A Conceptual Framework for the Evaluation of Agent-Based Trading and Technical Analysis

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The major part of research dedicated to technical analysis and active trading (*i.e.*, the management of financial portfolios using chartism or moving average indicators for instance) generally focuses on single "signals" giving the opportunity to buy or sell a financial commodity *frequently a well diversified portfolio* (see the extensive survey of Park and Irwin (2004)). In this context, it has been extensively argued that technical analysis is useless in order to outperform the market (Jensen and Benington 1969). The reason for that is, assuming informational efficiency (Fama 1970), all relevant piece of information is instantaneously aggregated in prices. Therefore, there is nothing to extract from previous quotations relevant for one willing to trade on this basis. Since information is, by definition, unpredictable, next price fluctuations will be driven by innovation and the price motion will fluctuate randomly as a result. Nevertheless, empirical investigations tackling this question of "technical trading" exhibit heterogeneous results. On the one hand, a large part of these researches shows that, once risk taken into account, no-one can seriously expect any rate of return over what can be earned with a simple *Buy and Hold* strategy (henceforth B&H). On the other hand, some intriguing results seem to attest that technical analysis is useful to a certain extent (Brock, Lakonishock, and LeBaron (1992), Detry and Gregoire (2001), Dempster and Jone (2005)). More generally speaking, this idea is trusted and shared by many practitioners.
We argue here that this confusion depicted by this heterogeneous set of results comes from ill-defined concepts, confusing measures and fuzzy evaluation procedures. We propose in this paper some elements to correct these imprecision and to elaborate a conceptual framework for technical analysis evaluation.

We consider these elements using an Agent-Based approach because we ultimately would like to investigate large sets of technical trading strategies, to encompass automatic trading issues and to generalize as much as possible our investigations. Thus, in this research, an *agent* is systematically an *artificial agent*, that is, a virtual entity endowed with *Artificial Intelligence*, mimicking a *real investor*, and

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able to deal with information, learning, and adaptation procedures.
Therefore, our propositions are a contribution to organize as rigorously as possible the large set of problems linked to the evaluation of automatic trading, technical analysis and related topics including those where *Artificial Intelligence* is used to investigate large sets of investment strategies.
This paper is organized as follows. In section 1, we discuss the basis upon which technical analysis is usually analyzed. We show why it must be distinguished between *signals*, *strategies* and *behaviors* although this distinction is seldom done in other researches. Section 2 focuses on the problematic link between technical indicators received by the traders and their ability to benefit from them when they try to implement them in "winning" strategies. Section 3 deals with the value added by increasing cognitive capabilities of the agents in plugging sets of technical signals rather than a single signal in their rationality. Section 4 enlarges the discussion to several strategies and addresses several questions around the design of tests for weak-form Market efficiency and automatic trading. It also serves as a conclusion.

1 Why confusing elements have lead to a controversy

If one considers the basic elements in most researches dealing wit technical analysis or weak-form market efficiency, it is often the case that one specific "strategy" (or a limited set of strategies) is systematically replicated over various time windows, using real stock market data. Performance is computed comparing this active-investment strategy to a specific benchmark, like a simple B&H behavior. Some refinements concerning the statistical properties of the performance distribution is also usually proposed, such as Monte-Carlo simulations or Bootstrap Reality Checks (see for instance White (2000)).
However, no one can seriously sustain that these tests directly assess what a real technical trader would do. This practitioner would certainly mix a large number of *"receipts"* to strategize his behavior. His performance is supposed to be grounded on various "signals", "special skills" allowing him to have a correct diagnosis, and a professional "know-how" : this mix makes any evaluation complex because the origin of performance (or lack of performance) is not easily observable. To make this point clearer, let's consider briefly figure 1. A large part of the evaluation complexity arises from the interaction between:

- elements constituting investors' intelligence (and consequently, virtual agents' artificial intelligence) : their cognition is a structured mix of information – extracted from market observation – and knowledge coming from the organization of these information *plus* the result of their past behavior,
- and external constraints : what kind of commodity are they allowed to trade ? Are they subject to budget or credit constraints ? Can they go *short* or not ?

