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Is Algorithmic Trading distinctively different?
Assessing its behaviour in comparison to informed, momentum and noise traders.

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Abstract

The concept of Algorithmic Trading emulates via electronic means a broker's core competency of slicing a big order into a multiplicity of smaller orders and of timing these orders to minimise market impact. Based on mathematical models and considering historical and real-time market data, algorithms determine ex ante or continuously the optimum size of the (next) slice and its time of submission to the market. Algorithmic trading models are gaining market share worldwide. As this might impact the order flow on the markets it is self-evident to investigate whether algorithmic trading can be categorized in the traditional way or whether it represents a new category of stylized trader. The paper assesses the upcoming sophisticated trading strategy of algorithmic trading against the background of the traditional categories of stylized traders in the literature, i.e. informed traders, momentum traders and noise traders. As a conclusion, in order to assess the of impact algorithmic trading on financial markets, the set-up of a new simulation model incorporating agents representing the specific properties and the trading behaviour of algorithmic trading is proposed.

1 Introduction

Due to the increasing demands on promptness and cost efficiency along with technological advances, the financial trading industry within the last two decades faced a dramatic revolution in the way trading is conducted on international securities markets. More and more stages of the trading process have been automated by substituting human activities with electronic systems. Starting with simple automated stop-loss systems, followed e.g. by quote machines, order routing systems or automated systems to support market surveillance, technology bit by bit conquered other stages of the trading process and the trading value chain. The most recent development are sophisticated quantitative trading models which gain more and more market share in the trading industry in the US, in Europe and in Asia. Those quantitative trading models are implemented in software programs which can rapidly process huge amounts of real-time and historical market data and are able to react promptly to new developments or events on the market. One such type of sophisticated software based on quantitative models is known as *Algorithmic Trading*, which "emulates via electronic means a broker's core competency of slicing a big order into a multiplicity of smaller orders and of timing these orders to minimise market impact."[1] In past tenses this has been done by (human) brokers as well and has been called *stealth trading*. A noteworthy portion of trading is already conducted in an automated manner, as e.g. algorithms take part in 30% of the transactions on Deutsche Börse's Xetra trading system[2].

Against this background it will be discussed in this paper whether algorithmic trading models can be categorized in the traditional categories of stylized traders, i.e. informed

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[1] Gomber & Gsell (2006).
[2] Benders (2006)

traders[3], momentum traders[4] and noise traders[5]. The following section 2 will give a review of the existing literature on stylized trader categorization and trader motivation. The subsequent section 3 will explain basic principles of algorithmic trading models and provide an overview of the sparsely existing academic literature. Based on this functional description section 4 will deduce why algorithmic trading models can be categorized neither as being informed, momentum nor noise traders. Section 5 concludes and gives an outlook on possible future research directly associated with the findings of this paper.

2 Stylized traders in the literature

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. *momentum traders* are acting[6]. Momentum 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

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[3] Informed traders are also called fundamental traders in the literature
[4] Momentum traders are also called technical traders, chartists or trend chasers in the literature
[5] Noise traders are also called liquidity traders in the literature
[6] For a more detailed empirical investigation on the motives for trading see Grinblatt & Keloharju (2001)

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 hot 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. If there is no noise and information collection is costly, then a perfect competitive market will break down because no equilibrium exists where one collects information." 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. However, different views on noise are existent and the precise definitions of noise trading differ in the literature. Kyle (1985) posited the existence of uninformed noise traders who trade randomly. Barber, Odean & Zhu (2006) on the other hand find a positive correlation of behaviour of individual (noise) traders. Whereas Shleifer & Summers (1990) constitute noise in a way that there are investors who not act fully rational and whose demand for assets is affected by beliefs or opinions rather than by fundamental news. Though, Black (1986, p.531) puts it this way: "Noise trading is trading on noise as if it were information." What can be agreed on as a common position is that "noise creates the opportunity to trade profitably, but at the same time makes it difficult to trade profitably"[7]. DeLong et al (1990) show that the price risk created by noise traders can reduce arbitrage This in consequence may cause prices to differ from fundamental values significantly although there is no fundamental risk.

For the following discussion, noise traders will be regarded as traders that submit orders arbitrarily for various reasons. Possibly they take noise for information and self-assess themselves incorrectly as informed traders.

