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The evolution of algorithmic classes

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The evolution of algorithmic classes

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1. Introduction

This paper aims to explore the key factors that drive the evolution of algorithmic classes. We analyse the impact of changes in regulation, the development of new trading venues, technological innovations, the economic environment, changes in market micro-structure, the availability and quality of data/information, and the progress in academic research. In many of the cases the joint impact of two or more of these factors leads to the appearance, mutation or decline of trading strategies, and we aim to explore such phenomena as well.

We consider algorithmic classes to be (not necessarily disjoint) sets of systematic trading strategies with similar objectives. One can differentiate between algorithmic classes by the types or number of assets involved, by the markets the trading is executed on, by the typical holding period /speed of turnover of capital etc (see section on the "Typology of Algorithmic classes").

Algorithmic classes constantly evolve. We will focus on large scale evolution, in particular on the birth, transformation, mutation, renaissance, decline and extinction of classes, moreover on co-evolution. First, from a historical perspective, we identify the key factors that drive the evolution and shape the universe of algorithmic classes through observed scenarios. Then, we consider possible scenarios for the future.

The typical scenario of the life cycle of an algorithmic (sub)class is as follows. Favourable circumstances - such as economic environment, decrease of trading costs, deregulation of markets, new trading venue (e.g. electronic communications networks, dark pools etc.), new product (e.g. exchange traded funds, commodity indices, etc.), extended access to existing products, technological development (trade execution at increased speed), etc. - result in the appearance of new trading strategies. In the beginning, a few market participants ("first-to-market traders" - Aldridge 2010) discover and exploit these opportunities making significant profits. These players are often smaller companies specialising in the new strategies. The availability of profit gradually attracts more players who adapt versions of the strategies. To obtain/maintain the market share, players invest into generating advantage (technology, market research, etc). Typically, bigger players – who might have been prudent at the appearance of the strategy – enter the game. The profit opportunities start to diminish due to the increased number of competitors, the advantage of the smaller players is lost to the bigger players. Often, only a few big diversified companies remain in the game making a portion of the profit that was available earlier.

The new opportunities are often due to some market inefficiencies, the spread of the strategies generates efficiency, and the almost complete extinction is induced by the increased efficiency maintained by the few remaining participants. Very often, the strategies mutate and adapt to the modified circumstances, or extinct if the favourable circumstances cease to exist.

Examples of co-existence and co-evolution are also common. E.g. the liquidity taken by certain classes is provided by the followers of certain other strategies. The circumstances favourable to both classes gradually develop – often reinforced by the spread of the strategies – transforming the strategies into part of the common practice. Another example is "fishing" and "gaming" simultaneously in dark pools and lit markets, strategies that have become common since the appearance of dark pools.

2. Typology of Algorithmic Classes

Before introducing the driving factors of the evolution of algorithmic classes, we give a brief typology of the broad classes following Aldridge 2010.

- Electronic trading – trading based on electronic transmission of orders (market share – above 95% of equity).
- Algorithmic trading / algorithmic execution – “systematic execution process, that is the optimization of buy-and-sell decisions once these buy-and-sell decisions have been made by another part of the systematic trading process or by a human portfolio manager” (ref.: Aldrigde 2010).
- Systematic trading - “computerized trading […] computer systems that process run-time data and make and execute buy-and-sell decisions” (ref.: Aldrigde 2010). The trade signal generation might be based on statistical arbitrage, event arbitrage, liquidity provision, etc.
- High frequency trading – fast turnover of trading capital, typically systematic, algorithmic and electronic (share of high frequency trading: 55% of equity trading in US and 35% of equity trading in Europe, source Financial Times 6/6/2011).
- Low latency trading – quickly routed and executed, however does not necessarily generate fast turnover of capital.
- Market making – automated liquidity provision, a particular subset of systematic trading.
- Exchange side algorithms – e.g. order routing to dealers and executing trades.

