On the Effect of "Stock Alerts" in an Agent-Based Model of a Financial Market

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Abstract

Nowadays, an increasing number of web sites allow people to directly trade stocks and several other types of investments in financial markets through the Internet. These sites offer many conveniences to the customers using the network infrastructure, such as "stock alerts", which are mechanisms that promptly notify the customer when a certain stock reaches a threshold price value, set in advance by himself. The expected action from the stock alert user, upon receiving this notification, is to place an order to buy or sell stock shares, as the threshold price is supposedly associated with the profit the user is aiming for. The question addressed in this paper is how features like "stock alerts" affect the overall behavior of a financial market, as the number of individual stockholders grows due to the increased access to the market allowed by the Internet. Initial simulation results with an agent-based model of a financial market are presented.

Introduction

Trading stocks has never been so easy. Nowadays, an increasing number of web sites allow people to directly trade stocks and monitor market indexes and stock prices through the Internet. While financial newspapers and magazines may still be the investors' first source of information, many web sites offer services that deliver up-to-date news to their customers, making information broadly accessible, and what is more important to be noticed, practically instant. Despite their recency, financial web sites may strongly reinforce the popularization of the stock trading as an individual activity, a phenomenon that is already witnessed in the USA (New York Stock Exchange 1998), where the number of individuals owning corporate stocks, through mutual funds or other types of accounts, has been increasing continuously.

Taking this into account, it seems natural, as much as inevitable, that in the future the behavior of individual stockholders will play an increasingly major role in defining the market aggregate behavior. Interestingly, up to now mainstream economics has largely overlooked issues concerning the rationality and normative power of the individual agents, building models that regard economic agents as perfect decision makers, empowered with unlimited error-free decision making mechanisms, disregarding any factor of psychological or social nature that could possibly influence their reasoning processes.

Specifically in the context of financial markets, experiments conducted by Fischhoff and Slovic (Plous 1993) showed that the majority of the subjects were sure they could predict future trend changes in the price of a stock, if given information about stock prices and trends, though less than half of the subjects could actually do so. The work concluded that the forecasting errors were mainly due to the overconfidence of the subjects in their predictions, which illustrates well the fact that to assume perfect decision making by the economic agents is too restrictive a condition, since other factors might affect the reasoning process conducted by them. These issues have been long discussed in the field of economics (Simon 1982). The question that arises now, regardless of which economic theory explains better the reality of markets, is how the popularization of stock trading brought by the development of the Internet infrastructure, as an activity held by individuals investors, will affect the behavior of financial markets? The Internet introduces a new tempo to the system, as information and action are almost immediate, thus it is important to clarify its influence in financial and other types of markets.

This increase in the visibility of the market may also reinforce social movements in where investors have their behaviors influenced by other investors' behaviors. As Shiller points out (1989), the idea that social movements such as fashions and fads have deep implications in the sometimes idiosyncratic behavior of an asset's price is not consensual among the different schools of thought in economics. Indeed, the new reality may turn out to be even more distinct from the theory.

In this paper, the influence of a feature found in some of the major financial sites, which we will generally call "stock alert", is investigated by means of simulations with an agent-based model of a stock market, and some
Stock Alerts

Conceptually, a stock alert is a very simple mechanism offered by financial sites like E*Trade\(^1\), where it is called smart alert, and by Yahoo! Finance\(^2\), where it is called instant stock alert. It works as a "watchdog" on a given stock's price; the price series is constantly monitored, and as soon as it achieves a certain threshold price value, the stock alert sends a notification to the customer, by email or through a ticker displayed in her computer. The stock and the threshold price value are freely customizable by the user.

It is fair to assume that, in the large majority of the cases, an action from the customer will immediately be triggered by the stock alert's notification; if there are no time requirements involved in the action of buying or selling stocks, i.e., if there is no need to the customer react quickly, much of the significance of using such a feature vanishes away. In a sense, the stock alert user may even feel compelled to correspond fast; it may strengthen the ludic aspect of trading stocks, as in lottery games or other wagering markets.

