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# Algorithmic Trading

An Overview and Evaluation of Its Impact on Financial Markets


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# ABSTRACT

Nowadays the Financial Services industry is experiencing a time of profound transformation and the players involved have to face changes that shake the market every day. In the last few years, numerous financial innovations, and the huge progress that technology made have favoured the birth and evolution of trading activities based on mathematical algorithms. Algorithmic trading strategies ensure a system based on rules to optimize capital use and position, manage possible risks and trading instruments, and detect trading opportunities. This study aims at analyzing and explaining the phenomenon of Algorithmic Trading and its impact and consequences in the financial markets, from its genesis until today. Namely, what are the most relevant and used strategies employed for the automation of orders, what are the effects and risks on the market and how does it affect traders and companies. Moreover, we will analyze what exactly happened on the $6^{th}$ of May 2010, the day of the Flash Crash, when stock indices, such as the S&P 500, Dow Jones Industrial Average and Nasdaq Composite, collapsed and rebounded very rapidly. It appears that behind one of the major crashes of the last 12 years, there was a single trader, Navinder Sarao, who managed to be the biggest contributor to the second-biggest intraday decline of the Dow Jones Industrial Average, through the manipulation of a trading algorithm. What happened during the infamous $6^{th}$ of May 2010 triggered action by regulating authorities both in the United States and in the European Union, that realized not only the power that trading algorithms had, but that if left unregulated they had the strength to possibly cause major disturbances and disruptions in the markets. Algorithmic trading has become an increasingly dominant force in financial markets in recent years, its ability to execute trades at lightning-fast speeds and make use of large amounts of data provides significant advantages over traditional human-based trading. However, it also brings with it a number of challenges and controversies. The potential for algorithms to be used for market manipulation and insider trading also raises important questions about the accountability and transparency of algorithmic trading. Despite these challenges, algorithmic trading is likely to continue to play a significant role in financial markets in the future. The increasing use of machine learning algorithms and decentralized finance are likely to further fuel its growth.

# TABLE OF CONTENTS

# LIST OF ABBREVIATIONS

The following table describes the significance of various abbreviations and acronyms used throughout this study.

| Abbreviation | Meaning |
|---|---|
| **AD** | Anno Domini |
| **AI** | Artificial Intelligence |
| **ARIMA** | Autoregressive Integrated Moving Average |
| **ARMA** | Autoregressive Moving Average |
| **AT** | Algorithmic Trading |
| **BATS** | Better Alternative Trading System |
| **CB** | Circuit Breaker |
| **CDA** | Continuous Double Action |
| **CESR** | Committee of European Securities Regulators |
| **CFTC** | Commodity Futures Trading Commission |
| **CME** | Chicago Mercantile Exchange |
| **DEA** | Direct Electronic Access |
| **DOT** | Designated Order Turnaround |
| **EC** | European Commission |
| **ECM** | Error Correction Models |
| **ECN** | Electronic Communication Networks |
| **EDA** | Event-Driven Architecture |

| | |
|---|---|
| **EEA** | European Economic Area |
| **EMH** | Efficient Market Hypothesis |
| **ESMA** | European Securities and Markets Authority |
| **ETF** | Exchange-Traded Funds |
| **EU** | European Union |
| **EUR** | Euro |
| **FBI** | Federal Bureau of Investigation |
| **FCA** | Financial Conduct Authority |
| **FINRA** | Financial Industry Regulatory Authority |
| **HFT** | High-Frequency Trading |
| **IEX** | Investors Exchange |
| **IP** | Internet Protocol |
| **ISDA** | International Swaps and Derivatives Association |
| **LP** | Liquidity Providers |
| **LSTM** | Long Short-Term Memory Network |
| **MAR** | Market Abuse Regulation |
| **MI** | Management Information |
| **MiFID** | Markets in Financial Instruments Directive |
| **ML** | Machine Learning |
| **MPT** | Modern Portfolio Theory |
| **MVC** | Model-View Controller |
| **NASDAQ** | National Association of Securities Dealers Automated Quotations |

| | |
|---|---|
| **NBBO** | National Best Bid and Offer |
| **NMS** | National Market System |
| **NYSE** | New York Stock Exchange |
| **OTC** | Over-the-Counter |
| **PEAD** | Post Earnings Announcement Drift |
| **PHD** | Doctor of Philosophy |
| **PRA** | Prudential Regulation Authority |
| **Q&A** | Question & Answer |
| **RBC** | Royal Bank of Canada |
| **RTS** | Regulatory Technical Standards |
| **RW** | Random Walk |
| **RWH** | Random Walk Hypothesis |
| **S&P** | Standard & Poor |
| **SBA** | Space-Based Architecture |
| **SEC** | Securities and Exchange Commission |
| **SIP** | Securities Information Processor |
| **SMA** | Simple Moving Average |
| **TCA** | Transaction Cost Analysis |
| **TDQN** | Trading Deep Q-Network |
| **UK** | United Kingdom |
| **US** | United States |
| **USD** | United States Dollar |
| **VIX** | Volatility Index |

# CHAPTER 1

## *1. What is Algorithmic Trading?*

In the last few years, numerous financial innovations and the huge progress that technology made have favored the birth and evolution of trading activities based on mathematical algorithms (Caivano, 2015). At their core, algorithms are procedures or sets of instructions that are used for a computer in order to perform a particular computation or accomplish a task (*Algorithm Meaning & Definition*, no date). Most of the computerized devices that are available to the public nowadays use algorithms to perform their functions in the form of software-hardware based routines. These processes have become essential in our daily lives, whether we are ordering something online, we are trying to book a flight for our next holiday or we are simply typing something on a search engine (Investopedia, 2022).
In the financial system that we traditionally know, order books have always served traders in the best way possible. However, while it's functional and intuitive, with the rapid pace of technological advancement things have changed a lot. As a result, the trading floor has gone online, and time between seconds and minutes makes enormous differences between heavy losses and big gains in the market. In this scenario, it could be an enormous risk to have a broker managing and dealing with the fluctuations in prices, especially in markets which are unpredictable like the cryptocurrency one (Tabora, 2020).
There has been an improvement in the age we are currently experiencing, what is commonly been denominated The Information Age.[1] In the financial landscape, it resulted, among the others, in the use of *Algorithmic Trading*, which is mainly focused on the minimization of implicit transaction costs in order execution (Gsell, 2008). The word refers to forms of trading strategies that can be made automatically, both in terms of executing and identifying trades using algorithms written into software (Lehner Investments, 2021). Algorithmic trading strategies ensure a system which is based on rules in order to optimize capital use and position, manage possible risks, and trading

[1] Historic period in the 21st century characterized by the rapid shift from traditional industry that the Industrial Revolution brought through industrialization, to an economy based on information technology.

instruments and detect trading opportunities. Most of the time entries and exits are carried out by algorithms as well, and this is possible as all systems are automated.
A very simple example of a trading system run by algorithms would be to imagine a trader that is always pursuing a criterion where he buys 100 shares every time the stock price shifts past and above the double exponential moving average. Synchronously, he sets a sell order if the stock price goes beneath the double exponential moving average. In this case, the trader can recruit a computer programmer that is capable of understanding the notion of the double exponential moving average. At this point in order to perform these trading activities the programmer will generate a computer code solely based on the two directions mentioned above. The dynamicity of the software that is employed is such that enables it to monitor live the prices of the financial markets and, on the other hand, trigger actions according to the indications above. It consistently allows the trader to save the time he would have deployed to monitor trading platforms for prices and collocate the orders (WallStreetMojo, *Algorithmic Trading*, n.d.).
Over the last few years, cryptocurrencies have undeniably been one of the most traded assets to trade amidst retail investors. While on one hand human day traders have sometimes turned out to be unfruitful in forecasting market fluctuations, algorithmic trading introduces extraordinary potential in the scenario because of their speed capabilities and bandwidth. Out of all the cryptocurrencies that are available on exchanges, Bitcoin is definitely the most renowned and precious, constituting about 43% of the whole cryptocurrency market. As the value of Bitcoin and other cryptocurrencies like Ethereum, Theter or Binance Coin, have 7% of their total value changing constantly on a daily basis, this market liquidity presents the perfect opportunity for algorithmic trading (Baker & Royal, 2022; Crone & Brophy (2021).
In addition to this, most industries and corporations are following a trend that leads towards automation and an increased use of automated trading systems is undoubtedly in place. According to a few reports that in recent years algorithmic trading has generated more than 50% of the volume of US equity markets (Hendershott et al., 2011; Curran & Rogow, 2009; Iati, 2009). Nevertheless, algorithmic trading is much more than merely a more efficient method to process commands and orders. Evidence suggests that traders and investors can take advantage of new playing fields like artificial intelligence, computing power and automation (Lehner Investments, 2021).
Algorithmic trading is widely used by hedge funds, pension funds, investment banks and mutual funds that might have the necessity to distribute the execution of particularly large

orders or perform peculiar trades that would be hard to react to for human beings. A research carried out in 2019 demonstrated that around 92% of trading in the Forex market was executed by trading algorithms rather than humans (Kissel, 2020). Hedge funds are relying more and more on automated trading in order to guarantee a swift execution of vast numbers of trades. Institutional brokers and banks employ stock trading algorithms to perform huge orders trying to make a minimum market impact. Algorithmic Trading, or AT, is also used by market makers to optimize their pricing in order to direct risk while at the same time producing profits. At the same time, algorithms are used by option traders to dynamically manage risk and hedge positions as prices displace. Day traders and professionals are starting to deploy algorithmic trading more extensively. As a matter of fact, there is a large availability of algorithmic trading platforms and trading platforms that are automatic for investors and retail traders. There are platforms that are particularly popular in the Forex Market as they can be programmed to operate 24 hours a day. Examples of these are *NinjaTrader* and *MetaTrader* which enable individuals with little or no programming knowledge to simply lay out automated systems. At the same time, among professionals, quantitative investing funds carry out extensive employment of technology in order to find relationships among securities and to make the best out of strategies. These types of funds merge mathematical and statistical models with computing power in order to maximize returns that are risk-adjusted and later on detect and perform trades in the fastest way possible.

*High-Frequency Trading*, or HFT, is frequently associated with algorithmic trading. Far fewer definitions and literature can be verified on HFT, as it is a new phenomenon in the AT landscape. Differently from AT, High-Frequency trading update abruptly their orders, do not present overnight positions and is based on algorithms as fast as lightning that take advantage of mispricing among exchanges (Arndt et al., (2011). *Figure 1* shows the exact relationship between AT and HFT. Anyhow, there is no doubt financial markets make more extensive use of computer programs as such, and slowly algorithmic trading is taking over nearly every part of the investment and trading industry. Moreover, there appear to emerge new overtures to money and trading management that are feasible only thanks to these new technologies.

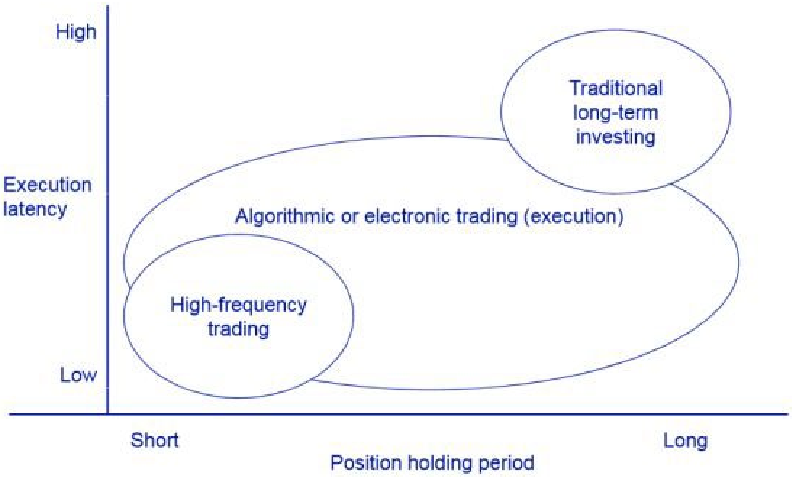


*Figure 1 Within the branch of Algorithmic Trading, there is High-Frequency Trading which, as previously stated, was created with the aim of identifying investment opportunities at very high speed to obtain small returns through a multitude of operations buying or selling following small price movements.*
*Source: Aldrige I. (2010), High-Frequency Trading: A Practical Guide to Algorithmic Strategies and Trading System.*

## *1.2 History and Development of Algorithmic Trading*

The history of the stock market is the history of the changing economy (Gupta, 2015). While on one hand automated trading has only in the last few years obtained widespread attention, it is certainly not new. The introduction of the New York Stock Exchange's "*Designated Order Turnaround*" system, or DOT, in 1976 and later the Super-DOT in 1984 can be considered as the beginning of the automatization of the order flow in financial markets (Jerry et al., 2008). These two systems made possible the exchange of orders to sell and buy securities to the appropriate trading post via electronic means. The orders popped up on a peculiar electronic workstation which was denominated "display book", that allowed each expert firm to perform orders for the market.

Until then, « financial information was disseminated slowly, usually by ticker tape, and telephonic communication was expensive. » In the previous floor-based trading era, who wanted to buy and who wanted to sell were literally standing next to each other, « allowing for the expeditious identification of counterparties » (Jerry et al., 2008). Nevertheless, executing orders, buying and selling them, became much quicker once exchanges began to implement computerized communication; instead of being present physically on trading floors, they were connected through means of a trading platform.

A few years later, in 1971, NASDAQ became the very first in its genre stock market to run electronically, one that enabled dealers to concur in the supply of quotes for securities. NASDAQ did not use a specialist auction system, but on the contrary, exploited market markers that were competing in an electronic quotation system (McGowan, 2010).

The historical period where floor-based trading was the main act came to an end in the 1980s with the arrival of entirely electronic financial markets and a particular trading strategy called *Program Trading*. Still employed nowadays, it can be defined by the NYSE as the setting of orders to sell or buy 15 or even more stocks which are valued more than $1 million in total (Furbush, 2010). This peculiar procedure came to be extensively used in the 80s in the trading landscape between the futures markets and S&P 500 equity. With the help of computers, programs traders were able to sell and buy stock index futures contracts, examples are the S&P 500 futures, and buy or sell a portfolio composed of up to 500 stocks at the New York Stock Exchange (NYSE) joined counter to futures trade. This particular program trade had the possibility to be programmed in advance into a computer in order to insert the order automatically into the NYSE's electronic order routing system in a period of time when the stock index and the futures price were far off enough to be able to produce a profit (Furbush, 2010). This peculiar procedure, known as *Stock Index Arbitrage,* would have been blamed later on by few as leading to the 1987 stock market crash (Moyer & Lambert, 2009).

In the 1970s and 1980s, while trading on NASDAQ and NYSE dominated the computerized trading landscape, the playground changed around the end of the 1990s with the coming to light of other electronic trading venues known as *Electronic Communication Networks* (ECNs). They can be defined as a particular kind of computer system that makes it easier to trade financial products, like currencies and stocks, outside of the traditional stock exchanges (Liebenberg, 2002). At the end of the 1990s Electronic Communication Networks became commonplace after the US Securities and Exchange Commission (SEC) allowed their existence with the Regulation Alternative Trading Systems. This piece of regulation was strongly wanted in 1998 by then SEC Chairman Arthur Levitt, that was not satisfied with the duopoly NASDAQ and NYSE had at the time. After Reg. Alternative Trading Systems, the rise of these alternative trading systems allowed individual investors to trade after the closing time of the exchanges, and finally, further computer systems started to develop which made easier the execution and entry of orders in an electronic way by algorithms (Markham & Harty, 2008).

By subscribing to ECNs, individual investors have the possibility to insert orders electronically within the grid through a custom computer terminal, and the Electronic Communication Network will in an automated way join and execute contra-side orders (Liebenberg, 2002).

In the case in which no match can be found, therefore an ECN order has the possibility to be forwarded to NASDAQ as soon as it comes to have the best price. This agreement enables ECNs to « function as a hybrid between a broker for counterparties, a broker-dealer or market-maker, and an exchange, and their gain has been at the expense of NASDAQ » (Liebenberg, 2002). As a matter of fact, the premature ECNs supplied many advantages upon the previous trading venues—comprising the cut in trading errors and costs, increase of efficiencies in operational regards, and other advantages linked to risk management. In the end, companies that were trading during the day that originally were seeking a bigger market access to NASDAQ, as brokerage firms, started to rush to set up ECNs; and the rate of growth of Electronic Communication Networks has skyrocketed from 1997 (Liebenberg, 2002). The rise of these ECNs at the end of the 1990s allowed a broader employment algorithmic trading and at last the growth of independent high-frequency trading firms.

Another landmark arrived in 2001, just after two years following Regulation Alternative Trading Systems, when stock exchanges began quoting stock prices in decimals instead of fractions. The “decimalization” of the exchanges shifted the lowest stock tick size from $1/16^{th}$ of a dollar to $0.01 per every share and encouraged even more algo trading by Electronic Communication Networks. This implied that « overnight the minimum spread a market-maker stood to pocket between a bid and offer was compressed from 6.26…down to a penny » (Moyer & Lambert, 2009). This step reduced the trading advantage of a market-maker and brought to the rise of liquidity,[2] that in turn at last took to the present boom in algorithmic trading. Inside this much more liquid market, traders from institutional backgrounds started to split up orders according to their algorithms to execute orders quicker and at an average price which was more advantageous.

The last and final relevant development in the troubled history of high-frequency trading came about in 2005 when the Securities and Exchange Commission enforced the Regulation National Market System (NMS). This particular regulation is fundamentally a series of ventures enacted by the SEC that were meant to modernize and make stronger the national equity markets. With Reg. NMS, the Securities and Exchange Commission has furthered a market system which was national, that incorporates rules like the Market Data Rules, the Access Rule, the Trade Through Rule and the Sub-Penny Rule. Previously with respect to Regulation NMS, broker agencies had much more wiggle room in order to sell, match or buy orders from the internal and bag the spread. Nevertheless, under the Regulation National Market System, and especially the brought up-to-date Trade-Through Rule, it is now enacted that « market orders be posted electronically and immediately executed at the best price nationally. » This piece of legislation was the last structural move which determined the stage for the revolution in electronic trading that we are experiencing nowadays. Currently, firms that employ high-frequency trading like GETCO and some hedge funds have convenience in the changes that happened structurally and that were implemented by Regulation NMS by « posting continuous two-sided quotes on hundreds of stocks » and also collecting the differences in prices that derived from temporary lags among exchanges (Moyer & Lambert, 2009).

Nowadays, the trading of equity in the US and Europe is controlled by high-frequency traders. Most of these trading firms employ a multitude of strategies and practices in order

[2] Liquidity is the degree to which an asset or security can be bought or sold in the market without affecting the asset’s price. Assets that can easily be bought or sold are known as liquid assets.

to consistently remain ahead of the market and carry out orders before there is anyone that could realize it. Most of the devices that produce profits and that AT traders use depend on relevant major elements that underlie all the algo trading strategies.

## *1.3 Literature Review*

The research on algorithmic trading is relevant because of its dominance in the financial scenario. In 2019 a significant percentage of the equity that was traded in the United States was carried on by automated algorithms, which represents 35.1% of the overall $32 trillion with an expected annual growth of 8.7% over the period that stems from 2020 and 2027 (Bucholz, 2019; StrategyR, *Algorithmic Trading World Market Report*). The main subject is particularly challenging due to the fact that it is comprised in three different areas of knowledge: Economics, Finance and Computer Science. In the same way, it shows many problems, only to cite a few. In the first place, its intricacy can be considered an entry barrier for any investor or small company, however, it's well exploited by institutional investors. Secondly, the amount of trading strategies and related data is enormous, which makes it hard to choose them. Lastly, the investment needs are idiosyncratic and therefore, it does not exist a trading strategy that fits everyone. The purpose of this paragraph is to articulate a critical and systematic literature review of Algorithmic Trading. The literature that exists is vast, complicated, and dispersed in three different academic areas, hence this is just an attempt to construct a holistic and comprehensive overview of the subject.