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[7] Black (1986), p.534

Harris (2003) provides a different taxonomy of trader types, which classifies traders by means of their motivation for trading in general and not by means of the way they generate their order flow. On the top layer Harris (2003) distinguishes three types of traders as well: profit-motivated traders, futile traders and utilitarian traders. "Profit-motivated traders trade only because they rationally expect to profit from their trades"[8]. If their expectations are rational, they can be mapped to the aforementioned categories of informed or momentum traders. This can be further justified by the fact that the taxonomy also explicitly mentions informed traders, information-oriented technical traders and sentiment-oriented technical traders as subcategories of profit-motivated traders.[9] "Futile traders believe that they are profit-motivated traders (…) their expectations are not rational"[10] for various reasons. This incorrect self-assessment permits to map them to the aforementioned category of noise traders, which also may act on 'information' that essentially is noise. As utilitarian traders are defined as traders that "trade to obtain some benefits besides trading profits"[11] their motivation for trading in general is extrinsic. As this does not give a clue how they generate their order flow they cannot be mapped smoothly to one of the aforementioned categories.

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)[12] has become a vital area of research, as agent-based simulation models can provide powerful insights into

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[8] Harris(2003), p.177
[9] Harris(2003), p.199, Figure 8-1
[10] Harris(2003), p.177
[11] Harris(2003), p.178
[12] For a broad overview of the field of ACE see LeBaron (2006)

the complex interactions of e.g. financial markets. The classification and stylisation of trader behaviour 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 really on three types of traders; namely informed traders, momentum traders and noise traders. Most of the research simulations of financial trading have been used to study individual traders' performance, behaviour and learning curve when following different strategies. Therefore, most of the simulation models abstracted from real-world markets, as they most often implemented simplified market models, which served their research needs sufficiently. Simplifications have been made in the way the matching of offer and demand and the corresponding price determination is performed. Those simulation models that implemented a realistic trading market model – e.g. the continuous double auction, which is the dominant market model for real-world trading of securities – mainly aimed 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 behaviour, trading strategies and techniques, i.e. the effect of the different stylized trader categories, on the overall market has only been investigated sparsely by simulation approaches, e.g. by Chiarella & Iori (2002) as well as Chiarella & Iori (2004).

3   What are algorithmic trading models doing?

For institutional investors it is hard to find a suitable counterparty, as they typically trade large quantities. On markets implementing an open order book approach, exposing their intended trade volume to the market would result in an adverse price movement, i.e. the exposure of a large volume to buy would force market prices to rise. Vice versa market

prices would fall when a large volume to sell is exposed to the other market participants. *Quantity discovery*, i.e. to find a counterparty that wants to trade similar quantities, is therefore an important issue for institutional investors. An alternative to avoid this market impact is provided by some *over-the-counter* (OTC) venues specialising in the trading of large orders (*block trading*) as they address the specific requirements for these kinds of orders, e.g. limited transparency and a specialized process for price determination. *Crossing Networks*, e.g. ITG's POSIT, are non-transparent order book systems which match hidden orders at a price imported from a liquid and transparent reference market. Systems for quantity discovery, e.g. Liquidnet or Pipeline Trading, bring anonymously together participants with matching trading interests in the same share and for at least similar quantities. As from a market efficiency perspective this fragmentation of order flow across different execution venues is undesirable, some venues operating open order book market models introduced special order types, e.g. the iceberg order, which do not expose the total volume of the order all at once. More sophisticated market model extensions have been proposed e.g. by Gomber, Budimir & Schweickert (2006).

Algorithmic trading models provide yet another opportunity to bring large orders to transparent markets and to minimise the market impact at the same time, as they are slicing large orders into a multiplicity of smaller orders and time the submission of these orders. 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 customers. Based on the sell-side business model of a virtual *Direct Market Access* (DMA), where orders are not touched by the broker 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.

