Portfolio Optimization and Trading Strategies: a simulation approach

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Abstract
This paper describes a community of investors forming their expectations with heterogeneous strategies in order to optimize their portfolios by means of a Sharpe ratio maximization. Traders are distinguished according to their methodology used in forecasting. Twelve acknowledged algorithms of technical analysis have been implemented to compare portfolios performances and assess profitability of each technique.

Keywords
Sharpe ratio, Financial markets, Portfolio performance, Simulations

1. Introduction

One of the main purposes of financial traders is to choose the optimal allocation of their money among possible investments. The first important contribution to the Portfolio Selection Theory was made by Markowitz [1], who based his studies on a mean-variance model in which each investor could choose the optimal composition of his portfolio. Despite the scientific importance of the classical Markowitz model, its adoption by investors has been truly contained due to its numerous limits, such as the large amount of data required to implement the model and the high estimation error [2] leading to biased portfolios toward few assets.

A number of models have been proposed to overcome these limits, such as the Capital Asset Pricing Model (CAPM) developed by Sharpe [3] and later also by Lintner [4] and Mossin [5]. Sharpe observed the link between stock price and market index performance, ensuring a reduction in the amount of data that are used to obtain the efficient portfolio. With CAPM, financial assets can be evaluated in a market equilibrium context, in which a risk-free asset is also considered. One of the assumptions of this model is the homogeneity of investors who have the same expectations, which leads them to have a combination of two assets only, i.e., the market portfolio and the risk-free asset (*Two-Fund Separation Theorem*, [6]). Other attempts have been made to reduce the estimation error and to improve portfolio performance, as in Black and Litterman ([7],[8]), who developed a model in which the CAPM equilibrium portfolio is used to estimate assets return. The main innovation of their model was the implementation

AMPM'21: First Workshop in Agent-based Modeling & Policy-Making, December 8, 2021, Vilnius, Lithuania

*Corresponding author. This paper results from the joint cooperation among authors. All text is by AEB and LM; section 2.1 is by AEB, LM, and DR. Simulative model by AEB. Data collection and simulations by LM.
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of opinions (views) of analysts about the market. Obtained results lead to more stable and diversified optimal portfolio into the Markowitz model. This model was studied by [9], [10], [11] and [12], among many others.

Another way to find the optimal portfolio is based on the maximization of a portfolio performance index, as the Sharpe ratio ([13],[14]), which is defined as a ratio of the expected portfolio return relative to his standard deviation. Actually, it was Roy [15] who first suggested a portfolio valuation strategy based on a risk-return index; later, Sharpe applied his idea to the Markowitz approach by creating his famous index, which is one of the most used one, despite it is based on unrealistic hypotheses (among which, for instance, the assumption of Gaussian-distributed returns).

Since standard deviation is not always an appropriate measure of risk, many alternatives to the Sharpe ratio have been advanced. Among others, the Treynor ratio [16] substitutes the standard deviation with the portfolio beta, while the Sortino ratio [17] uses the downside risk as a risk measure, and the ratio of Bodnar and Zabolotskyy [18] replaces standard deviation with VaR. Other portfolio performance indices have also been developed, such as Jensen's alpha [19] and many measures based on portfolios weights, as in [20], [21], [22] and [23].

Financial markets can be seen as complex systems ([24], [25]) in which agents cannot be described as copies of the representative agent [26] endowed with rational expectations ([27], [28] and [29]), but have heterogeneous features and base their behaviour on a bounded rationality ([30], [31]) and interact with each other ([32], [33]). Agent-based models (ABM) allow treatment of complex systems by putting the evidence on the relevance of interactions and the unpredictable sequentiality governing the system dynamics. The application of such a methodology to Economics is called Agent-based Computational Economics (ACE), defined by Tesfatsion [34] as "the computational study of economic processes modelled as dynamic systems of interacting agents". This methodology has been fruitfully applied to the study of financial markets, as in [35], [36], [37], [38], [39], [40], [41], [42], [43], [44] and [45], among others, as surveyed by LeBaron [46]. It is important to mention the work of [47] in which they used an agent-based model for a portfolio optimization. In this field, [48] made an experimental study to assess the effect of complexity on asset trading.

Heterogeneous expectations and behaviours are often studied in related literature, by referring to the endogeneity of the signal followed to form expectations (i.e., between fundamentalists -who maintain a view on an exogenous signal- and chartists -who define the expected dynamics by inferring the trend of past prices). A vast body of references can be reported, among which: Alfarano et al. [49] created an agent based model in which agents can switch between fundamentalist and chartist strategies; Alfi et al. [50] analysed price dynamics considering the presence of forces due to trend adverse and trend following strategies; Flaschel et al. [51] showed how chartists tend to destabilize the economy; Lux and Marchesi [52] developed a model in which fundamentalists, optimistic and pessimistic trend followers can switch between strategies, thus giving rise to more instability independently of expected news; Lux and Marchesi [53] studied the volatility clustering; Westerhoff [54] and Chiarella et al. [55] considered multi-asset markets, in which the interaction between them causes clustered volatility and fat tail of asset returns; Westerhoff and Reitz [56] estimated an heterogeneous agent model underlying the impact of fundamentalists.

The present paper proposes a model based on the Sharpe ratio maximization, in which agents form their expectations by following heterogeneous strategies, in order to optimize their portfolio. More precisely, we propose a set of behavioural rules of prediction widely acknowledged in technical analysis (see [57], [58], [59], [60], [61], [62], [63], [64], [65]): three variants of the Moving Average Convergence Divergence model - MACD; the Relative Strength Index - RSI; Rate of Change - ROC; Crossover; Stochastica; Linear Forecasting; and Compound Forecasting. Finally, we consider also fundamentals, chartists and the completely random approach, proposed in [66], [67], [68], [69], as detailed below. All algorithms have been implemented to create portfolios whose values have been compared in order to assess the profitability of each technique. In literature, there are some papers that compare the performance of different strategies, among others: [70],[71],[72],[73],[74],[75]. The paper is organized as follows: section two contains the model, section three shows results of simulations; section four presents concluding remarks.