Every evaluation problem has to take into account these elements to be satisfying. The most difficult of them, and clearly the less treated in the literature, tackles the ability of technical traders to evolve and to mix various elements to achieve good

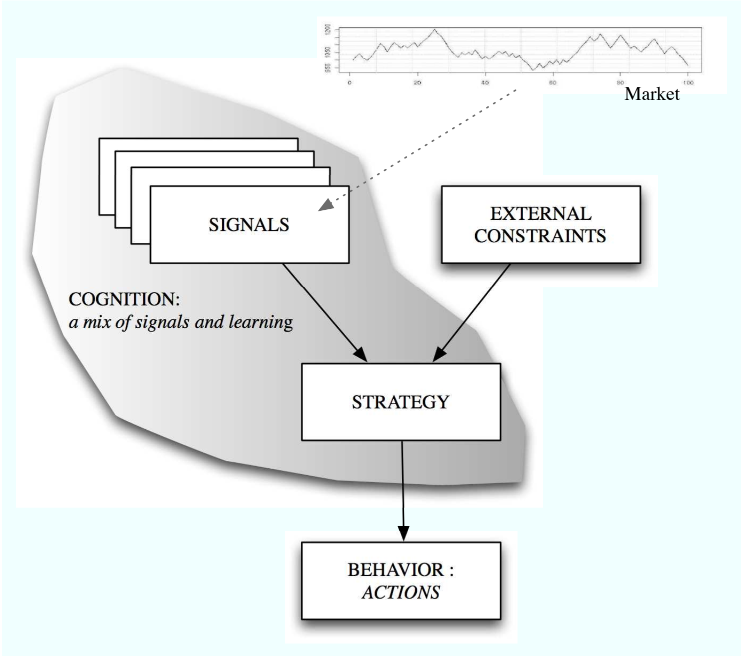

Fig. 1. Elements of complexity in performance evaluation

performance in the market. We will present this point at the end of the following example : to introduce the discussion, we propose first a basic situation, a very direct evaluation problem where trader's intelligence is limited since she applies systematically a strategy based on a "Mixed Moving Average 90-10 signal" (MMA_{90-10}). A "moving average" of range K (K being equal, in our example, to 10 and 90 since we mix these indicators) and a "mixed moving average (n, p)" are respectivily proposed in the following expressions 1 and 2 :

$$MA_{K,t} = \frac{1}{K} \sum_{t-K+1}^{t} p_t \tag{1}$$

$$MMA_{n,p} = \{MA_{n,t}, MA_{n,t}\} \tag{2}$$

Chartists consider the situation in which the short-term moving average crosses the long term one from the bottom to the top as a "buy" signal (*resp.* from the top to the bottom as a "sell" signal). We use the daily closing value of the Dow-Jones from 26/05/1896 to 22/11/2005 (27424 quotation days) to generate a series of 478 signals (figure 2 shows a subset of this signals from 21/05/1996 till the end). We consider that it is always possible to trade a tracker based on this index. The allocation rule for the trader is simply maximum investment (that is, to buy as much trackers as possible or to sell them massively).