Algorithmic trading models can be offered to customers at lower fees, as no (expensive) human traders are involved. Due to the increased cost consciousness on the buy-side, algorithmic trading models have become an attractive alternative. In contrast to program trading, whereby bundles of instruments are collectively bought or sold, algorithmic trading models focus on trades with individual instruments. Up to now, the concept of Algorithmic Trading is primarily used to work 'low-touch orders', i.e. plain-vanilla orders in liquid stocks, to unburden human traders and enable them to concentrate on 'high-touch orders', i.e. orders in less liquid stocks or high volume orders that need cautious handling in order to minimise market impact. Increasing sophistication of the algorithmic trading models is likely to shift these boundaries into more complicated transactions in the near future. Algorithmic trading models have first been adopted for equities, but more and more asset classes are to follow, as e.g. algorithmic trading models are currently gaining a foothold in the FX market[13]. The usage of quantitative trading models – and especially Algorithmic Trading – is increasing on international financial markets and for the future further growth is forecasted, as the following Figures 1 and 2 depict.

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[13] Jaworsky (2006)
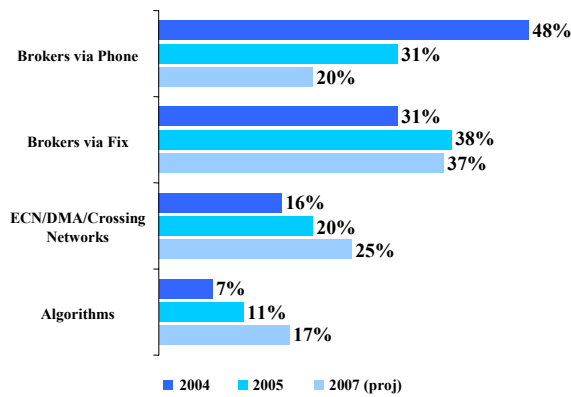
Figure 1: Order flow allocation from buy-side Trading Desks.
Source: TabbGroup (2005, p.8)
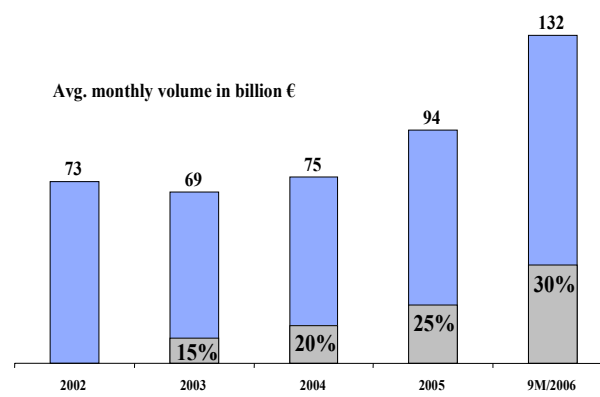
Figure 2: Algorithmic Trading share on Xetra
Source: Deutsche Börse (2006, p.9)

A variety of principles for slicing and timing are used for these algorithms that aim at reaching or beating an implicit or explicit benchmark. The benchmark used may be utilized to categorize the algorithms. E.g. a *volume weighted average price* (VWAP) algorithm targets at slicing and timing orders in a way that the resulting VWAP of its own transactions is close to or better than the VWAP of all transactions in the respective security throughout the trading day or during a specified period of time. A *time weighted average price* (TWAP) algorithm targets at a constant execution rate, which means either a constant number of executed orders or a constant portion of overall volume executed per defined time slot. An *arrival price* (AP) algorithm uses the prevailing market price at the time of submission of the order as benchmark for the execution of the timed and sliced orders.

In the future, offering a set of pre-packaged, standardized, sophisticated black-box algorithms might not be sufficient anymore. Providers of algorithmic trading models will rather have to offer customized algorithmic strategies that meet a client's specific needs and requirements.

The decision to conduct a large transaction may still be made by one or more (human) traders which may fall in one of the stylized trader categories mentioned above. However, with algorithmic trading models the transformation of this general trading decision into order flow, i.e. the slicing and timing of the large order, is conducted by a sophisticated piece of software. In past tenses this slicing and timing has been done by (human) brokers as well and has been called *stealth trading*. The new algorithmic trading models raise the tone of stealth trading to a new level. The order flow those models generate differs from order flow generated by humans, as increased market transparency, eased and fastened access to historical and real-time market data as well as improved communication technology enables the algorithmic trading models to implement even more sophisticated trading strategies. The success of algorithmic trading models is highly dependent on the speed of execution and the prompt availability of real-time market data. Already milliseconds can make a difference, which opens up a new source of revenue for market operators: proximity services. Some market operators[14] already started such services, which allow providers of algorithmic trading solutions to place their trading equipment adjacent to the technical infrastructure of the market itself. The thereby attained proximity to the market ensures low latency.