2. Model Description

The model simulates different processes of expectations formation, each using a different technique. Such expected values will be used in Sharpe-ratio optimization procedures by traders in order to determine the quantities of two assets in the optimal portfolio. All common caveats of Markowitzian optimization hold: first of all, we assume that each investor allocates all her wealth in both assets - thus assuming that any possible decision inherent to saving has been already taken and the investor has decided the amount of resources for financial trading; secondly, we admit that the whole informative set consists in the available data on market dynamics - this will have an exception for one category of investors, as it will be detailed below; finally, we are not considering any interaction or imitation among traders - thus, no exchange of information or influence is playing here.

2.1. Performances and Sharpe-ratio

The evaluation of portfolio performances is aimed to check whether given return and risk requirements have been met by fund management. This assessment is usually operated with reference to asset classes, i.e., major categories of assets (stocks, bonds and money market instruments), industrial sectors for a portfolio of national equities, or countries for portfolios of international equities. The measure of portfolio performance should be increasing with respect to the expected return and decreasing with respect to the estimated risk. The Sharpe ratio (SR) is one of the most discussed metrics within the class of reward-to-variability measures, as related to the classical mean-variance model of portfolio selection. In fact, under mild assumptions, the optimization problem of finding the maximum expected portfolio return, given a target level of risk as measured by the variance of portfolio return, is equivalent to the maximization of SR.

In the current paper we build a dynamic discrete time model where asset prices vary within a fixed time horizon $[0, T]$, $T > 0$. In term of performance evaluation, financial institutions usually split the strategic horizon $[0, T]$ into sub-periods of the same length, and try to predict the optimal sequence of portfolio weights maximizing its performance at the final date T. Then, let us choose SR as the relevant measure of performance and use subscripts to denote any integer time $t \in [0, T]$. The market price of the ith asset from time $t-1$ to time t is represented by p_t^i, the rate of return is $r_t^i = (p_t^i - p_{t-1}^i)/p_{t-1}^i$ and the investment horizon $[0, T]$ is a sequence of sub-intervals $[t-1, t]$ for $t = 1, 2, \ldots, T$.

An SR-optimizer trader maximizes the performance, measured by means of the SR, of her portfolio, composed by allocating, at time t, the personal endowment W_t to two assets, according to optimal weights x_t^i, with $\sum_i x_t^i = 1$.

The multi-period optimization problem solved by each trader at each time step can be stated as:

$$\begin{aligned} \operatorname{argmax}_{\mathbf{x}} \quad & \frac{\mathsf{E}(\mathbf{r}_T \mathbf{x}_T)}{\mathsf{sd}(\mathbf{r}_T \mathbf{x}_T)} && (1) \\ \text{subject to} & \\ (1 + \mathbf{r}_t \mathbf{x}_t) W_{t-1} &= W_t \qquad t = 1, \ldots, T && (2) \\ \mathbf{x}_t \mathbf{e} &= 1 \qquad t = 1, \ldots, T. && (3) \end{aligned}$$

The objective function is the SR, i.e., the ratio of the expected return of the portfolio to its standard deviation. The control variable is $\mathbf{x} = (\mathbf{x}_t)_{t \in N}$, which represents the result of different trading strategies to be set up for both assets at each time t and $\mathbf{e}$ is a vector of ones. Eq.(2) describes capital accumulation, i.e., the decision to invest the wealth's fraction W_t^i in the asset i at time t after the asset return r_t^i has been realized. Eq.(3) stands for no-leverage. The objective function can be written as

$$\frac{\mathsf{E}\left(\frac{W_T}{W_0 \cdot ((1+\mathbf{r}_1\ \mathbf{x}_1) \cdots (1+\mathbf{r}_T \mathbf{x}_T))} - 1\right)}{\mathsf{sd}\left(\frac{W_T}{W_0 \cdot ((1+\mathbf{r}_1 \mathbf{x}_1) \cdots (1+\mathbf{r}_T \mathbf{x}_T))} - 1\right)},$$

where the final portfolio return is expressed in term of the final wealth. A similar problem, for the maximization of the final portfolio return by keeping the final variance of portfolio return lower or equal to a positive given value, has been presented in [76], by using dynamic programming. Our model describes the sequence of optimization problems executed by all traders, at each time step $t \in [0, T]$, aimed at maximizing their SR.
The numerical implementation of problem (1) is then based on a sequence of one-time maximization problems within the horizon,

$$\begin{aligned} \max_{\mathbf{x}_t} \quad & \frac{\mathbf{x}_t \mathbf{m}_t}{\sqrt{\mathbf{x}_t \mathbf{C}_t \mathbf{x}_t}} && (4) \\ \text{s.t.} \quad & \mathbf{x}_t \mathbf{e} = 1. && (5) \end{aligned}$$

where $\mathbf{m}_t$ is the vector of expected returns, such that $m_i = \mathsf{E}(r_t^i)$ and $\mathbf{C}_t = [c_t^{ij}]$ is the covariance matrix of the returns $\mathbf{r}_t$, i.e. $c_t^{ij} := \mathsf{cov}(r_t^i, r_t^j)$ for each i and j.
The problem can be simplified as follows:

$$\begin{aligned} \min_{\mathbf{w}_t} \quad & \tfrac{1}{2} \mathbf{w}_t \mathbf{C}_t \mathbf{w}_t && (6) \\ \text{s.t.} \quad & \mathbf{w}_t \mathbf{e} = \kappa && (7) \\ & \mathbf{w}_t \mathbf{m}_t = 1 && (8) \end{aligned}$$

$$\kappa \qquad \geqslant 0. \tag{9}$$

The switching is based on the scaling $\mathbf{w}_t := \kappa\,\mathbf{x}_{t,}$, where $\kappa > 0$ is the scaling factor, and presuming the extra hypotheses that there is a feasible portfolio $\mathbf{x}_t$ such that $\mathbf{x}_t\mathbf{m}_t > 0$ and the obvious normalization $\mathbf{w}_t\mathbf{m}_t = 1$. The optimal solution is:

$$\mathbf{x}_t = \frac{\mathbf{m}_t\mathbf{C}_t^{-1}}{\mathbf{m}_t\mathbf{C}_t^{-1}\mathbf{e}}, \tag{10}$$

where $\mathbf{C}_t^{-1}$ is the inverse of $\mathbf{C}_t$. The quantity of each asset in the portfolio, is

$$q_t^i = \frac{x_t^i W_{t-1}}{p_t^i}, \qquad \text{for } \; t = 1, \ldots, T \; \text{ and } \; i = 1, 2.$$