Algorithmic execution is used by most of the market participants. Some investors might buy execution services of suppliers (e.g. investment banks), some investors might develop their own execution systems. The execution of hedge funds with medium or long term holding periods is not necessarily fully algorithmic, part of the trades might be allocated to human traders.

Each of the above classes consist of different sets of strategies. Some might be applicable only on certain types of trading platforms, some are more universal.

3. Regulation and Microstructure

As of 2011, the trading microstructure and infrastructure has evolved drastically compared to the 1980's and earlier. Orders can be routed to and trades can be executed on several competing exchanges and in alternative trading systems (ATS). Trading systems are linked within and across countries. Investors can trade directly with other investors without middlemen. Trade-execution is automated, orders are matched automatically at the best price available. There are specialised trading venues minimising market/price impact. The speed of both the information flow and the order execution has increased significantly. All these factors contribute to an improvement in market efficiency. However, this could not have happened without some side affects (e.g. “Flash Crash” 6 May 2010).

One of the major drivers of this evolution are technological innovations (see section "Technology and Infrastructure"). Another important factor is the interplay between regulation of trading and development of trading systems.

3.1 Brief overview of changes in regulation

In this section, we collect a few of the key historical milestones in regulation that led to the transformation of trading and to the appearance of alternative trading venues (ref.: Smith 2010, Markham et al. 2008).

- 1934: creation of the Securities and Exchange Commission (SEC). Since then, it has acted as regulator of stock exchanges in the US.
- 1968: the National Association of Securities Dealers (NASD) form NASDAQ – electronic quotation system, deals made over the phone through market makers.
- 1974: "Commodity Futures Trading Commission Act 1974" - created CFTC regulating the futures industry, was obligated to study what impact computers could have on trading (ref. Markham et al. 2008).
- 1975: "Regulation of the National Market System" (Reg NMS) passed by SEC – led to speed up connection between markets.
- 1976: DOT, the first electronic order routing system developed (NYSE), updated to SuperDOT in 1984 – allowed electronic transmission of orders, enabled program trading.
- Technology induced appearance and development of alternative trading venues (see section "Technology and Infrastructure").
- 1997: "Limit Order Display Rule" passed by SEC: that "requires that specialists and market makers publicly display certain limit orders they receive from customers. If the limit order is for a price that is better than the specialist's or market maker's quote, the specialist or market maker must publicly display it" (ref: SEC, http://www.sec.gov/answers/trdexbd.htm).
- 1998: "Regulation ATS" (ref.: [Reg ATS]) – allows alternative trading systems to register as a broker, or register as an exchange, or operate as unregulated ATS. This opened new opportunities for alternative trading systems, in particular for electronic communications networks.
- 2000-2001: decimalization of quotes on US exchanges, resulted in narrower bid-ask spreads and improved transparency (ref.: Unger 2001, Bessembinder 2003)
- 2000: NYSE repealed "Rule 390" - that had been used to limit the trading of NYSE listed securities off the exchange floor.
- 2004: "Markets in Financial Instruments Directive" - analogue of Reg NMS in the European Economic Area, harmonising the regulations of investment services (ref.: [MiFID]).

- 2005: Reg NMS revised by SEC (ref.: [Reg NMS]) - “Order Protection Rule” (ref.: [Rule 611]) – trades must be automatically executed at the best quote possible (with some exceptions).

Some of the inflexibility in the operation of the traditional exchanges (e.g. Rule 390 on NYSE), motivated the development of alternative trading venues. Many of these new platforms were successful in attracting participants, orders and hence liquidity. Moreover, with advanced technology, the trade execution has become faster and cheaper attaining even more participants. Changes in regulations (Reg ATS 1998, revised Reg NMS 2005) supported the efficient operation of the alternative platforms, motivating the traditional exchanges to build links with these venues

- In 2002, electronic communications networks (ECNs) accounted for 70% of NASDAQ volume (ref.: Tarquinio 2002).I

- In 2005, NASDAQ acquired Instinet's ECN operations.