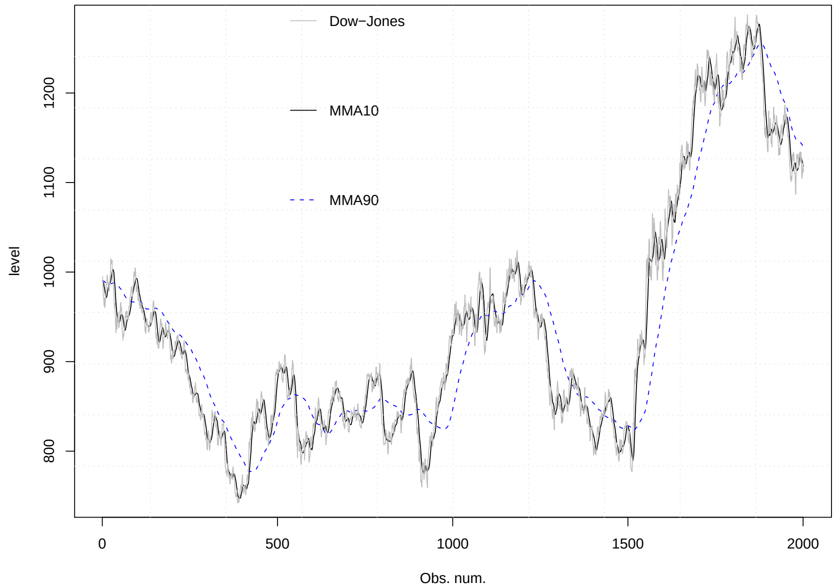

Fig. 2. Moving Averages 10 and 90 over 10 years of DJI

On the basis of the signals, the agent trades the DJ-tracker 477 times (the first signal being a “sell” signal). Do these chartist signals actually signal something useful for trading or not ***(question 1)*** ? Would a portfolio, solely composed of trackers based on the Dow-Jones Industrial, have benefited from such a trading rule if one considers various performance indexes ***(question 2)*** ? Especially, do these signals allow smart traders to elaborate strategies that outperform the market ***(question 3)*** ? Is it possible to improve dramatically this Limited Intelligence Trader’s performance in endowing her with higher cognitive skills ***(question 4)*** ?

question 1 :

The idea behind this question is the actual power of chartist signals to predict correctly, regularly and with a sufficient reliability, the next moves of one specific market. We can quantify this power with a very simple indicator called “Hit Rate”:

$$HR_{MMA_{90-10}} = \frac{\text{correct signals}}{\text{total number of signals}} \tag{3}$$

Others definitions of such indicator can be found in the literature (Hellström and Holmström 1998).The average score of our chartist signal, in terms of Hit Rate is here of 52%. This score may vary significantly over sub samples of time, and to some extent, it is hard to say that this 52% score is better than what a pure random rule would do. Nevertheless, we can still hypothesize that a subset of rules (whatever these rules are) in the infinite space of possible rules actually performs well.

question 2 :

Assuming the MMA_{90-10} signal has been selected by a trader, would she be able to obtain a good performance implementing it in a basic strategy [3]? Graphs 1 shows the evolution of a trader's portfolio composed of one tracker (at date 26/05/1896) and managing her portfolio with a basic strategy using MMA_{90-10} signals against a passive trader receiving at the same date the same tracker, and playing a B&H strategy. Rules for managing the portfolio are as follows : when a trader decides to sell her portfolio, all the trackers she holds are sold. When she decides to buy, she invests all her cash in trackers (considering she will have to pay in both cases transaction costs at $x\%$). One can easily observe that when transactions costs are zero (graph 3), the basic MMA_{90-10} seems to perform well whereas it is a good road to ruin when transaction costs are non-zero, even if they are extremely low (graph 4).

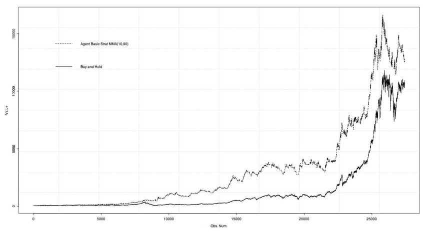

Fig. 3. Without trans. costs

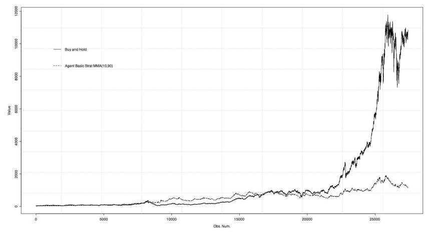

Fig. 4. With 0.5% trans. costs

question 3 :

The previous graphical analysis is obviously not sufficient. When applying standard performance indexes, especially those including a risk/return analysis (a Sharpe ratios as instance), one can clearly see that all supposed advantages for a MMA_{90-10} vanish as soon as transaction costs are considered (see Table 1).

question 4 :

Do increasing cognitive abilities for the agents lead to better results in terms of risk/return performance ? In other terms, assuming that *"perceiving good signals"*

[3] in other terms, following what the signals suggest : to buy when the market is supposed to rise, to sell when it is supposed to decrease

Transaction Costs		0%	0.5%
Buy&Hold	Mean return	2.0344 E-4	
	σ	0.01145	
	Sharpe Ratio	0.0177	
	Portfolio	10871.43	
Basic Strat.	Mean return	2.0964 E-4	1.2267 E-4
	σ	0.00724	0.0073
	Sharpe Ratio	0.02893	0.01679
	Portfolio	12852.61	1183.57