The theoretical support of algorithmic trading is various and extensive, some of them are based on financial theories that are well-established already, while some others on subjective trader experience. In this paragraph, we are going just to tackle the first one. Neoclassical finance offers the foundation for many trading strategies; nevertheless, behavioural finance is also starting to attract attention and interest among traders and market users.

Neoclassical finance finds its origin in neoclassical economics and started in the mid-Sixties. The main principle is that markets are efficient, and supply and demand find equilibrium due to the fact that participants are rational agents, and consequently, the prices of the assets are a reflection of this. Neoclassical finance sees the market participant as *Home Economicus,* who are characterized by rational decision-making and selfish motivation. A true pillar of neoclassical finance is the *Random Walk Hypothesis* which assumes that prices in the stock market follow a random pattern. A model which is based on the assumptions of the RWH implies that in each period the price takes a random step back away from the one that preceded it, where steps are both distributed independently and identically in size (Nau 2014). This concept can be traced in the work of Regnault

(1863), the thesis of Bachelier (1900) and expanded by many other experts, like Cootner (1964) with his book "*The Random Character of Stock Market Prices*", Malkiel (1973) in his work "*A Random Walk Down Wall Street*" where he compared the movement of stock prices to those of a drunken man, or Fama (1995) in his article "*Random Walks in stock market prices*" without the mathematical structure.

The Random Walk model is not an efficient predictor for time series that display a linear or exponential trend. For this exact reason, a subsequent model called the Geometric Random Walk model or better known as *Random Walk with Drift* is considered to be more effective in capturing this effect. It employs the natural logarithm to compute the changes from one period to another assuming that prices are iid like with the standard RW, but it adds a drift factor in natural logarithmic units (Nau 2014). *Figure 2* shows the differences between series with drift and series with trend. Both these two models are particular cases of the Auto-Regressive Integrated Moving Average, or ARIMA, model (Hamilton 1994); particularly ARIMA (0,1,0) and ARIMA (0,1,0)+c, both of extended use in econometrics.

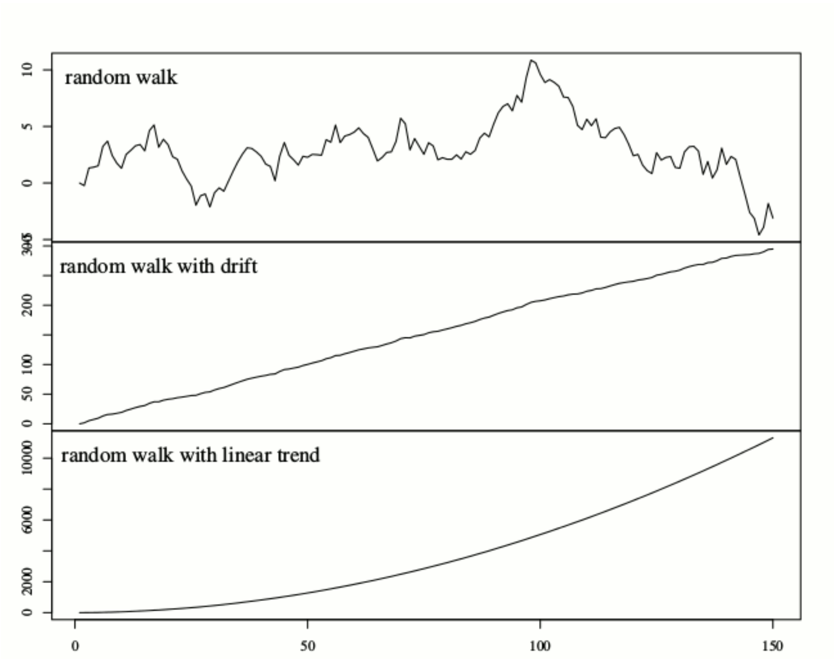


*Figure 2 The drift term in your equation with $\phi$=1 generates a deterministic linear trend in the observed series, while a deterministic trend turns into an exponential pattern in yt.*
*Source: StackExchange.*

Samuelson (1965) in his work "*Proof that Properly Anticipated Prices Fluctuate Randomly*" shows that in the instance of an information efficient market, prices should follow a Random Walk, and he stresses how the more efficient is the market, the better the prices will follow the Random Walk. This concept might sound as if it lacks logic and it is apparently contradictive, due to the fact that one can argue that the movement of prices, in general, is totally determined by the information that is available at that precise moment. This could be considered truthful; nevertheless, one can only make sense of the prices' move after the event (ex-post) and cannot be predicted before the event (*ex-ante*). Hence, under the assumption that the information arrives in a random manner in the market, without the knowledge of how said information will affect prices, the best model that represents this behaviour is the Random Walk.

Fama (1970) in his crucial article "*Efficient Capital Markets: A Review of Theory and Empirical Work*" perfectly captures the arguments of Samuelsson and the Random Walk Hypothesis. He formulates the so-called Efficient Markets Hypothesis, where he speculates if the prices of assets in the market follow a strong, semi-strong or weak correlation to the financial and economic information available. Along with strong evidence from the weak and semi-strong forms, Fama's empirical research supported the statement that the market is in fact efficient, and prices follow a RW with Drift.

In the case where both the Random Walk Hypothesis and the Efficient Markets Hypothesis hold true, they have a deep and meaningful impact on the financial industry as a whole and shake the conventional beliefs where investment techniques are rooted from their origin, like the fact that fundamental and technical analysis can produce abnormal investment returns. On the other hand, in the case in which prices follow a random pattern and they reflect all available information, the efforts of analysts, that carry on technical analysis employing historical data in order to spot trading opportunities, are destined to fail. In the same way, fundamental analysis, which tries to spot undervalued stocks by comparing their actual price to the intrinsic value of the firm, is destined to fail as well, due to the fact that the market already shows any kind of anomaly. *Table 1* shows some of the most relevant empirical studies about efficient and inefficient markets, some of which are mentioned in this study.

On the other side, inefficient markets suppose that prices are not efficient even if they reflect all available information, which means that it takes a long amount of time for prices to reflect the data and information that is present or do not at all; the direct consequence is that they partially fulfil the EMH or not at all. Moreover, a market that is inefficient might show trends which are characterized by the absence of unit roots. A characteristic trend is called *Momentum*, where the movement of the prices can be explained by a certain heard behaviour of investors.

| Author/s | Year | Market | Sample Period |
|---|---|---|---|
| **Efficent Market** | | | |
| Choudry | 1997 | 6 Latin American Markets and the United States | 1989-1993 |
| Kawakatsu and Morey | 1999 | 16 Emerging Markets | 1976-1997 |
| Narayan | 2005 | Australian and New Zealand Markets | 1960-2003 |
| Narayan | 2006 | NYSE Common Stock in the US | 1964-2003 |
| Narayan and Smyth | 2007 | G7 Countries | 1960-2003 |
| Qian et al. | 2008 | Shanghai Stock Exchange | 1990-2007 |
| **Inefficent Market** | | | |
| Lo and MacKinlay | 1988 | US Market | 1962-1985 |
| Fama and French | 1988 | US Market | 1926-1985 |
| Poterba and Summers | 1988 | NYSE Annual and 17 Countries | 1871-1985 |
| Chaudri and Wu | 2003 | 17 Emerging Markets | 1985-1997 |
| Narayan | 2008 | G7 Countries | 1975-2003 |
| Lee et al. | 2010 | 32 Developped and 26 Developing Contries | 1999-2007 |
| **Mixed Results** | | | |
| Lee et al. | 2014 | 60 Countries, OECD, G6, Asian and European Groups | 2005-2008 |

*Table 1 Some relevant empirical studies about efficient and inefficient markets.*
*Source: Author.*

Classical financial theory on the other hand assumes that human beings are perfectly rational agents, also called *Homo Economicus,* that take rational decisions in a consistent manner and with self-interest (Simon, 1955). The neoclassical financial theory states how few of the decision-making processes in financial markets with the Efficient Market Hypothesis and modern portfolio theory (Markovitz, 1952). The EMH states how stock prices trade at fair prices since they reflect all existing information, therefore an investor that is rational should just own a part of the market rather than choose an individual stock. The MPT also states how investors are rational agents that crave the maximum expected return of the portfolio for a determinate level of risk or volatility. Behavioural finance emerges as an alternative or complement to classic financial theory, combining psychological and sociological aspects as factors to interpret the shift of prices.

Behavioural finance assumes that the market users are not completely rational as they present a determinate psychological bias which controls their decisions. This school of thought stems from ideas that can be traced back to the early publication of Mackay (1841) “Extraordinary Popular Delusions and the Madness of Crowds” which describes a series of events from the side of crowd psychology, concepts which later would have been applied to finance and other quantitative sciences. *Table 2* categorizes literature for foundational articles, mental counting, heard behaviour, emotional gap, and anchoring. Authors like Simon (1955) create a behavioural model of rational choice which aids to argue that the Homo Economicus paradigm is not perfect. Fromlet (2001) assesses the worth of a few psychological biases such as heard behaviour, emotional gap, anchoring and mental counting, coming to the conclusion that irrational behaviours and psychology were of crucial importance in order to explain a certain phenomenon in the financial market.

| Author/s | Year | Title |
|---|---|---|
| **Foundational** | | |
| Mackay | 1841 | Extraordinary Popular Delusions and the Madness of Crowds |
| Simon | 1955 | A behavioural model of rational choice |
| Fromlet | 2001 | Behavioural finance-theory and practical application |
| **Mental Accounting** | | |
| Thaler | 1985 | Mental accounting and consumer choice |
| Thaler | 1999 | Mental accounting matters |
| **Herd Behaviour** | | |
| Chiang and Zheng | 2020 | An empirical analysis of herd behavior in global stock markets |
| Buchner et al. | 2020 | Herd behaviour in buyout investments |
| Wanidwaranan and Padungsaksawasdi | 2020 | The effect of return jumps on herd behavior |
| **Emotional Gap** | | |
| Richards | 2012 | The behaviour gap: Simple ways to stop doing dumb things with money |
| Housel | 2020 | The Psychology of Money: Timeless lessons on wealth, greed, and happiness |
| **Anchoring** | | |
| Fromlet | 2001 | Behavioral finance-theory and practical application |
| Kudryavtsev and Cohen | 2010 | Anchoring and pre-existing knowledge in economic and financial settings |

*Table 2 Categorized literature for foundational articles, mental counting, heard behaviour, emotional gap, and anchoring.*
*Source: Author.*

As we already stated before, Algorithmic Trading is a relatively an unprecedented and novel discipline. Many of the academic papers and articles are taken from a research position, meaning they mainly aim at testing certain financial theories. On the other hand, the literature which is relevant to the topic is captured in textbooks.

*Table 3* we redacted below shows which have been the most pertinent academic works for Algorithmic Trading categorized by the programming language that has been employed to conduct the research. Conlan (2016) and Georgakopoulos (2015) researches find their bases in *RStudio*, which is considered a natural choice for data analysts and statisticians; Clenow (2019) and Hilpisch (2018; 2020b; 2020a) employ *Python*; Chan (2009; 2013; 2017) uses *MATLAB* and *Python*; and Scarpino (2019*) C++* and *Python*. Notably, any programming language has the potential to be an efficient option for

Algorithmic Trading; however, the most common is Python for prototyping and low-scale applications and C++ or Java for enterprise applications.

| Author/s | Year | Title | Programming Language |
|---|---|---|---|
| **R Programming Language** | | | |
| Conlan | 2016 | Automated Trading with R: Quantitative Research and Platform Development | R |
| Georgakopoulos | 2015 | Quantitative trading with R: Understanding mathematical and computational tools from a quant's perspective | R |
| **Python Programming Language** | | | |
| Clenow | 2019 | Trading Evolved: Anyone Can Build Killer Trading Strategies in Python | Phyton |
| Hilpisch | 2018 | Python for finance: mastering data-driven finance | Phyton |
| Hilpisch | 2020b | Python for Algorithmic Trading | Phyton |
| Hilpisch | 2020a | Artificial Intelligence in Finance | Phyton |
| **Multiple Programming Languages** | | | |
| Chan | 2009 | Quantitative trading: how to build your own algorithmic trading business | MATLAB, Phyton, R |
| Chan | 2013 | Algorithmic Trading: Winning Strategies and Their Rationale | MATLAB, Phyton |
| Chan | 2017 | Machine Trading: Deploying Computer Algorithms to Conquer the Markets | MATLAB, Phyton |
| Scarpino | 2019 | Algorithmic Trading with Interactive Brokers: Python and C++ | C++, Phyton |

*Table 3 Some relevant empirical studies about Algorithmic Trading categorized by the programming language used.*
*Source: Author.*

The subsequent review of the available literature is not categorized by programming language but by the two key steps that Algo Trading requires. First of all, *backtesting* as the mechanism employed to evaluate and assess strategies through historical data; and secondly the strategies themselves.

Backtesting is the process of exposing your specific strategy algorithm to a flow of historical financial data, that provides a route to a set of trading signals. Each transaction will have a determinate profit or loss. The heard of this loss or profit over the length of your strategy backtest will give you the overall profit and loss (Quantstart, *Successful Backtesting of Algorithmic Trading Strategies)*. It is a fundamental step before launching the algorithm live. The popular *Microsoft Excel* is an ubiquitous too in the financial industry, due to the fact that it is familiar to most traders and brings an intuitive interlink between results and data employing simple formulas. Even though its effectiveness expands in a significant way with Visual Basic macros, it is not the most popular choice for backtesting. It tends to overlook bias and it is not entirely efficient when it comes to elaborate large volumes of data. Few authors (Chan, 2009; Pruitt, 2016) demonstrate its characteristics and include the Visual Basic tool, even though it is not the most commonly used. Backtesting demands a programming language that facilitates both the automated acquisition of data and the acquisition and processing of advanced trading strategies. For the purpose of backtesting prototyping Python and RStudio are very efficient; for production Java, C/C++ and C# are the most common due to the faster execution time. Python is certainly a prolific language employed by many authors (Pruitt, 2016; Hilpisch, 2018; Clenow, 2019; Scarpino, 2019; Hilpisch, 2020); others go for RStudio (Georgakopoulos, 2015; Conlan, 2016); MATLAB (Chan, 2009; Chan, 2013; Chan, 2017) or alternatively proprietary options like *EasyLanguage* (Davey, 2014; Pruitt, 2016) employed by TradeStation.

Traders need to be conscious of the downsides of backtesting in order to ensure that the algorithm will behave live like in the simulation. The most common problems are biases that are overlooked, data-snooping bias, stock splits and dividend adjustments, survivorship bias in stock databases primary versus consolidated prices, venue dependence of quotes, short-sale constraints, future continuous contracts and future close versus settlement prices (Chan, 2009; Chan, 2013). The majority of literary works (Georgakopoulos, 2015; Conlan, 2016; Hilpisch, 2018; Scarpino, 2019) do not mention the challenges of backtesting or show very little focus on them. A fundamental for backtesting is financial data in the form of financial time series, macroeconomic or sentimental data.

For what concerns *High-Frequency Trading* mentioned in the previous paragraph, the particular type of Algorithmic Trading characterized by high speeds and turnover rates, that allows one to buy and sell at extremely fast rates, particularly significant is the study by Brogaard et al. (2014), where they analyze the role of Algo Trading and specifically of High-Frequency Trading in price discovery. Generally, it is demonstrated how HFT increases the performance of prices, it does so by executing orders in the direction of stable changes in price and in the opposing direction of temporary errors in pricing. This is possible thanks to their marketable orders. Moreover, the paper provides evidence for the role that HFT has in establishing market stability, for which the authors do not find irrefutable evidence. Contrarily, they present proof that the total trade is generally performed in the direction of decreasing temporary errors in pricing both on average days and on the most variable days during a time of corresponding market turmoil (2008-

2009). In addition, Biais, Foucault, and Moinas (2011) discussed how the mere fact that High-Frequency Trading forces adverse selection costs for suppliers of liquidity during times of market stress, might cause non-HFT providers of liquidity to withdraw from the market. Brogaard et al. (2014) paper further explores how High-Frequency Trading affects the structure and efficiency of the market, done by identifying several types of public data related to automated trading, both macroeconomic communications and limit order book disequilibrium. However, their examination is based on a single market for a subset of HFTs, we believe that better data for both long-term investors and HFTs could allow more generic deductions. Hirschey (2013) found evidence of how HFTs were anticipating the actions of non-HFTs.

Theate and Ernst (2021) present a scientific analysis where the Trading Deep Q-Network algorithm, or TDQN, as the possible solution to the issue that AT has in establishing the optimal trading position at any point in time while trading activities are in progress. Their examination shows positive results, surpassing on average the benchmark trading strategies. However, the way TDQN performed might be perfected, as a matter of fact, various analyses indicate an advancement with respect to the solution suggested by the authors. Hausknecht and Stone (2015) employ the LSTM layers within the deep neural network that could help to elaborate better time series of financial data.

Scholtus et al. (2014) investigate the relevance of speed in trading rules that find their base on speed, and most importantly the influence of Algorithmic Trading on market quality when it comes to macroeconomic news being released. They find that generally, every market quality measure that took and Algo Trading proxies display a strong reaction to the release of macroeconomic news, with a stress on the ones at 10.00 a.m. Measures for depth decrease, while quoted spreads, adverse costs of selection and measures for volatility rise when short windows around news releases, overall leading to poorer market quality. The activity of AT decreases before the release then has a sudden and significant rise when the news is actually released to the public.

A rich literature is present on whether and how Algorithmic Trading affects liquidity. Chae et al. (2013) make use of a wide database from the Korean Market, they found that Algo traders do not make profits out of the exploitation of information; they profit by supplying liquidity to market users who ask for it. Backing up their findings, Vilijoen et al. (2014) expand those of Hendershott, Jones and Menkveld (2011) and suggest that ATs are advised. At the time the discovery that ATs were linked to an elevated information content is new and gives a contribution to the literature that was giving ATs for liquidity providers. Hendershott et al. (2011) suggest how Algorithmic Trading possibly decreases the trading costs and rises the quotes' informativeness. Amazingly, the revenues to LP rise with Algorithmic Trading as well, even though this consequence seems to be momentary. Hendershott and Riordan (2013) examined the role of ATs and liquidity demand and supply in 30 stocks on the Deutsche Börse in January of 2008 and found out that depicting 52% of market order volume, Algo traders were controlling more effectively market liquidity than human traders. As a matter of fact, Algo traders gobble liquidity when it is cheap and give it out when it is pricey.

For what concerns trading strategies the literature is abundant, the real challenge is to identify the most appropriate ones, the ones which adapt better to the risk-reward profile of the investor. Chan (2009) lists a few of the considerable sources classified by academic[3], financial websites and blogs[4] and trade forums[5]. The overall automated trading platforms scenario offers trading algorithms for the execution of trades on their platforms, some examples are QuantConnect, Modulus Financial Engineering, CloudQuant, AmiBroker or IG International Limited, being particularly efficient Quantpedia which is a library of 600 trading strategies, where 75 are for free, 525 are premium and with 412 algorithms for QuantConnect. The classification of trading strategies is diverse, and we are going to explore the technical functioning in a later chapter, in this one we will consider literature for mean-reverting strategies and momentum strategies.

- *Mean-Reverting Strategies*

  Mean Reversing in finance assumes that a time series tend to converge to the mean over time. This particular strategy has as one of its assumptions an inefficient market, an overall or partial rejection of the Efficient Market Hypothesis and a stationary or trend-stationary time series. This phenomenon is not just related to finance, some notable cases are the mean-reverting of the water of the Nile River from 622 AD[6] to 128 AD (Chan, 2013) or the study on how the performance of an athlete will drop after being published in Sports Illustrated (Kahneman, 2012) on the grounds that an athlete's performance follows the mean.

[3] *Id*, National Bureau of Economic Research.
[4] *Id*, Yahoo! Finance.
[5] *Id*, Elite Trader.
[6] *I.e.* Anno Domini.