Moving to the point-of-view of a stock alert user, there are some aspects to be considered. Online traders may have several analytic tools at hand to help them make their investment decisions, and in fact, some web sites offer such packages for the subscribers. Nevertheless, the population of individual traders can still be considered highly heterogeneous, a mix of sophisticated traders and more simplistic ones. Conjecturing on the characteristics of ordinary individual stockholders, it is difficult to envisage a scenario where the majority of the investors make complex calculations to find out a price value that will possibly maximize the profit within the desired period time. Ordinary investors may rather set their strategies and objectives according to subjective perceptions of the market dynamics, on what they "feel" would be most likely to happen to the stock price according to their past experience. They may also adopt more timid strategies and be more susceptible to behavioral changes on the arrival of economic and political news that put their investments at stake.

Another point that could be conjectured concerning stock alert users is that they will have expectations and beliefs transcription in the form of price values, which in the ultimate level synthesize several factors: what the investor thinks it is a feasible value to be reached, which is a belief that may vary with time, as the traders observe the market develop and their needs change; the period of time the investor is willing to wait until he can accomplish the trade, which is an individual demand. What is most important to notice is that prices in monetary currencies are values that are usually dealt with in several moments of a person's daily life. It is relatively easy to give a concrete value in terms of price for subjective and personal notions such as "expensive" or "cheap", "worthy" or "good profit", though people may not be aware or able to explain why and how they arrived to such values. Setting up price values as conditions for taking actions, as in the framework prepared by stock alerts, may facilitate traders to work with genuine and intuitive evaluations of worthinesses.

Stock alerts (indeed, online brokering mechanisms in general), thus, can be considered to be fast two-way connections linking a heterogeneous population of investors to the market. On the one hand, it quickly delivers information to the investors, and due to the very situation in which they are immersed (following the rationale that those who need to react immediately would be the most eager to make use of such convenience), it demands a quick reaction. The effect this feature may bring to financial markets, in the form of an increased influence by individual investors, is still to be confirmed. Though this may sound mere speculation wandering in the gray area of popular economic models, it should be recalled that the impact of the Internet in financial markets is still unclear, as it brings a complete new set of characteristics and dynamics to the markets (see (Varian 1998) for a short review of works in the field).

Experiments

The aim of this set of experiments was to identify eventual differences in the dynamics of the stock price due to the introduction of investors that behave as if they were using a stock alert, i.e. buying shares when the price gets below a lower limit and selling when it gets above an upper limit.

Experiments were performed using our implementation of the Santa Fe Artificial Stock Market (Arthur et al. 1997), using the Swarm Simulation System libraries (Minar et al. 1996). Our main interest in using the Santa Fe Artificial Stock Market is to have a basic, but nevertheless realistic, working framework of a stock market model. The market is comprised by a population of traders and a market specialist, whose function is to set up the price of the stock, based on the traders' orders to buy or sell stocks. The traders have to determine in each time step the composition of his investment portfolio, i.e. the distribution of money between a risk-free asset that pays a constant interest rate and stock shares. The dividend returned by the stock shares varies with time, following an autoregressive process unknown to the traders.

Several economic indicators reflect the market's state and are made available to the traders to guide their decisions; these indicators convey information on the fundamental value of the stock, i.e. the relation between the current stock price and the dividend, and also information on trends, which is usually used by

\(^1\)http://www.etrade.com
\(^2\)http://finance.yahoo.com

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brokers who perform technical analysis. The traders in the model make use each one of a classifier system (Holland et al. 1986), whose IF <condition> THEN <prediction> rules determine the composition of the portfolio. A rule will fire if the current market status matches its <condition> part. The <prediction> part calculates the rule’s forecast of the stock price in the next time step \( p_{t+1} \) plus the dividend \( d_{t+1} \), \( E[p_{t+1} + d_{t+1}] \). This estimation is obtained through a linear function of the type \( a_{t} (p_{t} + d_{t}) + b_{t} \), that take as arguments the current values of stock price and dividend. This estimation is fed into a CARA utility function (Constant Absolute Risk Aversion) to calculate the amount of shares the trader will buy or sell. The set of rules is periodically optimized by means of a genetic algorithm (Holland 1992).