Table 1. Performance evaluation based on a MMA90-10

necessarily leads to *"achieving a good strategy"* – and this assertion will be extensively discussed – can we design agents sufficiently smart to adapt their behavior to many signals and many external constraints to outperform the market ? Would this kind of agents *prove* really any ability in this game ? How should we design an evaluation framework taking these elements into account if we want to design automatic trading platforms and / or tests of market efficiency with agents duplicating as well as possible the behavior and the cognition of true technical traders ? What kind of implications, both theoretical and practical, these considerations can highlight ?

2 On the link between *good market signals* and the capacity for building up simple good strategies

In this section, empirical investigations use daily data from the Euronext Paris Stock Exchange between 1988 and 2005. The traded tracker is now based on the CAC40 index. Agents have access only to past values of this index. We first present some technical/theoretical arguments and propose a series of illustrations afterwards.
We first propose to distinguish two fundamental concepts that must be considered separately previously to be articulated. Technical trading is always based on "signals" indicating either that the market is about to increase or to decrease, and "strategies" based on these signals as well.

1. As evoked previously, a "signal" is generally grounded on the (controversial) idea that profitable persistence or inertia characterize the price motion in stock markets. One difficulty here is to detect which "signal" is actually able to reveal such persistency. We consider in this paper a large number of instances of signals; these instances are based on several generally accepted technical rules (moving averages, rectangle, triangle, RSI, momentum ...), each of them being modeled as a parametric function. These signals will be active or not, depending on the existence of "patterns" in prices provoking their activation. Once activated, the signal sends a recommendation to the trader expressed like: *"according to my own logic"*, *"the market should increase"* or *"should decrease"*.
2. A "strategy" is the way agents use these signals to build a trading behavior.

a) Some agents will only observe one signal (some being endowed with multiple signals), and will follow it systematically (we call this behavior "Basic Strategy").
b) Others will be "contrarians" (i.e. will follow an "Inverse Strategy")
c) Others will choose sometimes to follow the signals, sometimes to ignore them. We call them "Lunatic" traders.
d) ...

Extracting best candidates from a large soup of signals

In this section, a limited sample of results from a series of massive empirical investigations is reported. We select, among many thousands of chartist/technical signals, some of them exhibiting good "Hit Rates" (HR, see equation 3) and a minimum activity (that is, signals frequently activated and useful to manage a portfolio – at least one signal per week –). Table 2 shows a limited subset of this "good signals" (a "signature" is simply the name and the parameters used to compute this signal).

Num. of signals	with HR $\geq 50\%$	with min activity
110288	6640 (6.02%)	97 (0.08%)
Signature		
MMA-1-4 ; MMA-1-6 ; MMA-1-7 Momentum-2-1 ; Momentum-5-0 Variation-1-1-4 ; Variation-1-5-1 Variation-1-7-1 ; Variation-1-8-1 ; Variation-1-9-1		

Table 2. Subsets of "good signals"

Executing these best candidates with a simple strategy

We show how we can use the signals selected in section 2 to design "pseudo-good" strategies.

An agent decides, at each time step and according to the set of information it accesses, to manage the portfolio, selling, buying or letting the number of held trackers unchanged. This set of information is as follows:

- $S_1, S_2, ..., S_n$, the set of signals exploited by her strategy.
- $HR_1, HR_2, ..., HR_n$, the corresponding set of Hit Rates.

One can notice here that we did not design a very complex set of information, including performance evaluation in terms of risks-returns, rate of activity, memory etc... This is obviously possible but leads to an increasing computing time and a huge amount of data to analyze.

We focus here on the simplest imaginable strategy: one signal, one Hit Rate, no evolution, and a strict application of what the signal suggests : if the market is identified as a rising market, *"Buy"*, if identified as a decreasing one, *"Sell"*. In all other circumstances, *"stay unchanged"*. Table 2 presents the results for 10 strategies based on the signals in Table 2, for two transaction costs levels. It is illustrated that no strategy is able to outperform the market when transaction costs are fixed at 0.5%.

