

# Survival of the Chartist: An Evolutionary Agent-Based Analysis of Stock Market Trading

## (Extended Abstract)

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### Categories and Subject Descriptors

I.2.6 [Artificial Intelligence]: Learning

### General Terms

Economics, Experimentation

### Keywords

Learning and Adaptation::Evolution and co-evolution, Agent-based simulation::Complex systems

## 1. INTRODUCTION

A stock market is a highly complex dynamical system. Stock-price movements are not solely driven by fundamental values but in particular influenced by short term trading behaviour. Chartists use trends to forecast future price directions, whereas fundamentalists estimate stock prices based on dividend payouts or company earnings. Such strategies can similarly be deployed in automatic trading agents, which already account for a large portion of current trading activity. It is therefore vital to understand how these trading strategies behave in different scenarios, and how the interplay of strategies may lead to various market outcomes. In this paper we analyse the dynamics of three different trading strategies: fundamentalist, chartist, and zero-information traders, who base their trading behaviour on the current market price only. We simulate stock markets with various constellations of trading agents, and compare their evolutionary strength, using heuristic payoff tables and the replicator dynamics of evolutionary game theory. Our results show that it is not straightforward to predict in advance which trading strategy will perform best. Fundamentalists outperform other traders, and drive them out of the market, when information is freely available. If fundamental information is costly, chartists may thrive. As such, this paper sheds light on the various factors that play a role in determining success or failure of trading strategies in a complex market.

**Appears in:** *Proceedings of the 14th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2015)*, Bordini, Elkind, Weiss, Yolum (eds.), May 4–8, 2015, Istanbul, Turkey.  
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## 2. MARKET MODEL

Our market model is based on a continuous double auction with an open order book, in which all traders can place bids and asks for shares [1, 3]. The current value of a share is inherently determined by the revenue that one is expected to gain from holding the share in the future. In our model, these revenues come from dividends that are paid out regularly based on the number of shares owned at that point in time. The stream of dividends follows a Brownian motion random walk given by  $D_t = D_{t-1} + \epsilon$ , where  $D_t$  denotes the dividend in period  $t$ , with  $D_0 = 0.2$ , and  $\epsilon \sim \mathcal{N}(\mu, \sigma^2)$ .

We simulate the market over 30 trading periods, each lasting  $10 \cdot n$  time steps, where  $n$  is the number of traders present. All traders start with 1600 units cash and 40 shares, each worth 40 initially. At every time step a trader is selected at random who can then either accept an open order, or place a new bid or ask, according to his trading strategy. At the end of each period, dividend is paid based on the shares owned, and a risk free interest rate  $r = 0.1\%$  is paid over cash. The performance of the traders is measured as their total wealth after the 30 periods, i.e., the sum of their cash and share holdings.

### 2.1 Trading Strategies

We use three different trading strategies in this paper. *Fundamentalist* of information level  $F_j$  use their knowledge of the next  $j$  dividends to estimate the current value of the stock at period  $k$  following Gordon's growth model [2], and base their trading decision on that estimate:

$$E(V|F_j, k) = \sum_{i=0}^{j-1} \frac{D_{k+i}}{(1+r)^i} + \frac{D_{k+j-1}}{r(1+r)^{j-1}}$$

This results in a cumulative information structure, where insiders know at least as much as averagely informed traders. In this paper we use two types of fundamental strategies: averagely informed traders ( $F_3$ ) and insiders ( $F_9$ ). *Chartists* analyse past trading prices and look for trends. If they observe an upward trend in the market price they see this as an opportunity to buy; if the trend goes down they sell. Traders without any information use the *zero-information* strategy, taking only the current market price of the shares into account and trading randomly around that price. Specifics of these trading strategies can be found in Tóth and Scalas [3].

## 2.2 Cost Functions

Acquiring fundamental information might be costly: limited foresight knowledge might be obtained by reading financial news letters and company statements, whereas a detailed long-term outlook requires hiring experts. In order to model these effects we introduce three different cost functions and investigate their effect on the traders' performance. The fixed cost function assumes that each fundamentalist pays the same fixed amount per trading period, regardless of their information level. We can also assume that traders have to pay for each additional bit of information, yielding a linear cost function. Finally, the quadratic cost function is based on the idea that it gets increasingly difficult to obtain more information. Chartists and zero-information traders rely on current and past market prices only, which we assume to be freely available.

