Given previous results one would expect that the market homogenizes to one with purely long term Buy & Hold agents given that they have the greatest profits.

In the first experiments (see Table 6) — heterogeneous markets with informed and uninformed traders — one notes that, only when there is a reasonable degree of liquidity and a strong signal ($r = 100$), the market performs as expected. One sees in these cases a tendency to homogenize with respect to the Buy & Hold strategy in that the average number of Buy & Hold agents present is much higher than would be expected in a random population, which is 5. Additionally, our use of proportional selection introduces an extra "noise" element thus potentially confusing further the recognition of signal versus noise.

In the markets with informed and uninformed traders the number of uninformed agents is pretty much constant (13). This indicates that the market "noise" has more effect here, although in the more liquid markets the number of Buy & Hold agents is somewhat higher. An interesting phenomenon here, especially manifest

[2]The importance of the adaptation frequency has also been emphasized in the context of the SFM [8] but in a very different setting.

in the case of an initial population of Buy & Hold and uninformed agents at an adaptation period of 1 day, is the fact that *copycat* agents even though they start with the optimal strategy — Buy & Hold — can "lose confidence" and choose another inferior strategy.

5 Conclusions

We believe that the most surprising aspect of this first foray using the NNCP model is the richness and diversity of the output that naturally emerges from a model with very little input. In particular, the diversity of input strategies is small. Restrictions associated with different market organization models were seen to clearly directly affect both liquidity and volatility which in their turn were seen to adversely affect the profits of informed traders. We saw that the higher the number of informed traders the smaller the volume and the higher the volatility. In other words there is a liquidity squeeze in this case. 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 leads to very different trading performance. In other words it's not what you know but what you do with it that counts.

The results for a given adaptive agent were seen to depend on several key characteristics: market liquidity, signal to noise ratio, adaptation rate and the strategies used by the agent's competitors. All else being equal, adaptive agents tend to do better in situations of high Signal to noise ratio. i.e. large market bias and low volatility. High adaptation rates are preferred due to the reduced opportunity cost in processing new information and implementing a corresponding trading strategy. Market liquidity can affect both the statistical determination of a successful strategy and the exploitation of a successful strategy once found. i.e. once a useful strategy has been found one has to hope that someone is willing to take the counterpart of the trade. Adaptive agent performance also sensitively depends on who the agent is competing against and the type of adapting agent. This was nicely exemplified by the case of Buy & Hold agents. *copycats* need such agents in the population in order to learn from them while *analysts* prefer that they are absent in order to avoid competition from a superior strategy. Almost inevitably profits of adapting agent are at the expense of uninformed traders.

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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