Gomber & Gsell (2006) note that new execution concepts, such as Algorithmic Trading, "have significant effects on order handling and the structure of the order flow, as e.g. the average size of trades is shrinking at the major exchanges". This can be seen as a consequence of the twofold order flow movements for large orders – the move to OTC or specialized block trading systems on the one hand and the increasing usage of concepts that slice orders in smaller chunks on the other hand. Figure 2 exemplifies that the average

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[14] E.g. Deutsche Börse and Euronext.liffe started such services, see Finextra (2006a) and Finextra (2006b)

value of trades at the New York Stock Exchange (NYSE) and NASDAQ has nearly
quartered in recent years; at the London Stock Exchange (LSE) and on Deutsche Börse's
Xetra trading system it has halved compared to the average trade size in 1999.
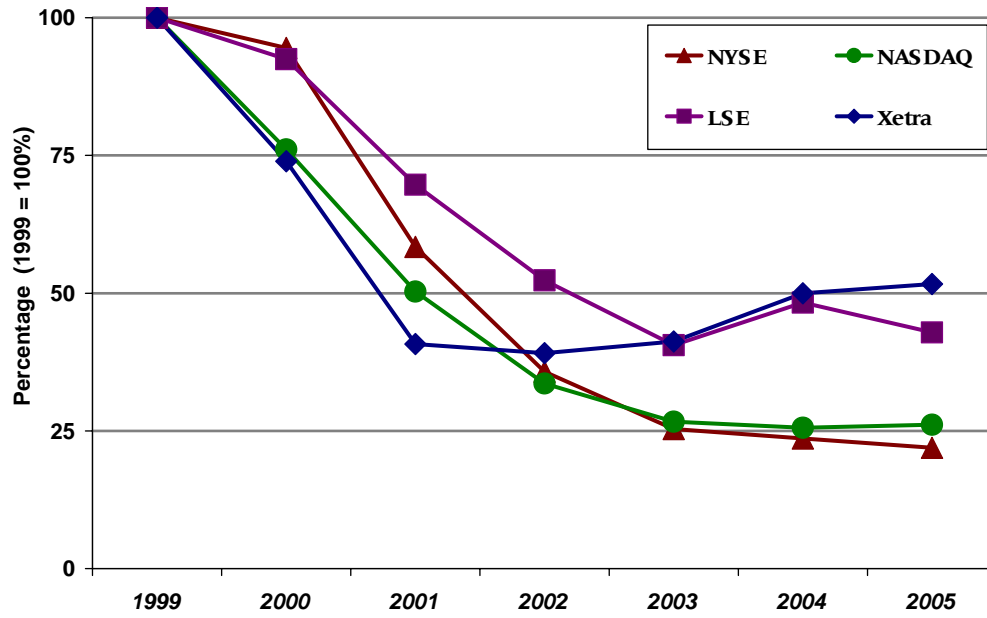
Figure 3: Average value of trades in percent
(based on data provided by the World Federation of Exchanges,
http://www.world-exchanges.org)

Up to now there is no extensive research concerning automated implementations of such
timing and slicing strategies and the impact the increasing usage might have. Kyle (1985)
suggested that investors may follow a strategy to spread their trading over time. Other
research, e.g. Barclay & Warner (1993), Chakravarty (2001) or Chakravarty, Kalev &
Pham (2005), addresses the strategic fragmentation of orders, i.e. slicing and timing, and
the influence of trade sizes on price movements. Farmer et al. (2004) show that large price
movements are unrelated to large transactions or the placement of large orders. In
academic literature there is a lack of coverage of the innovative trend of algorithmic
trading models and their impact especially from an empirical perspective. The sparsely

existing literature on the concept of Algorithmic Trading focuses on the investors' perspective. Yang & Jiu (2006) propose a framework to help investors to choose the most suitable algorithm. Konishi (2002) proposes an optimal slicing strategy for VWAP trades. Domowitz & Yegerman (2005) examine the execution quality of algorithms in comparison to traditional brokers' offering of stealth trading. They conclude that e.g. 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 stealth trading. In particular there is no literature regarding the impact the increasing usage of Algorithmic Trading might have on the efficiency, stability and integrity of financial markets yet.