- In 2005, NYSE announced merger with Archipelago Holdings Inc.

The resulting fragmentation is claimed to support competition, resulted in narrower bid-ask spreads, reduced transaction costs, made the trading at higher frequency affordable. The development of venues where investors can directly trade with other investors implied that central specialists or central broker-dealers play a far less dominant role compared to the pre-1990's trading systems.

The feasibility of high frequency trading also required platforms where orders can be submitted electronically. The introduction of electronic limit order books improved transparency of price formation, that motivated the development of strategies aiming to optimise execution.

The new trading systems and infrastructure brought new market making (“winning the spread”) strategies and high frequency alpha (“crossing the spread”) strategies to life. These algorithmic classes co-exist and co-evolve.

Different types of market makers dominate on markets of different asset classes (ref.: Large interview 2011). On stock markets, smaller companies dominate market making, whereas on foreign exchange markets bigger banks (e.g. Deutsche Bank) are dominant.

Large traders in anonymous trading platforms are exposed to less predatory trading compared to participants in OTC markets, where more is known about the identity of counterparties. Therefore, the nature of optimal execution strategies highly depends on the anonymity of the target trading venue. More sophisticated execution algorithms aim to optimally split orders across trading destinations using Smart Order Routers (ref.: Laruelle 2010).

3.2 Electronic communications networks

“An ECN is an automated trading system that disseminates orders to third parties and dealers and can execute such orders within the network itself.” (ref.: McAndrews 2000).

In the US, the development of such systems was motivated by the need to overcome the restrictive rules on traditional exchanges (e.g. Rule 390 on NYSE), and was supported by the amendments of Reg NMS (and by MiFID in Europe). The telecommunication technology boom was also essential in providing the technological conditions (ref.: Smith 2010).

In the securities industry, the first examples of automation is given by SuperDot on NYSE (1984) that allowed the transmission of orders to specialists electronically. In 2000, SuperDot was handling 90% of the volume on NYSE, whereas large trades were still “negotiated upstairs” (ref.: Markham et al. 2008).

The International Futures Exchange Ltd. (Intex) was created in 1984, and operated as the first computerised commodity exchange in Bermuda in order not to fall under the authority of Commodity Futures Trading Commission. Although “Intex was not particularly successful, it signalled the future” (ref.: Markham et al. 2008).

ECNs arrived to the US markets in the early 1990s. Initially, ECNs were regulated as broker-dealers and the SEC did not require them to register as a national securities exchange. Some of the ECNs have built significant market shares and sought registration as an exchange in order to compete directly with traditional markets (ref.: Markham et al. 2008).

A particular example is Better Alternative Trading System (BATS), that built up a 10% market share in US equities in less than two years and in 2007, filed with the SEC to become a fully licensed securities exchange. (ref.: Basar 2007). Archipelago Holdings LLC, became a stock exchange through an arrangement with the Pacific Exchange (ref.: Markham et al. 2008).

The competition was further increased, when the SEC approved the operation of a London ECN in the US without registering as a national securities exchange (ref.: Markham et al. 2008).

In 2002, ECNs captured roughly 70% of NASDAQ volume (ref.: Tarquinio 2002).

Ultimately, the events led to mergers of some of the traditional exchanges with ECNs (e.g. NASDAQ bought Instinet's ECN operations, NYSE announced merger with Archipelago, London and Frankfurt stock exchanges merged and entered into linkage with NASDAQ - Markham et al. 2008).

As of 2011, ECNs have a colourful landscape, ECNs differentiate from each other (McAndrews et al. 2000)

- by targeting different clientele
- by following different order routing strategies (destination-only ECNs vs ECNs which route orders to other networks)
- by the method used to select destination, speed, quality and certainty of execution
- by the type of information they provide for investors (full vs. limited access to limit-order books, etc)

The typical characteristics of ECNs are (ref.: Stoll 2005):

- automatic – trade execution proceeds without human intervention according to certain priorities (price/time etc)

- anonymous – the identity of the traders is not revealed
- low cost – typically low fees are charged to market makers, while some fee might be paid to liquidity suppliers, whereas some ECNs pay for market orders and charge low fees for limit orders
- fast execution
- can be programmed to offer complex orders.