Since the model designs the existence of N heterogeneous agents, we assume different, subjective, probability spaces $(\Omega^s, F^s, \mathsf{P}^s)$, for $s = 1, 2, ..., N$. More precisely, each probability measure P^s pertains to trader s-th and it is defined through what he expects from different hypotheses on market movements. Thus, different traders have the diverse expectations about future prices and fundamental values. Expectations are then used to define the probabilities P^s themselves, see [77] and [78]. Ω^s can be considered as individual conception of the ideal experiment associated to forecasting future prices, while actual experiments only reveal the level of traders observation. Therefore, for each trader (based on his subjective judgment) there is a different expectation $\mathbf{m}_t$ at time t. In order to compute it, each trader adopts a given strategy and make a forecast for the price for the next time step, thus obtaining the expected return.

2.2. Trading strategies

The basic setting is built upon nine different trader types, adopting the following strategies: *1)* fundamentalists; *2)* chartists; *3)* MACD traders (in turn divided in three groups, i.e., *3.1)* MACD-basic, *3.2)* MACD-plus, and *3.3)* MACD-divergence); *4)* crossover traders; *5)* RSI traders; *6)* random traders; *7)* stochastic traders; *8)* ROC traders; *9)* two econometric forecasting approaches, i.e., *9.1)* linear traders and *9.2)* compound traders. Strategies *2)*, *3)*, *4)*, *5)*, *7)* and *8)* are based on descriptions given in relevant related literature (see [57] for further details). In this paper, for each strategy, is considered a single trader who will decide to buy if the expected price is higher than the current market price and sell in the opposite case.

2.2.1. Fundamentalists

Fundamentalists consider the fundamental value of the asset, FV_t, as the relevant indicator to infer the dynamics of the price time series. Such a fundamental value is, according to their view, the true value of the asset, which embeds the "correct" evaluation of all relevant information and also includes the effects of the dividend yields. It is defined as an exogenous random variable whose dynamics may be assumed as a martingale-dividend-driven. Thus, the expected price, for a fundamentalist can be written as:

$$FV_t = FV_{t-1} + \mathbb{D}_t \tag{11}$$

where $FV_0 = \bar{\phi}$ and $\mathbb{D}_t$ is a random variable extracted from a normal distribution with zero mean and standard deviation σ_F, which is assumed to follow a random walk and represent the yearly *yield* of the asset. Thus the expectation of a fundamentalist is:

$$ {}_F p_t^{exp} = FV_t + \Theta_F \tag{12} $$

where Θ_F is randomly chosen in the interval $(-\theta_F, \theta_F)$, in order to account for the heterogeneity of investors. This implies that when the expected price is greater (resp., smaller) than the observed current market price she decides to buy (resp., sell), because she is expecting that the asset always converges to its fundamental.

2.2.2. Chartists

The second type of investos has been designed as momentum trader. Momenutm is the name of a very broad category of investment strategies, based on the observation of past values of financial time series. In particular, a very general definition of a momentum oscillator is given by:

$$ M = p_t - p_{t-x} \tag{13} $$

where the comparison between the current market price p_t and the past price registered a given x number of periods ago, p_{t-x} is used to infer the future dynamics. In particular, the basic momentum strategy is based on the sign changes of M:

$$ \begin{cases} - \rightarrow + & \text{BUY} \\ + \rightarrow - & \text{SELL} \end{cases} \tag{14} $$

Related literature calls "chartists” one of possible expressions of such a kind of strategy: a group of technical analysts who found their trading decision on the observation of trends and past dynamics of financial prices. More precisely, each of them refers to a time window, whose length is individually heterogeneous, and compute a reference value RV_t, computed at any t by averaging prices included in a time window of length S, different for each chartist and randomly chosen in the interval $(2, T_{max})$:

$$ RV_t = \frac{1}{S} \sum_{j=t-S}^{t} p_j. \tag{15} $$

Thus, the expectation determined by the chartist is

$$ {}_C p_t^{exp} = p_t \pm (p_t - RV_t) \tag{16} $$

where the choice of setting $\pm$ in the formula depends on whether p_t is respectively greater or less than RV_t.

2.2.3. MACD traders

The set of financial oscillators is very wide and a complete survey of them goes far beyond the scope of the present paper. Nonetheless, the model includes also other three kinds of traders based on technical analysis adopting the so-called Moving-Average-Convergence-Divergence (aka MACD) strategy, developed by Gerald Appel. Such an oscillator combines exponential moving averages, EMA^d, referred to different time intervals, d.

The basic computation is considered as the difference between the averages over $d = 12$ and $d = 26$ days:

$$MACD = EMA^{12d} - EMA^{26d} \tag{17}$$

where $EMA_t^d = EMA_{t-1}^d + w\left(p_t - EMA_{t-1}^d\right)$, with $EMA_0^d = \sum_{i=t-d}^{t} p_i/d$, and $w = \frac{2}{d+1}$. Oscillations of the two moving averages are different: the wider the days interval over which it is calculated, the slower it moves. Thus the slower is used to observe the trend, whereas the faster provides the trigger signal: when the latter crosses the former from the bottom (top), it is a bullish (bearish) signal. Such an oscillator is used according to three different versions, basically responding to the same rationale with different levels of refinement and data usage. The first, henceforth named MACD-basic, is:

$$\begin{cases} MACD > 0 & \rightarrow \text{BUY} \\ MACD < 0 & \rightarrow \text{SELL} \end{cases} \tag{18}$$