	0% rate				0.5% rate			
Signature	Mean (10^{-4})	σ	Sharpe Ratio	Rank /97	Mean (10^{-4})	σ	Sharpe Ratio	Rank /97
B&H	3.0879	0.0109	0.0283	–	3.0879	0.0109	0.0283	–
MMA-1-4	3.9428	0.0074	0.0529 *	13	-0.010	0.00870	-0.1151	88
MMA-1-6	4.4715	0.0074	0.0599 *	2	-6.006	0.00852	-0.07043	69
MMA-1-7	4.1877	0.0074	0.0562 *	7	-5.6647	0.00845	-0.06701	67
Mom.-2-1	3.2710	0.0081	0.0402 *	51	-9.3296	0.00915	-0.10194	83
Mom.-5-0	4.1035	0.0074	0.0552 *	8	-6.3746	0.00835	-0.07630	70
Var.-1-1-4	3.9915	0.0074	0.0535 *	12	-6.5312	0.0083	-0.0778	72
Var.-1-5-1	3.1547	0.0107	0.0294 *	67	1.5685	0.01081	0.01450	23
Var.-1-7-1	3.0960	0.0108	0.0285 *	70	2.8503	0.01087	0.02622	5
Var.-1-8-1	3.0403	0.0108	0.0279	71	2.8839	0.01088	0.02650	4
Var.-1-9-1	2.9761	0.0108	0.0273	73	2.9091	0.01088	0.0267	3

MMA : mixed moving average, Mom. : momentum, Var.: Variation
** stands for "actually outperform the Market"*

Table 3. Performance evaluation of 10 strategies based on "good signals"

In figure 5 we show that a good signal (MMA 1-4) can lead to disastrous results when transaction-costs are non-zero, while it can be profitable when transaction costs are not paid. This is linked to the fact that a good Hit Rate can produce a lot of activity that will not be profitable because the costs for transacting exceed the benefits one can obtain with small upwards or downwards in prices.

In figures 6 and 7 and we have extended this analysis including the entire set of agents endowed with signals presenting a HR $>$ 50% (6640 signals, see section 2). They are plotted in a risk/return space. Agents under the market line (black plain line) underperform the B&H strategy.

It appears that once transaction costs are implemented, the number of agents being able to exploit their signals in order to "outperform" the market decreases extremely rapidly with limited increments for these costs. It is noticeable that the agents seemingly well-performing are not those endowed with best signals.

3 Do Intelligent Agents outperform ZIT ?

In this section, we want to address the following question : do agents endowed with a set of signals of size N behave systematically better than agents endowed with a set of signals of size $N - i, i \in [1, N-1]$? Do "smart" agents behave better than Zero Intelligence Traders (ZIT) ? In other terms, does increasing cognitive skills, that

