AGENT BASED SIMULATION OF MULTIPLE FINANCIAL MARKETS

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Abstract: This work describes the first steps into the attempt of simulating several interacting financial markets in a realistic manner. We use populations of diverse artificial traders and investors, whose typologies are simplified versions of those existing in real markets. The agents can trade on several markets simultaneously and can establish an investment portfolio with several assets. Preliminary results of the simulations are encouraging. However, to increase the similarity with respect to actual financial markets some planned extensions have to be carried out. The number of agents should be increased and a portion of the traders should be given more adaptive capabilities.

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1. Introduction

Distributed, decentralized, interacting assemblies of agents are commonplace in biology and ecology. One may think for instance of ant or bees colonies, fish schools or flocks of birds as well-known natural examples of the emergence of ordered, coherent collective behaviour without any central control or authority. These and other systems are all complex, evolving and adaptive. No general theory of such systems is yet known; rather, their collective behaviour seems to result from the non-linear aggregation of simple local rules followed by the agents. In other words, the agents have a limited horizon and limited prevision and computation capabilities but, in spite of these limitations, the system as a whole appears to behave according to regular patterns.

Artificial Life is a new discipline [1] that strives to use computers, robots, and other artificial means to the study of life-like phenomena. The approach is synthetic rather than analytic and it works mainly by putting together systems that behave, in some respects, like living organisms. Computer simulation of populations of artificial entities is central to such an approach and has given insight into the

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behaviour of complex systems that would have been difficult to obtain with classical approaches such as differential equations dealing with aggregate quantities.

Economic, financial and social systems share many features with the aforementioned natural ecologies and their artificial life counterparts. Many important economic processes are complex in the sense that it is difficult to decompose them into separate parts that can be studied in isolation and aggregated to give the whole picture. Furthermore, economic agents do not seem to possess in reality the perfect rationality and computation abilities that the classical economic theory attributes to them. Issues of beliefs and prediction about the future become important and the individual beliefs and choices when aggregated shape the economic indicators, the market prices and ultimately the world that the agents must deal with. Moreover, this world is dynamical, as a result of the constantly changing collection of beliefs and strategies of the agents in their strive to adapt to the system evolution. In the real world, contrary to common economic assumptions, there is also diversity between agents due to different computing abilities and computing procedures and different time horizons and risk profiles in the financial field. Computerized collection of diverse, adapting agents should then prove useful, especially in studying the dynamical aspects of economical systems which are often neglected in standard theories. Some recent work has shown that the approach usefully complements the classical ones and can offer new insights of its own [2,3].

Of course, there are limitations to the simulation approach. The first question is: how simple can the agents be? Although very simple reactive automata have been employed for simulating economic scenarios, we feel that some of them are a poor approximation to the complex decision-making processes that real agents in real economies undergo. On the other hand, too complex agents are difficult to come by, are computationally expensive and unnecessarily complicated. We have chosen a middle ground in which agents possess a certain amount of computational and forecasting abilities, are of diverse types and are able to learn and evolve to some extent. Another criticism concerns the simulation itself. A simulation implies that a choice has to be made of what are the important components of the "world" to be simulated. There are no unique answers to that question and a simulation can always be criticized on this ground. Likewise, it is difficult to draw quantitative conclusions from simulations: only trends, general behaviour and statistics are obtainable.

Nevertheless, simulations can be valuable as they may also give a partial solution to the hard problem of doing experiments with real socio-economic systems under controlled conditions [4]. It is difficult to study the consequences of specific policies or rules of behaviour in an orderly way because these systems are dynamical and ever-changing. However, the computational appproach allows to do so easily, repeatedly and without risk. This makes them useful as pedagogical devices and also as a source of ideas for new methods of analysis.

2. The Market Simulation Environment

In this work, we are interested in the generic dynamical properties of financial markets. The artificial market is build around the behaviour of the real actors and these actors are represented by computer agents which interact together according to the rules of trading in the artificial market. The originality of the approach presented here resides in its multi-market nature. Until now, market simulations have been done in a single market context and with a single good traded (see for instance [5]). While this can be helpful to simplify the simulation and to control its parameters, real markets are strongly correlated, especially financial markets. Therefore, we strived to include inter-market effects in the simulation, albeit in a very simplified form, by linking several markets and allowing trading on several of them. As well, we have tried to stay as close as possible to real markets by using a plausible market typology and geographical distribution.

