Researchreport

Algorithmic Trading and its Impact on Markets

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.

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Introduction

A dramatic revolution of electronic trading on international financial markets can be observed: The industry experiences increasing demands on speed and cost efficiency. As both demands are to some extent satisfiable by technological advances, 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.

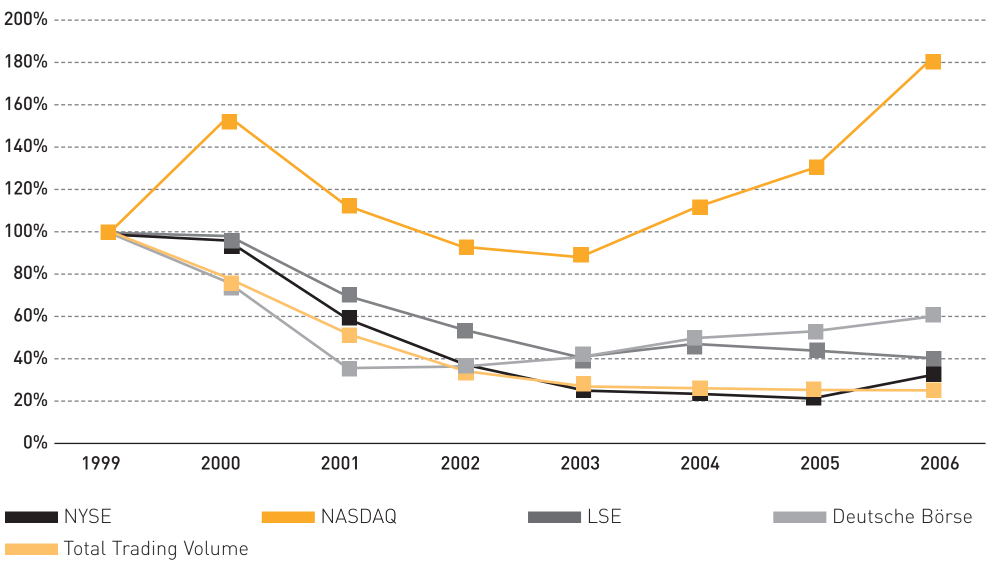

Figure 1: Shrinking average value of trades at major market venues based on data provided by the World Federation of Exchanges

If a large order is sent to one market venue implementing an open order book, displaying the intended trade volume causes adverse price movement. In order to avoid this, a block trader may circumvent the disadvantages of an open order book by submitting the order to a non-transparent block trading system. 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. It emulates via electronic means a broker's core competence of slicing a big order into a multiplicity of smaller orders and of timing these orders to minimize market impact. The determination of the size of the slices and their time of submission is based on mathematical models, which consider historical and realtime market data.

Evolution of Algorithms

Algorithmic Trading models aim at achieving or beating a specified benchmark by their executions. 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. A 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 reevaluate their strategy at each single decision time, which enables them to respond to market developments dynamically by altering their aggressiveness of trading adequately.

Assessing the impact on markets

The increasing usage of automated slicing concepts leads to manifold consequences on the markets themselves. Shrinking average trade sizes are observable at major market venues worldwide although traded volume has raised (Figure 1), which indicates an increasing usage of slicing concepts. As more and more investors rely on those fast and automated trading concepts, latency becomes a critical factor: Leading market venues already offer special dedicated high-speed data feed and colocation services, which allow investors to move their algorithmic trading servers nearby the market servers in order to minimize latency.

However, further effects have not been thoroughly investigated yet in academic research. In order to assess the impact of such concepts on the market outcome, e.g. effects on the price formation or the volatility of prices, we have setup a simulation environment that provides implementations of algorithmic trading behavior and allows for modeling latency. Here, lower latency is modeled as an increased probability for a single trader to submit an order to the market.

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 (Schwartz & Francioni, 2004). 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/excluding an agent constituting an algorithmic trading model in its trading behavior.

Two implementations of algorithmic trader agents have been used. One implementation represents a static execution strategy, where the order is worked linearly over time. The other implementation represents a dynamic execution strategy, where aggressiveness varies over time, depending on the current market situation and the strategies previously achieved performance with regard to the applied benchmark. Both implementations are tested for different order sizes and for different qualities of latency. The order sizes that have to be executed by the algorithmic trading models are expressed as percentage of the average daily trading volume (%ADV) in the market without algorithmic trader agents. Latency is expressed as a multiple of the uniformly distributed probability for a 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.