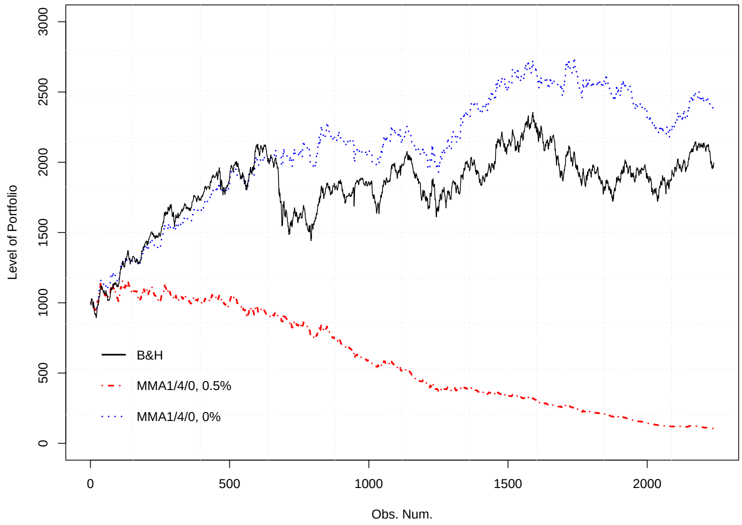

Fig. 5. Agents using MMA(1,4) signals

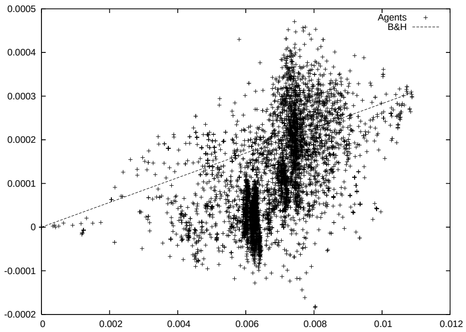

Fig. 6. Without trans. costs

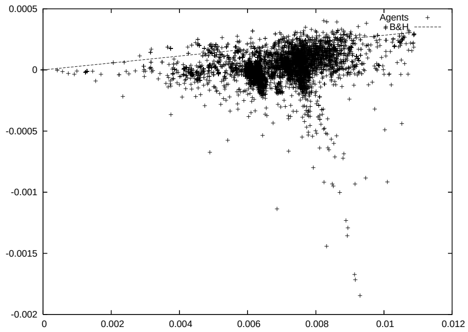

Fig. 7. With 0.5% trans. costs

is, the ability to detect potential opportunities to trade, actually lead to a better performance ? This is a recurrent question in economics and finance that has provoked many intriguing results (see as instance Gode and Sunder (1993), Dave and Bruten (1997) or Greenwald and Stone (2001)). As stated previously, a first obstacle is the profitable implementation of good signals in the agent. One potential solution could be to allow the agents to select the signals upon which they trade on the basis of their individual Hit-Rate (or some indicator based on this measure).

Technical elements

The first step here consists in allowing each agent to let her rationality evolve along time. To a certain extent, we must consider agents endowed with learning capabilities or adaptive reasoning. This is a specific topic in Agent Based literature (see for example Weiss (1996)), which is not developed here. We just exhibit a limited treatment for this problem:

1. Agents are endowed with N signals (in the following examples $N \in [1, 11]$), previously selected on a large set of signals in order to ensure some (arbitrary) level of "effectiveness" [4].
2. At each time-step, agents compute for each signal the corresponding Hit-Rate.
3. Every P time steps, agents observe which signal has performed well in terms of HR and select this predictor to trade over the next P time steps. In the following developments, and for the sake of simplicity, $P = 100$.

It is relatively easy to imagine various learning and adaptive procedure that may lead to better results, and it could be argued here that the results shown might be dramatically improved. This is presumably true, although this should be done with a correlative increased complexity of agents' design, solution which has not been retained in this article.

Basic strategies based on sets of best signals

We present now one typical answer to an instance of the generic question proposed at the beginning of this section: *"On the basis of the 10 best signals proposed in Table 2, is it possible to create basic strategies using many signals (*$2, 3, ..., 10$*) in order to outperform the market?"*
It is particularly contra-intuitive to imagine that adding cognitive skills to the agents should lead to a decrease in performance. One should expect to observe a rise in performance for agents accessing a larger set of decision rules when evolving in the market. This is not actually the case.

To answer these questions we create a series of agents endowed with an increasing number of signals, from 1 to 10, $Agent_i$ being endowed with the $i - th$ first signals in terms of Hit-Rate. We then investigate their relative performance when transaction costs are respectively fixed at a 0% rate and 0.5% using the adaptive procedure proposed in the technical discussion above. Figure 8 and 9 clearly show that increasing the number of signals in the agents do not systematically allow for obtaining a higher level of performance in terms of Sharpe Ratio. This is obvious when transaction costs affect the agents'global performance, but it is also generally true with no transaction costs. We have tested all possible values for P between 10 to 500 days, and obtained similar results. These considerations suggest that either the complexity of agents is not appropriate to increase their performance, either an other kind of rule should be implemented to select "good signals" (like their average

[4] We mix three indicators : individual Hit-Rate, number of emitted signals, balance between "buy" and "sell" signals.

