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# Assessing the Impact of Algorithmic Trading on Markets: A Simulation Approach

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# ASSESSING THE IMPACT OF ALGORITHMIC TRADING ON MARKETS: A SIMULATION APPROACH

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## Abstract

*Innovative automated execution strategies like Algorithmic Trading gain significant market share on electronic market venues worldwide, although their impact on market outcome has not been investigated in depth yet. In order to assess the impact of such concepts, e.g. effects on the price formation or the volatility of prices, a simulation environment is presented that provides stylized implementations of algorithmic trading behavior and allows for modeling latency. As simulations allow for reproducing exactly the same basic situation, an assessment of the impact of algorithmic trading models can be conducted by comparing different simulation runs including and excluding a trader constituting an algorithmic trading model in its trading behavior. By this means the impact of Algorithmic Trading on different characteristics of market outcome can be assessed. The results indicate that large volumes to execute by the algorithmic trader have an increasing impact on market prices. On the other hand, lower latency appears to lower market volatility.*

*Keywords AUTONOMOUS AGENTS, ECONOMIC MODELS OF IT IMPACT ON ORGANISATIONS & MARKETS, EMERGING TECHNOLOGIES, FINANCIAL SERVICES.*

# 1 INTRODUCTION

The way electronic trading is conducted on international financial markets has dramatically changed in recent decades as more and more stages of the trading process have been radically altered by electronic means. One of the most recent developments is Algorithmic Trading, which primarily focuses on the minimization of implicit transaction costs in order execution.

If a large order is sent to a market venue implementing an open order book, solely exposing the intended trade volume would cause an adverse price movement (market impact), i.e. the exposure of a large volume to buy would force market prices to rise. Vice versa market prices would fall in case a large volume to sell is exposed to the other market participants. Volume discovery, i.e. to find a counterparty that wants to trade similar quantities, is therefore an important issue for Institutional Investors. In the past, orders were delegated to (human) brokers that aimed at finding a suitable execution for the incoming orders. As this is kind of a routine task for “low-touch orders”, i.e. plain-vanilla orders in liquid securities, computer systems have been implemented to automate it, enabling human traders to concentrate on the more complex trading task of “high-touch orders”, e.g. orders in illiquid securities.

In order to alleviate market impact, a block trader may circumvent the disadvantages of an open order book by submitting the order to a non-transparent block trading system, e.g. ITG’s POSIT. Alternatively, a block trader may adapt to the characteristics of an open order book by blurring the intended trade volume - which is achieved by algorithmic trading models. They enable investors to submit large orders to transparent markets and to minimize the market impact at the same time, as they are slicing the large orders into a multiplicity of smaller ones and time their individual submission. Based on mathematical models and considering historical and real-time market data, algorithmic trading models determine ex ante or continuously the optimum size of the (next) slice and its time of submission to the market. Such systems have been used internally by sell-side firms for years; recently they have become available to their buy-side[1] customers. Based on the sell-side business model of a virtual Direct Market Access (DMA), where orders are not touched by brokers anymore but are forwarded directly to the markets, the buy-side was enabled to develop their own solutions or to use the offerings of independent software vendors (ISV). Additionally, the sell-side offers algorithmic trading models directly to their customers as well. With the automation of the slicing and timing tasks, the speed of execution and the prompt availability of real-time market data have become success factors. As already milliseconds can make a difference leading market operators already started to offer co-location services, which allow users of Algorithmic Trading to place their trading equipment adjacent to the technical infrastructure of the market itself and thus ensure low latency. Comparison of different venues in terms of latency is hardly possible, as measurement is difficult and the methods used are inconsistent.[2]

Shrinking average trade sizes are observable at major market venues worldwide although total trading volume has risen in recent years (Figure 1), which may be explained by an increasing usage of order slicing concepts. According to Deutsche Börse (2008, p. 14) on Xetra, the electronic trading system of the German Stock Exchange, the proportion of order flow that is generated by Algorithmic Trading rose to 39% in 2007. This increasing usage of automated slicing concepts implies manifold consequences on the markets themselves. E.g. Prix, Loist & Huetl (2007) were able to indentify certain Algorithmic Trading patterns in the order flow on Xetra.

[1] Buy-side refers to investment management companies that are ‘buying’ trading services from the sell-side, i.e. investment banks and brokers (Harris 2003).

[2] Budimir & Schweickert (2007) developed a first latency measurement methodology.