It is obvious how these features can trigger the evolution of certain algorithmic classes. ECNs attracted market makers. The automation, and quick execution provides favourable conditions for high frequency trading strategies. The speed and anonymity of ECNs made the implementation of improved execution of larger orders possible (quicker at lower cost – at lower market impact).

Initially, ECNs were best suited to active stocks and moderate size trades (ref.: Stoll 2005). Small, inactive stock may still require dealer sponsorship in order to maintain liquidity. Often, large trades, that traditionally are “negotiated upstairs”, also found their way to ECNs, although more suitable venues have been created (see the next section on “Dark Pools”).

3.3 Dark pools

The appearance of institutional investors, and in particular the portfolio rebalancing of institutional investors based on large buy and/or sell orders resulted in market moves that were not linked to any new information on the fundamentals (ref.: Mallaby 2011).

Large trades were often “negotiated upstairs” instead of routing them to the trading platforms (ref.: Harris 2002). Alternatively, large trades can be split into smaller blocks, that have smaller and more likely temporary-only price impact. Minimising impact motivates the use of many small blocks over a longer period of time, however during a too lengthy execution price fluctuations may work against the participant executing the large trade.

Even more severe losses can be suffered if the intention of large trade execution is leaked and other participants aim to earn profits by predatory trading. One particular example of predatory trading is the alleged predation of the hedge fund LTCM (ref. Jorion 2000, further examples: Malllaby 2011).

The anonymous trading platforms might prevent information leakage, the blocks of a large trade might be better hidden from predatory intentions. There have been several research papers published (see the section on “Impact of Research and Methodology”) on optimal execution in order books, aiming to maximise speed and minimise price impact.

An even more efficient solution that preserves the anonymity of traders, prevents information leakage, and offers trading opportunities without (direct) price impact is offered by dark pools. The two typical features of dark pools are (Mittal 2008, Kratz et al. 2010):

- liquidity available in darks pools is not quoted making the trade execution uncertain and unpredictable
- dark pools do not determine prices; instead, trades are executed at reference prices determined by primary exchanges (lit pools).

One can differentiate between dark pools by features such as ownership, clientele restriction, crossing procedure etc. (Mittal 2008).

In 2002, there were over 40 dark pools operating world-wide, and this number has grown since (ref.: Mittal 2008). Dark pools have gained a significant (10-15%) market share in US (ref.: Carrie 2008, Rosenblatt Securities 2009).

The introduction and popularity of dark pools again motivate the development of trading strategies exploiting the new features. In particular, "trade execution algorithms need to be fundamentally adjusted when a dark pool is introduced" (Kratz 2010). The execution strategies are no longer targeted to one type of venue, some aim to benefit from simultaneous trading in dark pools and the related lit venues determining the reference price. For example, small buy orders in a lit pool are likely to push the price up (this strategy is referred to as "gaming" - Mittal 2008), and hence large sell orders in dark pools (if executed) yield higher profit.

Other strategies aim to estimate or detect liquidity in dark pools (e.g. "fishing" - Mittal 2008). Often, gaming and fishing are used jointly (Mittal 2008, Kratz 2010), demonstrating the co-evolution of trading strategies.

3.4 Future

As long as regulation supports the existence and evolution of the fragmented trading landscape, the fragmentation is likely to develop even further. When that happens, algorithmic classes are likely to co-evolve. The diversity of the trading strategies will increase, linked strategies will jointly follow and adapt to each other.

Intensive fragmentation is often followed by a consolidation cycle. Within five to ten years, the markets are likely to observe consolidation at a less fragmented level. In particular, a lower number of ECNs will likely gain dominance. Similarly, a lower number of dark pools will be available for large trade execution. The demand of market participants for certain features will determine which alternative trading venues will survive the consolidation process; destabilising features like flash orders are likely to decline.