The market environment contains eight markets. There are three stock markets and three bond markets in three different currencies and two foreign exchange markets for the interconnection of the different currencies regions. This is similar to the three main actual financial regions: Asia represented by Japan, Europe represented by Germany and the United States of America. This allows to simulate also international diversified portfolios and enhances the variability of the agents, because the trading profile of an investor is different from the trading profile of a speculator. Another advantage of the different markets is the possibility of analysing the relations between different regions and different assets.

Only one good is traded in each market. This is realistic and easily understandable for the currencies exchange markets. The bond and stock markets are simplified because there is only one asset traded in each market, whereas in reality different stocks and bonds are traded in one single market. The bonds are assumed to have the same duration and the same coupon. The assumptions are simple but realistic because they amount to a situation very similar to trading an index or to trading the derivative financial instrument of the future markets. The future markets are today very important with high and increasing volumes in practice. The market environment seems to be realistic and allows to simulate inter market relations and to compare the simulation with time series of the real financial markets around the world.

The trading process is iterated, and consists of the following steps:

- Order placement of the agents.
- Calculation of the price.
- Accounting of the orders in the book of the agents.

Firstly, every agent places his buy or sell orders in the order book of the desired market. The order book contains all orders of a specific asset. The agents can only use market orders, which means that the order is executed at the best possible price that can be obtained at the time. The next step is the calculation of the price for every asset. The price of the asset for the actual trading cycle is calculated with the following formula:

$$p_t = p_{t-1} + 0.1\,\frac{p_{t-1}\,(o_{buy} - o_{sell})}{|o_{buy}| + |o_{sell}|}$$

where p is the price, t is the time or trading cycle number, o_{buy} is the number of buy orders and o_{sell} is the number of sell orders.

The third and last step of a trading cycle is the accounting of the executed orders: the assets and the cash are added or removed to or from the account of the agents based on the calculated price, and the new value of the cash and asset portfolio is calculated for every agent. Then the next cycle can begin with the placement of the orders of the agents based on theirs trading rules.

All placed orders are executed at every trading cycle because there exists a market maker for every market, who has the obligation to execute the difference of buy and sell orders for its own account. The assumptions of the market environment are simple but realistic and comparable to real exchange markets [6].

3. Trading Strategies of Agents

There are different agents for every market with different trading profiles, trading rules and home currencies such as technical traders, arbitrage traders, investors and market makers. The agents are simple reactive agents in the present model. The input to the agents are the past prices of the assets and their output is the order which they place every trading cycle in the order book. The agents do not have any information about the behaviour of the other agents with the exception of the price behaviour of the different assets. The importance of an agent increases with its success. The lot size of the trades increases with the accumulated profit of the agent. This should simulate the flows of trading and investment capital to the successful players in the financial markets. The next sections describes the trading rules of the different kind of agents.

3.1 Technical Traders

Technical analysts study market data in an attempt to gain insight into the future behaviour of the asset. They do this by looking for recurring patterns of price movements. In our artificial population, technical trading agents are univariate short-term traders. Many technical analysts believe in a trend behaviour of the markets and try to use moving averages or momentum analysis for detecting trends. The disadvantage of the trend theory is that the traders buy assets when they are high or expensive and sell when they are low or cheap. The contrarian traders do the opposite: they buy things which are out of favour and they run against the crowd [6].

There are two types of technical trading agents. The first kind are the trend followers: they buy if the price difference of the last trading cycle and the previous last trading cycle is greater than a threshold value, they sell if the price difference is smaller than a threshold value and they do nothing if the price is between the upper and lower threshold value. The second type are the contrarian traders which do the opposite: they sell if the price difference of the last trading cycle and the previous last trading cycle is greater than a threshold value and they buy if the price difference is smaller than a threshold value. They do nothing if the price is between the upper and lower threshold value.