Financial time series with returns that are mean reverting are especially interesting for trading strategies due to the fact if the pattern holds true, one could easily take advantage of them in a systematic way. Unfortunately, this behaviour does not occur as often as one might think but can be constructed by cointegrating two different time series. Chan (2009) creates a stationary and cointegrated time series by combining ETF Gold and ETF gold miners. The difference is called *Spread*, which if positive requires buying one ETF and selling the other one, and vice versa if negative. The author also creates an additional stationary time series combining Coca-Cola securities and Pepsi ones, however without including examples of the source codes. Hilpisch (2018) develops a strategy using Ordinary Least Square, or OLS, regression in order to predict future movements in the exchange rate EUR/USD. He assumes that the time series is stationary due to the fact that is based on a log return. However, this is not a sufficient condition (Hamilton 1994). He performed backtesting from 2010 to 2018 with a total cumulative return of 33% excluding transaction cost and omitting to mention of the number of trades.

- *Momentum Strategies*

  A Momentum happens in the event of a slow diffusion of information. As traders and investors are aware of new information more individuals decide to trade and as a consequence, they create a trend. Additional momentums are produced by herd behaviour of traders, which is a well-studied aspect of behavioural finance (Ritter, 2003) and is present when bubbles and bursts of stock market happen. Chan (2009; 2013) provides various examples of momentum strategies. For instance, one algorithm exploits the *Post Earnings Announcement Drift*, or PEAD, effect which creates a trend after a particular earning announcement. Consequently, the strategy consists in buying when earnings exceed expectations and selling otherwise (Chan, 2009). Another idea is to benefit from the calendar effect in order to create a seasonal trending strategy (Chan, 2009). It requires to buy or sell certain stocks at a fixed date of the year and buy or sell at another. Chan takes advantage of the *January Effect*, the idea that investors sell the losers in December to benefit from tax losses, which produces an additional downward pressure to buy back in January. He implements an algorithm in MATLAB for S&P 500 small-cap. However, the author does not debate the results or provide specific statistical output data. Hilpisch (2018) presents a trading strategy based on Simple Moving Average a strategy which was already been described by Brock et al. (1992). It entails the creation of two SMA with two different time constants, the buy/sell signal is defined by the intersection of the two SME curves. The author focuses more on the implementation of the algorithm rather than on its final performance.

# CHAPTER 2

## *2. Algorithmic Trading Execution Strategies*

Algorithmic trading strategies, which are also known as black-box trading or algo trading strategies, are programmed trading instructions which allow the automation of the execution of orders. These directions are fundamentally lines of code which particularize the details on when to sell or buy, and they might comprise price arbitrage analysis, chart analysis, volatility analysis or only trend that follows the movements of the price (Solanki, 2022).

Large hedge funds and investment banks pay out millions every year on teams that trade and are specialized in developing black-box trading models to make the best out of the market. These peculiar teams are usually composed of engineers, mathematicians, and PhD scientists and the possible removal of human error is undoubtedly one of the main attractions of the black-box trading models. The management of emotions and feelings like greed and fear are some of the greatest obstacles for human traders, and algorithmic trading strategies do not suffer these types of problematics (Solanki, 2022). Another great appeal of algo trading is surely the fact that can trade 24 hours a day.

A broad variety of algorithmic trading strategies new and that are operating, more advanced are continuously being crafted by experts.

## *2.2 Algorithmic Trading System Architecture*

We can define a system's architecture as the infrastructure inside which components of an application, that satisfy requirements of a functional nature, can be executed, employed, and specified. Functional requirements are the functions that are expected functions of both the system and what composes it. On the other hand, non-functional requirements are actions via which the quality of the system can be assessed. Fully satisfying functional requirements does not mean that a system could meet expectations in the case in which non-functional requirements are not (Turing Finance, *Algorithmic Trading System Architecture)*.

*Figure 2* shows the conceptual architecture of the algorithmic trading system. A view is considered conceptual and describes concepts to a high level and mechanisms which happen in the system at the highest level of granularity.[7] At this level, the algorithmic trading system pursues what is denominated an *Event Driven Architecture* (EDA), which can be broken down to four layers and two aspects (cross-cutting concerns that span multiple elements) that are of an architectural nature. Patterns (proven, generic structures that are used to obtain specific requirements) and reference architectures are employed for each aspect and layer. An EDA can be defined as an architecture that generates, identifies, wears out and reacts to events. In this category, we include movements of the market real time, particularly intricated trends or events and trading events.

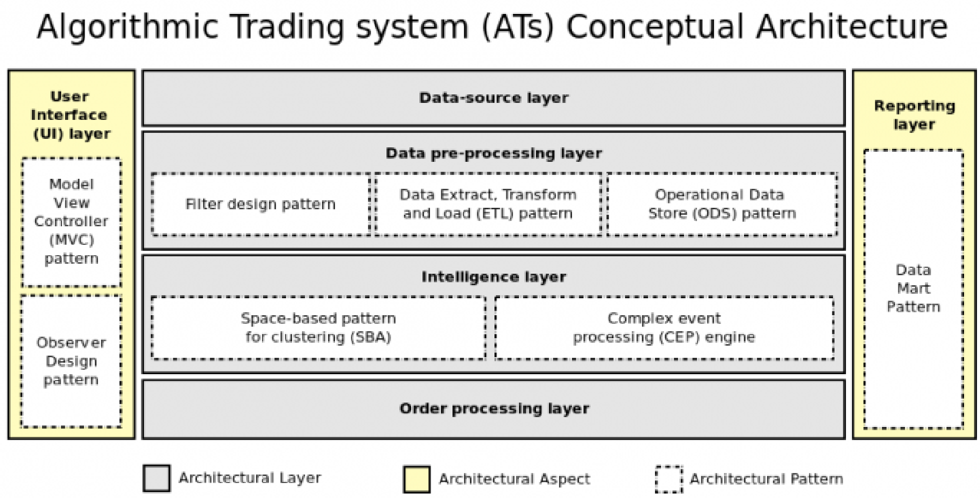


*Figure 2 Conceptual architecture of the algorithmic trading system.*
*Source: Turing Finance, System Trading Architecture Algorithmic.*

[7] The scale or level of detail present in a set of data or other phenomenon.

Another type of architecture used in algorithmic trading is the reference one. It can best be described with an analogy. This kind of architecture is analogous to the blueprints for a load-bearing wall: it could be used again for different designs of buildings careless of how is built as long as it satisfies a range of customary requisites. Likewise, a reference architecture determines a template which holds structures that are generic and mechanisms that can be employed to build a solid software architecture that meets specific requirements. The architecture that is used in the systems of AT employs what is called a *Space-Based Architecture* (SBA) and a *Model-View Controller* (MVC) (Turing Finance, *Algorithmic Trading System Architecture)*. SBA enables various components to interact with one another by the exchange entries through one or even more spaces that are shared (Wikipedia, *Space-based architecture)*. MVC is an application design model which is composed of three parts that are interconnected: the model (data), the view (user interface), and the so-called controller (process which handles input) (TechTerms, *MVC)*. *Figure 3* shows a diagram of an Algorithmic Trading system high-level deployment.

On the other hand, the architecture's structural view displays the elements and sub-elements of the AT system. It proves how these elements are used onto infrastructures that are physical.

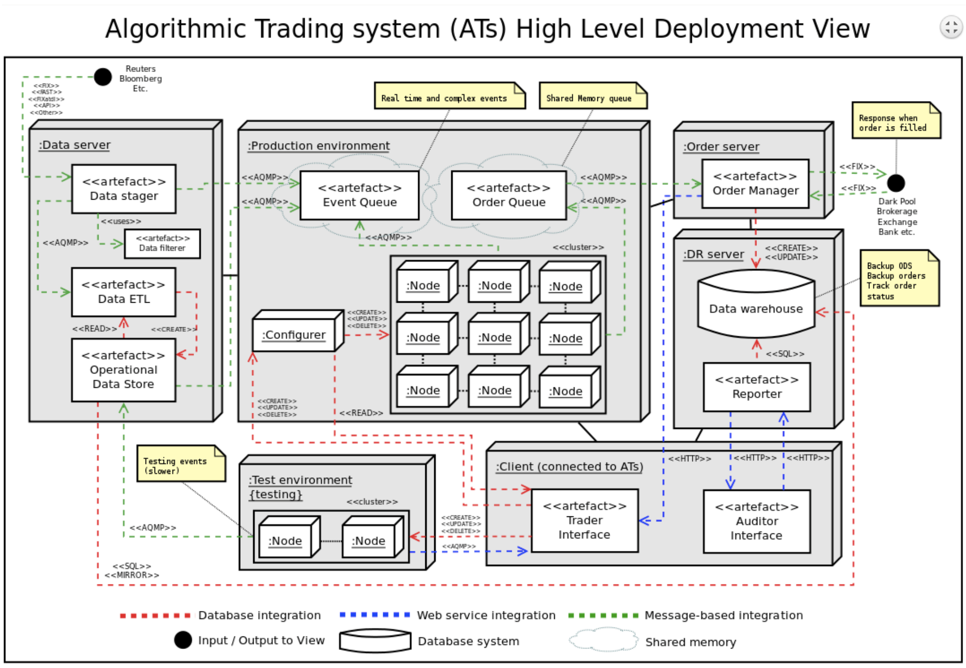


*Figure 3 Algorithmic Trading system high level deployment diagram.*
*Source: Turing Finance, Algorithmic Trading Architecture System.*

The architectures that we have proposed above have been conceived to meet general requisites that are identified for AT systems. Generally speaking, algo trading systems are aggravated by specific factors that change with every execution:

1) Reliance on enterprises which are external and exchange systems.
2) Nonfunctional qualifications that are usually challenging.
3) Constantly evolving architectural constraints.

Hence, the software architecture that is proposed here needs to be adapted to each case so that to satisfy requirements of an organizational and regulatory nature, and also to exceed regional constraints (Turing Finance, *Algorithmic Trading System Architecture)*.

### *2.2.1 Pairs Trading*

The first well-known strategy that is spreading across trading is denominated *Pairs Trading, Figure 4* gives a general idea behind, and is usually used on common stock and it can be categorized as a convergence trading and statistical arbitrage strategy (Kanamura, 2008). Here the trader has to identify two brands of stock prices which are possibly highly correlated given the history of their prices and begins the trades by opening the short and long positions of the selected stocks. With the assumption of *Mean Reversion*[8] in mind, the algorithm is expected to produce profits from the irregular fluctuation of prices.

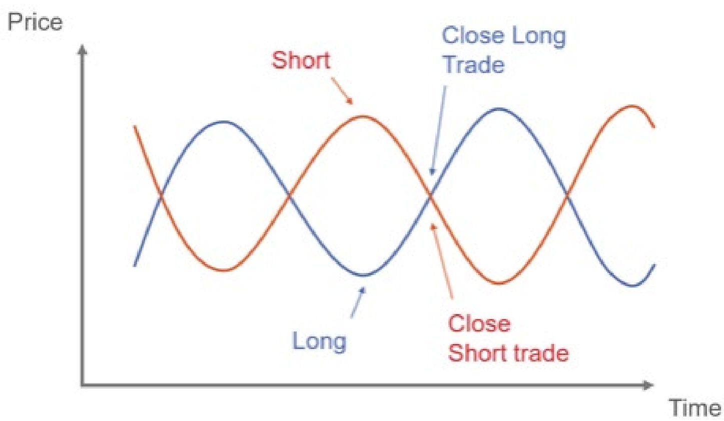


*Figure 4 General idea of pairs trading.*
*Source: AlgoTrading101, Pairs Trading – A Real World Guide, 2021.*

[8] Theory used in finance that suggests that asset price volatility and historical returns eventually will revert to the long run mean or average level of the entire dataset.

The crucial part of this specific strategy is to determine which stocks are correlated and the method to settle a divergence of prices. Correlation is measured by the correlation coefficient ρ which has a range that goes from -1 to +1. This coefficient quantifies the degree of correlation that exists among two variables, where a value of +1 indicates a perfect positive correlation, -1 indicates a perfect negative one and a value of 0 detects no correlation at all. If there exists a high correlation value, like 0.7, it means that there exists a strong relationship between the two stocks and traders could choose that pair to execute pairs trading. This means that if one stock goes up, there are good chances that the second stock will go up as well. In this case, a *Market Neutral* strategy[9] is put into action where the first stock is bought and the second one is sold. It has to be stressed that these resolutions are made based on their individual patterns (Gupta, 2019). However, we must point out that looking just at the correlation could produce spurious outcomes,[10] for this exact reason using only correlation for pairs trading is not specifically advised (Gupta, 2019). It's here that cointegration comes into the game.

Even if it is usually concurred that individual stock prices are hard to predict, evidence is present that hints at the possibility of forecasting the spread series of some stock portfolios. An ordinary way method to try this is by designing the portfolio in such a way that the spread series presents stationarity.[11] In order to obtain stationarity of the spread, where two stocks are the only components of the portfolios, it can be attempted to detect cointegration irregularities among the prices of the two stocks series which commonly displays stationary correlation. This anomaly is presumed to be filled and forecasts are made so to be in the opposite direction of said anomaly (Carol, 2001). Regardless of whereby the portfolio is designed, if the spread series presents stationarity, therefore it can be shaped, and afterwards forecasted, employing specific stochastic processes of time series analysis. Between the ones which are more appropriate for pairs trading, we can cite the *Ornstein-Uhlenbeck* models, the *Autoregressive Moving Average* (ARMA) models and the *error correction models* (ECM) (Mudchanatongsuk et al., 2008; Schmidt, 2008).

Spread series of a portfolio that are concretely forecastable are convenient for traders for two distinct reasons:

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[9] Where one seeks to profit from both increasing and decreasing prices in one or more markets while attempting to completely avoid some specific form of market risk.

[10] When two factors appear casually related to one another but are not.

[11] Meaning that the statistical properties of a process generating a time series do not change over time.

1) A direct trade of the spread is viable through the buying and selling of the stocks in the portfolio.
2) The forecast and its error bounds yield a valuation of the risk and return linked to the trade.

Whether pairs trading ends up being successful strongly depends on the forecasting and modelling of the spread time series.
Nowadays, this strategy is frequently executed using algo trading on an execution management system, an application that traders employ to visualize market data and supply quick access to destinations of trading with the aim of transacting orders (Wikipedia, *Execution management system)*. These peculiar strategies are usually designed around models which determine the spread based on historical data mining and analysis. The deviations in prices are monitored by algorithms, and they automatically buy and sell in order to capitalize on the inefficiencies of the market (Wikipedia, *Pairs Trade)*.
Pairs trading first originated in the United States, particularly it was pioneered by Gerry Bamberg who paved the way for this technique, and later it was further developed by the quantitative team at Morgan Stanley in the 1980s led by Nunzio Tartaglia (Zambarbieri, 2020).

### *2.2.2 Delta Neutral Strategies*

It is commonplace for strategies of stock trading to imply the presence of an expectation to know which stocks are going to go down and which ones are going to go up. However, it's hardly ever that straightforward, but it is a basis of strategies of stock trading to have some sort of forecast of how the prices of stocks are going to move.
The trading of options paves the road for a few strategies which allow traders to make profits from the stock's movements without the limitation of having to know how and in which direction. This gives traders the instruments to take benefit from high-leverage events, in which a stock might move a lot, even if they're not sure of the precise outcome – whether it could be favourable for the firm or not. Delta neutral strategies enable traders

to benefit from that volatility, or absence thereof (Market Chameleon, *Delta Neutral Trading)*.

We can define *Delta* (Δ) as the measure of change in an option value as a result of a move in the underlying market. Its value ranges between 0.0 and 1.0 and from 0.0 and -1.0. Traders employing this strategy look to position in a manner in which the Delta is 0.0 or near that value. It's quite straightforward to spot the logic and attraction of this trading strategy. In the case in which the Delta's value is 0, the position won't obtain nor shed as an effect of small movements in the market. This scenario leaves the stand completely to the passing of time – decay of time, to make its journey and erode the value of the option – which is the final goal of all the sellers of options (Traders Edge, *Delta Neutral - Trading without predicting market direction)*.

In order to set up a Delta Neutral position, a trader would sell or buy options and subsequently sell or buy the stock's shares to counteract the option trade's Delta that accumulated. Every stock share that a trader purchase constitutes +1.0 Delta in this strategy. *Table 4* assembled below explains the basic relationship between selling and buying options with the underlying stock.

| **Delta Neutral Trading** | |
|---|---|
| **Options** | **Stock** |
| Buy Call | Sell Stock |
| Sell Call | Buy Stock |
| Buy Put | Buy Stock |
| Sell Put | Sell Stock |

*Table 4 In order to establish a delta-neutral position, a trader would buy or sell options and then immediately buy or sell shares of the stock to erase the accumulated delta of the options trade. This is the basic relationship between buying or selling options with the underlying stock.*
*Source: Market Chamaleon.*

In the end, with the correct arrangement of stock and options, the net Delta will be 0.0, and the trader will be eventually covered against the possibility of the price of the stock shifting down or up (Market Chameleon, *Delta Neutral Trading)*.

The very existence of a portfolio which was Delta Neutral was demonstrated as a portion of the primary proof of the *Black-Scholes model*, used to assess the theoretical value or fair price for a put or call option grounded on six variables like risk-free rate, strike price, time, type of option, volatility and underlying stock price (The Economic Times, *What is*

*'Black-Scholes Model')*. Starting from the *Taylor expansion*[12] of an option's value, we obtain the change in the value of an option, $C(s)$, for a change in the value of the underlying asset ($\epsilon$):

$$C(s+\epsilon) = C(s) + \epsilon C'(s) + 1/2\epsilon^2 C''(s) + \cdots$$

*Equation 1 Taylor expansion of an option's value.*
*Where C'(S) = Δ (delta) and C''(S) = Γ (gamma).*

For each tiny change in the underlying, we are allowed to ignore the second-order term and employ the quantity Δ in order to assess how much to sell or buy of the underlying to produce a hedged portfolio. Nevertheless, in the instance in which the difference in the value of the underlying is not small, the second-order term, Γ, in no way can be ignored. In conclusion, keeping a delta-neutral portfolio requests a continuous recalculation of the Greek's positions and a rebalance of the position of the underlying, which is usually performed on a daily or weekly basis.

Traders and professional experts reason in terms of option spreads, and they hedge their trades so to remain neutral with respect to the market direction. From their point of view, the asset's direction is not as critical as the Implied Volatility. The latter will determine when to sell or to buy options, and at the same time it will define whether the price of the option is expensive or cheap.

Another element which is key is to operate the trade when needed. If the position gets too bearish or too bullish, whoever performs the trade should operate instantly and adjust it back to neutral. As it works with more strategies, the break-even's downside and upside have to be calculated in order to identify the profit's range. A trader should spot potential maximum loss and profit so to see whether the trade is possible, changed or discarded (Keiran, 2020).

[12] An expansion of some function into an infinite sum of terms, where each term has a larger exponent like x, x^2, x^3, etc.

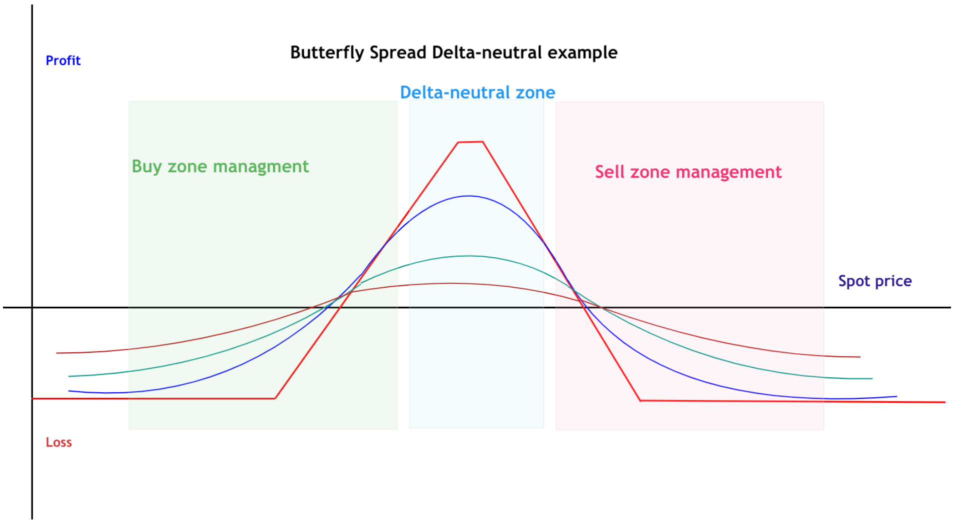

*Figure 5 Strategies with zero Delta include buying or selling straddles and strangles, as well as Butterflies. It can also be created by a combination of underlying and options, such as buying one lot of a forex pair and selling two at-the-money calls of the same asset.*
*Source: Forex.Academy, Forex Options Part 15 Delta Neutral Strategies, 2020.*

As shown in *Figure 5*, strategies that have zero Delta comprise selling or buying straddles, strangles and Butterflies. It can also be generated by a mix of options and underlying, for example purchasing one lot of a forex pair and selling the same asset's at-the-money calls. The most popular Delta Neutral position is denominated *Ratio Spread*. This position entails an uneven number of options to be bought and sold. The underlying asset can be mixed with spreads, which need to be based on the current conditions of the market. These positions are fairly attractive that show a wide profit region; however, they present unlimited risk as well; hence, the position must be carefully controlled and administrated (Keiran, 2020).