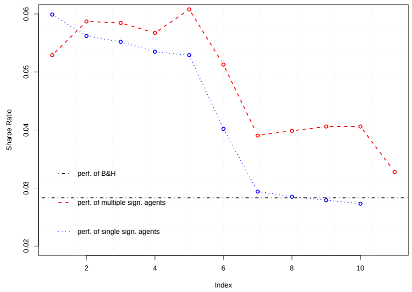

Fig. 8. With 0% trans. costs

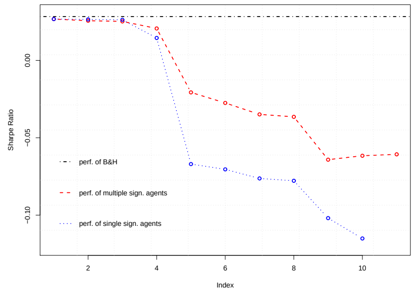

Fig. 9. With 0.5% trans. costs

profitability in terms of return, which is especially complex), or that the market being efficient, technical trading is definitively useless.

4 On the validity of technical trading arguments

A last point must be explicitly evoked now : technical trading, and more generally speaking the weak-form market efficiency have been studied using sophisticated statistical tests[5] to verify if *simple* technical rules can convincingly outperform the market. Nevertheless, a research tackling the question of the relative performance for *complex* technical trading rules, including artificial intelligence agents, able to evolve in a wide decision-rules universe, has still to be done.

This would be the ultimate stage to obtain a strong test for market efficiency. As it has been shown in a previous communication (Brandouy and Mathieu 2006), even if one explores an enormous number of signals individually "plugged" in artificial traders playing a "Basic" strategy, it seems to be impossible to obtain risk-adjusted rates of return in excess to a simple Buy and Hold strategy. This is an empirical evidence that strongly support the weak-form EMH.

The following illustrations suggest that if one does not accept to increase significantly the complexity of the agent-based architecture used in this kind of research, it will certainly not be possible to obtain strong evidence of an abnormal over-performance.

Four strategies and the Tale of Technical trading efficiency

In this last empirical investigation, we report results that clearly illustrate the previous discussion. We consider here four strategies using various sets of "good signals". These four strategies are :

[5] Including risk/return measures, in-sample selection and out-of sample tests, data-snooping control procedures (see Lo and MacKinlay (1990) for a technical point and Park and Irwin (2004) for a general survey about these topics).

1. Basic strategy, that will serve as a benchmark.
2. Inverse Strategy
3. Deterministic Lunatic Strategy
4. Stochastic Lunatic Strategy

Firstly, we focus on agents endowed with multiple signals[6] applying them on the daily closing price of the Dow-Jones (see section 1). These signals have been selected considering their Hit-Rate over a subsample of observations. Agents try to exploit these signals using various strategies, as proposed previously. Their relative performance are compared to a simple Buy and Hold behavior on the same sample. In this example there is no transaction costs.

Strategy	Mean return	Standard deviation of returns	Sharpe Ratio
BH	$2.0152\ 10^{-4}$	0.0113	0.0177
Basic	$1.6459\ 10^{-4}$	0.0072	0.0227 *
Inverse	$1.9481\ 10^{-4}$	0.007466	0.02608 *
Lunatic D.	$1.8826\ 10^{-4}$	0.0080	0.0234 *
Lunatic S.	$1.0989\ 10^{-4}$	0.008160	0.01346 *

** stands for "actually outperform the Market"*

Table 4. Performance of 4 strategies based on "(pseudo)good signals"

Considering this simple illustration, one can see that the best strategy here consists in doing exactly *the opposite* of what the signals suggest (*i.e.* to follow an Inverse Strategy, see table 4) . One can also achieve a better Sharpe Ratio with the "Deterministic-Lunatic" strategy than with the "Basic" strategy. One has to keep in mind that this result does not prove any inefficiency in the market because it might well be due to data-snooping, because its stability and robustness has not been checked, and last but not least, because it has been obtained without transaction costs. It is proposed for the sake of illustration and we therefore do not argue that it *proves* any dominance in performance. We only highlight the fact that whatever the "strategy" we consider, one can achieve a similar result with any other kind of strategy (apart "Stochastic-Lunatic", which basically is similar to a coin toss).

Some other amazing results

We now briefly propose some results of massive investigation on French data (see section 2) leading to similar conclusion.

Cheating is not playing: The following "strategy" is only given to fix some kind of boundaries. We call it the "cheating strategy". It has been designed to allow the agents to know at date t what will happen at date $t + 1$. They can therefore

[6] RSI_{42-20}, RSI_{15-34}, $Momentum_{17-6}$, $Momentum_{13-10}$.

directly benefit from this information to (easily) outperform the market. The result of this behavior (Sharpe Ratio = 0.46349) is presented in figure 10. Our best non-cheating agent using a single signal is only able to produce 14.35% of this performance.