The second one, henceforth named MACD-plus, is augmented by a third moving average, computed over an interval of $d = 9$ days, EMA^{9d}, adopted as the trigger:

$$\begin{cases} MACD > EMA^{9d} & \rightarrow \text{BUY} \\ MACD < EMA^{9d} & \rightarrow \text{SELL} \end{cases} \tag{19}$$

Finally, the third version, henceforth named MACD-divergence, is based on a more detailed data observation, which is based on divergences. In particular, in a windowed period of past days, the original time series of the asset price and the correspondent MACD time series are compared. If either the two maximum points or the two minimum points in the interval of both series are oriented in the same direction of the trend in the same interval, then there is not a divergence. If, instead, a divergence exists, then it serves as a trigger. Let us indicate by α_S the slope of the trend inferred by the time series and by α_M the slope of the line joining the two local extrema included in the considered time window. The signalling role on the trading strategy played by the divergence can be described as:

$$\begin{cases} \alpha_S < 0 \;\wedge\; \alpha_M > 0 & \rightarrow \text{BUY} \\ \alpha_S > 0 \;\wedge\; \alpha_M < 0 & \rightarrow \text{SELL} \end{cases} \tag{20}$$

2.2.4. Crossover traders

The Crossover method, inspired by the triple crossover method mentioned for the first time by R.C. Allen ([79], [80]), requires exponential moving averages for different time periods (d),

EMA^d, as for the case of MACD strategies. More precisely, this method considers three moving averages, with $d = 12$, $d = 20$ and $d = 26$, calculated as above described. A buy signal will occur in a downtrend, in which the shorter average (12 day) is bigger than both the medium (20 day) and the longer ones (26 day). A sell signal, instead, will occur in the opposite situation, in which the longer average is the biggest one.

$$\begin{cases} EMA^{26d} < min(EMA^{20d}; EMA^{12d}) & \rightarrow \text{BUY} \\ EMA^{26d} > max(EMA^{20d}; EMA^{12d}) & \rightarrow \text{SELL} \end{cases} \tag{21}$$

2.2.5. RSI traders

Inspired by the Relative Strength Index, introduced by Wilder [62], our corresponding trading strategy considers once a time window of the recent past $S = 30$ values of the time series to infer possible forecasts on future dynamics. In particular, the index is computed as

$$RSI = 100 - \frac{100}{1 + RS} \tag{22}$$

where: $RS = \mu_\uparrow / \mu_\downarrow$; $\mu_\uparrow = (1/S) \sum_{k=1}^{S} p_k \forall p_s > p_{s-1}$; $\mu_\downarrow = (1/S) \sum_{k=1}^{S} p_k \ \forall p_s < p_{s-1}$; and $K \leq S$. The simplified strategy here adopted is based on the comparison between the RSI series referred to the entire original price series and the RSI series referred to the given interval of observation. The local trend of the index within the given time window and the global one may exhibit a divergence or not. If a divergence exists, the difference between the two highest local peaks is added (resp. subtracted) to the current price if the trend of the global RSI is increasing (resp. decreasing), in order to create the expectation.

2.2.6. Random traders

The role of random traders has been investigated in several contributions under the names "zero-intelligence", "noise", etc. They are defined as traders who decide when/how to invest at random. For such a reason, they have been used as the representation of the lack on influence/imitation in order to challenge the normal financial dynamics and show interesting insights to dampen market fluctuations, i.e., reducing volatility. In the present model, random traders are the sole group that will not use a portfolio optimization: they will simply decide whether to buy or to sell by tossing a fair coin. The quantity of both assets to have is extracted randomly by the algorithm governing the simulations, in such a way that both weights, $w_1 \in [0, 1]$ and $w_2 \in [0, 1]$, always sum up to 1.

2.2.7. Stochastic

The stochastic oscillator, popularized by George Lane, is based on the idea that when prices rise, closing prices tend to approach the upper end of the price range. The opposite occurs where prices fall. We present a simplified computational version of this method, that we implement as follow. Recent past values of prices are selected in order to compute two indexes:

$$K = 100 \cdot \frac{C - L5}{H5 - L5} \qquad \text{and} \qquad D = 100 \cdot \frac{H3}{L3} \tag{23}$$

where: C is the last price; $L5$ is the minimum value in the last 5 days; $H5$ is the maximum value in the last 5 days; $H3$ is the sum of the last 3 days of $C - L5$; $L3$ is the sum of the last 3 days of $H5 - L5$. The strategy can therefore be described as:

$$\begin{cases} K > 80 \wedge D > 80 \\ 20 < K < 80 \wedge D > 80 \\ K > 80 \wedge 20 < D < 80 \end{cases} \rightarrow \text{BUY} \tag{24}$$

$$\begin{cases} 20 < K < 80 \wedge 20 < D < 80 \\ K < 20 \wedge 20 < D < 80 \\ 20 < K < 80 \wedge D < 20 \\ K < 20 \wedge D < 20 \end{cases} \rightarrow \text{SELL} \tag{25}$$

2.2.8. ROC traders

The rate of change (ROC) is a ratio which assumes increasing values in cases of an upward trend and decreasing values in cases of downward trend. It is computed as follows:

$$ROC = \frac{V}{Vx} \tag{26}$$

where: V is the latest close price and Vx is the former closing price. Once defined a given threshold $c = 0.05$, ROC traders' strategy has been simply modelled as follows:

$$\begin{cases} roc \geq 1 + c & \rightarrow \text{BUY} \\ roc < 1 + c & \rightarrow \text{SELL} \end{cases} \tag{27}$$

2.2.9. Econometrician forecasters

Two last techniques adopt OLS estimation in order to predict future prices, by means of a linear and a compound model. In the first case, the prediction is obtained by:

$$Y = a + b \cdot t \tag{28}$$

where a and b are, respectively, the constant and the slope of the trend-line, and t indicates time, thus implying a constant growth.

The second approach assumes, instead, that the variable grows by a constant proportion each period. In this case, the prediction is obtained by:

$$Y = c \cdot d^t \tag{29}$$

where c and d indicate a constant and the growth proportion, which could be interpreted as $d = 1+$ growth-rate, and t indicates time.

Table 1
Time series used to perform simulations.