It should be recalled that the main point clarified by Arthur et al. is the existence of two market dynamic situations, which are realized depending on how frequently the traders are allowed to learn, i.e. update their forecasting rules according to the genetic operations. Briefly explaining, they found that under low learning rates, a market regime characterized mainly by low trading volume, relatively low price variations, and the absence of technical trading emerged. This was named rational-expectations regime. As the learning frequency was raised, a more realistic market regime emerged, with the occurrence of temporary price bubbles, crashes and technical trading. This was called the complex or rich psychological regime. We attempted to reproduce the rich psychological regime in our own implementation by setting up a suitable set of values to the model parameters.

Two distinct simulation sessions were conducted. In the first session, a market with \( N = 50 \) traders, each one equipped with its own classifier system, was let run for a 300,000 days. These traders were named "complex traders". As we wanted to investigate eventual effects brought by the use of stock alerts, in the second session the market had \( N = 50 \) traders, from which 8% of the traders were models of stock alert users and the rest constituted by "complex traders". This model was first let run for 150,000 days with the stock alert users kept inactive, reproducing an identical situation to the first session (with the difference in the total number of traders). In the second period of the simulation, the stock alert users were allowed to participate in the market. This scheme supposedly allows the "complex traders" to learn about the market before the stock alert users get in to action.

The "complex traders" optimized the rules using a simple genetic algorithm. The frequency of update (learning ratio) was in average 1/1000. The total number of rules was set to 100. Whenever the learning algorithm was activated, the rules were ranked according to their forecast accuracies and 5% of the low ranked rules were optimized. To carry out a rule optimization, first a rank-selection scheme was used to choose a second rule from the rule base. The information contained in the second rule was then "mixed" with the original rule; subsequently, the reformed rule would suffer mutation in its contents. The initial values of the parameters \( a, b \) of each rule were randomly selected from a uniform distribution in the interval \([0.7 \ldots 1.2]\) and \([-10 \ldots 19.002]\), respectively. (The rule update procedures of the genetic algorithm and the values of other relevant parameters of the model were the same as in (Arthur et al. 1997).)

**Modeling the Stock Alert Users**

Compared to the "complex traders", the models of the stock alerts users have a much simpler structure. They were basically built on two threshold prices: \( MBuy \) and \( MSell \). Whenever the market price of the stock share was below the \( MBuy \), with half chance the stock alert users put an order to buy one unit of a share. In the same way, whenever the price was above the \( MSell \), with half chance the stock alert users put an order to sell whatever amount they had at that moment of stock shares. This is in accordance to the hypothesis that stock alert users in real markets may make offers or bids to the market as soon as the stock price reaches a given threshold.

\( MBuy \) and \( MSell \) were initialized as follows. A random number would be first sampled from a normal distribution with mean 100 and variance 15. This range of initial values was arbitrarily chosen from what it was thought reasonable, after some inspection of the prices practiced in the market model. Then, a second number would be generated by adding or subtracting, with equal chances, a random number from the interval \([-5 \ldots 5]\) to the first number. The lowest of the two numbers would be the initial \( MBuy \) and the other the initial \( MSell \).

Stock alert users were also equipped with a simple parameter adjusting algorithm, that worked as follows. In case of a successful transaction, the stock alert user would count the number of successful orders, and when that number reached a threshold, \( Si \), he would increase his margin, aiming larger profits, and reset the number of successful orders. If the market can not clear, the orders are unsuccessful and each stock alert user would increment the number of deceptive orders in a row. When the number of unsuccessful orders reached a threshold, \( Ui \), the user would decrease his margin, demanding more modest profits. The number of unsuccessful orders would be reset whenever a successful order was accomplished, or when it reached the threshold \( Ui \).