3.2 Arbitrage Traders

Arbitrage is the simultaneous purchase and sale of assets in order to profit from distortions in usual price relationships. Variations include the simultaneous purchase and sale of bonds or stocks in different markets. Arbitrage is riskless because the buy and sell orders are simultaneous; it exploits transient inefficiencies in the financial markets. Arbitrage trading is important for a realistic interconnection of the different markets in the simulation environment. Arbitrage traders are multivariate short-term traders.

The first type of arbitrage traders connect the three bond markets. They buy the bond with the lower price, and sell simultaneously the bond in the other market with the higher price.

The second type of arbitrage traders connect the three stock markets. They also buy the stock in the cheaper market and sell it in the expensive one. The valuation of a stock must also take into account the currency exchange rate of the two stock markets. The reason of different stock prices in different markets can also be a mispricing of the currency exchange rate. The arbitrage traders of the stock markets have also to sell and buy the related currencies. The arbitrage traders of the bonds do not need to take into account the currency exchange rate because the bond price are the discounted cash flows of the future and these cash flows are in the same currency for a straight bond.

3.3 Investors

In actuality, an investor has more long-term oriented objectives than those of the previously described artificial traders. The difference between investors and the traders or speculators is the portfolio approach. The investor is not concentrating on some specific markets or assets because he believes in the efficient market theories according to which it is impossible to forecast markets for profitable trading. The investor diversifies his capital in different markets and tries to reduce the risk with an efficient portfolio without loosing opportunities of profit offered by the different assets. He is thus interested in long-term multivariate investment decision.

Most investment consultants make a distinction between tree types of investors. Firstly, the risk averse investor is interested in protecting his capital. The second type is interested in making a profit with an acceptable risk level. The third type believes in a high profit and accepts the risks of the aggressive strategy [6].

The risk is measured as the variance of the portfolio. The general formula for the variance of a portfolio is as follows [6]:

$$\sigma = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_{ij}$$

where: N is the number of assets in the portfolio, i, j are subscripts used to refer to particular assets and w is the weighting of the portfolio invested in each asset.

The first type of investors, the risk averse investors, try to minimize the variance of his portfolio in the simulation environment. The second growth-oriented type tries to optimise the reward to risk ratio which is the coefficient of the profit and the risk. The third type seeks to optimise the profit. The investors adjust their portfolios monthly based on the past profits, variances and covariances of the assets. They can only buy stock and bonds and they buy only currencies for buying stock or bonds in foreign markets. The investors are not allowed to take short positions of stocks or bonds and they can only sell assets that they own. The investors have different home currencies, which means that the profit is measured in different currencies and the strategies could be different depending on the home currency of an investor. Some investors are also limited in investing in foreign markets. They only invest in their home market.

3.4 Market makers

The market makers have the obligation to execute the difference of buy and sell orders of the other agents for their own account. They always clear the market and guarantee a liquid market.

4. Simulation

The primary goal of this work is to show that minimal conditions of real markets are satisfied with the assumptions and design of the presented artificial markets to observe real life phenomena. The similarities of the artificial markets and real markets are measured by comparing the price time series of the artificial and real financial markets. Introducing a number of ad hoc parameters (obtained from past time series observation in real financial markets) one could get a more realistic and reliable model of artificial markets without loosing the advantages of pure artificial markets. This allows to integrate different partial theories especially coming from the micro or agent level or the macro level of the markets and to test this hypothesis about the structure and the development of the real markets by making predictions about the trend and volatility of the different markets [7].

The real market data are daily time series from 1. October 1991 to 30. June 1995. The length of the time series allows to simulate around 900 trading cycles. The three stock markets are represented by the following stock market indices:

- Nikkei 225 for the Asian region
- DAX for Europe
- S&P 500 for the United States of America

The bond markets are represented by the following interest rate futures with a similar duration and coupons:

- Japan Government Bond for Asia (JGB)
- German Government Bund Future for Europe
- 10 Year US Treasury Note for USA

The currency exchange rates are:

- YENUSD

- DEMUSD

The used time series span the most important financial markets of the world and represent a large part of the daily trading activities around the financial world.