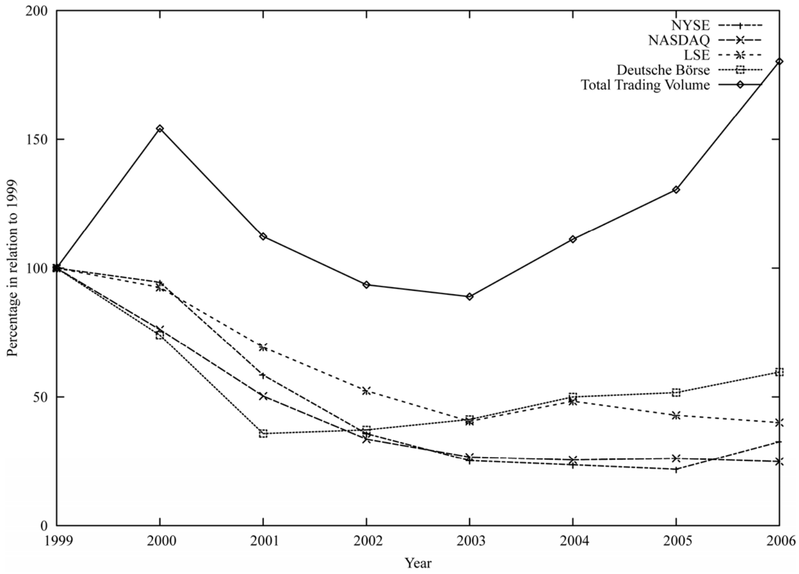


*Figure 1: Average value of trades at major market venues in relation to the year 1999 (based on data provided by the World Federation of Exchanges)*

Further effects have not been thoroughly investigated yet in academic research. This lack has been the motivation for this research. In order to assess the impact of such concepts on the market outcome in terms of effects on the price formation or the volatility of prices, a simulation environment has been set up, which provides implementations of algorithmic trading behavior and allows for modeling latency. As simulations enable to reproduce exactly the same basic situation, an assessment of the impact of algorithmic trading models can be conducted by comparing different simulation runs including and excluding a trader constituting an algorithmic trading model in its trading behavior.

The following section 2 will give a brief overview of academic literature on Algorithmic Trading and on simulation of financial markets. The subsequent section 3 will illustrate the simulation model used and explain the different types of traders implemented. Section 4 presents the results obtained by simulation. Section 5 concludes and gives an outlook on possible future research.

# 2 RELATED WORK

## 2.1 Algorithmic Trading

Algorithmic trading models typically aim at achieving or beating a specified benchmark with their executions and can be distinguished by their underlying benchmark, their trading style or aggressiveness (Kissell & Malamut 2006). The algorithms utilized have evolved over time and may be categorized in three distinct generations (Almgren 2007). The first generation of execution strategies implemented in algorithms aims to meet benchmarks generated by the market itself, which are largely independent from the actual order, e.g. by using the volume weighted average price (VWAP) or an average of daily open-high-low-close (OHLC) prices. The second generation of implemented execution strategies aims to meet order-centric benchmarks, i.e. benchmarks generated at the time of order submission to the algorithm. The execution strategy targets at minimizing the implementation shortfall, i.e. the difference between decision price and final execution price. Such second generation algorithms implement static execution strategies, as they predetermine (before the start of the actual order execution) how to handle the trade-off between minimizing market impact costs on the one hand by trading slowly and minimizing the variance of the execution price on the other hand by trading immediately. Third generation algorithms implement dynamic execution strategies, as they re-evaluate their strategy at each single decision time, which enables them to respond to market developments dynamically by altering their aggressiveness of trading adequately (Almgren and Lorenz 2007). Concerning the use of Algorithmic Trading multiple surveys exists, e.g. Financial Insights (2005, 2006) or Edhec-Risk (2005). Typically these surveys possess a descriptive perspective. Yang & Jiu (2006) propose a framework to help investors to choose the most suitable algorithm. Morris & Kantor-Hendrick (2005) address some abstract factors that shall be regarded when deciding whether to build or buy an Algorithmic Trading Solution: trading style and frequency, the investment in technology infrastructure, regulatory obligations and the traders' experience as well as technological proficiency. Konishi (2002) proposes an optimal slicing strategy for VWAP trades. Domowitz & Yegerman (2005) examine the execution quality of algorithms in comparison to brokers' traditional offering of handling large orders. They conclude that VWAP algorithms on average have an underperformance of 2bps. Nevertheless, this underperformance can be overcompensated by the fact that algorithms can be offered at lower fees than human order handling. Kissel (2007) outlines statistical methods to compare the performance of Algorithmic Trading solutions. Among academics, up to now, there has been no extensive research concerning the impact that the increasing usage of automated implementations of timing and slicing strategies might have. Only recently, Hendershott et al. (2007) presented evidence, that Algorithmic Trading and liquidity are positively related. The existing literature on the concept of Algorithmic Trading focuses on the investors' perspective. This paper aims at investigating Algorithmic Trading from a market perspective, i.e. the impact of such concepts on the market outcome shall be addressed.