Initial results

Increasing volumes that have to be executed by the algorithmic trader agent lead (as expected) to an increasing impact on the price curve. High volumes to buy raise the prices generated on the market, while high volumes to sell beat down the price.

Furthermore, the impact of different volumes and latency factors on market volatility has been investigated. On the basis of Kissel (2007) a Wilcoxon signedrank test has been applied in order to compare the market volatility of a simulation run excluding algorithmic traders with the market volatility of simulation runs including an algorithmic trader. Figure 2 shows, based on this test, the error probability for the assumption that the algorithmic trader will lower market volatility. The results indicate that lower latency, i.e. a higher latency factor, yields lower volatility of the simulated market. 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. Smaller order size will lead to fewer partial executions, which means that generated prices will not change as often. This yields lower volatility. Though, if the volume to execute is raised, the error probability is increasing as well. This can be explained by the fact that an increasing size of the sliced orders will cause more partial executions and hence more price changes.

Outlook

Further extensive simulations will be conducted to confirm these results and to identify further impacts on the markets itself that might arise from the increasing usage of Algorithmic Trading concepts. Their impact on the quality of markets will be assessed in order to derive policy implications for market participants and market operators.

References

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Statistical Methods to Compare Algorithmic Performance, Journal of Trading, Spring 2007, pp. 53-62.

Schwartz, R.; Francioni, R.:
Equity Markets in Action: The Fundamentals of Liquidity, Market Structure & Trading. Wiley, Hoboken, NJ, 2004.

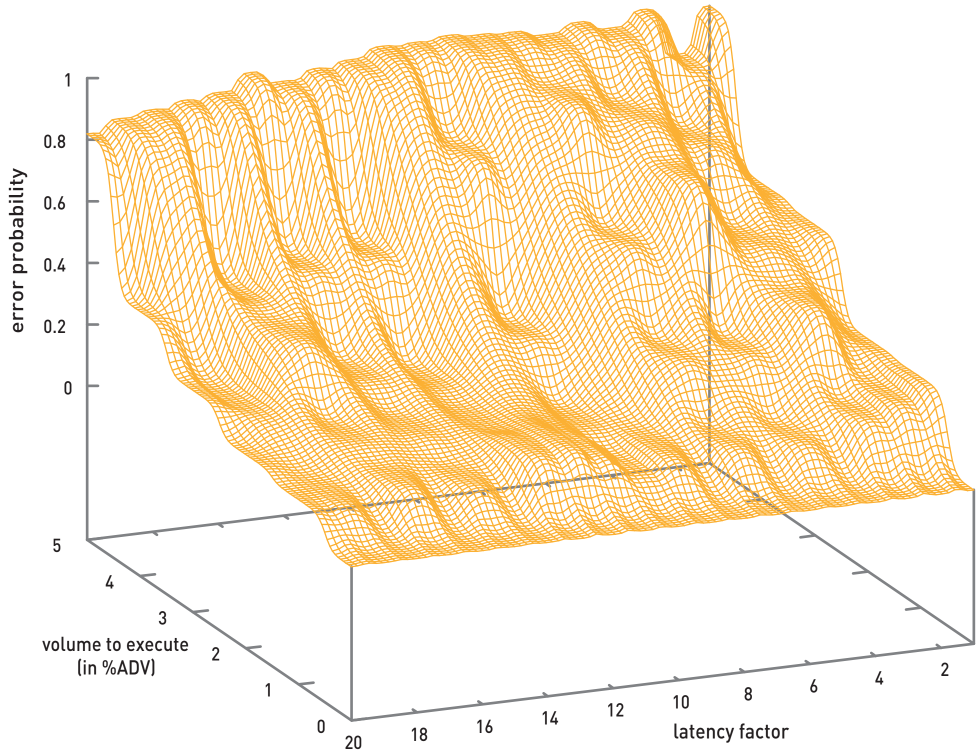

Figure 2: Error probability for the assumption that an algorithmic trader will lower market volatility (interpolated)