A simulation environment should allow to make experiments which are impossible in reality because the parameters of the environment can not be controlled. This is a general dilemma of social sciences and also of economy. The experiments of the simulation environment are only meaningful for the reality if the simulation environment and the reality have the same properties. The environment is realistic and useful if the behaviour of the simulated prices are similar to the observed prices of the different financial markets. If the simulation is qualitatively faithful with respect to the reality, then a further step would be to use the simulation to qualitatively forecast (trends and trend reversals) the actual financial markets.

5. Results

Although predicting the levels of price change is desirable, in finance foreseeing the sign of change is equally important. The following metric measures the success of trend prediction:

$$d = \frac{1}{n} \sum_{i=1}^{n} a_i$$

with

$$a_i = \begin{cases} 1 & \text{if } (x_{t+1} - x_t)(y_{t+1} - y_t) > 0 \\ 0 & \text{otherwise} \end{cases}$$

where x is the time series, y is the predicted time series and n is the number of test data sets.

The d statistics has a simple interpretation: $d = 1$ implies that the estimator is predicting 100% of the directional changes; $d = 0$ implies 0% prediction in directional changes. Therefore, any estimator with $d > 0.5$ offers a better result than relaying on tossing a coin. The statistics should be used with care because it is relatively easy to obtain a higher value for d in a trending market [8]. The d statistics for the different markets are shown in table 1.

The profit calculation also takes into consideration the magnitude of the change. Profitability is always calculated in the context of a trading rule and the estimate of expected returns must be turned into investment actions. For instance, consider a simple strategy in which positive expected returns are executed as long positions, and negative expected returns are executed as short positions. The net return of such strategy is given by:

$$r = \sum_{t=0}^{n} p_t \left(x_{t+1} - x_t\right)$$

where

asset	d
DEMUSD	53%
YENUSD	49%
Treasury Note	45%
S&P 500	44%
Bund	43%
DAX	49%
JGB	46%
Nikkei 225	50%

Tab. 1.

asset	d
DEMUSD	7%
YENUSD	-3%
Treasury Note	-9%
S&P 500	-11%
Bund	-7%
DAX	6%
JGB	-1%
Nikkei 225	-4%

Tab. 2.

$$p_t = \begin{cases} 1 & \text{if } (y_{t+1} - x_t) > 0 \\ -1 & \text{if } (y_{t+1} - x_t) < 0 \\ 0 & \text{if } (y_{t+1} - x_t) = 0 \end{cases}$$

assuming away transaction costs and slippage [8].

The returns are calculated in annualised percents for a better comparability of the different markets and are given in table 2.

The results are not very good at first glance. DEMUSD is the only time series which is better simulated than just using coin tossing, which means that the simulation environment have some realistic proprieties. The DEMUSD foreign exchange market satisfies this condition of reality and gives hope of improvements in the other markets. This hopes are justified by some limitations of the approach at the time of writing such as the limited number of agents and the fact that the stock and bond markets are restricted to one trading asset in the current version.

The outlook of our future work in the next section gives proposals for the improvement of the simulation environment in order to obtain a more realistic artificial market.

6. Conclusions

This work has presented the general simulation environment and has discussed a number of fundamental choices that have been made about market structure and the nature of the artificial agents. At the time of writing, the artificial market environment is not realistic enough for meaningful experiments, if one takes into account the hard constraint of at least qualitative adherence to real financial markets behaviour. However, the work done to date does shows that we are at the beginning of a new very promising way for a better understanding of the behaviour of financial markets. For example, it is possible to explain the behaviour of the DEMUSD exchange rate with the presented simulation environment.

We have planned the following steps to further pursue our study in the near future. First, the number of agents should be increaded. At the moment there are about 25 agents in every market due to present time and computational limitations, which is not realistic. This will be raised in the near future to more representative numbers, such as hundreds of traders. The influence and possible scaling effects of an increasing number of traders on the market behaviour will also be studied.

We said in the introduction that agents should be adaptive. In the present model they aren't but we plan to use a proportion of adaptive artificial agents in the trading populations that will be represented by simple rule automata or artificial neural networks. These agents will be able to modify their behaviour as a function of their self-observed performance and of the generally available market information. This will increase the diversity of the agents and should be closer to reality, in which many different trading strategies co-exist and co-evolve. These improvements should lead to a realistic simulation environment for financial markets.

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