## 2.2 Simulation of financial markets

In recent years simulation has become an accepted and acknowledged tool in many areas of economic research as it provides for the repeatability of exactly the same situation with different parameters, which enables to assess the impact of a single parameter (factor) on the outcome. The field of Agent-based Computational Economics (ACE) has become a vital area of research, as agent-based simulation models can provide powerful insights into the complex interactions of e.g. financial markets. For a broad overview on the topic see e.g. LeBaron (2006). The classification and stylization of trader behavior and the corresponding order flow is of material importance for simulation models of financial markets. In order to generate the order flow, such models usually rely on three types of traders; namely informed traders (or fundamental traders), momentum traders (or chartists) and noise traders. In a perfect theoretical market, there should only be completely rational traders and prices should always fully reflect all available information. However, if all information is revealed by prices, there is no incentive for traders to produce (costly) private information themselves. Furthermore no trading will be conducted. This is one of the major results of Grossman & Stiglitz (1980) and Milgrom & Stokey (1982) and is termed the 'no trade or no speculation' problem. They exemplified, that it is impossible under most circumstances for an individual agent with superior information, i.e. an informed trader, to realize profits from that information by trading. Though, in real-world markets trading and realizing profits can obviously be observed. This trading may be based either on superior information, i.e. informed traders are acting, or on expected market movements, i.e. chartist traders are acting. Chartist traders try to extract information about the fundamental value or expected market movements from publicly available information, e.g. past and current prices, volumes and market pressure, by technical analysis. A model for technical analysis with a focus on volume is given by Blume, Easley & O'Hara (1994). A possible solution to the 'no trade or no speculation' problem is the noise trader approach. Noise traders have been a topic in academic literature for many years, as already Grossman (1976, p.574) concluded: *"If information is costly, there must be noise in the price system so that traders can earn a return on information gathering."* Black's (1986, p.529) conclusions that *"noise trading is essential to the existence of liquid markets"* and that it is noise that makes observations imperfect have become common knowledge.

Most of the research simulations of financial trading have been used to study individual traders' performance, behavior and learning curve when following different strategies. Therefore, most of the simulation models abstract from real-world markets, as they most often implement simplified market models, which serve their research needs sufficiently. Simplifications have been made in the way the matching of offer and demand and the corresponding price determination is performed, e.g. Raberto et al. (2001). Those simulation models that implement a realistic trading market model – e.g. the continuous double auction, which is the dominant market model for real-world trading of securities – mainly aim at generating realistic order flow for human trading experiments in teaching or research, e.g. Schwartz, Francioni &Weber (2006), and less to retrieve empirical data for further research. The effect of trading behavior, trading strategies and techniques, i.e. the effect of the different stylized trader categories, on the order book and overall market has been investigated through simulation. by Chiarella & Iori (2002) as well as Chiarella & Iori (2004).

# 3 THE SIMULATION MODEL

The model used to generate the underlying order flow for this research is based on the one developed by Chiarella & Iori (2002, 2004). However, adaptations have been made to the model. There are two distinct types of traders within the simulation: stylized traders and algorithmic trading traders. Their orders are matched according to the rules and procedures of the continuous double auction.

## 3.1 Behavior of Traders

Stylized traders are simulated by software agents, each representing a special combination of characteristics of stylized trader types, i.e. informed trader, momentum trader and noise trader as described in standard market microstructure theory (Madhavan 2000, Schwartz & Francioni 2004). Unlike many other simulation models, here stylized agent types are not implemented separately. Instead each agent is at least to some extent behaving like an informed, a momentum and a noise trader. These risk-averse agents are supposed to know the fundamental value $p^f$ of the tradable asset as well as the history of prices. The stylized trader agents determine their demand based on this information, using a weighted behavior model. Variety among agents is ensured as each agent incorporates a unique weighting of these stylized behavioral patterns.