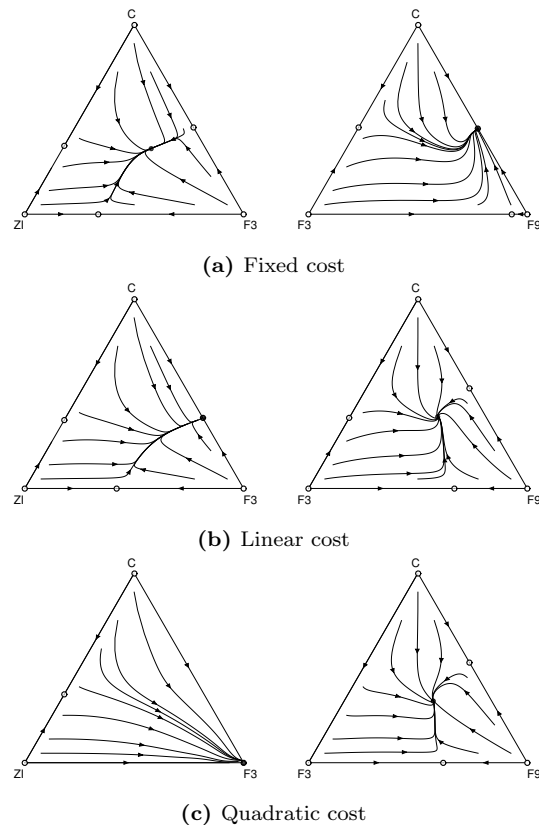
## 3. EVOLUTIONARY DYNAMICS

We investigate the dynamics of a market in which traders are free to change their strategy at any time based on their performance. We consider four trading strategies: zero-information (ZI), fundamentalists of types  $F_3$  and  $F_9$ , and chartists (C). We follow the procedure described by Walsh *et al.* [5] to compute a heuristic payoff table (HPT), using 24 traders distributed over those four strategies. This yields 2925 different discrete permutations in the HPT. For each permutation, the relative performance of the involved strategies is estimated by running 1000 simulations of the market. The resulting HPT is used as basis for the replicator dynamics model of multi-agent learning [4], which we inspect visually. This analysis gives insight into the evolutionary strength of various trading strategies, and the fixed points of the dynamics predict the distribution of trading strategies that may be found in a market in equilibrium.

Fig. 1 shows two faces of the four-dimensional simplex, corresponding to the strategy sets  $\{ZI, F_3, C\}$  and  $\{F_3, F_9, C\}$ . When no costs are incurred, both C and ZI traders are consistently outperformed by fundamentalists, in line with expectations (omitted in Fig. 1). When fixed costs apply (Fig. 1a) a stable attractor appears where ZI,  $F_3$ , and C co-exist. Averagely informed traders ( $F_3$ ) incur relatively large costs in this scenario, and are driven out of the market when insiders ( $F_9$ ) are present. The linear and quadratic cost functions (Figs. 1b and 1c) revert this imbalance, yielding an interior equilibrium where  $F_3$ ,  $F_9$  and C prevail. Interestingly, in these scenarios ZI traders go extinct. The omitted face  $\{ZI, F_3, C\}$  yields an internal equilibrium under all three cost functions, and the situation without chartists has been thoroughly examined in previous work [1]. Numerical analysis of the full four-dimensional simplex unveils single stable attractors for each cost scenario, showing the shifting balance between  $F_3$ ,  $F_9$  and C as costs change (Table 1).

## 4. CONCLUSIONS

Our findings highlight the limits of fundamentalists and show when it is possible for chartists to survive in the market. We observe a variety of outcomes depending on whether costs are a driving factor of the market. As such, a good understanding of the underlying dynamics is of vital importance if any reasonable predictions about market outcomes are to be made. The replicator dynamics model of multi-agent learning proves a valuable tool to aid such analysis.



**Figure 1:** Dynamics of a market with four trading strategies and different cost functions. Stable attractors are indicated with ● and unstable attractors with ○.

**Table 1:** Stable equilibria of the four-dimensional simplex.

Cost function	Equilibrium ( ZI, F <sub>3</sub> , F <sub>9</sub> , C )
No cost	(0.00, 0.07, 0.93, 0.00)
Fixed cost	(0.27, 0.00, 0.39, 0.34)
Linear cost	(0.36, 0.10, 0.21, 0.33)
Quadratic cost	(0.35, 0.15, 0.22, 0.28)

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