### *2.2.3 Arbitrage Strategies*

We can define Arbitrage strategies as event-driven strategies, and accordingly, they are market movement-neutral (Biswas, 2020). This strategy entails taking advantage of small differences in prices of the same asset but not in the same markets, particularly with price variations that are short-term. *Figure 6* shows the basic mechanism behind this strategy. A commodity is bought by a trader, which could be a stock, a crypto, or a currency, from one market where it presents a low price and resells it to another market at a price which is slightly higher. It must be stressed that both trades happen *simultaneously*, at the same time. In arbitrage trading, the principal concept is to produce a small fraction of profit from each trade that is successful. Scholars believe that this strategy is beneficial in maintaining the market's balance, it makes sure that prices in markets will not deflect long-term (Robertson, 2022). Arbitrage often entails the employment of very large amounts of money and various transactions in order to get a meaningful return, which makes it an expensive approach to investing. Whilst markets infrequently run as efficiently as they should in the faultless world of theory, the differences in prices are minor, and arbitrage possibilities vanish as quickly as they are discovered (Jackson & Schmidt, 2021).

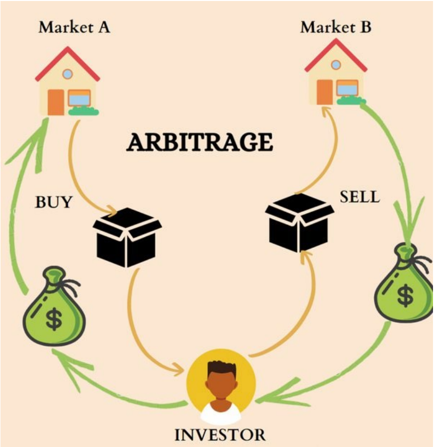


*Figure 6 Arbitrage is the simultaneous purchase and sale of the same asset in different markets to profit from tiny differences in the asset's listed price.*
*Source: Quora.*

Nowadays, financial professionals employ algorithmic trading to detect and take advantage of arbitrage strategies. It happens frequently that the discrepancies in prices which are at the centre of arbitrage entail various geographies, just the one that can be spotted in the foreign exchange (forex) market. They happen when an information lag occurs as well, which could be the case of crypto arbitrage or stock that trade on different exchanges (Jackson & Schmidt, 2021). Arbitrage as we know it is commonly caused by three circumstances that we will define as conditions:

- *Unequal Information*: Those who participate in multiple markets can access various information that take them to evaluate an asset in different ways (Reed, 2019). This is not as common as it was a long time ago. Communications technology enabled a network which is not only global but immediate, a net of information which is publicly available and changes in prices in an asset are passed on around the world instantly.

- *Inefficient Markets*: We can define "Inefficiency" as the instance in which the prices in the market don't match the true value of the market. This could occur for various motives like political climate, speculation, unequal information and much more. When one market is acting less efficiently than another one it will cause a gap in prices that traders interested in arbitrage can use. By behaving in this precise way, traders will support the adjustment of market inefficiencies.
- *Uncertain Valuation*: There are instances where markets work both in an efficient way and using correct information but still, they are pricing an asset differently. This is something that happens frequently when traders merely fail to agree on what is the actual value. An everyday example is set in *blockchain trading*. This is a strongly speculative class of assets with important market inefficiencies but at the same time a diffused debate on the actual value. Traders and investors have different opinions on what they believe individual crypto is actually worth and thus deal the same tokens for dissimilar prices (Reed, 2019).

The arbitrage that we can define as "simultaneous" is the one that can be considered as the least risky, however, apart from the crypto markets, it's not an event that happens very often and it's something that does not have much of a length timewise. The most common modelling of arbitrage centres around the estimation of the extent to which the asset's price deviates from the price of the equilibrium. In mathematical terms, we can define the *Arbitrage Pricing Theory* model as:

$$E\left[r_j\right] = r_f + b_1P_1 + b_2P_2 + \cdots + b_nP_n$$

*Equation 2 Arbitrage Pricing Theory model.*

$E\left[r_j\right]$ = *Expected Return for the given asset*
$r_f$ = *Risk Free rate*
$b_n$ = *Sensitivity of asset price*
$P_n$ = *Risk Premium of factor*

This model describes the asset's returns as a linear combination of the regressors. As the models calculate an expected return, we would then compare them against the fair market price. It is relevant to point out that the Arbitrage Pricing Model does not assure profits like the simultaneous one, however, it supplies a high probability for arbitrage

opportunities if the model is backtested in the correct way (Medium, *Algorithmic Trading 101 — Lesson 3: Introduction to Arbitrage Strategies)*.
Arbitrage comes with some types of risks which depend on the fact that it depends on looking for opportunities from gaps that are left (Thakar, 2022). We are going to explore in detail one of them, the *Mean Reversion*, in the next paragraph.

### *2.2.4 Mean Reversion*

We can define Mean Reversion the financial theory which implies that, after a price moves drastically, prices of assets tend to return to normality or at least at average levels. It's a common routine for prices to shift around the mean or around the price average, nevertheless, they tend to go back to that same average price over again. Whoever takes a chance at mean reversion trading has discovered many ways to take advantage of the theory. In any case, they are betting that an exceptional level, which might be a technical indicator, growth, volatility, or price, will revert to the average one (CMC Markets, *Mean Reversion)*. MR, such as momentum strategies, are better when taken into consideration as a first step in algorithmic trading, as they have been time-tested as possible strategies, given that they are implemented in the correct way (Bruyelle et al., 2020). *Figure 7* shows a year's worth of daily candlesticks. There are instances in which the price moves back and forth around the mean. On the other hand, there are moments where the price drifts away from the mean. The simple moving average follows and the two meet each other again.
In order to understand and correctly compute mean reversion, users need to compute the mean. We can define the mean as the average price over a number of data points which are given. On the trading chart[13] of an asset, the mean is shown in an easy way by the *Simple Moving Average* or SMA. The simple moving average computes the average price in the series of prices. Over time, prices have the tendency to oscillate around the average, and eventually revert back to it. Normal trading can use various standard measurements, like the actual distance from the simple moving average, in order to set up on a permanent basis when the price could regress back to the mean.

[13] Aspect of technical analysis that allow traders to study the price action of various financial assets.

There exist technical indicators such as Envelopes, Keltner channels, Bollinger Bands, and regression channels[14] each own their own personal formula and they try to let traders know when the price is close to extreme levels and might revert. Nevertheless, as it often occurs in trading, these indicators can only supply signals, a not transparent indication of a reversal (CMC Markets, *Mean Reversion*).

*Figure 7 This chart displays a year's worth of daily candlesticks. There are instances in which the price moves back and forth around the mean. On the other hand, there are moments where the price drifts away from the mean. The simple moving average follows and the two meet each other again. Source: CMC Markets, Mean Reversion.*

Since the market is a sort of reflection of the majority, quite a few investors will use *Sentiment Indicators*[15] such as investor confidence. From historical records, surveys performed by investors have demonstrated how investors turn out to be more pessimistic when there are market lows and surer of themselves close to market peaks (Marwood, 2021). *Figure 8* displays the AAII Investor Sentiment Index which shows both the percentage of investors who are neural, bearish, or bullish on stocks and clear mean reversion peculiarities.

[14] Technical options that traders in the currency markets can apply to capture profitable opportunities in swing action.
[15] Market psychology-based indicators attempt to quantify sentiment, in the form of figures or graphically, to predict how current beliefs and positions may affect future market behavior.

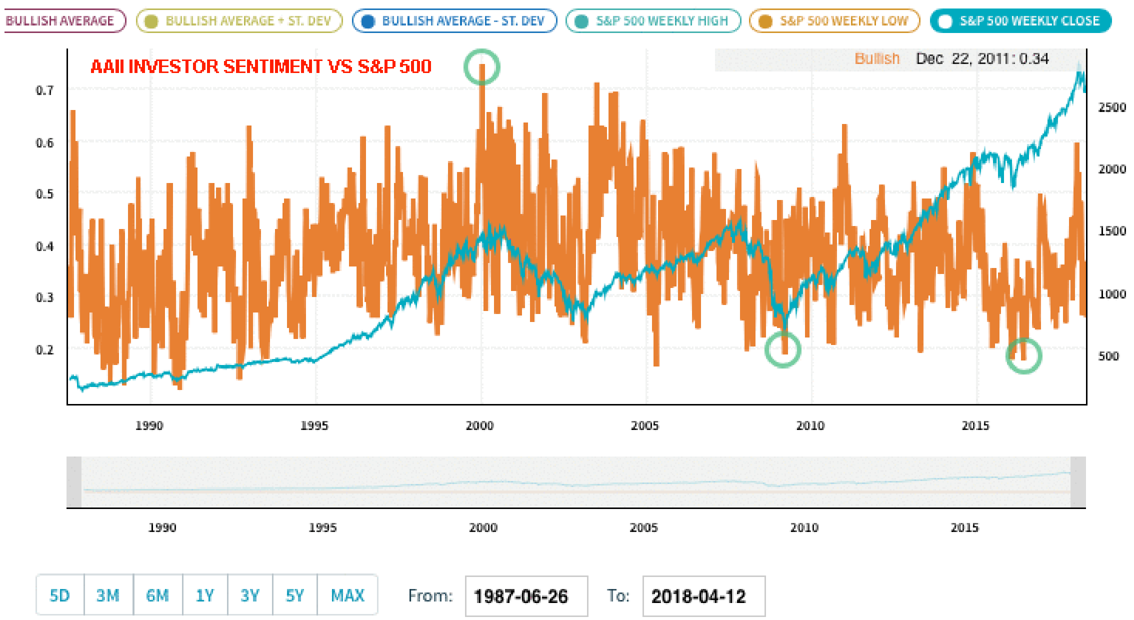


*Figure 8 This chart is the AAII Investor Sentiment Index which shows both the percentage of investors who are neural, bearish, or bullish on stocks and clear mean reversion peculiarities. The blue line represents the S&P 500 Index. We can identify market peaks in investor sentiment in January 2000, but also in correspondence with market lows like in March 2009 and May 2016.*
*Source: quandl.com*

### *2.2.5 Scalping*

Scalping came to be one of the most employed trading short-term strategies, involving the gain of tiny profits as fast as possible. The trader closes and opens a trade in a span of a bunch of seconds to few minutes during the day. Scalpers do not leave their trade open for hours due to the quick nature of the trades made on tiny timeframes (Samuelson, 2022). This strategy makes feasible profit as long as prices move less than this spread and usually employs the establishment and the liquidation of a position in a quick way, in a matter of minutes or even less. In order to perform correctly this strategy, a trader is required to have strict control over their exits and entries. This is where to own an algorithmic trading strategy can allow to maintain control on the prices they trade at (Rakheja, 2022).

In nowadays market, this strategy is for the most part automated, as it is almost impossible to profit from it with an approach that is discretionary (Samuelson, 2022). As a matter of fact, this peculiar algorithmic trading strategy was the bread-and-butter for a lot of floor traders or day traders over the course of the years. Scalping opportunities have paved the way for intelligent algorithmic traders and developers. On the other hand, narrower spreads and more efficient computers made the life of a manual trader much more difficult and more challenging as well (ProfessorAlgo, *Algorithmic Trading 101)*.

### *2.2.6 Spoofing*

Last but not least, *Spoofing* (or bluffing) is a dangerous algorithmic trading strategy which plays with the structure of the financial market by coming up with the misinterpreted perception of the demand or supply of a traded security, commodity, or currency. Traders who usually use this peculiar strategy often place an overall big number of trades to sell or buy securities like futures, stocks, and bonds; however, with no actual intention of executing the order. This naturally brings other users to be convinced of the fact that there exists some sort of pressure to sell or buy the specific financial product and urges market prices to shift. Once spoofers manage to successfully originate this artificial illusion for supply and demand, they place huge numbers of minuscule trades at once for that particular security. This mauver makes spoofers gain a noteworthy profit, all starting when they tricked the financial market by employing a significantly big order which was erased later on (Blueberry Markets, *Spoofing in Forex Trading*). *Figure 9* below shows this exact mechanism.

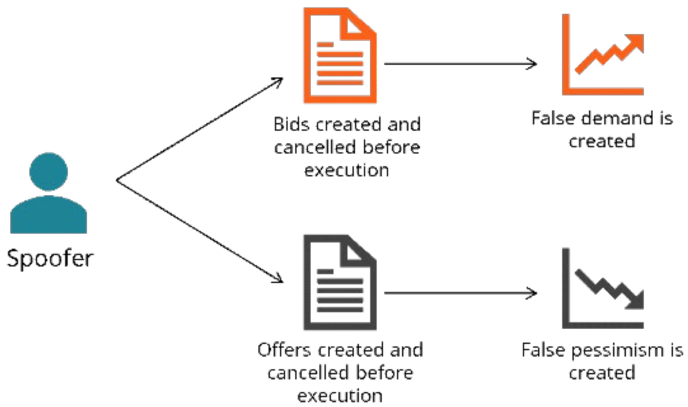


*Figure 9 Spoofing mechanism.*
*Source: SimTrade.fr.*

Traders have been using this particular strategy for years and years. It has to be stressed that the introduction in the latest years of quick and powerful trading systems that are based on computers, this procedure turned out to be more usual as the application of scientific knowledge was advancing at incredible speed (Blueberry Markets, *Spoofing in Forex Trading*).

It is no doubt how algorithmic trading and automated trading technologies have given important advantages to financial users, comprising enhanced executing velocity and decreased costs. Moreover, it has also made possible to reach more transparency and clarity in the market with the brand new electronic auditing and improved reporting. Nevertheless, the automation of trading has also enhanced other types of risks. Spoofing is the main protagonist of the 2010 Flash Crash, which we will explore more in detail later on in our research. It was the first so called *Flash Crash,* a market crash that lasted for only a matter of minutes, which rose from algorithmic and automated trading where a huge and non-permanent decrease in prices caused a connected rise in the volume of trades (Nahum, 2022).

It is rare, but it can also happen for an unwilling Spoofing, that can happen if a trading algorithm begins to execute trades in a pattern that does not comply with the law, but without the responsible trader to know that is happening. As we have stressed before, if the human being might have been executing orders thinking that they were complying, it is still a violation of the rules for the manipulation of the market and might find the eye of regulators. This instance could be extremely expensive for traders and market users that meant well and had no intention of manipulating the market but were let down by their algorithms or inadequate trade scrutiny structures.

Since this strategy is an overall not difficult manner to manipulate markets and make profits rise, it is a normal process for few corporations and firms, even though it is not legal. A renowned example is the JPMorgan Chase case in the fall of 2020 when they received a fine of $1 billion by the SEC after the firm was found to practice spoofing in the market for precious metals. Moreover, the corporation was also caught in the crossfire of the CFTC and the Department of Justice for unlawful practices that happened in 2015 and 2016 (Becker, 2021). Big companies are not the only players that can be found by authorities in the act of manipulating the market. In the summer of 2020, a single day trader was found trying to manipulate the financial market by means of spoofing, practices that were worth almost $140.000 in gains. The unfortunate trader was forced by the CFTC to pay a fine of over $200.000. However, it has to be said that even though there are big players being caught that make to the headlines, it is overall difficult to find spoofers. Since with the aid of algorithmic trading, there are thousands of trades being ordered and executed at the same time, it is intricated and potentially very complicated to spot and identify fake trades in real time (Becker, 2021).

# CHAPTER 3

## *3. Effects on Markets and Agents*

The revolution of information systems has not only drastically changed socio-cultural conduct, the economy, politics, and business; it has also changed the *modus operandi* in which the financial markets have operated until then. If we look back at the bustling and hustling that was still happening just a decade ago and comparing them to the regular buzzing of nowadays computational trading floors, we have clear evidence of how algorithmic trading has had an incomparable effect on the method in which financial assets have the ability to change and mutate (Hilbert & Darmon, 2020).

Generally speaking, traders make use of algorithmic trading in order to make their local operations more predictable and reliable. The biggest part of processes that are digitally automated, which include all kinds of AI, trading algorithms and bots, go after a set of deterministic local rules which can either answer to instructions which are programmed or patterns which are learnt. As we already stated above, algorithms are defined as “an ordered set of unambiguous, executable steps that define a terminating process” (Brookshear, 2009). Consequently, we can state with a high degree of certainty that algorithms execute a list of steps so to reach an unavoidable conclusion that defines the way they behave in a deterministic way (Hilbert & Darmon, 2020).

If we go back to the first rough analysis on algorithmic trading, it is quite transparent how “digital agents constantly obtain significantly larger gain from trade than their human counterparts” (Das et al, 2001). Execution algorithms, quickly reacting algorithms and algorithm market making, are among the groups of AT that contribute to this. As a consequence, we are framing the dynamics of the market in terms of the bid-ask spread which evolves constantly, the principal indicator for a margin that is obtainable (Hilbert & Darmon, 2020).

We can notably define the bid-ask spread as the difference between the price that is the highest that a buyer is eager to pay for some asset and the price that is the lowest that a seller is ready to agree to sell it. In what in what is known by scholars as the *continuous double action* or CDA, buyers make known bid prices at any time, and sellers are freely able to ask for unequal offer prices. At whatever time of the day, any seller is able to “hit”

any bid. For this exact reason, the bid-ask spread is the principal indication in order to show how demand and supply are closely balanced (Hilbert & Darmon, 2020).
The spread is traded in "ticks", which can be defined as the smallest possible price movement of the market right up to the decimal. It is important to remember that after 2006, some of the major stock exchanges, like the New York Stock Exchange, increased significantly automation paving the way for hybrid markets, that reduced a lot the execution time for orders made on the market, from 10 seconds to less than one (Hendershott & Moulton, 2011). It is thought that the Electronic Broking Service[16] made changes to the tick sizes in order to make the market more attractive to algorithmic trading (Mahmoodzadeh, 2015).

**Hypothesis 1.** *The employment of algorithms is linked with more complex trading dynamics.*
From the economic theory's perspective, trading algorithms make available a transparent example of rationality that is bounded (Simon, 1972). By bounded rationality, we mean that algorithms that are individual are constrained by the information that they are provided with, by the limited time they have to finalize a decision and by their abilities to process and biases. It can be stated that algorithms are extremely specialized in rules that are based on decision-making. As a matter of fact, this is essential according to a fundamental mathematical theorem, called 'no-free-lunch', according to which "that for any algorithm, any elevated performance over one class of problems is offset by performance over another class" (Wolpert & Macready, 1997). As a consequence of this theorem, it is implied that in order to perform all the functions that are requested of trading algorithms, the world of their cooperative enterprise must be highly diverse. "Consequently, the universe of computer algorithms is best understood as a complex ecology of highly specialized, highly diverse, and strongly interacting agents" (Farmer & Skouras, 2013). An increasing evidence can be found that "even relatively 'dumb' bots may give rise to complex interactions", fabricated by conflicts, disagreements, fights and repetitive interactions (Tsvetkova et al., 2017). In addition to the growing diversity, every entity presents more complexity as well. "Computers have driven the creation and trading of increasingly complex financial products" (Farmer & Skouras, 2013), that along with

[16] Wholesale electronic trading platform used to trade on the foreign exchange market (FX) with market-making banks.

the high complexity of the reciprocation of effects and the nature of the market's economy that is multi-platform is comparable with a highly complex ecosystem. Altogether, these exchanges are able to generate a new regime of a behavioural nature. This would clearly hint at how algorithmic trading is correlated with more complex dynamics of the market. However, some more quantitative analysis has been indication of the exact opposite: less intricacy. Jo, Moon, Park, Yang & Won Lee (2007), scrutinized the S&P500 among 1983 and 2006 and they came to the conclusion that a higher flow of information would lead to simpler and shorter repeating sequences. Chaboud et al. (2014) discovered a diminishing degree of autocorrelation in trades based on algorithms, this was due to the fact that they seemed to reflect new information faster and with more precision. This decreased autocorrelation is an indication of a simpler sequence since less temporal signatures which provide the series of events with some sort of distinguishable rhythm are present (Hilbert & Darmon, 2020).