Besides consolidation, the centre of mass of these alternative trading venues might shift geographically according to the following arguments.

Regulation is a trial and error process. New rules - no matter how thoroughly designed - often result in undesired side effects, and/or do not have the planned impact. Nevertheless, they shape the economic landscape, the evolution is often irreversible as the following example shows.

Competition has the following limiting effect. Exchanges are not motivated to alter their self-regulation in order to eliminate side effects, if that could jeopardise competitive advantage. Harmonised self-regulation of trading venues is an unlikely event. By adopting revised regional regulation, regulators can promote harmonisation and the elimination of certain undesired effects on a group of trading venues. However, the authority of each regulator is limited to a certain geographical region. The impact of harmonisation in region A, might be temporary, if the venues in region B offer services with properties similar to the services of region A prior to the harmonisation. Even if such venues do not exist in region B but only the regulatory and/or technological/infrastructural conditions exist, trading platforms that attract participants might be developed fairly quickly and trading might be shifted to these venues. According to Cliff et al. 2011, there are regions/countries with such potential, making this scenario possible within the next 10 years. Under this scenario, systematic trading will adapt. Some will specialise in fast order routing to the new venues of region B, some will gain advantage from the closeness to region B, some will benefit from trading across the platforms in regions A and B, some will find new products in region B impacting the price formation of these products inducing increased correlation between products/asset classes. Some strategies specialised in region A platform specific trading might decline or extinct.

In the light of the above scenario, the advantages that exchanges with regional monopoly can benefit from are also temporary.

4. Technology and Infrastructure

One can differentiate elements of technology (including hardware and software) used in relation to algorithmic trading by

- technology supporting trading venues
- technology used by investors
- technology of connection across trading venues and between trading platforms and investors.

The first category consists of the technology of computerised execution, of order routing, of communication and data flow, custody, clearing etc. This category contributed to the implementation of ECNs offering automated and fast trade execution at a low cost. These technologies make the order book data accessible with minor time delay, supporting high-frequency trading, optimal execution, etc.

The second category is the technology of processing data (data collection, cleaning and analysis), trading models and trading signal generation (including high frequency strategies and algorithmic order execution), real time risk management and performance analysis.

The third category is required for smart and fast order routing. The purely technology based low-latency arbitrage builds on fast data access and execution at a speed that beats other investors or even the speed of communication between exchanges.

4.1 Future

The existing strongly technology based trading strategies might evolve if they are supported by new improved technologies. New, innovative trading protocols, new trading platforms might appear, aiming to attract investors with certain needs from other platforms by offering them new and more efficient (cheaper, faster, stealth, etc.) solutions or other advantages. This can generate migration from existing platforms to new platforms, motivating traditional venues to partially or fully adapt the new technology. The existing strategies might quickly improve exploiting the new infrastructure.

New technologies that have been developed with certain objectives often create unexpected (side) effects. In particular, in the presence of new technology, alternative opportunities that haven't been considered during the design of the system might be discovered and exploited by new strategies. Often, smaller, less risk averse, specialised participants make this discovery, and gain significant profits, until other competitors adopt or even improve the technology.

Fast order routing led to low latency arbitrage, which heavily depends on technological advantage. Such an advantage is typically only temporary. Larger, diversified participants can maintain their advantage due to economies of scale, forcing smaller specialized participants out of the market.

The appearance of such side-effects is hard to predict, even if the systems are carefully designed due to their complexity and the fact that these systems interact with many other complex systems that might evolve creating unexpected links and interaction.

To give a future vision of technological innovations, we consider the following two approaches: disruptive technologies and inductive thinking based innovations.