Good performance on bad basis: It is perfectly possible to design good agents (obtaining a Sharpe Ratio over the B&H one). As instance, signals "Variation-2-7-14" and "MA-85" obtain very bad Hit-Rates. When these signals are "plugged" in an agent playing a Basic strategy and switching from one to the other every 500 dates (with respect to their relative Hit-Rate at these dates) we obtain a very satisfying performance with a Sharpe Ratio of 0.0288, while B&H Sharpe Ratio is 0.0283.

Signals do not signal anything : As quoted previously, it is frequently better to do exactly the opposite of what the signals suggest : if one wants to trade using a signal "indic-7-18-5" with an "Inverse Strategy" one should obtain a Sharpe Ratio of 0.0666 while following this signal would lead to a Sharpe equal to -0.0292 with a "Basic Strategy".

On the nature of the best strategies : Our set of signals is composed of 360.288 elements, 250.000 of them being "periodic signals" : they propose to go long after "n" days and to go short after "m" other days. They cannot really be called "technical" signals but they can catch some special patterns such as the so-called "Monday Effect". Nevertheless, many of them can simply be analyzed as stochastic signals or zero-intelligence signals. Nevertheless, each of the 200 first agents ranked by Sharpe Ratio use these kind of signals. The best agent is therefore plugged with a "periodic signal 21-56" (obtaining a Sharpe Ratio equal to 0.0467). It is easy to find a similar agent using an "Inverse" strategy based on periodic signals, and behaving nearly as well as this pseudo-champion.

Thus, if one only scratches the surface of weak-form market efficiency, there is nothing to expect from technical trading. In other words, little evidence in terms of superior performance should arise from a cautious analysis of simple active trading rules. Nevertheless one cannot seriously affirm that these last tests completely answer the question.

This set of results as well of the elements we have discussed in this paper strongly suggest that :

1. Automatic trading based on technical analysis depends upon external factors such as leverage, transaction costs. There is an enormous variability in performance linked to these parameters.
2. It appears necessary to separate at least "signals" and "strategies". Nave increases in agents cognitive skills are also useless to achieve satisfactory levels of performance(once incorporating risk). A fine-tuning aiming to balance the complexity of agents' capabilities and information resources is necessary.
3. To go deeper in this analysis would imply the definition of generic strategies describing learning procedures, adaptation and decision making processes.

Therefore, from a conceptual point of view, a robust framework for the evaluation of Agent-Based trading and technical analysis should systematically answer each

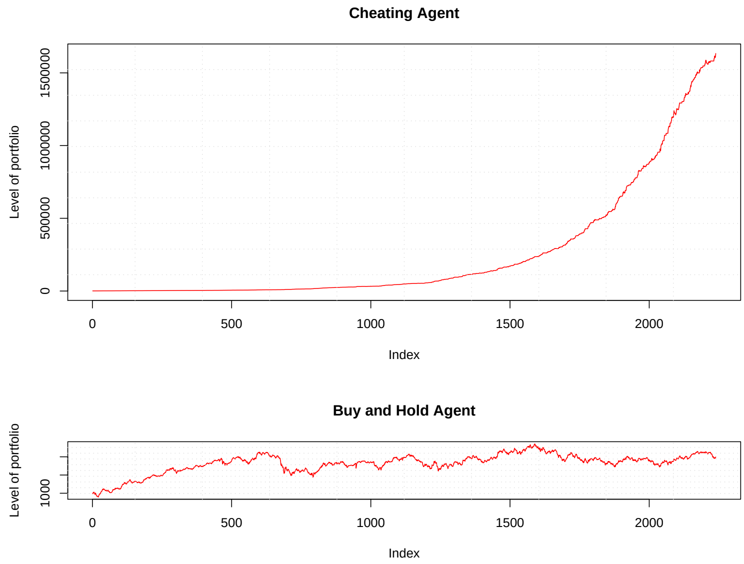

Fig. 10. With 0% trans. costs

of these 3 points at least, which obviously constitute a first step before rigorous statistical examinations.

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