In each trading round one stylized trader agent $i$ is randomly chosen to submit an order. Therefore it first estimates returns according to equation (1)[3].

$$\hat{r}^i = \frac{1}{g_1^i + |g_2^i| + n^i}\left[ g_1^i \frac{(p^f - p_t)}{p_t} + g_2^i \bar{r} + n^i \varepsilon \right] \qquad (1)$$

$$g_1^i \sim |\mathrm{N}(0,\sigma_1)|, g_2^i \sim \mathrm{N}(0,\sigma_2), n^i \sim |\mathrm{N}(0,\sigma_n)| \ , \ \varepsilon \sim \mathrm{N}(0,1)$$

The factors $g_1^i$ and $g_2^i$ represent the weights given to the fundamentalist and chartist behavior. For each agent $i$ these values are randomly chosen. $n^i$ is the weight for the noise term $\varepsilon$. The sum of these weighted estimates is normalized by the first term. The agent's estimated stock return $\hat{r}^i$ is then used to calculate the expected price $\hat{p}_{t+\tau}^i$ according to equation (3)[4]. For the estimation an individual time horizon $\tau_i$ is assumed. Traders having a strong weight on their fundamentalist behavior should have a longer time horizon than those with a strong weight on their chartist behavior. This is achieved

[3] This differs from Chiarella & Iori (2004) as in their formula the fundamental behavior is impacted by the fundamentalist time horizon and the chartist behavior is impacted by the agent's individual time horizon.

[4] This estimate of the future price differs from the estimate used by Chiarella & Iori (2004).

by calculating the individual time horizon of agent $i$ according to equation (4), where $\tau$ denotes a reference time horizon.

$$\bar{r} = \left(\frac{p_t}{p_0}\right)^{\frac{1}{t}} \quad (2) \qquad \hat{p}_{t+\tau}^i = p_t(1+\hat{r}^i)^{\tau_i} \quad (3) \qquad \tau_i = \left\lceil \tau \frac{1+g_1^i}{1+\left|g_2^i\right|} \right\rceil \quad (4)$$

In line with Chiarella & Iori (2004), the optimal number of shares an agent wishes to hold is given by equation (5), where $\sigma_{\tau_i}^2$ is the variance of returns within the agent's individual time horizon $\tau_i$[5]. $\alpha^i$ denotes agent $i$'s individual risk aversion, which is calculated according to equation (6) upon the individual weights for behavior and a reference risk aversion $\alpha$.

$$\pi^i(p) = \frac{\log(\hat{p}_{t+\tau}^i) - \log(p)}{\alpha^i \sigma_{\tau_i}^2 p} \quad (5) \qquad \alpha^i = \alpha \frac{1+g_1^i}{1+\left|g_2^i\right|} \quad (6)$$

If $\pi^i(p)$ is larger than the number of shares currently owned by the agent, the agent would be willing to buy the difference. If $\pi^i(p)$ is smaller, the agent would be willing to sell the difference. In the following the neutral price level $p*$ is estimated at which agent $i$ would be satisfied with its current portfolio $S_t^i$.

$$\pi(p*) = \frac{\log(\hat{p}_{t+\tau}^i) - \log(p*)}{\alpha^i \sigma_{\tau_i}^2} = S_t^i \quad (7)$$

At any price $p < p*$ agents are willing to buy shares. Vice versa at any price $p > p*$ agents are willing to sell shares. As budget constraints shall be imposed, values need to be restricted to $p \le \hat{p}_{t+\tau}^i = p_{\max}$ in order to ensure $\pi(p) > 0$ and avoid short selling. To ensure an agent has sufficient cash, the smallest value of $p$ is defined by equation (8), where $C_t^i$ denotes the current cash position of agent $i$ at time $t$.

$$\pi(p_{\min}) - S_t^i = \frac{C_t^i}{p_{\min}} \quad (8)$$

This equation can be solved via a recursive approximation of the Lambert-W function. The agent then randomly picks a price $p$ in the interval $(p_{\min}, p_{\max})$. If $p < p*$ the agent submits a limit order to buy $s^i$ shares, with $s^i = \pi^i(p) - S_t^i$. In case $p > p*$ the agent submits a limit order to sell $s^i$ shares, with $s^i = S_t^i - \pi^i(p)$.