ASSET NAME (FROM)	ASSET NAME (FROM)	ASSET NAME (FROM)
3M (2/1/73)	General Electric (2/1/73)	Pfizer (2/1/73)
Accenture (19/7/01)	General Motors (18/11/10)	Philip Morris (17/3/08)
Adidas (17/11/95)	Goodyear (2/1/73)	Philips (1/1/73)
Adobe Systems (24/11/86)	Heineken (1/1/73)	Samsung (2/7/84)
Alphabet (19/8/04)	Henkel (2/7/96)	Royal Dutch Shell (1/1/73)
American Express (2/1/73)	Hewlett-Packard (2/1/73)	Siemens (1/1/73)
Apple (12/12/80)	Intel (2/1/73)	Sony (1/1/73)
AT&T (21/11/83)	Intesa San-Paolo (1/1/73)	Telefonica (2/3/87)
Barclays (30/12/64)	Johnson&Johnson (2/1/73)	Tesla (29/6/10)
BMW (1/1/73)	JPMorgan (2/1/73)	Texas Instruments (2/1/73)
Cisco (16/2/90)	EssilorLuxottica (28/10/75)	Thomson Reuters (12/6/02)
Colgate/Palmolive (2/1/73)	Microsoft (13/3/86)	Netflix (23/5/02)
Daimler (26/10/98)	Deere&Company (2/1/73)	Total (1/1/73)
Danone (1/1/73)	Morgan/Stanley (23/2/93)	Volkswagen (1/1/73)
Deutsche Telekom (15/11/96)	Nestlé (1/1/73)	Walt Disney (2/1/73)
Exxon (2/1/73)	Oracle (12/3/86)	Amazon (15/5/97)
Ford Motor (2/1/73)	Starbucks (26/6/92)	

3. Simulations

The model has been engineered as a sort of *back-testing* framework in which a fictitious reality is simulated. In Table 1 time series used for simulations are listed, each reporting the initial date of the time series. The simulation considers all possible couples of assets and defines a financial market where traders try to get the highest gain in terms of portfolio value. For each couple, the length of the simulation is set to the length of the shortest time-series, in such a way that at every simulation step, traders will always have newly disclosed prices for both assets. In such a configuration, the simulated market will operate as if investors were living in the past, thus making the measurement of performance possible, while a sort of financial race is run among traders, in order to discover which strategy accumulates the highest wealth. Each trader adopts a strategy and cannot change it. At the beginning, all traders are given the same amount of money, $m_i = \bar{m} = 250$. By means of their trading decision they will trade assets, thus computing their wealth, w_i, possibly greater or smaller than the initial endowment. Further, traders are assumed to be marginal with respect to the market, which means that they will always find the possibility to negotiate assets as they want. In other words, they will not be constrained to buy and sell selected quantities. If a trader goes bankruptcy, he will not be replaced and this will correspond to the worst outcome
(i.e., $\Delta w_i = -100\%$).

Unlike fundamentalists, all other types of traders considered observe past values of assets to take decisions. In particular, most of these traders are momentum traders and we assume that they must have at least 30 data available for each asset. Instead, econometrician forecasters operate by observing a wider time window of at least 180 data.

Table 2
Ranking of strategies with daily data

STRATEGIES	1st	2nd	3rd	FAILURES
Stochastica	330	225	141	77
Crossover	203	214	164	67
Fundamentalists	202	160	149	60
RSI	175	89	168	56
RND	94	97	92	160
MACD-divergence	79	80	99	129
Chartists	69	72	96	126
MACD-basic	33	86	112	118
ROC	16	31	64	208
MACD-plus	10	32	95	106
Linear	10	25	28	398
Compound	4	14	17	557

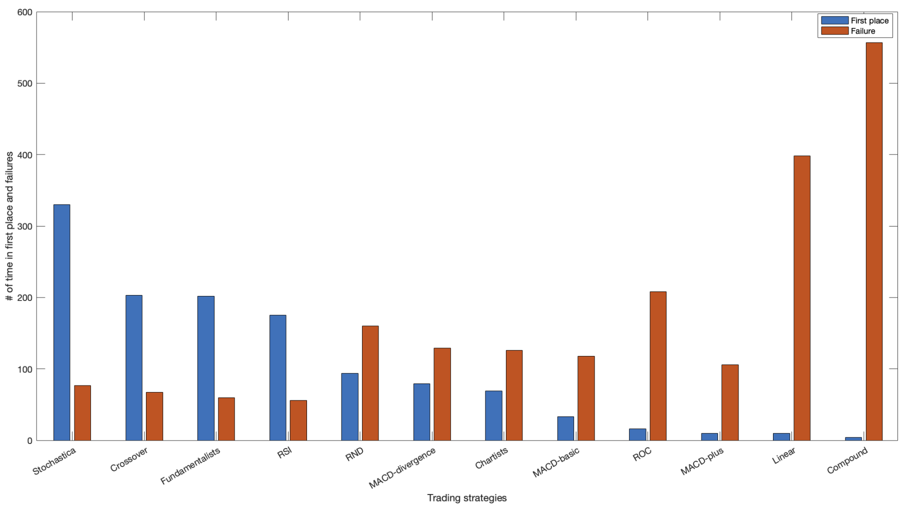

Figure 1: Occurrences for various strategies in the first position in the ranking or failures with daily data.

3.1. Results

Results reported in Table 2 show the number of times that each strategy scored the first, the second and the third in the ranking and the amount of times they fail. Fig.1 compares how many times the strategies have placed first and fail while Fig.2 shows how many times they arrived in the first three positions of the 1225 rankings analysed.