The value of \( MBuy \) was decreased when the last order to buy shares was successful and the number of successful orders = \( S_i \), according to the following rule:

\[
MBuy_{new} = MBuy_{old} - \mid MBuy_{old} - p_t \mid \times \delta
\] (1)

Correspondingly, if the last order to buy was unsuccessful and the number of unsuccessful orders = \( U_i \),
MBuy would be increased as follows:

$$\text{MBuy}_{\text{new}} = \text{MBuy}_{\text{old}} + |\text{MBuy}_{\text{old}} - p_t| \times \delta$$  \hspace{1cm} (2)

For the upper limit, if the last order was a successful order to sell and the number of successful orders = \(S\), \(m_{\text{Sell}}\) would be incremented as follows:

$$m_{\text{Sell}}_{\text{new}} = m_{\text{Sell}}_{\text{old}} + m_{\text{Sell}}_{\text{old}} - p_d$$  \hspace{1cm} (3)

Correspondingly, if the last order to sell was unsuccessful and the number of unsuccessful orders = \(U\), \(m_{\text{Sell}}\) would be decreased as follows:

$$m_{\text{Sell}}_{\text{new}} = m_{\text{Sell}}_{\text{old}} - |m_{\text{Sell}}_{\text{old}} - p_t| \times \delta$$  \hspace{1cm} (4)

The parameter adjusting rules described above are very simple, based on the rationale that an unsuccessful order is a signal that the trader is being greedy, leading her to decrease the margin, in order to increase the chances of having a successful order in the future. On the other hand, too many successful orders makes the trader increase her margin, trying to obtain higher profits. They do not perform any technical analysis nor directly try to detect price trends.

Values of \(S_t, U_t\) were randomly sampled in the interval \([10 \cdots 20]\), and \(\delta\) was initialized for each stock alert user by sampling random numbers in the interval \([0.0005 \cdots 0.001]\).

**Results and Discussion**

Experiments were realized with the model described above and were divided in two sessions; in the first session, the population of traders was composed only by "complex traders" (identified by only CT), and in the second session, "complex traders" and "stock alert users" (identified by CT and SAU) were present in the market. In each session, 20 instances of the model were run. A set of 20 different random seeds was prepared to initialize the models in both sessions, so that the dividend series \(d_t\) would be pairwise identical. The results obtained are summarized in Tables 1, 2, 3, and 4.

Table 1: Summary statistics for the stock price, after 300,000 days (average of 20 runs)

<table>
<thead>
<tr>
<th></th>
<th>only CT</th>
<th>CT and SAU</th>
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<tbody>
<tr>
<td>mean</td>
<td>93.35</td>
<td>93.63</td>
</tr>
<tr>
<td>standard deviation</td>
<td>6.83</td>
<td>6.94</td>
</tr>
<tr>
<td>kurtosis</td>
<td>0.88</td>
<td>3.94</td>
</tr>
<tr>
<td>skewness</td>
<td>-0.11</td>
<td>-0.44</td>
</tr>
</tbody>
</table>

The first point that calls attention is related to the higher kurtosis presented by the model with stock alert users, in Table 1 and 3, relative respectively to the total period of simulation and the last 150,000 days, i.e. the situation where the complex traders cohabitate the market with the stock alert users after being alone for 150,000 days. Apparently, this is due to a simulation artifact, generated by the sudden appearance of the stock alert users in the market. Looking to the results in Table 4, which takes in consideration only the last 100,000 days, i.e. leaving out the singular period when the stock alerts suddenly become active, indeed both kurtosis and skewness values are less than the values presented in the situation where only "complex traders" are present. For the agent-based model of the market, the market becomes more silent when the stock alert users are around.