The trading behavior of algorithmic trader agents is expected to differ from the behavior of stylized trader agents (Gsell 2006). Therefore their behavior is modeled separately from the one of the stylized trader agents. To assess the impact of Algorithmic Trading on market outcome, the two strategies A and B of algorithmic trader agents have been implemented. Strategy A represents a simple static execution strategy, where the overall volume to execute $V$ is worked linearly over time. As with this strategy the algorithmic trader wants to steadily participate in the market, it only submits market orders. The corresponding order volume $v_t$ is calculated according to equation (9) as the difference

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[5] Chiarella & Iori (2004) used the overall variance, i.e. they did not restrict it to the agent's time horizon.

between the share of volume that should already have been worked at time $t$ and the already bought or sold number of shares $\tilde{v}_t = \sum_{k=1}^{t-1} v_k$ .

$$v_t = \frac{t}{T} V - \tilde{v}_t \qquad (9)$$

The other implementation of algorithmic trading behavior – strategy B – represents a dynamic execution strategy, where aggressiveness varies over time depending on the current market situation and the algorithm's previously achieved performance, i.e. the currently achieved VWAP of own executions. Based on the current value $\varsigma_t$ of the benchmark and on the order direction $\mathrm{I}$ the volume $\mathrm{X}(\varsigma_t, \mathrm{I})$ is determined, which is executable at a price "better" than $\varsigma_t$. "Better" means a higher or lower price, depending on the order direction I, i.e. whether the algorithmic trader agent is selling or buying. In case this volume is greater than zero the algorithmic trader agent will be aggressive and submit a market order to execute this volume, as this can only improve its performance with respect to the benchmark. If no volume is available at a price better than $\varsigma_t$, the algorithm will submit an order with a limit equal to the midpoint of the current bid-ask spread, in order to further participates in the market. The volume for this limit order is determined in the way the aforementioned static algorithm determines volume.

$$v = \begin{cases} \mathrm{X}(\varsigma_t, \mathrm{I}) & \mathit{if}\ \mathrm{X}(\varsigma_t, \mathrm{I}) > 0, \mathrm{I} = \begin{cases} 0 & buy-order \\ 1 & sell-order \end{cases} \\ \frac{t}{T} V - |\tilde{v}_t| & else \end{cases} \qquad (10)$$

### 3.2 Parameterization

Parameter combinations have each been tested for 100 different random seeds to ensure that the parameters are not overfitted to the generated sequence of pseudo-random numbers. All simulation runs have been conducted with 1000 stylized trader agents each. Their initial endowment with shares $S_0^i$ has been determined by drawing from a uniform distribution between 0 and a maximum of 10.000 shares. Each stylized trader agent's endowment with cash depends on its initial endowment with shares. An agent that has been endowed with a lot of shares gets less cash than an agent that is endowed with only a few shares. This is to ensure that all stylized trader agents have similar initial wealth and are able to conduct transactions. The weights for the fundamental and chartist behavior as well as the noise component are drawn from normal distributions with the following parameters: $\sigma_1 = 3$, $\sigma_2 = 1$, $n^i = 0.1$. The reference risk aversion $\alpha$ has been set to 0.1 for all simulation runs. The reference time horizon $\tau$ has been set to 2. In order to ensure that the order book is populated and that the stylized trader agents' estimates of prices are based on a sufficiently large price history, there are a few thousand not-evaluated trading rounds taking place before the evaluation phase starts. Per trading day, i.e. per simulation run, $\mathrm{T} = 50.000$ trading rounds are evaluated. Both implementations A and B of algorithmic trader agents have been tested for different order sizes and for different qualities of latency. Simulation runs excluding algorithmic trader agents for 100 random seeds yielded on average a trading volume of about 8.9 million shares per simulation run. As this volume is comparable to the "average daily volume" (ADV) on real-world markets, it has been taken as a reference value for specifying the volume $V$ that has to be executed by the algorithmic trading models. The volume $V$ is specified as a multiple of 1% ADV. As Domowitz and Yegerman (2005, p.35) show that algorithms mostly work a volume of less than 5% ADV each, simulations have been conducted for volumes ranging from 1 to 5 % ADV.

Lower latency is modeled as an increased probability for the algorithmic trader agent to submit an order to the market. It is expressed as a multiple of the uniformly distributed probability for a stylized trader agent to submit the next order, i.e. the algorithmic trader agent's probability to submit an order is higher. The multiplier is referred to as the latency factor. A higher latency factor yields a lower latency. If the algorithmic trader agent is chosen to submit an order in the current trading round it will submit its order in addition to the order submission of a stylized trader agent. This means, if 50.000 trading rounds are simulated, there will be 50.000 order submissions from stylized trader agents plus the orders submitted by the algorithmic trader agent.