4   Why algorithmic trading models are different

A first obvious but crucial distinctive difference between algorithmic trading models and the categories of stylized traders is the fact, that algorithmic trading models by their nature only work one-sided orders, i.e. they either exclusively have to buy or sell a specific position. The stylized trader categories do not know such a constraint. A corollary of this insight leads to a second just as well obvious but crucial distinctive difference in comparison to the traditional categories of stylized traders: algorithmic trading models do not trade for profit, they trade to minimise potential losses! The main purpose of those models is to work a given order with a minimal market impact. Therefore a sophisticated strategy for slicing and timing is applied to the given order that aims at minimizing the price impact of the own trading behaviour. Another – though less crucial – distinction is that the categories of stylized traders do not know time as a factor influencing their behaviour. For an algorithmic trading model the time left to work the given order is a very

important factor. The less time is left, the more aggressive the model may act in order to fulfil its goal. In contrast to the stylized trader categories there is a kind of time-pressure for algorithmic trading models. The following subsections will explain in more details how these differences influence the trading behaviour and consequentially why those models can not be categorized in the traditional way, as the order flow they generate differs significantly.

In the further course of the paper it will be distinguished between two notions of algorithmic trading model's performance: On the one hand there is the *intrinsic performance*, which either refers to the money spent when buying shares or to the money received when selling shares respectively. This may be continuously expressed by the VWAP of the own transactions. On the other hand there is the *extrinsic performance*, which refers to the achieved convergence to the used benchmark. For an explicit TWAP benchmark this means to achieve a constant execution rate. For the category of implicit benchmarks, e.g. VWAP, this means the gap between the intrinsic measure and the used benchmark. For the later category of benchmarks both measures are obviously influenced by the algorithmic trading model's behaviour in different market situations. The following Figures 4 and 5 depict which impact the choice of a fundamental behavioural alternative, i.e. to either participate in the market or to remain passive, has on both performance measures. Possible impacts on both measures are improvement (↑), worsening (↓) or invariance (─). It should be noted that improvement of the intrinsic measure refers to an increase of the measure when selling shares, and refers to a decrease of the measure when buying shares respectively, as it is desirable to sell at higher prices and buy at lower prices. When remaining passive the extrinsic measure improves and worsens in the

opposite directions, as the benchmark moves accordingly and enlarges or reduces the gap. When participating in the market, the benchmark alters in the same way as the intrinsic measure, e.g. in a rising market both the market VWAP and the VWAP of the own transactions increase. Apart from marginal differences this causes the extrinsic measures to stay more or less invariant in the short run[15], as it is defined as the gap between the both.

algorithmic trading model

Market		participate	remain passive
rising		intrinsic: ↑ extrinsic: —	intrinsic: — extrinsic: ↓
falling		intrinsic: ↓ extrinsic: —	intrinsic: — extrinsic: ↑

Figure 4: Behavioural impact of a selling algorithmic trading model on intrinsic and extrinsic performance

algorithmic trading model

Market		participate	remain passive
rising		intrinsic: ↓ extrinsic: —	intrinsic: — extrinsic: ↑
falling		intrinsic: ↑ extrinsic: —	intrinsic: — extrinsic: ↓

Figure 5: Behavioural impact of a buying algorithmic trading model on intrinsic and extrinsic performance

4.1 Are algorithmic trading models informed traders?

Both the definition of Schwartz, Francioni & Weber (2006) as well as the definition of Harris (2003) assumes that informed traders have knowledge or cognition about the fundamental value of a share. Both definitions see the aim of this category of traders in realizing profits based on this superior knowledge. If the current bid is above the fundamental value they will sell shares, if the current ask is below the fundamental value they will buy shares. They realize a kind of arbitrage versus the fundamental value.