More in detail, stochastica strategy have been place in the top three position of the ranking 696 times, followed by the crossover strategy with 581 placements, fundamentalists with 511 and the RSI with 532. Then we find the RND with 283 placements and MACD-divergence with

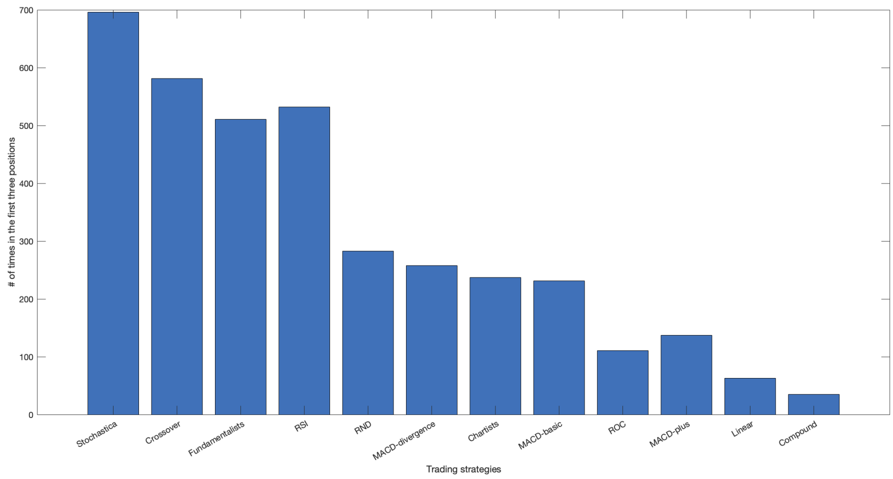

Figure 2: Number of times in which strategies have been placed in the top 3 positions with daily data.

258, continuing with the chartists that have been in the top three positions 237 times and the MACD-basis strategy with 231 placements. The ROC with 111 times follows the MACD-plus strategy with 133 placements. At the end there are the two econometric forecasting approaches, linear (59) and compound (37).

Data show that, overall, the stochastica strategy performed the best and that the worst are, instead, the econometric forecasting approaches.

For each couple of assets, simulations give twelve vectors containing portfolio values obtained by each strategy. The volatility of the best performing strategy has then been computed as the standard deviation of the distribution of portfolio values associated to that strategy for all occurrences in which it has ranked first. Fig.3 compares the volatility of all winning strategies, thus showing that even best performing ones manifest wide variability across the distribution of results.

We carried out the same analysis considering also the intraday data, more specifically the hourly data and data with a frequency of five minutes and one minute. All data were downloaded using Refinitiv's Eikon ©, and the intraday series were considered with their maximum available length, corresponding to the last year for hourly data and the last three months for five minutes and one minute data. For data with a frequency of five minutes and one minute, the given threshold for the ROC strategy was reduced ($c = 0.01$).

For hourly data we found the following results,reported in Table 3, Fig. 4 and Fig. 5.

Observing these results, we note that chartists reached the first position more times than the others, but by observing the number of times in which strategies have reached the top three and last positions, it is noted that the strategy that has performed better overall is the crossover, which it finished in the top three 468 times and fail 397 times. The worst are confirmed to be MACD-plus and the econometrician forecasters, with compound strategy that failed 1118 times out of 1225.

For data with a frequency of 5 minutes we found the following results, reported in Table 4,

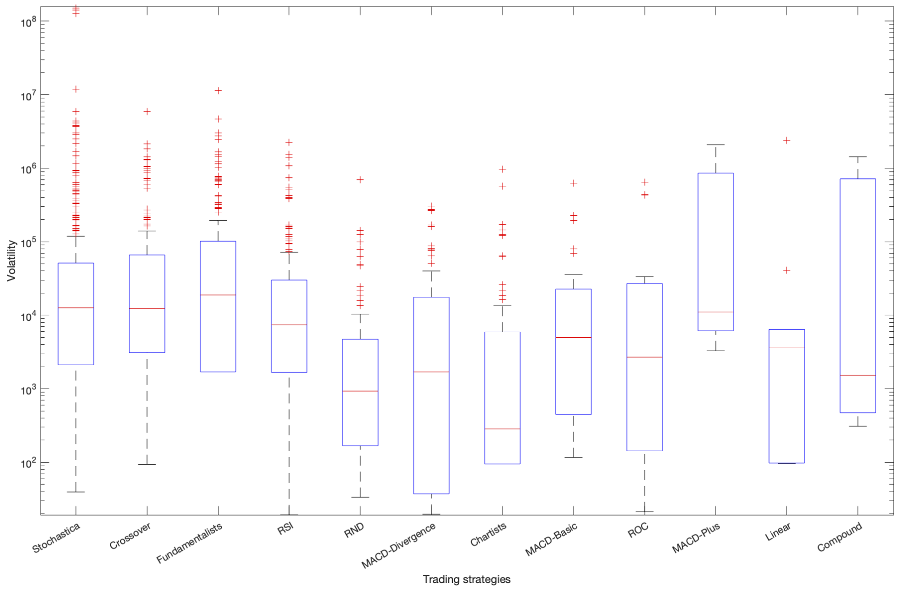

Figure 3: Volatility of portfolio values for different strategies with daily data.

Table 3
Ranking of strategies with hourly data

STRATEGIES	1st	2nd	3rd	FAILURES
Stochastica	97	120	102	469
Crossover	157	186	125	397
Fundamentalists	127	82	119	125
RSI	170	138	89	489
RND	77	166	127	392
MACD-divergence	106	160	122	319
Chartists	207	66	79	448
MACD-basic	90	129	166	256
ROC	129	39	62	634
MACD-plus	11	21	84	523
Linear	48	74	86	651
Compound	5	10	11	1118

Fig. 6 and Fig. 7.

In this case fundamentalists reach top three positions several times (482 times) and failed only 237 times. The crossover strategy didn't get many first places but overall it finished in the top three 345 times. Excellent results were achieved by MACD-basic which ranks 490 times in the top three strategies and failed only 342 times.

For data with a 1-minute frequency we found the following results, reported in Table 5, Fig. 8 and Fig. 9.