**Hypothesis 2.** *Algorithmic trading is linked with less uncertain and more predictable bid-ask spreads.*

The recent innovations in technology are guided by a race worth billions of dollars where the aim is to make algorithms both quickest respondents and predictors that are more efficient. From the time when the innovative economist Léon Walras transformed into a concept the process of coordinating supply and demand by the means of successive trial and error in the late 1800s (or *tâtonnement* in French), market experts and strategists have used more complicated instruments to achieve an acceleration and destroy completely this mismatch. Trading algorithms that are controlled by machine learning are the latest pinnacle of these attempts since they incorporate the automation of this exploring procedure of trial and error to equal demand and supply. Along with better forecasting, they end up requiring less trials and not many errors and end the bid-ask spread (Hilbert & Darmon, 2020).

As a consequence, if someone ends up asking about the effects that algorithms used for trading have on predictability is almost taken for granted, given the fact that nowadays' AI is all about forecasts. Nowadays' artificial intelligence is mainly identical to machine learning, and MI's main point is to find patterns from data (which is always from the past) and employ them to make forecasts about the future (Ng, 2016). Algorithms used for trading which are better at forecasting imbalances in markets and margins are more commercially successful (Hilbert & Darmon, 2020).

Chaboud et al. (2014) discovered that algorithmic trading hustle and bustle in the Forex market decreases the number of chances for triangular arbitrage since AT traders answer fast to the quotes that are posted by traders that do not use algorithms and that make profit from whatever type of arbitrage, which could be a measure for effective forecasting. Civitanic & Kirilenko (2010) came up with an electronic limit to the order market and they found out that after the entrance of an algorithmic trader, the way that prices are distributed has more mass around the center and narrower around the tails. They exhibit that the quickest traders submit and differentiate their orders, the more money the machine produces since they are able to forecast more precisely the forces that stimulate growth (Hilbert & Darmon, 2020).

**Hypothesis 3.** *Algorithmic trading is linked with a positive effect on firm value.*

As already explained, there is a large literature that documents how AT has revolutionized the microstructure of markets and their quality, and how dramatically it changed the way securities are traded, managed, and submitted. However, there is very little if not hesitant literature regarding if and which are the effects on fundamentals of firms and the actual value of firms (Hatch et al., 2021).

There is a high probability that the actual impact of algorithmic trading can be seen through few stock characteristics, like skewness, volatility, and liquidity. Based on the evidence that we have in hand we can, however, conjecture that AT has an effect of a nonlinear nature on a firm's value. Hatch, Johnson, Wang & Zhang (2021) used a proxy for algorithms trading on messages sent electronically, and subsequently found relevant effects on three different peculiarities of firm's value and characteristics of stocks. They employed the 2003 New York Stock Exchange implementation of auto quotation[17], they used it as a shock of an exogenous nature. In this way, there was evidence of an impact of a causal nature of the value of the firm and demonstrated how AT has a positive effect, achieved by increasing idiosyncratic skewness and improving stock liquidity. Moreover, Hatch et al. (2021) have demonstrated successfully that the cumulative abnormal returns that were previously attributed to a shift upwards in AT regarding the use of auto quotation quoted in the work of Amihud et al. (1997). It is also remarked how the positive impact of AT on the value of firms is more intense for firms that are bigger and also in

[17] Indicative prices that generated for many of the financial options contracts. Auto quote calculates prices for all series by processing variables captured in real-time from other systems and trading members each time the underlying price changes.

the period of time after 2007 when the magnitude of algorithmic trading is higher (Hatch et al., 2021).

**Hypothesis 4.** *Algorithmic trading caused a change in the workforce needs of financial institutions and corporations.*

On the other hand, what is the effect on the human side of this match against machines? The trading of assets and especially equities has become so common with information that the knowledge on how to code and how to create successful algorithms is as relevant as understanding the structure of the market itself. Nowadays requirements of trading need a velocity of execution that humans cannot reproduce. Namely, clients want efficiency as they might require hundreds of orders, and algorithms can process orders and react efficiently to several variables without encountering any distress, making possible to perform functions which a human brain could not with such easiness (Thind, 2014). It is known how some of the biggest stock exchanges of the world had to go through severe cost cuttings among desk traders after the 2008 financial crises. This along with a shrinking buy-side commission pool driven by some new regulatory changes, which will be discussed in the next paragraphs, brought algorithms to show cost-effectiveness results (Brown, 2010). As a matter of fact, trades processed electronically cost almost half the amount which is requested by a traditional broker. In this scenario, institutional investors and other actors complain about the loss of connections with the brokers in flash and bones. Experts believe that traditional sales traders will not have much of a future in the market unless they develop and improve their electronic trading skills which need to be paired with personality traits that always characterized their role. As a matter of fact, it is no doubt how some of the biggest financial institutions have already started merging their sales trading desks along with their pure operations of trading in order to create a new form of hybrid market specialists. Another example of how AT has caused a shift in the kind of employees that have jobs in the financial industry is the interdisciplinary movement denominated *Econophysics*, that is used to indicate the way some physicists have started to perform some research in the field of finance and economics (Farmer, 1999).

### *3.2 Algorithms: Inscrutable Black Boxes of Decision-Making?*

The growing complexity and intricacy of algorithms and their explosion across a multiple range of businesses, industries, and purposes, is almost turning them into some sort of inscrutable black box. Objectivity and infallibility that surrounds their aura may be ascribed, but nonetheless, they are subject and vulnerable to various and potentially dangerous risks, like frauds, errors, and biases that can be either accidental or unintentional, that inevitably produce the question of whether trusting these systems might be wise. The increasing complexity, lack of transparency, unwise use and poor design of algorithms are some of the few reasons why AT is vulnerable to problems. To embrace its complexity and the creation of mechanisms that deal with such risks will arrive in due time in order to efficiently tackle the strengths of algorithms. The benefits are massive, AT can be employed to achieve huge business goals, boost growth in the long term and increase differentiation in the financial market. Financial institutions that will be aware of the risks of algo trading will have the chance to employ it in such a way to lead the market, navigate the regulatory system and revolutionize the firms thanks to innovation (Albinson et al., 2017).

A lot of common checks and balances are meant for dealing with risks that are conventional where algorithmic trading is not playing a big role. However, they are not enough to deal with nowadays decision-making system based on algorithms. These specific and peculiar risks have the power to cascade across a company and affect badly everything from its revenues until its reputation. This is the exact reason why it is so crucial for corporations and financial institutions to fully comprehend and deal proactively the dangers presented by algorithmic trading.

The risks that arise from algorithmic trading nowadays have their origins in the way data are used in analytics and in the way it’s employed in technology based on cognition in both automated and semi-automated environments.

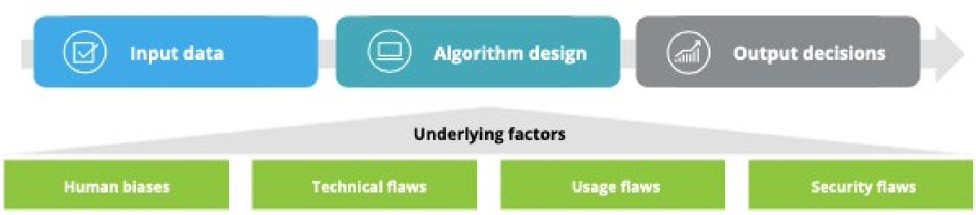


*Figure 10 Framework for understanding algorithmic risks.*
*Source: Deloitte.*

*Figure 10* gives a clear understanding for the various areas that are sensitive to such risks and the subsequent underlying factors that might cause them. The first area related to algorithms that are vulnerable to attacks is input data, for example irrelevant, outdated, and incomplete data; diverse or not large enough sample size; biases in the data employed; techniques that are not appropriate for the collection of information or mismatching among the information employed for training the algorithm and the actual input information in the midst of processes. Another area which is sensitive to problems is the very own design of algorithms, such as coding errors, biased logic, and mistakes in identifying spurious patterns in the information that is trained. Finally, output decisions are not exempt from risks as they might encounter misleading use of the output, paying no attention to the underlying assumptions, or most importantly the incorrect employment of the output.

These areas could be at risk for several reasons. The first and most common are what are called human biases, which could have the form of cognitive biases that developers of software could have. Moreover, we can spot missing governance, mismatches among the corporation's core principles and individual actions of employees could be causes of human biases. Another factor that could put in danger the target areas are technical flaws, which can be due to lack of a specific rigor or a poor development that could compromise the conceptual soundness of the algorithm. In addition, an incorrect validation, training, or testing might be the reason for an output that is not correct. Misusage by end users, errors in the employment and execution of algorithms, the way they are integrated in the daily operations can lead to poor decision making. Finally, flaws in security could attract potential threats both external or internal that are interested in fraudulent actions like manipulating outputs or algorithms designs and input data.

While on one hand, we have been using algorithms for a long time, there comes a need to critically evaluate them for all the vulnerabilities that they present, from the absence of technical rigor to the increasing problems with security. There are several reasons why these algorithms are becoming so prominent.

It is no surprise that the adoption of the tech of machine learning and data analytics that is advanced, the usage of algorithms is turning out to be integral to processes across companies and purposes, as shown in *Figure 11*. Frey & Osborne (2013) predict that around 47% of jobs will be automated by 2033.

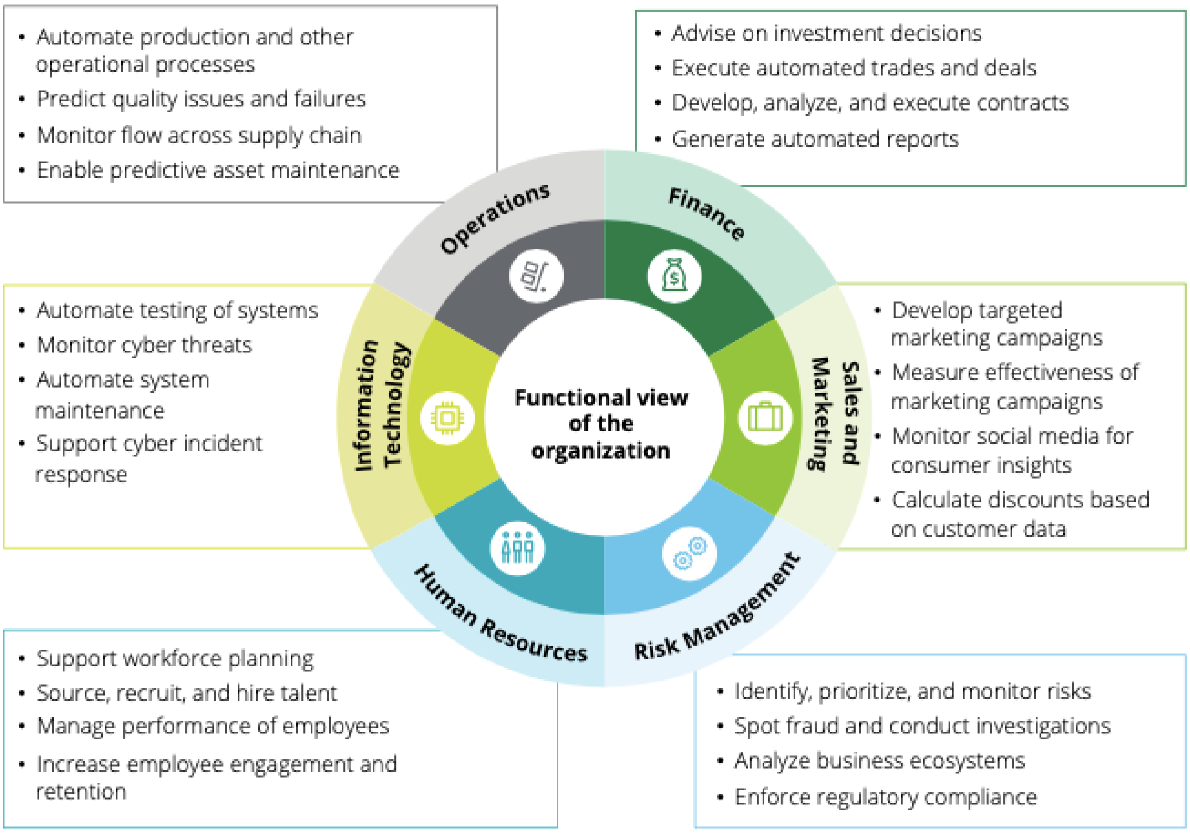


*Figure 11 Algorithm use across business functions.*
*Source: Deloitte.*

There has been an evolution of power in computation methods which are coupled with the availability of huge amounts of data that are trained, which are leading the progress in machine learning. The increased popularity of neural networks made them possible to be a way to implement MI. These progresses in techniques for MI are making possible the birth of algorithms that have more enhanced predictive powers, but at the same time they are more complex (Albinson et al., 2017).

It is not just that algorithms are becoming more prevalent, but without any doubt, the strength and the duty that is accorded to them is increasing. As a matter of fact, nowadays, algorithms are used to make possible relevant decisions, for example, discoveries of crimes and saving the life of patients.

Most of the times, algorithms used in algorithmic trading are run in the background and they oft function almost as black boxes. Given their particular inner workings and their purposes mainly conceived from end users and developers, to control them can be very hard. Lots of the brand new techniques for ML are so not transparent that it is basically impossible to get how they reason and how they arrive to the conclusions, hence making it difficult to form an opinion on their correctness.

Last but not least, algorithms used in ML are extremely vulnerable to hacker attacks, which are usually interfering with the data that is live to which the algorithms are put it to. A 2016 Forbes report explained how cyber criminals make soothing around 5 million dollars every day just by deceiving algorithms that purchase advertisements with fraudulent click data, that are created by bots instead of human beings (Brewster, 2016).
But what is the difference between the management of the risks that the use of algorithmic trading brings to the companies and users and managing any other type of risk in this field? It is certainly relevant nowadays to understand the way algorithms were managed up until some years ago may not be as effective today. On the other hand, firms, data scientists and engineers should recalibrate few of the processes for management that already exist taking into account the nature of algos and the manner in which are used within firms. As a matter of fact, algorithms are usually founded on data that are proprietary, as well as techniques and models. Not only that but they are also considered trade secrets and most of all an origin of competitive advantage. The result of this is that corporations and organizations are not willing so easily to share the origin of the codes, the inner working of the algorithms and the data itself. This scenario makes it difficult and hard for regulatory agencies to keep track of them (Albinson et al., 2017).
In the unlikely outline where corporations were to disclose the codes to their algorithms, recognizing them could be hard as well due to their inmost entanglement. Most of nowadays trading algorithms are constructed on MI and further up to date technologies, and there are instances where not even the developers are able to foresee or give an explanation of their conduct. This is due to the fact that algorithms run by machine learning are able to set in motion their own language in order to interface with each other. This is a field that arises potential risks and possibilities, taking into consideration the foreseen growth in the *Internet of Things*[18] and machine-to-machine transmission.
Another field which I will explore in later chapters is the obvious lack of regulations and standards regarding algorithmic trading and their management. In the financial services world, the validation of models has come out to be extremely relevant over the last years. Standards like the SR 11-7: Guidance on Model Risk Management have limits when it comes to being applied to techniques in MI like deep learning. Nowadays, standards that can be applied widely and across industries do not exist, and the result is that there exist

[18] The Internet of things (IoT) describes physical objects (or groups of such objects) with sensors, processing ability, software and other technologies that connect and exchange data with other devices and systems over the Internet or other communications networks.

an absence for a consistent development control, use and implementation. Often developers employ their exposure and awareness to come up with these decisions without oversight, causing differences in operations and the growing likelihood of fallacies.
Moreover, regulations in this field are still in the process of evolving and they have relevance only in a restricted set of algorithms, for example, those that relate to stress testing in the banking sector and those in capital management. There is still an absence of clarity which will be explored later, and a lot of questions whose answers are still not present, and this same absence makes if hard to manage transparency and answerability in the employment of algorithms in trading (Albinson et al., 2017).
The last question that needs to be answered is how a firm can effectively approach the management of risks related to algorithmic trading. In order to fairly manage these risks, there is a need to recreate the old fashioned management frameworks. Firms and corporations should employ and use modern approaches which are constructed on solid bases of organizations' risk management and lined up with the major practices and regulatory requisites. *Figure 12* shows these approaches and its peculiar components.

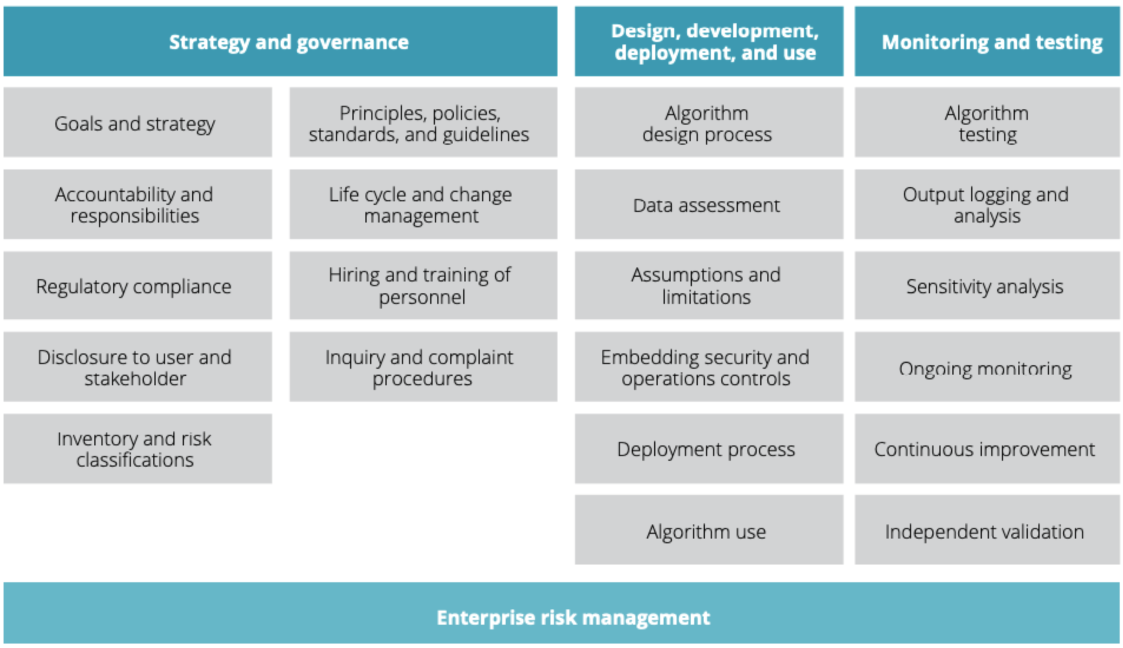

*Figure 12 A framework for algorithmic risk management.*
*Source: Deloitte.*

Regarding strategy and governance, there needs to be a specific strategy and governance structure that deals with the management of cultural and technical risks. This should comprise standards, regulations, and principles; duties and roles; processes and control procedures; and suitable selection of personnel and technical training. If you manage to provide clarity and procedures to manage queries it can help organizations to employ algorithms responsibly. Moreover, developing procedures and attitudes which are aligned with the structure of the governance in order to direct the life of the algo cycle from the selection of data to its design, integration and the proper employment during production is extremely crucial for the firm that wants to succeed. Another important point is the establishment of procedures for overseeing and monitoring of data inputs and working when they become available, both externally and internally (Albinson et al., 2017).