Algorithmic trading models have private information as well. Though, unlike informed traders they do not have private information concerning the fundamental value but concerning their remaining order volume yet to work. This private information represents

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[15] For a longer time horizon these marginal differences may of course add up to a substantial difference

a value, too. However, algorithmic trading models can not realize this value as the value consists in knowledge about future volumes on one side of the market. This information would be profitable for other traders detecting a running algorithm as it gives evidence in which direction the market impact of this volume will slightly move the market. Algorithmic trading models cannot capitalise on this information themselves as on the one hand the market impact works against them, as it will move the market in the wrong direction (from their perspective). On the other hand the goal and benchmark of the algorithmic trading model is to particularly minimise this market impact. Therefore the information about the remaining volume yet to be worked represents a value if front-running the model is possible, but for the algorithmic trading model itself the information is just worthless. The remaining volume may in conjunction with imposed time restrictions influence the behaviour of the algorithmic trading model. If the time to work the overall order is running out and there is still a noteworthy remaining volume, the model can adjust its behaviour to be more aggressive, e.g. by submitting more market orders. In this case the private information directly influences behaviour, but it does in another sense than intended in the definitions of informed traders, as the knowledge once more cannot be used to realise profits. Far from it! The knowledge about the volume increases the pressure of time and leads to a more aggressive strategy which in turn probably yields even higher losses rather than profits, as the model is urged to take some action immediately which may counteract the goal of minimising the market impact. The more aggressive the strategy becomes, the higher the negative impact on the performance measures will be.

Even if in the sense of Harris' profit-motivated traders one defines a minimal market impact as the profit of algorithmic trading models, they still cannot capitalize their private information about the volume, as this information does not give any evidence how to increase the profit. Actually, the volume is the models' problem. The information about the volume to work gives a clue about how big that problem may be, but not how to solve it.

4.2 Are algorithmic trading models momentum traders?

Stylized momentum traders react to a series of price movements in the same direction. If they recognize a rising market they start to buy with the expectation to sell later at a higher price if the trend proves to be stable. Or they sell short in a falling market with the expectation to buy those shares back at lower price if the market goes further down. A core feature of the momentum trading strategy is to use expected market movements to realise a 'buy low, sell high' (or in reverse order, if short-selling is possible) strategy. To implement such a strategy no private-information is necessary. Momentum traders just have to observe and technically analyse the market, the prices it generates, the corresponding volumes, the current market pressure, as well as in which direction bids and asks are moving.

As algorithmic trading models by their nature only work one-sided orders they cannot implement a 'buy low, sell high' (or vice versa) strategy at all. Their job is to either buy or sell a large block of shares. To prevent detection and consequential exploitation of their trading strategy by other market participants they may submit opposing orders every now and then, but it is not their primary aim to make profits from buying and selling. Due to working one-sided orders, using market trends to make some profit is no option for algorithmic trading models. Therefore they cannot be categorized as momentum traders.

They may use favourable short-term trends to further improve their intrinsic and/or extrinsic performance. But they would use the trend in another fashion than pure momentum traders. In contrast to momentum traders they would want to sell in rising markets and buy in falling markets (depending whether they currently have to sell or buy shares). A stylized momentum trader in a rising market would want to buy when the trend starts and sell when the trend is at its end (which means at the highest price). An algorithmic trading model that has to sell shares would in a rising market want to sell shares as long as the trend goes on, as every further transaction would improve the models intrinsic performance and participating in the market will not influence its extrinsic performance in the short run. When the trend ends and prices are falling again the algorithmic trading model would stop selling, as falling prices would worsen its intrinsic performance[16]. However, if the market trends in an unfavourable direction, algorithmic trading models may also have to trade to get their order done in the specified time. This means in contrast to pure momentum traders, algorithmic trading models can also be faced with time-pressure, as they only have a predefined time to work their order, which may force them to transact even if the market is moving against them, which of course worsens their performance.

4.3 Are algorithmic trading models noise traders?

In theory noise traders follow no specific strategy; they submit orders arbitrarily as they possess no superior information. In real-world markets they often think they have information, but actually they act on noise which they take for information.