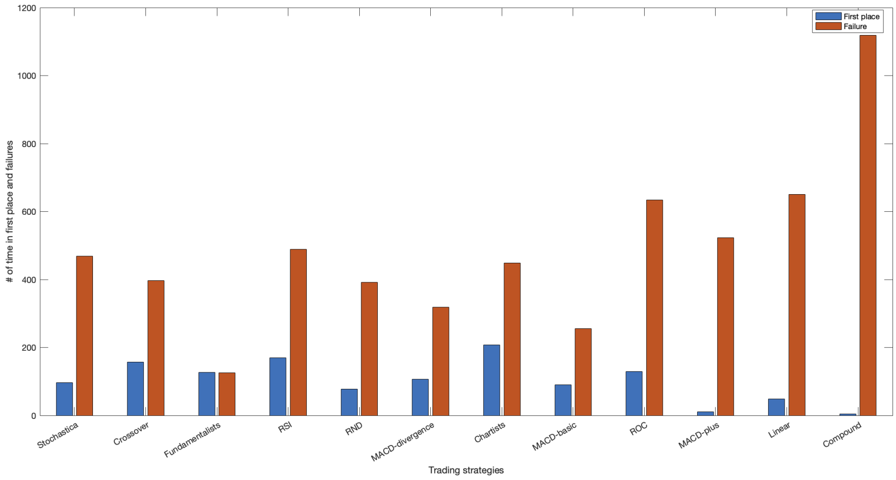

Figure 4: Occurrences for various strategies in the first position in the ranking or failures with hourly data.

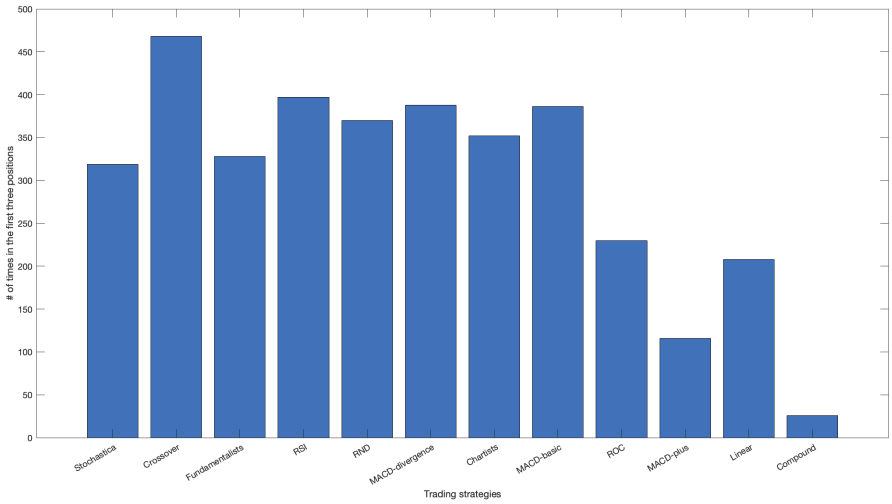

Figure 5: Number of times in which strategies have been placed in the top 3 positions with hourly data.

The best performances are those of fundamentalists (in the top three positions 387 times and, again, with the least number of failures 211) and once again the MACD-basic strategy which reaches the top three positions 480 times . Chartists have reached the first position several times (206) but have failed many times (631). The worst is the compound strategy, that failed 1210 times.

Table 4
Ranking of strategies (5 minutes)

STRATEGIES	1^{st}	2^{nd}	3^{rd}	FAILURES
Stochastica	96	118	116	620
Crossover	74	159	112	603
Fundamentalists	214	115	153	237
RSI	121	119	84	626
RND	100	172	120	549
MACD-divergence	174	166	75	455
Chartists	150	44	58	696
MACD-basic	163	130	197	342
ROC	78	31	48	831
MACD-plus	7	32	84	664
Linear	47	70	57	841
Compound	1	4	2	1196

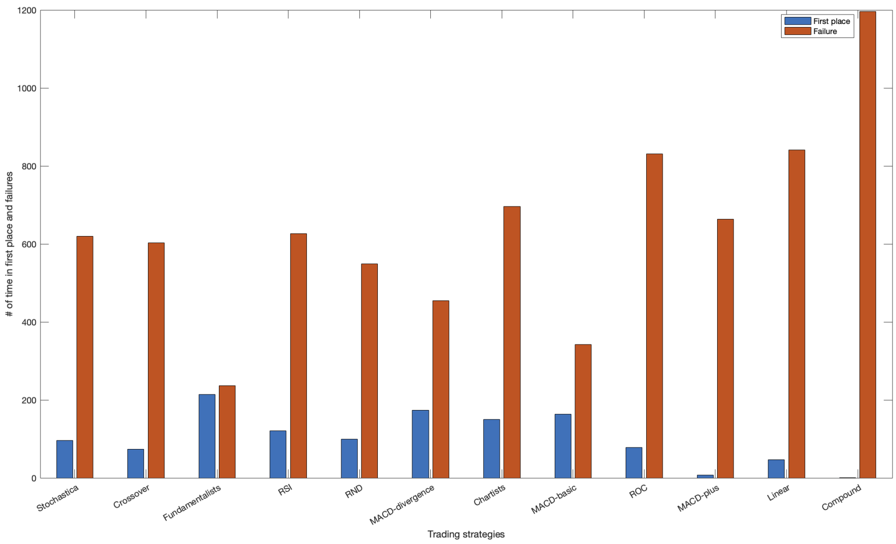

Figure 6: Occurrences for various strategies in the first position in the ranking or failures with (5 minutes).

4. Concluding remarks

In this paper we presented a model testing different strategies, based on technical analysis, of expectations formation and show how they affect performances of investors.