In conclusion, the quick expansion of strong algorithms in the financial scenario is in full power and it probably going to grow even more in the years to come. The wide employment of intelligent algorithms provides a vast range of possible advantages to firms, from disruptive products to enhanced customer experience, to efficiency of operations and strategic planning, and also the management of risk. However, few of these advantages might be depowered by risks associated with the structure, application, and employment of trading algorithms – risks that have the potential to increase unless firms and corporations provide capital to effectively manage the capabilities of these instruments. It has to be stressed that this is not a journey that firms have to take by themselves. There is a growing presence of awareness among scholars and researchers, lawmakers and regulators, that will contribute to a rising body of knowledge about risks connected to algorithms and the standards used to manage them. In the meanwhile, it is crucial for corporations and bodies to assess their employment of trading algorithms in situations that are or could be of high risk and high impact and implement processes to deal with those risks smartly so that the algorithms can be employed for a competitive advantage. Dealing with the complexity of trading algorithms can and it is a chance to navigate, dominate and disrupt the financial industry (Albinson et al., 2017).

# CHAPTER 4

## *4. The 2010 Flash Crash: A Perfect Storm for Markets: The Events*

The 6th of May 2010 the US Dow Jones and the New York Stock Exchange were hugely affected by trading of a high volatility nature at big volumes. The fault fell on an individual trader in the United Kingdom, Navinder Singh Saroa, who supposedly changed a trading algorithm so to enable him to trick the market. Saroa placed demands to buy stocks, however cancelling the transaction afterwards before it was executed. Details state that in a span of minutes, the biggest stocks like Accenture and General Electric had reached $0, and the general market fell by 6% (AI Incident Database, *Incident 28: 2010 Market Flash Crash)*. In this, we going to scrutinize and unravel what actually happened, and what are the implications that the power of trading algorithms can have.

But what exactly happened that day? The morning of the 6th of May 2010 started to economic and political news that were quite unsettling, regarding the debt crisis that was going on in Europe at the time. In this peculiar environment, most of the participants of the market requested for higher premiums in order to deal with the increased risk. There are multiple proofs that that day there was an increase in risk, evidenced by numerous indicators. For instance, premiums on credit default swaps raised for multiple European sovereign debt securities, which includes debt coming from Ireland, Italy, Spain, Greece, and Portugal. Moreover, the Euro was experiencing pressure of a downward nature in global currency markets. During the day, the index that measures the expected volatility of the S&P 500 called VIX, saw an increase of 31.7%. In addition to that the prices of futures of gold increased by 2.5%, at the same time as yield of 10 year treasuries decreased by almost 5% while investors took part in "a flight to quality". From 1.00 p.m. a general rise in risk started to be obvious as well in the volatility of prices of individual equities. By 2.30 p.m., the pressure on selling has forced the Dow Jones down by about 2.5%. At this point, liquidity at the buy-side in the E-Mini has decreased from what was in the early-morning level of about $6 billion to $2.65 billion, accounting for almost a 55% decrease. In the same way, buy-side liquidity in SPY had a drop from the early day $275 million to $220 million, corresponding to a 20% decline for SPY (U.S. Securities and Exchange Commission, 2010). *Appendix I* gives an insight into both SPYs and E-Mini contracts that were one of the focal points of ths event. At 2.32 p.m., to fight back this uncommon volatility and narrower liquidity, a huge fundamental[19] trader, such as a mutual fund complex, started a sell program to sell an aggregate sum of 75.000 E-Mini contracts, counting on an amount of almost $4.1 billion, as an hedge to an equity position that already existed. In general, a client has multiple alternatives as to perform a big trade. In the first place, a client might select to approach an intermediary, that would on his part execute a block trade or manage a position. In second place, a client might decide to insert manually the orders in the market. In third place, which is the one we are interested about and that we have exploring in this paper, is the fact that a client can perform a trade through an automated execution algorithm, that could satisfy the client's requests by looking at volume, time, or price. We can hence say that a client has and must decide whether or how much human judgment is in place when executing a trade.

This large fundamental trader decided at the time to sell through a sell algorithm which we have discussed earlier in this study, which was set to cater for orders into June 2010 E-Mini market to pick out a rate of execution set at 9% of the volume of the trade, computed over the minute before, but with the lack of time or price. The performance of this sell algorithm followed in the biggest net change in a position recorded daily of any trader in the E-Mini from the start of the year at that time. Just two single-day sell algorithms of same or bigger size were used in the E-Mini in the year that anticipated that precise moment. When it came to the moment for this fundamental trader to use these trading algorithms it used a mix of trading that was done manually and multiple automated execution algorithms that took into consideration volume, time, and price as well. In that particular instance, it was needed more than 5 hours for this customer to perform the first 75.000 contracts (U.S. Securities and Exchange Commission, 2010).

Nevertheless, that day on the 6th of May 2010, in a situation where markets were already under pressure, the sell algorithm that was selected only to target trading volume, performed the sell exceptionally quickly, in only 20 minutes. Intermediaries and High Frequency Traders were the possible first buyers of the first unit of orders given away by the sell algorithm, and this resulted in these players adopting a temporary long position. Nevertheless, among 2.41 p.m. and 2.44 p.m., High Frequency Traders sold in an aggressive way almost 2000 E-Mini contracts so to decrease their nonpermanent long positions. In the same moment, High Frequency Traders dealt just about 140.000 E-Mini

[19] Market participants who are trading to accumulate or reduce a net long or short position. Reasons for fundamental buying and selling include gaining long-term exposure to a market as well as hedging already-existing exposures in related markets.

contracts which correspond to more than 33% of the whole trading volume. This is coherent with HFTs common use of dealing huge amounts of contracts, yet not herding an overall inventory further on three to four thousand contracts in both directions. The algorithm that was used in this particular trade answered to the rising volumes by rising the rate at which it was dealing the orders with the financial market, even if trades that it had sent to the market already were seemingly not entirely absorbed by fundamental buyers or cross-market arbitrageurs. As a matter of fact, particularly when important volatility is present, high trading volume is not automatically a dependable indicator of the liquidity of the market. What went on to happen next can be described as two liquidity crises: the first one at the wider index level in the E-Mini; the second one with regards to stocks that were individual.

The combination of the pressure of selling from the trading algorithm, High Frequency Traders and other users got the price of the E-Mini to fall by 3% in only four minutes. In the meantime, cross-market arbitrageurs that actually bought E-Mini, sold at the same time equivalent quantities in the market for equities, moving the price of SPY down as well by almost 3%. Since there was still a lack of demand from cross-market arbitrageurs and fundamental buyers, High Frequency Traders started to swiftly buy and resell contracts among one another, generating a "hot potato" consequence for volumes due to the same positions being quickly passed back and forth. At this point, buy-side market which was deep in the E-Mini decreased to almost $58 million. While liquidity was disappearing, the price of the E-Mini fell by an extra 1.7% in only 15 seconds. The improvise drop in both liquidity and price is a symptom of the fact that prices were progressing extremely fast, cross-market arbitrageurs and fundamental buyers were impotent or reluctant to supply sufficient buy-side liquidity (U.S. Securities and Exchange Commission, 2010). In the four minutes after 2.41 p.m. prices of the E-Mini had declined by 5% and prices of SPY were subject to a fall of more than 6%. Cross-market trading firms that got interviewed at the time claimed that at this precise time, they were buying the E-Mini and selling index products, individual securities, or SPY. Among 2.32 p.m. and the subsequent 13 minutes, while the prices of the E-Mini were quickly falling, the trading algorithm sold almost 35,000 E-Mini contracts, with a total worth of almost $1.9 billion, of the 75,000 that were imagined at the beginning. In the meanwhile, all fundamental sellers sold over 80,000 contracts, and all fundamental buyers purchased 50,000 contracts, for a discrepancy of 30,000 contracts. This amount of selling from fundamentals is basically 15 times bigger than what was done the three days preceding the flash crash, while the buying level was 10 times bigger. At 2.45 p.m. the trade of E-Mini contracts was put on pause for 5 seconds by the Chicago Mercantile Exchange was prompted in order to avoid a wave and a more extreme decline in prices. In that minuscule time, the pressure on the sell-side was reduced and the interests in the buy-side rose again. Trading started again and prices were not overturning, not a long afterwards the E-Mini appeared to recuperate, come behind by the SPY. The trading algorithm kept on executing orders and trades as the prices were quickly increasing in either E-Mini and SPY (U.S. Securities and Exchange Commission, 2010). *Figure 13* shows exactly how the S&P 500 declined throughout the day, and how just before 2:45 p.m. there was a massive acceleration in selling.

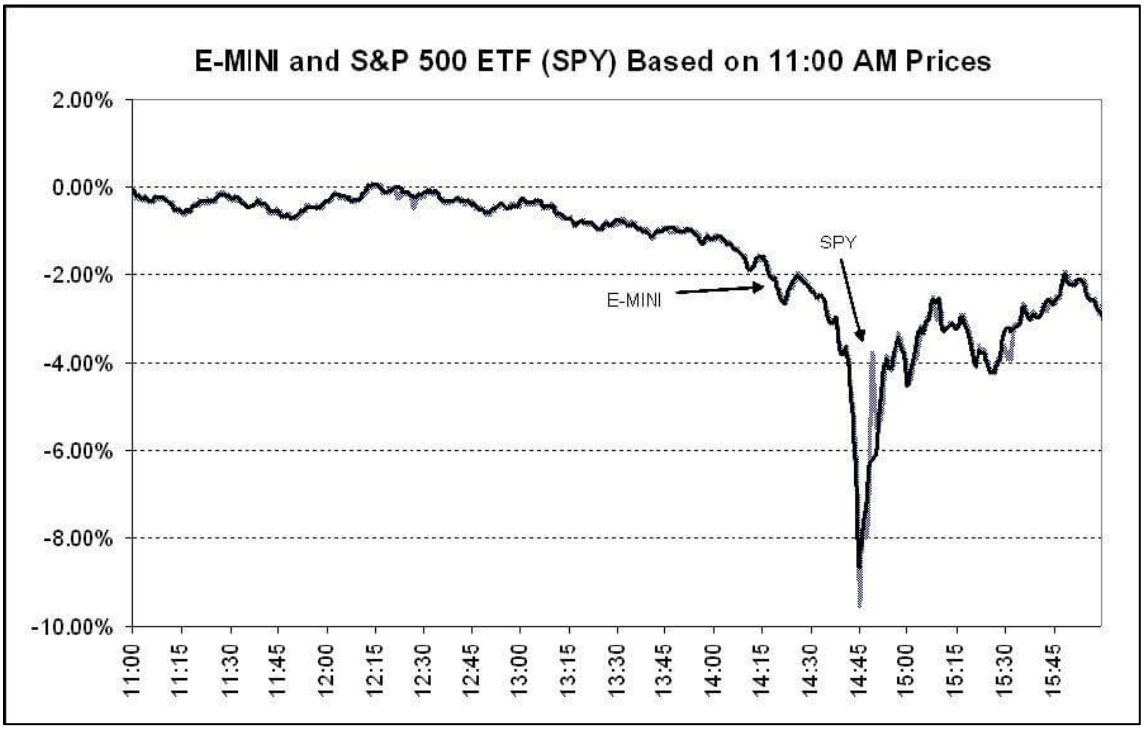


*Figure 13 The chart above shows the S&P 500 had been declining throughout the day, but just before 2:45 p.m. of the 6th of May 2010 there was a massive acceleration in selling.*
*Source: Invezz.*

The second crisis in liquidity happened at the same time in the market for equities at 2.45 p.m. According to reports of the time with people that were involved, trading systems that were automated employed by few providers of liquidity momentarily put in pause as a reaction to the improvise price drop seen during the first liquidity crisis. These particular ad hoc stops are planned in order to avoid systems that are automated from executing trades when prices shift beyond thresholds that are pre decided so to permit traders and risk managers to wholly evaluate the conditions of the market before the execution of trades can resume. After this forced stop, individual market users had to evaluate the risks connected with the continuation of the execution of trades. Users stated that these evaluations incorporated these considerations: if noticed extreme price shift could be an artifact of data that were erroneous; the shock of said shifts on limits of positions and risk; shocks on profits and losses; the possibility for traders to be shattered, pulling out of their corporations unwillingly long or short on one way of the financial market; the possibilities of their systems to manage the extremely high volume of orders that they were handling that day. Moreover, numerous users stated that since there was a simultaneous drop in prices across multiple kinds of securities, they were concerned the incident of a disastrous event of which they were not conscious of and that their game plan were not meant to handle. According to their single evaluation of risk, few market users and more providers of liquidity expanded their spreads for quotes, few more decreased offers for liquidity, and an important number of users retired from the financial markets. Few of them went back to the manual execution of trades, however, they had to be careful to put their attention to just a subset of financial products since they were not capable to keep up with the almost ten-fold rise in volume that happened as prices in a lot of financial products quickly decreased. High-Frequency Traders who are usually in the market for equities and who often give and take back liquidity as a slice of their strategies, executed trades in a proportional way as the volumes were increasing, and in general, were net sellers in the market that was quickly decreasing with most of the users. Few of these corporations kept on trading as the overall indices started to regain and single securities began to experience extreme price dislocations, while few others decreased or stopped executing trades totally (U.S. Securities and Exchange Commission, 2010). Many other OTC market makers that would have not executed internally started disorderly retreat most of these trades straight from the public exchanges where they played with other trades for straightly available liquidity. However, even if after 2.45 p.m. E-Mini and SPY were regaining strength from the extreme decreases, see trades set for few individual securities and Exchange Trade Funds discovered decreased interests, that brought to additional price decrease in those products. Among 2.40 p.m. and 3.00 p.m., around 2 billion worth of shares exchanged with an overall volume surpassing $56 billion. More than 98% of all the shares were traded at prices among 10% of their 2.40 p.m. worth. Nevertheless, as liquidity totally evaporated in an amount of single securities and Exchange Trade Funds, users told to either buy or sell at the market found not straightly afterwards available buy interests with the result of orders being done at absurd prices as low as one penny or as high as $100.000. These orders happened as a consequence of stub quotes.[20]

The extreme shift that was noted in a lot of securities were brief. As market users had the time to respond and evaluate the uprightness of their systems and data, sell-side and buy-side interested went back to normal. At 3.00 p.m., most of the financial products had gone back to being traded at prices that were reflecting the actual consensus worth. However, during the period lasted for 20 minutes among 2.40 p.m. and 3.00 p.m., more than 3000 different products, such as a lot of Exchange Trade Funds, were performed at prices 60% or further away from their prices at 2.40 p.m. After the closure of the markets, the exchanges and FINRA[21] gathered and agreed together to delete or break all the trades that were under the "clearly erroneous" rules of trade (U.S. Securities and Exchange Commission, 2010).

| | May 3–5 | May 6 |
|---|---|---|
| Daily trading volume | 2,397,639 | 5,094,703 |
| # of trades | 446,340 | 1,030,204 |
| # of traders | 11,875 | 15,422 |
| Trade size | 5.41 | 4.99 |
| Limit orders % volume | 95.45% | 92.44% |
| Limit orders % trades | 94.36% | 91.75% |
| Volatility (log high-low price range) | 1.54% | 9.82% |
| Return | −0.02% | −3.05% |

*Table 5 Statistics for the June 2010 E-Mini S&P 500 Futures contract for May 3rd-5th and May 6th 2010.*
*Source: Kirilenko et al.*

*Table 5* shows statistics for the June 2010 E-Mini S&P 500 Futures contract for May 3rd-5th and May 6th, 2010. The first column displays averages computed for the 3rd of May through the 5th, between 8.30 and 15.15 Central Time. The number of traded contracts is represented by volume. The number of trading accounts which executed trades at least once during the day is showed as the number of traders. Trade size and order size are calculated in number of contracts. The employment of limit orders is shown as in both percentages of the number of transactions and volume of trading. Volatility is measured

[20] An order to buy or sell shares that is deliberately set far lower or higher than the prevailing market price. Stub quotes are used by market makers who wish to fulfill their liquidity obligations without intending for their orders to be executed.
[21] The Financial Industry Regulatory Authority (FINRA) is a private American corporation that acts as a self-regulatory organization (SRO) that regulates member brokerage firms and exchange markets.

as the natural logarithm of the highest price over highest price within a trading day. On the other hand, *Figure 14* prices and trading volume of the E-Mini S&P 500 stock index futures contract on May 6th, 2010 in 1-minute time resolution.

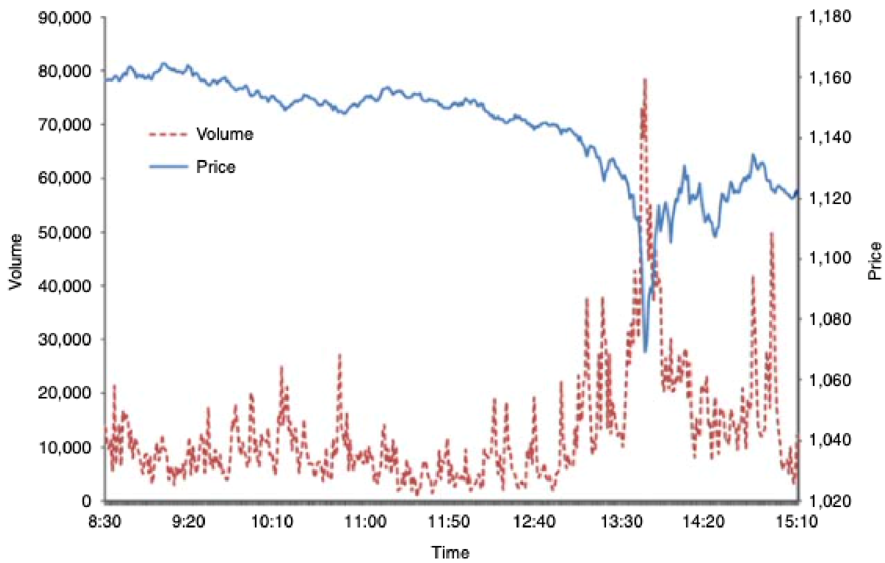


*Figure 14 Prices and trading volume of the E-Mini S&P 500 stock index futures contract on May 6th, 2010 in 1 minute time resolution.*
*Source: SEC.*

## *4.2 How a mystery trader with an algorithm may have caused the Flash Crash*

From a humble house in a residential area of Hounslow in West London, where airplanes fly and roar, a self-taught trader was about to be the main character in one of the most appalling instances in the history of Wall Street. Navinder Singh Sarao was an unknown day trader – the Street would have described him like this. But on the 6$^{th}$ of May 2010, US authorities now state that Sarao was one of the reasons why the Dow Jones Industrial Average value shifted by 1000-points in an extreme journey that we described in the paragraph above as the *Flash Crash*. According to the reports of regulators, he was in charge for the incredible one out of five sell trades that were executed during the hysteria of the infamous day. He ended up being arrested in 2015 by the police enforcement of Scotland Yard and accused in the United States of 22 criminal charges, comprising market manipulation and fraud. The day in the aftermath of the arrest the 36 years old British man showed up in London court to fight for the deportation bid, which would allow him to hold up the United States case for years. Sarao at the time had no history of having been linked or employed by a big player in the financial scenario in both the United States and the United Kingdom. When the flash crash took place that 6$^{th}$ of May 2010, Sarao was living in a rented apartment in the neighbourhood of Hounslow, where he was executing and clearing his order thanks to the firm that was once owned by Jon Corzine, an American financial executive who had previously worked for Goldman Sachs, and that now is dead, MF Global Holdings Ltd (Brush et al, 2015).

The unlawful profits that Sarao managed to profit amounted to over $40 million, and they were possible to achieve thanks to a history that is years long of computer trading as fast as lightnings are. Reports and various account that were made at the time and afterwards, confirmed that Sarao and his modified trading algorithm was not the only cause of the flash crash, however many experts in the industry concluded that a combination of various factors, that included algorithmic trading, was likely behind the market failure of that day. Overall, the 2010 flash crash was so much more than a simple technical setback, as it made market users and authorities think about how potentially unsafe the financial markets are nowadays, to the high-velocity, computer-based trading which has become dominant and prevailing in the financial scenario in general.