Disruptive technology (ref.: Christensen 1997) "under-perform[s] established products in mainstream markets, but [it has] other features that a few fringe (and generally new) customers value. Products based on disruptive technologies are typically cheaper, simpler, smaller and more frequently, more convenient to use." Christensen 1997 describes ECNs as an example of disruptive technologies. As the chronology in section "Electronic Communications Networks" suggests, disruption induced by ECNs is obvious. Cliff et al. 2011 explore further potentials for such innovations on both the exchange-side and the investor-side.

Some of the technological innovations are fuelled by existing needs. In other cases, new applications of existing technologies are discovered (ref.: inductive thinking – Hammer et al. 1993). Algorithmic trading is a typical field with potential for inductive thinking based innovations.

Finally, we give a practitioner's vision (Upton interview 2011). The pace of research (simulations and experiments) has been accelerated by cluster computing supported by open source software. On the execution side co-located boxes have been installed and will be commonly used for time trades. What AHL expects from the next 2-5 years, is further increase in the pace of research and simulations, more robust and quicker implementation, improvements in open source software, algorithmic trades run on co-located boxes.

5. Economic Environment

Beyond the technological and infrastructural conditions and supportive regulation, a favourable economic environment is often necessary for the active presence of certain algorithmic classes.

In particular, high frequency strategies can earn huge profits when the traded volume is high as well as the volatility. Whereas for efficient execution high volume, tight bid-ask spreads are required and lower volatility is preferred. According to practitioners (ref.: Schöneborn interview 2011), in 2007, properly tuned execution algorithms did make a difference. In 2008, after the bust of Lehman Brothers, the low liquidity and high volatility was not favourable and the objectives were reduced to "get it [the deal] done".

It is clear, that unfavourable economic conditions can cause the temporary or permanent decline of certain strategies/algorithmic classes. Another economic downturn might shift the focus from ECN-based or cross-ECN based execution strategies and might induce the popularity of dark pools or the development of yet another type of platform.

5.1 Financialisation

The impact of the increase in the popularity of index trading and exchange traded funds (ETFs) on the statistical nature of commodity price processes has been a recurring topic on a recent Commodities conference ("The New Commodity Markets," Oxford-Man Institute, Oxford, UK, 13-15 June 2011, organisers: Thaleia Zariphopoulou and Rene Carmona).

Index trading has been possible for years on commodity markets, however its popularity has increased recently when large institutions discovered commodities as new asset classes. Traditionally, commodities showed small correlation with each other or with the stock markets. This segregation suddenly ceased to exist as a consequence of index trading. In particular, as the trade volume rose, correlation across commodities (the ones constituting the indices) and correlation with stock markets have become significant (Wei Xiong, Rene Carmona, Ronnie Sircar – 2011).

Among others, hedge funds with medium term holding period have been present in commodity trading (e.g. AHL – Upton interview 2011), and such funds keep targeting commodity markets. Moreover, the high traded volume, the increased liquidity attracts high frequency traders as well. The increased correlation and cross-dependencies are leading to the re-adjustment of existing trade signal generating algorithms.

6. Impact of Research and Methodology

According to Aldridge 2010, quantitative research is crucial to support generation of trading signals, optimising the execution of trades, real-time risk analysis and risk management of trading strategies.

6.1 Generating trading signals

Trading signals are generated in many different ways:

- arbitrage based on price discrepancies between quoted prices of derivatives and prices due to some model (quantitative finance)
- forecasting the impact of macro events, news feeds (event trading)
- identification of trading party order flow through reverse engineering of observed quotes
- identification of statistical relationships between assets (e.g. co-integration)
- identification of recurring patterns, forecasting occurrence using advanced statistical techniques, time series analysis, artificial intelligence based pattern recognition techniques, etc.
- etc.

All of these are supported by research in academia and industry. On the one hand, cutting edge technologies used in areas such as engineering, computer science, biology, speech recognition, image processing, automated translation etc. have been adapted to systematic trading. On the other hand, new methods have been designed specifically for the purpose of trade signal generation.