# 4 RESULTS OBTAINED

Table 1 summarizes some descriptive statistics for simulation runs incorporating a buying algorithmic trader agent implementing strategy A. The values are averaged over the different random seeds and the different latency factors. The column "0%" contains the values for the basic simulation runs without any algorithmic trader. Increasing volumes that have to be executed by the algorithmic trader agent lead (as expected) to an increasing impact on the volume-weighted average price (VWAP) generated on the market. Also it can be observed that the volume executed on the market is increasing with the volume to work as well. The algorithm's additional demand seems to attract additional supply, which is due to the market's increased VWAP, as at a higher price more agents are willing to sell shares. However, volume is not increasing as strongly as the additional volume to work would suggest. This can be explained by the fact that the algorithmic trader is removing shares from the market as it is only buying them but not selling anymore. Without an algorithmic trader agent, a share could have been bought and sold several times (each time increasing the volume executed on the market). Furthermore, the simulation runs including the algorithmic trader agent exhibit a higher number of executions, which is due to the implemented strategy that ensures that the algorithmic trader is participating in the market throughout the whole simulation run. The increased number of executions comes along with a lower number of shares per execution.

| | | Volume to work by algorithm (in %ADV) | | | | | |
|---|---|---|---|---|---|---|---|
| | | **0** | **1** | **2** | **3** | **4** | **5** |
| Overall Market | **VWAP** | 98.8053 | 98.9140 | 99.0350 | 99.1526 | 99.2710 | 99.3905 |
| | **Volume (shares)** | 8935088 | 8940264 | 8959361 | 8972973 | 8989469 | 9000425 |
| | **#Executions** | 12764 | 15280 | 15289 | 15289 | 15292 | 15283 |
| | **Shares/Execution** | 700.04 | 585.10 | 585.99 | 586.91 | 587.84 | 588.93 |

*Table 1. Averaged descriptive statistics for strategy A*

Table 2 provides descriptive statistics for simulation runs incorporating an algorithmic trader agent implementing strategy B. Here increasing volumes to work show again an increasing impact on the VWAP generated on the market. However, as the implementation does not ensure that the algorithmic trader is participating throughout the whole simulation run, the algorithmic trader may behave greedy and execute its entire volume to work ahead of time. If the shares are removed from the market at an earlier stage, this avoids an increase in the executed volumes and number of executions, as the shares available for trading are reduced. As the stylized trader agents are not able to perform short selling, i.e. they are only able to sell what they possess, they cannot contribute more liquidity to market, although they might be willing to sell shares due to the higher price.

| | | Volume to work by algorithm (in %ADV) | | | | | |
|---|---|---|---|---|---|---|---|
| | | **0** | **1** | **2** | **3** | **4** | **5** |
| Overall Market | **VWAP** | 98.8053 | 99.0201 | 99.2316 | 99.4233 | 99.6036 | 99.7674 |
| | **Volume (shares)** | 8935088 | 8889649 | 8838461 | 8788916 | 8744740 | 8710373 |
| | **#Executions** | 12764 | 12766 | 12734 | 12688 | 12636 | 12581 |
| | **Shares/Execution** | 700.04 | 696.37 | 694.08 | 692.70 | 692.03 | 692.34 |

*Table 2. Averaged descriptive statistics for strategy B*

Furthermore, the impact of different volumes and latency factors on market volatility has been investigated. As for each single parameter configuration simulations have been conducted for 100 different random seeds, there is sufficient data to obtain statistically robust results from tests. On the basis of (Kissel 2007) a Wilcoxon signed-rank test has been applied in order to compare the market outcome of a simulation run excluding algorithmic traders with the market outcome of a simulation run including one algorithmic trader. For each of the 100 simulation runs per parameter configuration, the volatility is compared to the volatility of the corresponding simulation run excluding algorithmic trader agents. The absolute values of differences are computed and ranked. Depending on the sign of the original difference, the ranks are assigned a sign. The summary statistic, that is required by the Wilcoxon signed-rank test, is defined as the sum of all ranks with a positive sign. Based on this summary statistic simulation runs can be statistically tested, $H_0$ stating that the market volatility is equal or higher for simulation runs including an algorithmic trader agent and $H_1$ stating that it is lower. Figure 2 shows, based on the Wilcoxon signed-rank test, the error probability (p-value) for rejecting $H_0$ when using an algorithmic trader agent following strategy A. At the base of the figure, contour lines for different levels of the error probability are shown. The results indicate that a higher latency factor, i.e. lower latency, yields significantly lower volatility of the simulated market ($\alpha = 0.01$). This might be explained by the fact, that due to lower latency more orders can be submitted to the market and therefore the size of the sliced orders is decreasing. Due to smaller order sizes, fewer partial executions will occur as there will be more often sufficient volume in the order book to completely execute the small order. If less partial executions occur, price movements will be narrowed as the order executes at less limits in the order book. Smaller price movements entail lower volatility. For higher volumes to work the effect is no longer significant an $H_0$ can not be rejected.