Not much is known about Sarao and his transactions, other than what has been already said in the files divulgated by the Department of Justice of the United States and other additional brief insights given by a civil suit filed by the Commodity Futures Trading Commission of the United States. As stated by the American authorities, the Briton trader used the six years previous the infamous flash crash tricking regulators, while in the meantime employing complex computer software conceived to willingly manipulate the financial markets. In particular, adding to charges of manipulation and fraud, Sarao was charged with *Spoofing,* whose mechanism, and implications we have explained thoroughly in one of the above paragraphs, with the clear intent of creating and subsequently deleting orders before they are executed. In May 2010, it was uncanny how the actions of the Briton trader generated disequilibrium in the market for derivatives which than overflowed to stock markets, making the crash hysteria worse (Brush et al, 2015).

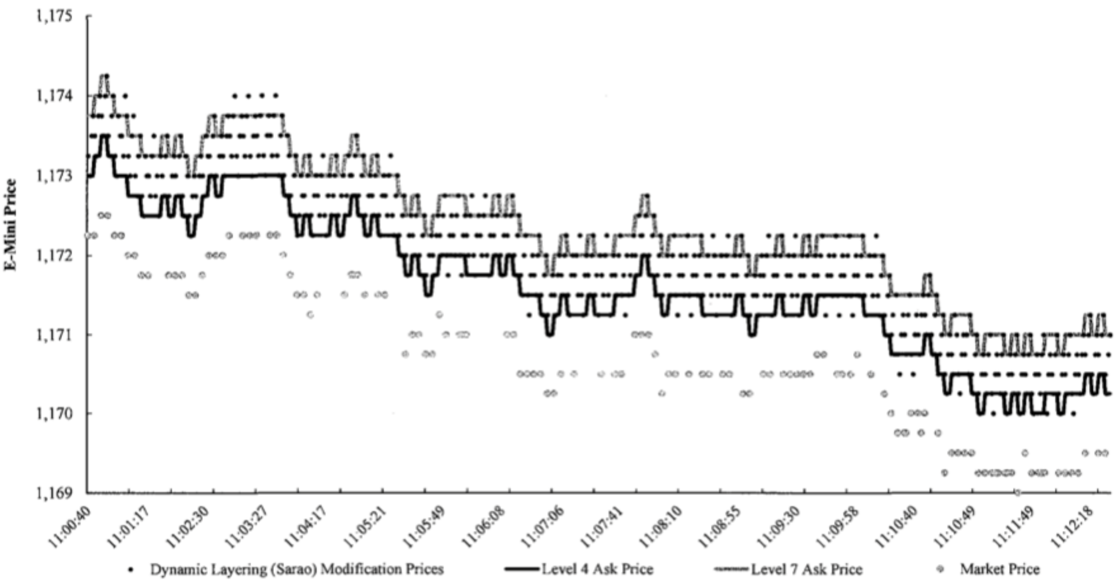


*Figure 15 Example of dynamic layering order modifications.*
*This chart displays one active Dynamic Layering period. The blue dots show modification prices on Sarao's four Dynamic Layering orders in this period. For the purpose of this exhibit, Market Price is the most recent transaction price that occurred less than 0.1 seconds prior to the time of each Dynamic Layering order modification.*
*Source: United States District Court, Northern District of Illinois.*

Witnesses of Sarao's practices at the time reported that his screens almost always showed the data for futures matched to the S&P 500 Index and that interplays were usually constricted to employee that were setting up new trading algorithms. *Figure 15* shows an example of dynamic layering, showing both Sarao's practices and market price. According to authorities' report, Sarao's manipulation of the financial market started in

2009, when he started to use intricated and home-made software, which he subsequently asked to alter in order to let him place and delete orders in an automatic way. It came to the point where he asked the software engineer for the codes, expressing the willingness to have fun with them, in order to create new versions of them.

It has to be noted that in the year that anticipated the 2010 Flash Crash, Sarao did not went unnoticed to the eyes of regulators, as a matter of fact, according to an FBI report of the time, exchanges in the United States and Europe noticed that he was frequently placing and then swiftly deleting big volumes of trades. CME Group Incorporation, a company that regulates an exchange for one of the largest derivatives connected to the Standard & Poor 500 Index, got in touch with the Briton trader after realizing that few of his transaction and activities were having an apparent relevant impact on the opening prices. Sarao gave an explanation to his actions in March 2010 saying that he was just trying to show an acquaintance how the markets were actually working.

On the infamous May 2010, the same company got in touch with Sarao and he assured that all the orders he was placing were entered in good faith with the aim of placing bona fide trades. The exact same day as we have explained thoroughly in previous paragraphs, he used layering and spoofing algorithms so to execute thousands of trades for E-Mini contracts. The transactions had a total value of around $200 million worth of bets that the financial market would have gone down, a transaction which stood for between 20% and 29% of the overall sell transactions at that time. The trades were then substituted or changed 19.000 times before being erased later during the day. The disequilibrium on the exchange venue caused by the orders Sarao placed played a significant part to the conditions of the market that that day led the contracts for derivatives and the overall market jump.

The Flash Crash creeped investors, came to be front page around the whole world, leaving regulating authorities wonder how it could have happened. Nobody ended the Briton trader's activities for an additional five years (Brush, 2015). We can positively say that he contributed to create the "perfect storm" to origin the Flash Crash. The modification that happened since the crash occurred to avoid it to happen again took the form of regulation, which we will explore in the next chapter, and circuit breakers which we will discuss in the next paragraph (Duronio, 2012). *Appendix II* gives an insight into Michael Lewis's novel *"Flash Boys: A Wall Street Revolt"*, where for the first time was taken into consideration how algorithmic trading were using speed to take advantage from ordinary investors.

## *4.3 Circuit Breakers*

Trading venues were announced to introduce brand new trading curbs called *Circuit Breakers* for the major stocks in the United States that would have went on for a six month trial period program, as regulating authorities were on to find ways to circumvent the events of May 6th of 2010 (Reuters Staff, 2010). The purpose of these circuit breakers was to stop trading for a limited time of five minutes on any Standard & Poor 500 which increases or decreases by over 10% in a time range of 5 minutes, and they would have been set up to just five of the Standard & Poor 500 firms on the 11th of June 2010 in order to test their efficiency. By the 15th of June, the new rules had been applied to all the 404 Standard & Poor 500 stocks that were listed on the New York Stock Exchange (Hum, 2010).

The brand-new circuit breakers were triggered the 16th of June 2010, when various trades made by mistake made the shares of The Washington Post Co. go up by more than double their original value. In this specific instance, the circuit breakers were triggered by a trade that was erroneous in his nature (Tse, 2010).

On September 10th of 2010, the Securities and Exchange Commission approved the expansion of the program in order to include all the stocks in the Russell 1000 Index and few Exchange Trade Fund. By means of establishing limpid and easy to understand standards to break erroneous trades, the fresh norms would have helped giving anticipated assurance as to which transactions were going to break, and permit participants of the market to handle these risks in a more efficient and skilful way (SEC Staff, 2010).

The principal problem of these tools is the so called "magnet effect", caused when investors speed up their trading in reaction to an *anticipated* stimulation of the breaker; and the impossibility for investors to understand their trading needs after the circuit has been activated. Nevertheless, it is really difficult to believe that these costs of circuit breakers are material when a totally not expected trading algorithm moves financial markets by a huge quantity as it happened during the 2010 Flash Crash. A trading algorithm of this kind is not likely to employ a magnet effect exactly due to the fact it is not predictable. Moreover, the regard during the crash of 2010 was a momentaneous and unpredictable slip in the financial market at completely random prices with fundamental values and during this event, the aim is to avoid trade at these prices not to make trades easier. Additionally, as we remarked before, during the crash prices dropped so fast that trading venues had to erase trades that were already been placed. This kind of event severely mines the confidence that investors have within. As an investor one cannot imagine that a trade that is already been placed is going to be erased the subsequent day. A circuit breaker has the peculiar benefit of avoiding this kind of trade erasing due to the fact that when the market is shut down because of the circuit being triggered, not one single trade can be executed (Subrahmanyam, 2013).

Eventually, when prices drop, Avery and Zemsky (1998) state that investors and traders could influence their orders just on past sell ones and sell even whether their own data suggest them to buy. This behaviour might cause a market crash. By stopping a succession of sell trades, a circuit breaker is also able to avoid this type of event.

Given what happened with the Flash Crash there is an amazing case to be done for CB which would stand as a soothing effect on the financial market and construct the confidence of investors. This point is also stressed by Kirilenko et al. (2011) that state that "appropriate safeguards must be implemented to keep pace with trading practices enabled by advances in technology." Nevertheless, there are various problems to be solved before the CB are effectively used to avoid Flash Crashes and different types of moves in prices.

In the first place, with strongly segmented and interconnected assets, it is a challenge to make popular CB in the contemporary scenario. For instance, if a breaker is stimulated in a major exchange, the volume is certain to shift off-exchange, particularly, in the event of institutional volume, to a dark pool where companies can straightforwardly cross trades.

Due to the segmentation, it is of vital importance that breakers are coordinated. If they are not, a rowdy algorithm will just look for execution at venues rather than the closed exchanges, shifting the rowdiness somewhere else. As a matter of fact, one problem that the 2010 Flash Crash brought up was exactly that of coordinating CB. In the crash of 2010, the exchange for derivatives (CME) stroke CB by the NYSE did not. This signified that the CME derivatives stopped trading, but NYSE did not. This absurdly led to events where trades for equities were performed and got erased, while derivatives hedges did perform when financial markets opened after the trigger of the breaker, leading investors to lose money on the hedges (Madhavan, 2012). If the CB would have been applied to both of these venues, this event would have not taken place. In the overall picture, the previous statements firmly state that closures should be coordinated between financial markets to avoid the chance of turbulent trading shifting to other markets.

The last problem concerns trigger points. It is clear how investors would rather have a continuous market to achieve their needs in trading. For this exact reason, the triggers for circuit breakers should be placed broad enough so as not to interfere with the process of trading. A breaker triggered by a specific price should be employed just during periods of outermost stress of markets due to the extreme imbalances in orders. Moreover, unequal markets have different degrees of volatility and different index levels. As a result, triggers for prices should find their bases on percentages and not on point moves, to allow for similar triggers across markets. Whereas the breaker, once it is enforced, should be harmonized, if unequal markets possess exceptionally varying levels of volatility, the trigger might also base oneself on the levels of volatility on every individual market (Subrahmanyam, 2013).

# CHAPTER 5

## *5. European Legal Framework for Algorithmic Trading*

The paradigm of the traditional stock market, which finds its origin in the stock's intrinsic value (and thus the firm) traded on exchange venues, has moved to a brand-new model which calculates the values of stocks based on the modeling of algorithms and equations. Basically, there has been a dissociation between the price of the stock and its value. What makes this an underlying movement is that it is now shifting beyond the "quants" and into a more essential method, to the point where traditional market participants such as managers of funds, traditional brokerage companies and also retail traders are being attracted by this phenomenon (Hendershott et al, 2011).

This phenomenon clearly showed new challenges for regulatory authorities. As of tradition, authorities at the Securities and Exchange Commission, or SEC, have always been much more interested on the firms that issue securities rather than the products themselves. The regulation of the financial market is something that the Securities and Exchange Commission has generally always left on a side. The period of time that stems from the Eighties until the 2008 financial crisis was recognizable due to an increase in the oversight de-regulation of underwriting activities and traditional trading. The chill atmosphere of regulation which was a result of the revoke of the Glass Stegall Act during the administration of Clinton appeared as a sign that a new era in the relationship between Wall Street and the SEC. In the meantime, new financial instruments were becoming popular, usually created by financial analysts and engineers, who were totally unknown to regulatory authorities (CNN Money, 2012). Instead of actually regulating, the SEC opted for an attitude that was focusing towards observing these new funds and securities, mainly because they were not completely sure of their potential and they thought they were not a relevant niche of the market (Waters, 2013). As a consequence, this pushed brokerage firms to look into the activities of these funds and to start their own version, guided by these new figures, financial engineers or "quants". As time passed there started to be a regulatory answer to the birth of electronic trading. Examples are the 1997 rules for the handling or orders and the 2001 rules for decimalization which brought extreme decreases to the costs of transactions. Regulation NMS wiped away regulatory obstacles to trading carried out electronically and caused rising competition among market centres

(Angel et al., 2010). During the time technologies have developed, it seems that a lot of the ancient trading perks stayed the same. As how it happens with many innovative applications, the rise of Algorithmic Trading has surpassed its primaeval intent, as the markets decelerate to reach new peaks and regulatory authorities race to put together guidelines to supervise practices carried electronically. Nevertheless, the expansion of AT has left a non-fading impression on the world of investments; it has permanently moved the financial market frameworks "from a human-intermediated market to a computer-intermediated market with little human interaction or real-time oversight" (Angel et al., 2010; Kunz & Martin, 2013).

The financial market of the European Union, or EU, stands for one of the major securities markets in the world, it represents 252 trading exchanges, almost 100 markets which are regulated across all the member states, and over 150 facilities for trading. The capitalization of the European market stocks is worth over €12 trillion, with Germany, France and UK being more than half of the total. It is also one of the most advanced and contemporary of them all with over 80% of trading stemming from High-Frequency and Algorithmic Trading, 15% from other off-electronic venues and 2% from dark pools. Usually, state and trans-state legal frameworks generate risk-informed regulation strategies by evaluating trading and market functioning. In this scenario, the new surge of regulatory mechanisms and tools which are related to Algorithmic Trading are seized in the European Union in the *Market Abuse Regulation*, or MAR, and in most recent times, in the *Markets in Financial Instruments Directive II*, or MiFID II, are nowadays a part of a new social and economic environment for risk (Cunneen et al., 2018). Moreover, we are going to discuss further updates that were released by ESMA in July 2022 regarding trading functionalities and compliance regarding the use of Algorithmic Trading.

## *5.2 The worries behind the European Legal Regime*

The debate of how the mutations that Algo Trading brought to the financial scenario and the European markets should be legally regulated commences with the review of the building blocks of this "toughest" of regimes. Particularly, we think it is worth pondering on how the European Union arrived to approve such regime as the first step to assessing its comprehension of the event driven by technology that it tried to regulate. The idea that technology can overtake financial regulation has been preoccupying the European Union for a long time and worries about technologies for an automated trading started from early 2009, nearly ten years before its AT framework came into force. As a matter of fact, in 2010 the Committee of European Securities Regulators, or CESR, had noticed that "technological advance had facilitated strong growth in algorithmic and high frequency trading", addressing the need for a legal framework to tackle the shock that AT was having on the execution of major orders and the rising employment of High Frequency Trading (CESR, 2010). A plan of action would have been put in place by the European Markets Authority, or ESMA, which had its peak in the acceptance of guidelines for organizational dispositions which were applicable to algorithmic traders and exchanges providing Algo Trading, and also norms to rule DEA facilities making AT possible (Pereira, 2020). As ESMA was concluding its rules, the European Union was also processing of accommodating its legal framework to AT, and the very first proposal for an improved MiFID, the second, which was meant to be an answer to the staggering "growth of automated trading and high frequency trading" (EC, 2011). Moreover, the European Union was worried that "automated and high frequency trading had raised issues about how regulators monitored such trading and whether [the EU market abuse framework] adequately captured specific strategies that may be abusive practices" which ended up in an additional MAR where the European definition for the manipulation of markets would be revised in order to add a direct mention to AT and HFT (EC, 2011). In the end, it seems that the new European legal framework was hence fueled by three main preoccupations: an overall worry with the employment of algo trading processes and the strategies which ease that same employment; and two worries with the High Frequency Trading strategies and the processes of manipulation of the market through AT (Pereira, 2010).

## *5.3 MiFID II in the Context of Algorithmic Trading*

MiFID II and its related regulation MiFIR, comprise various aspects of financial regulation within and into the EEA, covering, among the different topics, Algorithmic Trading which are detailed in *Regulatory Technical Standards 6*, or RTS 6, obligations for trading securities and derivatives, transparency, reporting of transactions and senior management obligations. From the 3rd of January 2018, MiFID norms became effective for all investment firms (Sheridan, 2017). Critically, companies have to carry out an annual self-assessment and evaluation of their algorithmic trading businesses again the legal requirements. Moreover, the outcomes of these evaluations can be demanded by regulatory authorities at a short forewarning. In February 2018, the FCA and PRA both made obvious their focus on the subject by releasing papers establishing their respective forecasts: the FCA's *AT Compliance in Wholesale Markets* report, and the PRA's *AT Consultation Paper 5/18*, from which derived the Supervisory Statement in June 2018. We are going to set out what are the main requirements, and the major challenges companies have to face in complying to them.

- *The Definition of Algorithmic Trading*

The definition of AT as depicted in MiFID II is not a transparent task as one might think. The major standard is whether an algorithm formulates decisions about specific trading parameters, like the size and price of an order, its timing, and whether there is human input. Furthermore, the regulation states that a company should redact documents and give an evaluation for all the algorithms that they exploit, even if it would not directly fall into the definition laid out by MiFID. Companies need to have a detailed inventory of algorithms that they were able to identify, and it should portray their differences and their functionalities, who are they owned by, and how their risks are controlled. For this exact reason, a company's algorithm inventory should be as detailed and vast as possible (Bayley, 2018).

- *The Development and Testing*

A major characteristic of the legal framework was that companies must have rigorous methods for the development of fully functional algorithms as well as for the examination of their workings and strengths before they are launched in the financial markets. MiFID gives the example of a company whose new AT software in 2012 was the cause of a loss worth $400 million. For this exact reason, MiFID expects this pre-launch regime:

- All functions for control
- Wide chance for challenge of the same control functions
- Thoroughly testing that must result in a transparent audit of examination and sign-off
- Secure distribution of new or reviewed algorithms that requests for the collaboration of several 1st and 2nd line functions.

- *Control for Risks*

The employment of algorithms for beating and the execution of orders has been under the eye of regulators for several time, even more after the notorious 2010 Flash Crash that we discussed in previous chapters. Regulatory authorities have been worried about the possible causes of algorithms that presented malfunctions on the daily workings of venues. For this exact reason, companies are required to have pre- and post-execution controls which would restrict the possible impact that a dysfunctional algorithm could have on the company and the market overall (Bayley, 2018). Controls for pre-trade might comprise limitations for price collars, the maximum size of orders and credit risk and markets in general. Controls for after the trades are done should put their attention on the credit risk exposure. The most important being the kill-switch function, which allows a senior manager to retract all orders executed with a possible dysfunctional algorithm. This requires companies to set out and evaluate what would be the possible scenario in which the kill-switch might be used.

- *Structure & Supervision*

The governance structure of companies must transparently present their controls and systems regarding Algo Trading. Management of the company has to be responsible for them, and the information must be laid out so to efficiently supervise the activities. Understandably, the risk function has a crucial role since is the main actor in overseeing the financial market. Furthermore, MiFID hands to the Compliance Function a specific role to oversee the trading business carried out by AT and requests that its personnel are enough prepared to embrace this role. According to the FCA, it is crucial that Compliance substantially takes part in the development and use of AT software and had a straight line to the senior manager who has control over the kill-switch.

- *Market Behaviour*

Considering the strength of algorithms that might be employed to perform market abuse and to be the objective of users who look for the manipulation of markets, regulatory authorities request tough controls specific to these risks. Particularly, companies are requested to take into consideration the characteristic risks relegated to market abuse relating to the use they make of algorithms. MiFID II strengthens the Market Abuse Regulation obligation that we mentioned above in the sense of the overseeing behaviour linked with the unlawful employment of algorithms. It precises that companies have to carry out monitoring in real-time and punctually revise their automated warnings in order to reduce false negatives and positives (Bayley, 2018).