The importance of research was recognised gradually (ref.: Hoggard interview 2011). In the mid 80s, the main difficulty was the lack of good quality data. That situation motivated some companies to invest in data sourcing and data cleaning. The industry used Fortran, C, C++ for data analysis, high level statistical languages (R, S-PLUS, MatLab Statistical toolbox etc.) became available and widely used in the 90s. Investors could collect data on increasing frequency: initially daily min/max/open/close quotes then quotes on intraday level, until tick-by-tick order book data had become available on most of the markets. The increased and more detailed data motivated the adaptation of new techniques.

Some investors kept focusing purely on technology based profit generating opportunities, others believed there was more potential for profits through sophisticated research. Tension due to such conflict led to the split of the fund AHL. Two of the founders started a technology based spin off, whereas AHL recruited more researchers, who aimed to identify “market edges” (Hoggard interview 2011).

Meanwhile, other (new) funds turned towards similar research-based strategies, in particular Winton Capital, BlueCrest, etc. The increase in the number of participants made the identification of market edges harder.

Meanwhile, the liquidity improved partly due to the research based funds (Hoggard interview 2011). The increased liquidity, the increased number of smaller sized trades led to the propagation of high frequency strategies that aimed to pick up intraday trends and to speculate on the behaviour of trading parties (beating less sophisticated algorithmic execution systems). High-frequency funds (e.g. DE Shaw, Renaissance Technologies) have become successful.

Market participants also invest in the development of robust techniques in order to test the strategies aiming to exploit the newly identified market edges.

Research is being carried out in order to model the impact of noise traders on commodities markets; in particular, on how speculative index trading changes the characteristics of price formation and increases correlation across the different commodities (ref.: Sircar 2011).

6.2 Optimal execution

Improving technology, infrastructure and market conditions led to the increase in positions at hedge funds in general, not only big institutional investors had the need for the execution of large trades, which motivated the research of market microstructure and price impact in limit order books (Hoggard - interview 2011).

Empirical studies of price impact and market microstructure (ref.: Bouchard et al. 2009, Gatheral 2010) led to the classification of market impact (ref.: Alfonsi et al. 2010):

- instantaneous or temporary impact or slippage – only affects the current order
- transient impact – significant for a certain period after the placement of the order
- permanent impact.

Academic research and development of models of market impact and optimal execution picked up in the early 2000s. Papers by Almgren et al. 2001, and Almgren 2003 formed a conventional approach.

More recent works focus on more complex price impact models, on the optimal choice between “stealth” and “sunshine trading” (that is announcing intention of large trade liquidation if competitors are likely to participate instead of following predatory behaviour) (ref.: Schöneborn et al. 2009). Further papers have been published on optimal liquidation on illiquid markets (Schied et al. 2008), on optimal split of orders across liquidity pools (Laruelle et al. 2010), and on optimal liquidation in dark pools (Kratz et al. 2010).

The practical applicability of these academic results is not obvious. Some practitioners (for example Schöneborn) claim that the assumptions underlying the conventional academic approach are not realistic, and some empirically observable phenomena are neglected. Some models (see the ones analysed by Alfonsi et al. 2010) suggest that optimality can be reached using “round trips”, that is a series of net zero buy and sell orders. Many of the practitioners (in particular Large, Ledford interview 2011), reject the use of such strategies and claim to follow conservative execution applying no round trips. Moreover, round trips qualify as proprietary trading that many of the market participants are fully or partially banned from.

Another practical problem is caused by the fact that the optimal execution trajectory suggested by the models is typically not achievable in practice due to insufficient liquidity, data noise, delay in signal detection or delay in order routing and execution, etc. (ref.: Schöneborn interview 2011).

Estimation and calibration of price impact is also challenging in practice. Practical methods for cross asset price impact calibration are yet to be developed (ref.: Schöneborn interview 2011).

Nevertheless, the trade execution at AHL (mainly medium term holding period) is only partially automated. A significant proportion of trades – especially the large ones – are assigned to human traders (Large interview 2011).