Table 2: Summary statistics for the stock price, first 150,000 days (average of 20 runs)

<table>
<thead>
<tr>
<th></th>
<th>only CT</th>
<th>CT and SAU</th>
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<tbody>
<tr>
<td>mean</td>
<td>93.07</td>
<td>93.75</td>
</tr>
<tr>
<td>standard deviation</td>
<td>7.09</td>
<td>7.19</td>
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<tr>
<td>kurtosis</td>
<td>1.13</td>
<td>1.16</td>
</tr>
<tr>
<td>skewness</td>
<td>-0.10</td>
<td>-0.11</td>
</tr>
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Table 3: Summary statistics for the stock price, last 150,000 days (average of 20 runs)

<table>
<thead>
<tr>
<th></th>
<th>only CT</th>
<th>CT and SAU</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>93.63</td>
<td>93.50</td>
</tr>
<tr>
<td>standard deviation</td>
<td>6.54</td>
<td>6.65</td>
</tr>
<tr>
<td>kurtosis</td>
<td>0.48</td>
<td>5.76</td>
</tr>
<tr>
<td>skewness</td>
<td>-0.09</td>
<td>-0.72</td>
</tr>
</tbody>
</table>

Table 4: Summary statistics for the stock price, last 100,000 days (average of 20 runs)

<table>
<thead>
<tr>
<th></th>
<th>only CT</th>
<th>CT and SAU</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>93.59</td>
<td>93.44</td>
</tr>
<tr>
<td>standard deviation</td>
<td>6.48</td>
<td>6.35</td>
</tr>
<tr>
<td>kurtosis</td>
<td>0.49</td>
<td>0.33</td>
</tr>
<tr>
<td>skewness</td>
<td>-0.09</td>
<td>-0.08</td>
</tr>
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</table>

It is important to notice that the complex traders and the stock alert users are inherently distinct in what relates to the reasoning process that leads to an action. The complex traders make use of a CARA utility function to determine the composition of the portfolios; on the other hand, the stock alert users adopt a simplistic (intuitive) strategy of acting on the market when the price is higher/lower than their individual reservation prices. As mentioned before, it is possible that in the context of stock alert users, the market becomes more silent when the stock alert users are around.
of "noise" in the market should also be an interesting investigation of how the usage of stock alerts will influence the amount of noise trading in the market, as defined in (Long et al. 1993), due to the arrival of a large population of non-experts into play.

It would be interesting to try similar experiments in a larger model to detect eventual issues related to the behavior of software agents. As advocated in (Kephart et al. 1998), it is likely that in a close future the Internet will be populated by software agents, who will interact with other software agents and with human users in order to facilitate transactions and disseminate information. Such a scenario is as interesting as it is unknown, and deserves further investigation.

### Table 5: Initial and final mean and standard deviation for MBuy and mSell (average of 20 runs, population composed of 4 stock alert users and 46 complex traders in each run, after 300,000 days)

<table>
<thead>
<tr>
<th></th>
<th>( \mu_{t=0} )</th>
<th>( \sigma_{t=0} )</th>
<th>( \mu_{t=3e5} )</th>
<th>( \sigma_{t=3e5} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>MBuy</td>
<td>98.23</td>
<td>4.49</td>
<td>80.94</td>
<td>0.87</td>
</tr>
<tr>
<td>mSell</td>
<td>100.60</td>
<td>4.28</td>
<td>101.40</td>
<td>4.07</td>
</tr>
</tbody>
</table>

While still an open issue, the question of how the Internet will change the behavior of financial markets should include also a discussion on the impact of computational autonomous agents. As advocated in (Kephart et al. 1998), it is likely that in a close future the Internet will be populated by software agents, who will interact with other software agents and with human users in order to facilitate transactions and disseminate information. Such a scenario is as interesting as it is unknown, and deserves further investigation.

### References


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