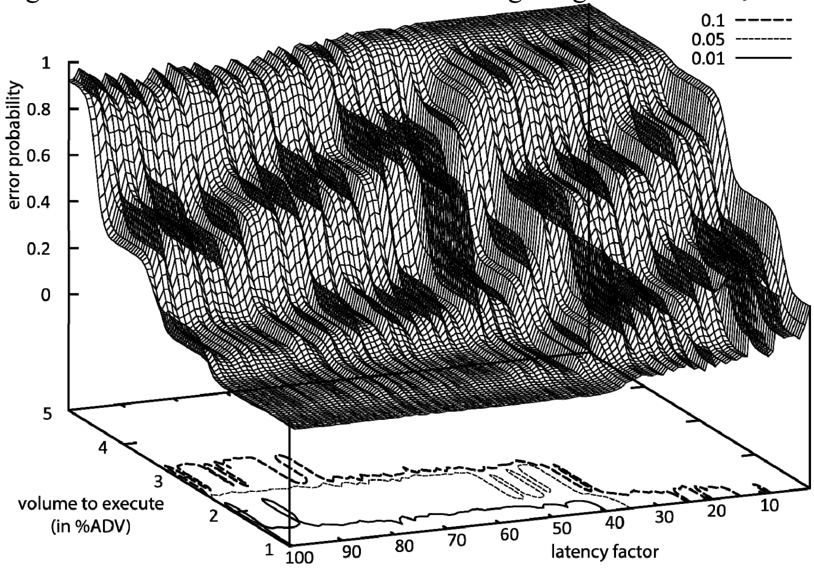


*Figure 2. Error probability for rejecting $H_0$ when using an algorithmic trader agent following strategy A (interpolated)*

Figure 3 exhibits test results when using an algorithmic trader agent following strategy B. Again larger volumes to execute cause the error probability to rise, although the increase is less steep than for strategy A (depicted in Figure 2). However, in general the results are only significant for a few parameter configurations at the $\alpha = 0.1$ level.

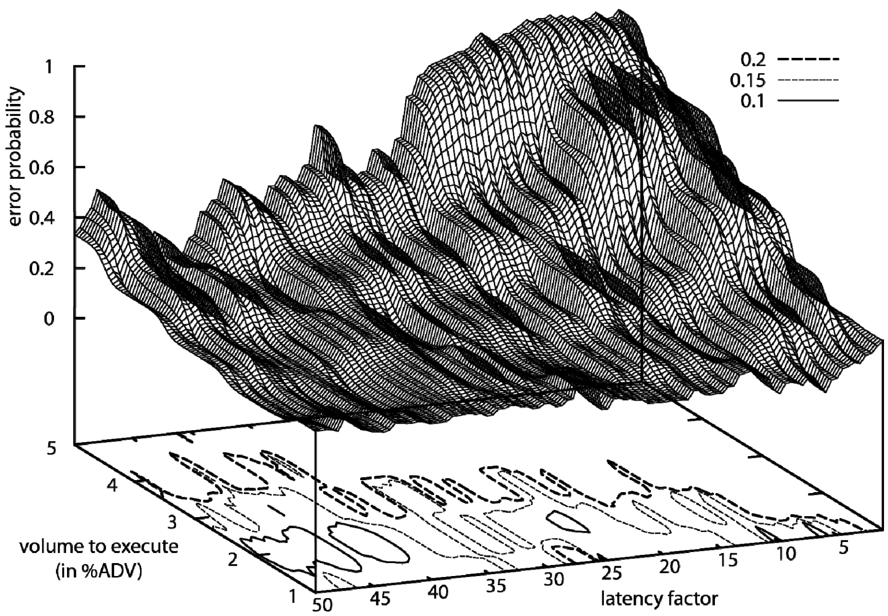


*Figure 3. Error probability for rejecting $H_0$ when using an algorithmic trader agent following strategy B (interpolated)*