The proposed approach lies on back-testing simulations over true data. Data is used with reference to each day, as agents experience each time step ignoring the future. Thus, they choose on the basis of their expectations only, thus making it possible to measure performance of their portfolio investments, as in a financial race. Portfolios are obtained by considering all

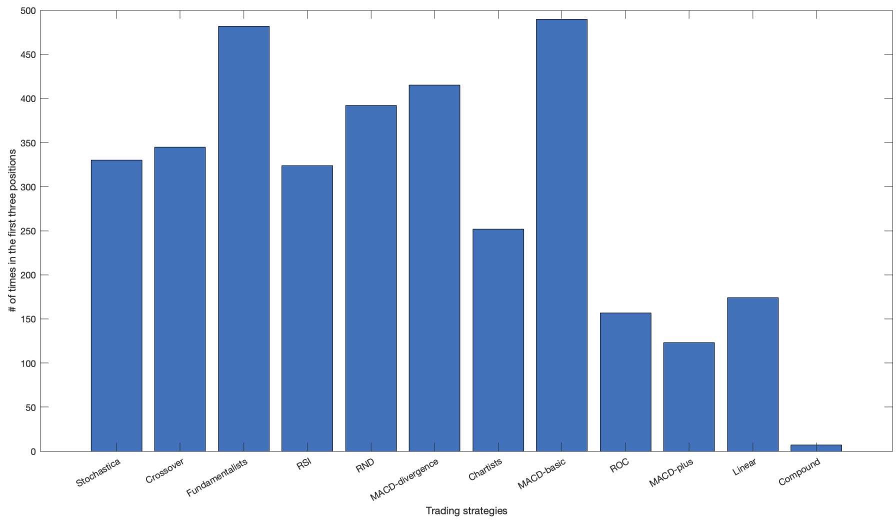

Figure 7: Number of times in which strategies have been placed in the top 3 positions (5 minutes).

Table 5
Ranking of strategies (1 minute)

STRATEGIES	1^{st}	2^{nd}	3^{rd}	FAILURES
Stochastic	131	156	99	584
Crossover	116	124	126	572
Fundamentalists	130	109	148	211
RSI	158	127	81	627
RND	72	175	152	540
MACD-divergence	115	161	112	484
Chartists	206	31	77	631
MACD-basic	156	170	154	346
ROC	92	31	48	829
MACD-plus	4	31	65	598
Linear	44	48	52	840
Compound	0	1	2	1210

possible couples of the 50 assets.

Simulations have been devoted to investigate two sets of aspects. First of all, the performance of different strategies has been analysed. For each couple of assets, a ranking of strategies was identified on the basis of portfolio values. Overall, results show that there are no concordant rankings of various strategies at different time lengths resolution. Thus, for instance, a winning strategy in simulations with daily data reveals to loose if used with infra-day data. This provides evidence that optimal strategies are more a desire of investors than an actual results. The reason why financial success can be reached in speculative investments must depend on occasional reasons and not on the chosen strategy. In other words, the complexity of the system prevents

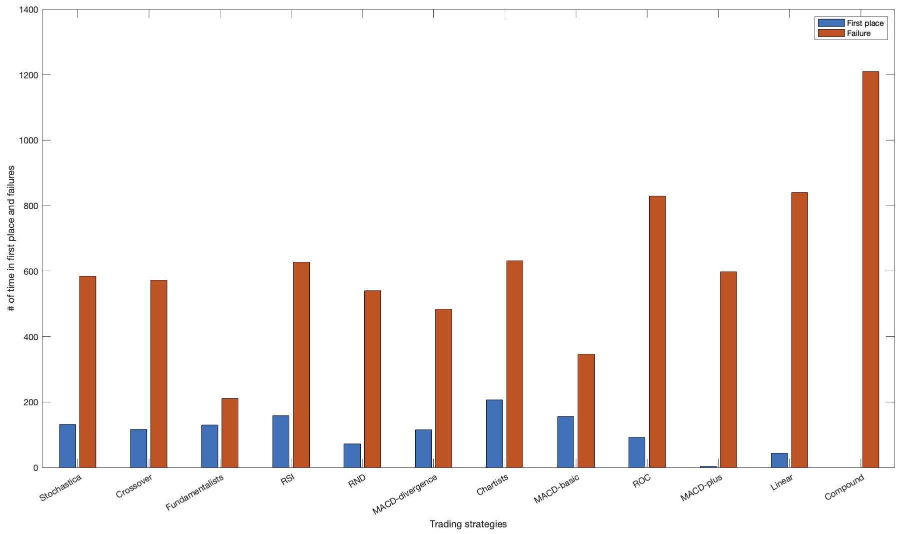

Figure 8: Occurrences for various strategies in the first position in the ranking or failures with (1 minute).

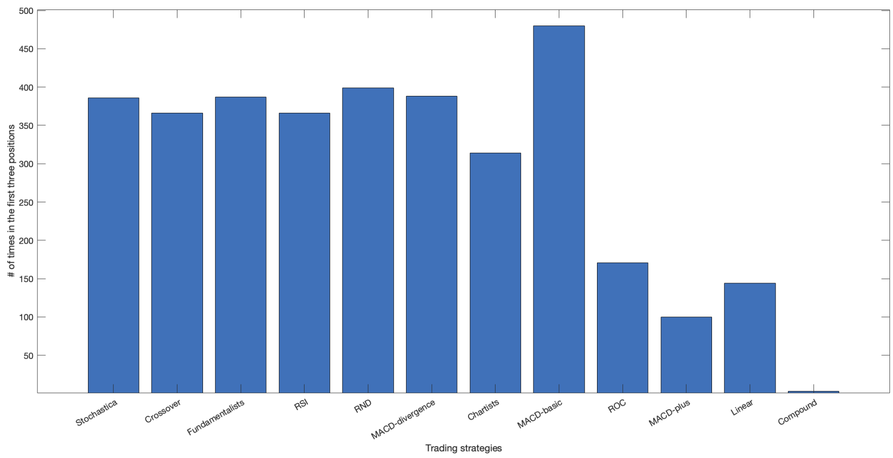

Figure 9: Number of times in which strategies have been placed in the top 3 positions (1 minute).

any forecast and past trends, elaborated as much as algorithm and experienced traders want, need not be replicated.

Secondly, we analysed the volatility of the best performing strategy and the instability of the market. Consequently to our first finding, we found that even best performing strategies manifest wide variability. One can conclude that the variability of results is not simply linked to the goodness of the adopted strategy. Something lying between the lines makes all strategies uncertain and potentially harmful.

The methodological innovation to the literature proposed in this paper is that possible strategies of actual trading have been compared by agent-based simulations. Although here the model is limited to portfolio composed by two assets only, further research will be dedicated to this topic, by considering interactions and contagion among traders and a ticker multi-asset settings to determine the weight of big traders, such as hedge funds and institutional investors, on the overall market dynamics.

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