6.3 Risk management

The real-time monitoring of risk taken by algorithmic strategies is yet to improve; in particular the risk due to the interaction of multiple black box strategies. The risk of interacting automated strategies inducing flash crashes is being analysed and modelled. According to Lehalle (Lehalle interview 2011), the theory of complex dynamical systems is one potential approach.

6.4 Human capital, education

The collaboration between higher education institutes and practitioners contributes to fresh graduates gaining a better understanding of the landscape of trading markets and market microstructure.

The prestigious Master course in Probability and Finance organised by N. El Karoui, G. Pagés and M. Yor at the Université Pierre et Marie Curie (Paris 6) and École Polytechnique offers courses related to high frequency data analysis as well as a course on quantitative trading. The latter course is lectured by C.A. Lehalle (Head of quantitative research Crédit Agricole Cheuvreux).

Another, recently established Master course in Mathematical and Computational Finance at the University of Oxford, offers a practitioner lecture series covering – among other areas – market microstructure, quantitative trading, etc. The introduction of a core lecture course focusing on these topics is being considered.

Other master or higher level courses also started to give more emphasis to systematic and algorithmic trading, several PhD projects focus on the topic.

The increased emphasis in the near future on market microstructure and systematic trading at higher education level contributes to the growth of the number of experts in the area which is likely to fuel innovations and the improvement of the existing strategies and the development of new strategies, solutions, and algorithms.

6.5 Future

As of the 2010s, "deterministic edges clear quickly, statistical edges live longer" (Ledford interview 2011). Even simpler statistical edges clear quickly. For example, there is less profit made from pairs trading compared to the profits made two-three decades ago. This motivates high frequency alpha seekers to adopt and/or develop new research techniques, explore links between assets, markets, and trading systems. As trading is getting cheaper and faster, high frequency and ultra high frequency strategies become profitable, inducing the improvement of signal processing techniques.

The fragmentation of trading also requires the research of order routing and execution across trading venues, especially if venues with new features are created.

As of 2011, many larger hedge funds are investing into developing and implementing their own execution strategies rather than buying services from suppliers (Large, Upton interview 2011). This tendency is likely to continue, making the landscape of execution algorithms less transparent. Moreover more opportunities are arising for those who aim to make profit from outperforming/beating weak or poorly implemented execution strategies.

The collaboration between industry and academia is likely to become stronger. On the one hand, industry will continue to headhunt the crème of PhD graduates; currently, Man Group and D.E.Shaw employ the highest number of PhDs; other hedge funds will aim to catch up.

On the other hand, market participants seek to collaborate with industry. The successful operation of the Oxford-Man Institute (http://www.oxford-man.ox.ac.uk/) launched in 2007 funded by Man-Group, is one of the examples of such collaboration. Academics from Oxford University – including prominent researchers such as Thaleia Zariphopoulou, Mike Giles, Terry Lyons, Neil Shephard, etc. - and employees of Man-Group work and interact in the same location, organise and share seminars and conferences etc.

Another example is the Princeton-based INTECH Investment Management LLC (indirect subsidiary of Janus Capital Group), whose Co-Chief Investment Officer, Robert Fernholz is the inventor of Stochastic Portfolio Theory. INTECH collaborates with prominent academics such as Ioannis Karatzas (Columbia University).

7. Summary

The paper presents a brief survey of the main factors that drive the evolution of algorithmic classes. Some of the analysed factors – e.g. technological conditions – are results of accumulating innovations and their impact tends to be irreversible. Others – e.g. economic environment – are periodic; in certain phases they fuel the progress and propagation of trading strategies, in other phases they have the opposite impact, they might result in the decline or extinction of certain types of trading strategies. Trading systems also go through cycles of fragmentation and consolidation that traders will adapt to.

Probably the most important factor - the hunt for trading profits - induces extreme competition. Any advantage is only temporary, competitors invent/adopt similar strategies and market edges clear eventually. Market participants are forced to constantly invest into research and technological development. Such a competitive environment is favourable to the evolution of systematic trading strategies.

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