To get a more detailed understanding of the impact of lower latency on the performance of strategy A, another set of tests has been conducted. This time the market volatility of the simulation runs has not been compared to the simulation runs excluding algorithmic trader agents, but to simulation runs with a strategy A trader agent that had a latency factor of 1 and a volume to execute of x%ADV. $H_0$ states that for simulation runs with higher latency factor the market volatility is equal or higher. $H_1$ states that it is lower for these simulation runs. Figure 4**Fehler! Verweisquelle konnte nicht gefunden werden.** depicts exemplary for x=1 that high latency factors significantly lower the market volatility for the same volume to work.

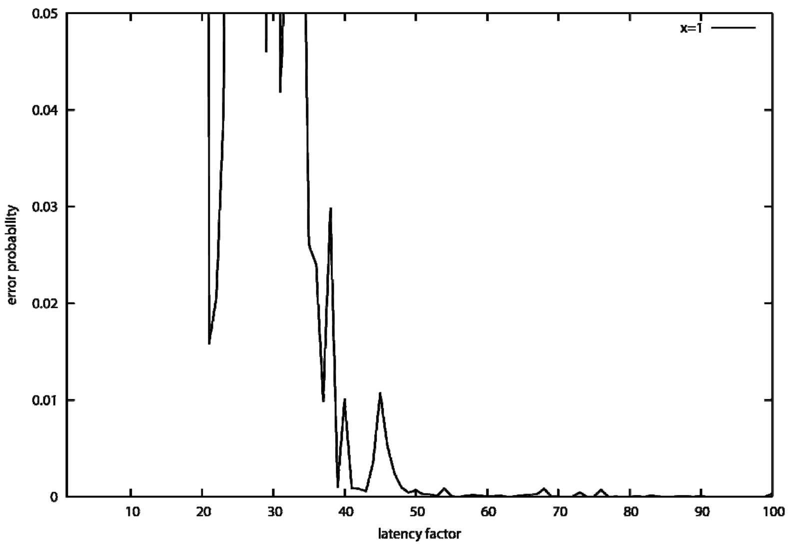

*Figure 4. Error probability for rejecting $H_0$ when comparing to strategy A with a latency factor of 1 and same volume to execute (interpolated)*

For higher latency factors the results get significant at the $\alpha = 0.01$ level. The tests for the other volumes to work all show the same highly significant effect of increasing latency factors on market volatility.

# 5 CONCLUSION AND OUTLOOK

The results of the presented simulation setup show that the implemented Algorithmic Trading concepts have an impact on market outcome in terms of market prices and market volatility. On the one hand, low latency showed the potential to significantly lower market volatility. On the other hand, large volumes to execute had a negative impact on both market prices. However, as up to now only simple algorithmic trading strategies have been implemented within the simulation environment, it is not valid to conclude that algorithms in general are not capable of handling large order volumes appropriately. Further extensive simulations will have to be conducted to confirm these results and to identify further impacts on the markets itself that might arise from the increasing usage of such automated execution concepts. Given that in the real-world market operators offer special high-speed data feeds and co-location services, it seems to be reasonable to conduct simulations with even higher latency factors. As for lower volumes to work high latency factors had a significantly positive effect on market volatility in the conducted tests, this also seems reasonable in order to lower the error probability of the results for higher volumes to work.

Intentionally rather simple algorithmic concepts have been implemented, in order to show their fundamental impact. More sophisticated algorithms might actually have a lower impact, which probably will be harder to identify. It may be determined in future simulations or maybe deduced from proprietary empirical data either provided by market operators or by investment firms which realized their investment decisions with the help of Algorithmic Trading. Based on more precise data, the economic loss caused by the impact of those models could be assessed.

Furthermore, against the background of the increasing market share of Algorithmic Trading concepts, the interaction of such systems and consequential side-effects resulting from it should be investigated. As more and more algorithms are actively trading on securities markets, these algorithms do to some extent conduct trading amongst each other, i.e. one algorithmic strategy is about to compete with the other instead of trading with a counterparty that has no high-speed access. Being aware of this changing nature of the counterparties entails policy implications concerning the strategy that is implemented by Algorithmic Trading.

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