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[16] Furthermore a selling algorithmic trading model with a VWAP benchmark would stop selling and remain passive due to the fact that in a falling market the market VWAP is lowering, which improves the model's extrinsic performance

Algorithmic trading models however do not act arbitrarily, as they act according to a sophisticated mathematical model which incorporates real-time and historical market data. Those real-time and historical market data is no noise, as it represents actual information on current and past transactions, the corresponding prices and quantities. Furthermore current bids or offers can be incorporated which provide information about current liquidity and market pressure. However, to what extent the algorithmic trading models can exploit this information in order to e.g. detect any reliable patterns in short-term liquidity or market pressure, obviously depends on the quality of the implemented model. If the implemented model is not reliable, i.e. the patterns detected are not existent, one could argue that it acts on noise. Nevertheless, the kind of information and the consequences for trading are different for both noise traders and algorithmic trading models. In contrast to noise traders in the traditional sense, algorithmic trading models try to exploit another kind of information. For noise traders the available information – or the noise they take for information – refers to the fundamental value of the respective asset. Noise traders assume they have an informational advantage over the other traders which they can capitalize on, as they believe to know in which direction the price will move. For noise traders this information is valuable regardless whether they have to buy or sell according to the information, as they from their perspective try to conduct a 'buy low, sell high' strategy. Algorithmic trading models on the other hand do not exploit information on the fundamental value, but information on the available liquidity to slice and time their orders accordingly in order to minimise the market impact of their own transactions. Such information is valuable to the model regardless to which side of the market it refers. If the model recognizes increasing market pressure on one side of the market it will react

accordingly by either being more aggressive or by acting more passively, whichever is appropriate depending on the order to work by the model.

4.4 What are algorithmic trading models after all?

If at all, algorithmic trading models could be categorised as Harris' utilitarian traders, as their external benefit of getting rid of a position or get a grip on a position may be greater than the losses they generate. On the other hand, Harris aims at real cash losses in his definition. What algorithmic trading models realize are calculative losses at best, as the losses are losses in relation to the benchmark they aim to reach. Algorithmic trading models are not responsible for the potential cash losses that may have risen since the position they are selling right now has been bought or vice versa. The manager deciding about the overall order is responsible for those potential cash losses, as due to his failure to sell/buy the position at a more suitable point in time the opportunity to realise a potentially better overall price has been missed.

5 Conclusion

Up to now there has been no research conducted dealing with the impact the increasing usage of algorithmic trading models might have on the markets. As deduced before, algorithmic trading models cannot be mapped to the traditional categories of stylized traders, as none of these categories represents the distinctive properties of algorithmic trading models accurately. None of the stylized trader categories – nor any combination of them – reproduces the order flow that results from the special interaction of one-sided trading, minimising losses instead of maximizing profits and time-pressure that influences the aggressiveness of trading. Against the background of increasing usage of algorithmic

trading models it is self-evident to investigate the impact the order flow they produce has on financial markets. Hence, (simulation) models that want to assess the impact of such trading will have to take account of this crucial distinction and will have to incorporate and explicitly model these specific properties.

In future research, a simulation model will be set up that enables to assess the impact of Algorithmic Trading on market efficiency on a more empirical basis. Market efficiency – in terms of informational efficiency – will be measured in the simulation environment by comparing the thereby generated market prices with the simulation's inherent fundamental value of the tradable asset. After completing a variety of simulations, e.g. upward, sideward, or downward moving markets, and measuring the corresponding efficiencies, exactly the same simulation set-ups will be run again this time including implementations of stylized algorithmic trading models, representing e.g. a buying or selling VWAP, TWAP or AP algorithm. Afterwards the measured efficiencies of these simulation runs will be compared with the measured efficiencies of the initial simulation runs. With this setup, the impact of algorithmic trading models on market efficiency can be assessed. Additionally, the impact of algorithmic trading models at different volumes to work, expressed as percentage of the on average traded volume per initial simulation run[17], can be measured. Due to latency's crucial role for algorithmic trading models, the simulation design will also allow for modelling latency as an additional performance influencing and efficiency impacting factor. The intended goal of the upcoming research is to assess the impact of the usage of different Algorithmic Trading strategies on market efficiency in different market situations and to consequentially reassess the relative advantage of the concept of Algorithmic Trading.

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[17] The term of "on average traded volume per initial simulation run" is comparable to the „average daily volume" (ADV) on real-world markets

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