### ***5.3.1 Legal regime around Circuit Breakers in the EU***

We have discussed their role in the aftermath of the 2010 Flash Crash, however, how are *Circuit Breakers* regulated in the European Union? Article 48 from MiFID II requests regulated markets in the EU to own these systems which enable them to momentarily stop or reduce trading if an extreme movement of prices in a short time span occurs (Lee & Schu, 2022). ESMA describes the subsequent kinds of circuit breakers as trading halts under Article 48: Devices which stop trading on a specific financial product for a prearranged period of time and devices which modify trading from continuous to a call auction. Both groups are enforced during continuous trading stages and have the ability to expand the period of time during an auction (ESMA, 2017). The measurable factors for these stops should be adequately calibrated taking into consideration of the divergent categories of financial products and market structures.[22] In order to guarantee ordinary standards, Article 48 gives ESMA the right to produce guidelines on the design of trading halts so that trading venues can use them when they have to design their systems (ESMA, 2017).

In their recommendations, ESMA requests venues to design their circuit breakers according to prearranged structures which are supported by statistical methods, and which take into consideration specific factors. Among these factors which should be taken into consideration are the features of the securities, their respective volatility and liquidity profiles, as well as possible order disequilibrium which would need a re-design of the circuit breaker. The CB which are enforced in the European Union are just specific to the

[22] Directive 2014/65/EU of the European Parliament and of the Council of 15 May 2014 on markets in financial instruments and amending Directive 2002/92/EC and Directive 2011/61/EU (2014) OJ L 173/349.

stock and halt trading activities for one financial security where the thresholds are overridden. In different countries from the European Union countries, market-wide CB are employed which halt trading on the entire market or sections if the price of an index triggers a threshold (Guillaumie et al., 2020).

Nevertheless, the ESMA instructions are not too specific and give room for member states and trading exchanges to calibrate protection for volatility. This is the reason why differences are present, and the CB employed across the European Union are very heterogenous and not coordinated. For instance, the unequal length of trading halt that can be determined by each exchange alone. It changes from less than a minute up to 50 minutes in some exchanges (Kern & Loiacono, 2018). The fact that every exchange owns its outlook towards taming volatility could also be viewed as a way to keep undisclosed their strategies (Gomber et al., 2018).

Even though the CB on single exchanges are different and might have a peculiar impact on trading activities, the functionalities are not different overall from a design viewpoint. The designs shown on the exchanges are quite flexible, and this characteristic permits every exchange to calibrate CB to adapt best to their necessities while guaranteeing that the legal framework norms are correctly enforced. The requirements the European legal regime guarantee a standard of safety against risks stemming from Algorithmic Trading which is most successful due to the suitability to each venue (Lee & Schu, 2022).

### *5.3.2 The 2022 ESMA Update*

In July 2022, ESMA released updates for both MiFID II and MiFIR structures of the market Q&A document that comprises an adjourned section on Algorithmic Trading in order to give more insight on several issues, especially around the problems of the management of order's automation and systems of third parties (Handler, 2022). It was made clear in middle July that the first update corroborates that trades carried out through trading mechanisms that provide automated handling of the trades do qualify as Algorithmic Trading. As described in Article 4 of MiFID II, AT means "trading in financial instruments where a computer algorithm automatically determines individual parameters of orders such as whether to initiate the order, the timing, price or quantity of the order or how to manage the order after its submission, with limited or no human intervention" (Better Regulation, *Article 4 Definitions* ). This signifies that trades which are carried out with the aid of functionalities that (in addition to directing trades to trading venues) provide a management which is automated (for example the automatic redirection portions of said trades that were not executed to other exchanges) do fall under the scope of the MiFID II formulation. ESMA explains that these operations are different from the typical order automation directing system, as this specific one barely decides the trading venue to which the trade has to be dispatched without modifying any parameter of said trade. Contrarily, AT contains both the automatical creation of trades and the fact that it optimizes the process of the automation of the execution of trades by automated mediums.

The document endorses that companies trading done through these specific operations should be treated in AT and thus must meet the relative legal requirements (as established in Article 17 of MiFID II and RTS 6). Furthermore, the document explains how companies should make sure that they are meeting the relevant regulatory norms when employing systems of third parties that provide AT functionalities. The European Securities and Markets Authority furthermore explains that however, the absence of direct oversight over the system, its functionalities and the algorithms that are used, might prevent these companies to objectively guarantee that all the regulatory norms are satisfied. In these cases, companies are permitted to guarantee the meeting of the regulations with any technical requisite that could not be met in another way, this is done through contractual dispositions with the system provider (McAughtry, 2022).

### *5.3.3 The Challenge of an Equilibrium between Compliance and the Protection of Intellectual Property*

As explained above, Article 10 of the EC delegated regulation C(2016) 437 (additional article 48(6) of MiFID II) requests entities that are regulated and make use of algorithms not only to attest that the algorithm has been examined in order to prevent market malfunction but also to fully disclose to the regulatory authority of the examination put in place. Considering the fact that AT might comprise possible unique strategies, disclosing the testing might spread intellectual property (IP) to the regulatory authority, that might in turn be disclosed by accident to possible competitors. This does not absolutely assume that the regulatory authority would ever carelessly violate its responsibility of confidentiality. Nevertheless, there could be aware or unaware leakage of precious proprietary strategies since companies' staff shift from regulatory authorities to regulated entities (Sheridan, 2017).

The challenge for EU regulated entities is to put into equilibrium compliance with regulatory authorities and at the same time secure IP in the shape of trade secrets. This business issue was brought into the spotlight by the International Securities and Derivatives Association, or ISDA, in its answer to the FCA's suggested Market Abuse Regulation 7 A, when it stated that "ISDA members would like to understand if the intention of the FCA is to capture the detailed cases of each type of test ... which may include proprietary information detailing the behaviour of the algorithm" (Xtra Press Workshop, 2013). According to Article 4(2) of the European Commission delegated regulation C(2016) 437 (additional Article 48(6) of MiFID II) companies that are regulated which exploit algorithms have to make sure that their Compliance function "has at least a general understanding of the way in which algorithmic trading systems and algorithms operate". If the objective rise of costs related to the daily reporting and audit to the Financial Conduct Authority are dubious, these might be considerable. Furthermore, several FinTech entities in their initial phase do not have substantial funds for the Compliance function. According to section 138 J FSMA, the European regulatory authorities have an obligatory duty to do a cost-benefit analysis of the new legal framework. For what concerns Algorithm Trading that same analysis is far more intricate (Sheridan, 2017).

## *5.4 The Misalignment between the Algorithms and Market Regulations*

Disorders that arise from the comparison of algorithms and market regulations permit us to examine the latter developments that saw marketplaces under the spotlight. Our study has explained so far that financial markets nowadays are going through a significant change regarding the nature of their legal framework. As a matter of fact, the quick spreading of trading algorithms makes doubt the capability of regulatory authorities to have a solid grasp over the new scenarios that those tools made possible. Ethnographic fieldwork made feasible to have intuitions into the probable representations of AT, and to lay out one of the several contentions they create. The change in danger here is the possible inflexibility of standards through their enclosing in a coded script which is meant to improve the performance of transactions in financial markets. Locking some states of the reality of markets in patterns that were established in advance makes doubt the supervision of the behaviour of markets. Cases like the 2010 Flash Crash displays that apparent errors such as the spoofing of market cannot be identified as easily as one might think. In the meantime, the machine takes part in cluttering the representations in the financial scenario. If time and space are both cut down to dimensions in which is objectively hard to interact, at that point compliance with a functioning legal framework could become difficult (Lenglet, 2011).

It follows that if AT gives a robust conciliation between markets and traders, they all convey that there is a combination of several points of view which prevents furthermore the attribution of responsibility when disturbances arise. If the legal norms usually require that intermediaries designate a figure that has to oversee the exploitation of AT, they do not approach the issue from a practical viewpoint. What actually happens when standing in front of the trading stations? As a matter of fact, the intercession that algorithms create modifies the relationship that traders have with their entrusted actions in the marketplace. If it is the case where this new relationship does not ease the responsibility of the human trader for what his algorithms do, then how can the legal framework be functionally applied? This makes AT, and the debates they generate, a political problem for the regulation of the marketplace.

In conclusion, the clash between algorithms and the legal framework, once laid out as a fabrication which involves several viewpoints, comes out as the sealing of a space instead of the inception of hermeneutic opportunities. What we intend to say here is that even prior to the action taking place in the financial market, the room for opportunities for interpretation is locked within the tool. This undoubtedly enhances challenging problems for regulatory authorities, particularly when the interpretation of the legal framework is of the biggest importance when evaluating the nature of a trading activity. In a certain way, it the difference between tools and ends which is in danger here, with a stress on the part played by technologies which cause disturbances in order to readapt (Lenglet, 2011).

# CONCLUSIONS

This study has examined thoroughly various aspects of nowadays' fast adoption of trading automation, which has left no industry unaffected. The quantity of data and information collected is constantly making use of trading algorithms for the improvement of processes and operations. It is not only present in the major trading venues of the world, but in our daily lives as well, from booking travel tickets to ordering food from our homes. The automation of financial markets and the extensive availability of analytical tools are generating a common marketplace into a community driven by technology (Matade, 2022). We explained how Algorithmic Trading is mainly winning over the advantages of the traditional method of trading, with traders sitting in front of big monitors and carefully and manually monitoring price fluctuations for hours on end. AT functions differently, as it takes all relevant tasks and automates them, using predetermined rules which find their foundation in historical data and predesigned algorithms.

This study has also thoroughly analyzed how the 2010 Flash Crash is frequently called out as an event which provides a peek into the deeper functionalities and possible downsides of Algorithmic Trading and nowadays financial markets. We have examined the problematic nature of the event, as in what was the cause of it, and whether it had an ordinary or crucial meaning for the AT scenario. Without any doubt this gives the Flash Crash a polyvalence which is unique in its genre, and the more exceptional observation is that not all users and authors agree on the fact that it was a turning point regarding the automation of trading, as we explained it to be. In a similar way, while worries related to advanced algorithms could find various back up in nowadays market users, eventalization of the notorious event which stresses the crash tendency of algorithmic finance tends especially to put an emphasis on the negative features of the event while sharply ignoring the following upturn (Borch, 2017).

Based on the study carried on in this paper, we ponder why the 2010 Flash Crash keeps on attracting the eyes of so many people. In order to understand this, it is crucial to understand how the Flash Crash falls into eventalization. In a specific way, the conversation deploys two recognizable contemporary cliches, which both make this event as notorious as it is today. Therefore, worries related to technology and herding play a pivotal role in eventalizations of the 2010 Flash Crash and they merge with it. As a matter of fact, preoccupations regarding technology mutate into preoccupations over algorithm mechanics that round-up in manners which are otherwise mainly features of the human domain.

Eventually, we came to the conclusion that it could be logic to think of the Flash Crash as of how it contributed to the discussions around economic sociology conversations about quant finance and the development of a sound and functional European legal framework for Algorithmic Trading found in MiFID II and MiFIR. If the 6$^{th}$ of May events are considered as a feasible chance to have massive insights into how AT works and operates in marketplaces, thus this could push a revaluation of how we envisage resonance and dissonance, herding into sociological reports of quant finance. Moreover, the 2010 Flash Crash could prompt authors and market participants to analyse how the interaction of completely automated algorithms could form new, unique conformation of market sociality, the comprehension of which could well require new sociological categories.

If the legal framework will keep on sustaining the existence and development of a trading scenario that is undoubtedly fragmented, this state of being broken will keep on evolving even more. If that will be the case, AT classes will develop as well as the differences among the strategies used for trading will rise, and linked strategies will follow and adjust to the new environment. This intense broken state is usually followed by a cycle of consolidation. In a span of five to ten years, the financial market is probably going to go through consolidation at a minor fragmented level. Particularly, a minor number of *Electronic Communication Networks*, or ECNs, is going to take over. In a similar way, fewer dark pools are going to be available for the execution of major orders. The exigency of market users for determinate characteristics will define which alternative trading venues are going to outlive this process of consolidation. Regardless of the consolidation, the centre of gravity of these alternative venues for trading could geographically displace for the reasons we're going to enounce. We could state that regulatory requirements are a process of trial and error. Even if designed specifically, a new legal framework could have unwanted side effects – we have profusely talked about how there is a thin line between the disclosure of trading strategies and algorithms and the possible leakage to competitors' advantage for MiFID II. However, they mold the financial scenario. Competition has a limitative consequence, trading venues are not pushed to change their self-regulation so to erase collateral effects, in the case in which they would endanger competitive advantages. A congruous self-regulation of exchanges is certainly an improbable possibility. The adoption of revised regional legal frameworks could boost coordination and the deletion of specific unwanted effects. Cliff et al. (2020) state that there are countries and regions that have the potential to do so in a scenario with the subsequent 10 years (Gyrukó, 2010).

Regarding the European legal framework, it can be said that it mistakenly presumes that not every mechanism regarding Algorithmic Trading is worth of legal restrictions and that the employment of AT has supported a rising risk of manipulation of the market. The consequence is that the European framework fails to regulate determinate kinds of trading algorithms that could seriously threaten the quality of the European financial markets and originates unwanted suspects that specific AT behaviours bring risks for market manipulation. For this exact reason, there is the fear that the European legal regime leaves its door open for risks that originate from simpler algorithms, while at the same time demoralizing healthy market conduct. However, whatever are the EU misjudgments regarding Algorithmic Trading, it is without any doubt that there is a lot that the MiFID II and MAR get right. Their composition and the way it is comprehensive is staggering, which comprise not only norms that aim at mitigating the risks related in the general exploitation of AT, but also norms to manage the several strategies created by market users in response to the rise of Algorithmic Trading practices. All of this shows a deep understanding of how much the European capital markets were in necessity of security and protection. The legal norms in MiFID II and MiFIR, which regulate the employment of AT functionalities and strategies in exchanges and several intermediaries, show a widespread worry for proportionality. The same feeling emerges for the light trade-offs between the advantages and the downsides that AT strategies and functionalities originate (Pereira, 2020).

Nevertheless, this must not be taken as if there is no space for the exploration of completely different options for the regulation of Algorithmic Trading: on the contrary, new market designs, pre-trade clarity and norms for dark pools, norms for disclosure, norms for the execution of trades and financial taxed might be crucial in order to further regulate Algorithmic Trading.

But what does the future hold for Algo Trading? It is no doubt that trading algorithms are continuing to gain popularity among traders and corporations, with reports showing that they are using automation more than ever. It is an additional confirmation of the rising complexity and overall reception (Bloomberg Intelligence, 2021). It is reported that on average, the biggest buy-side companies assign 33% of their trade flow to their major providers. However, this does not signify that they a limited in their choices. Bloomberg Intelligence reports that these companies increased the size of their algorithmic providers to nearly 12 each. This is merely an example of the new arms race that is taking place among providers to create trading algorithms which employ AT to get, or anticipate, financial markets states. We have seen how progressively fragmented and intricate market conditions aid power the ongoing competition for generating the next novelty which will make automated trading quicker and more efficient (Clapp & Hundley, 2021).

Given the fact that there has been a shift in *Transaction Cost Analysis*[23] being incorporated into sell-side and buy-side functionalities and operations, traders have to deal with much the same challenges in coming up with ways to employ TCA on their tables. Trades are ordinarily examined for unique performance benchmarks and statistics. Nevertheless, TCA is solely the measurement of a result. It does not give any comprehension to the trader into how to settle any weak trading outcome. As trading techniques and algorithms have turned out to be more complicated, it had turned out to be almost out of question for a trader to match weak TCA outcomes to what settings, in a succession of complicated systems, might affect the trading results. In the next years, we will witness a rising stress on real-time instruments which will understand TCA outcomes into functional systems designs. That exact feedback process will be the necessary missing element on each trading station which makes TCA essential from a reassurance when a disturbance appears to a necessary tool affecting trading results.

As the quantity of trading algorithms and the amount of possible settings are increasing exponentially, traders are subject from a heavy data and information excess. Nevertheless, companies' management has apparently become less prone to trade large volumes, preferring smaller quantities. As we have seen this can be done through AT which splits big orders into smaller ones which might be scattered across various exchanges and performed against several pools of liquidity in order to refine the features of their trades and to aid their customer to decrease trading costs. In the next future, we will take in core algorithms to become sharper and more reactive to market states, for instance with the introduction of Quod Financial's AI/ML-powered Peg-Offset conduct, a product which has become available in December 2021. The peg itself commonly rises the efficiency of passive trading within any trading algorithm by mixing it with forecasting functionalities

[23] Transaction Cost Analysis (TCA) lets investment managers determine the effectiveness of their portfolio transactions.

to anticipate little shifts in the market which will enable traders to catch various additional Basis Points. Moreover, this aids brokers in presenting new characteristics of Algorithmic Trading without experiencing the process of trying to convince customers to trust more intricated AT functionalities. This third generation of trading algorithms will be adaptable and will exploit Machine Learning technology, with the help of real-time deep intuitive understanding trading algorithms can recalibrate on their own when executing the trade.
An additional trend which has become predominant in the last year, and we think it is destined to gain even more popularity is the extended employment of trading algorithms across asset classes.
Ultimately, the growth that we have witnessed expands into automation. As trading stations are coerced to manage customers' orders quicker, with less traders and rising volumes, the sole resolution is automation. Rules have developed from easy routing norms to context-based guidelines computing financial market settings. Constructing these intricate instructions enable complete automation of trade flow and to advise specific strategies and possible routes. Indeed, traders and marker users can accelerate their decision-making the moment the order is placed (Quod Financial, *The Future of Algorithmic Trading: 5 Key Trends)*.
In conclusion, algorithmic trading has become an increasingly dominant force in financial markets in recent years. Its ability to execute trades at lightning-fast speeds and make use of large amounts of data provides significant advantages over traditional human-based trading. However, it also brings with it a number of challenges and controversies. One of the key challenges is the risk of flash crashes, where trading algorithms can amplify market volatility and lead to rapid and unexpected drops in market value. The potential for algorithms to be used for market manipulation and insider trading also raises important questions about the accountability and transparency of algorithmic trading. Additionally, the increasing reliance on algorithms in financial markets raises concerns about the role of human traders and the potential impact on employment in the financial industry.
Despite these challenges, algorithmic trading is likely to continue to play a significant role in financial markets in the future. The increasing use of machine learning algorithms and decentralized finance are likely to further fuel its growth. Regulators will need to be proactive in addressing the potential risks and challenges posed by algorithmic trading, to ensure the integrity and stability of financial markets and protect the interests of investors.

Finally, this study has explored the development and impact of algorithmic trading in financial markets. It has analyzed the benefits and drawbacks of algorithmic trading and considered the future trends and challenges it poses. While algorithmic trading has the potential to improve the efficiency and speed of financial markets, it also brings with it important risks and controversies that must be carefully considered and addressed.

## APPENDIX I - The Anatomy of the Flash Crash: SPY & E-Mini Contracts

As we thoroughly explained in one of the previous chapters, the infamous 2010 Flash Crash was made of two inter-related liquidity events: one in the deep market for *E-Mini* index futures and the *S&P 500 Index ETF* (SPY); and another in the market for individual stocks. But what exactly are these two instruments whose movements caused the biggest financial crashes of the last 15 years?

The word E-Mini S&P 500 pertains to futures that are traded electronically and options contracts on the so-called Chicago Mercantile Exchange or CME. Created by this institution in 1997, this instrument is accessible to all investors (CME Group, *Timeline of CME Achievements)*. It makes it possible for users to hedge their bets or speculate on the shift of prices of the S&P 500 Index. The contract is settled by cash and is priced at $50 times more than the worth of the main index (CME Group, *E-mini S&P 500)*. The S&P 500 index tracks the biggest 500 American companies that are publicly traded by the value of the market, and it is considered one of the most popular benchmarks for the wider US market for equities. On the other hand, futures are financial contracts which force the trader to sell or buy an asset at a price which is predetermined by a date which is set as well. The Chicago Mercantile Exchange created various standard contracts which were usually only possible to buy to institutional investors. As the number of investors that were looking for alternative investment options was increasing, the CME created a smaller set of future contracts denominated E-Mini. These contracts made trading for future feasible for a multifariousness of traders, among which there were retail ones. If one has the desire to trade E-Mini contracts, they have to open an account with a brokerage firm. As we have specified above, investors frequently employ these contracts in order to hedge their bets on the S&P index or to gamble on how they move. For this exact reason, since they provide major affordability, low volatility and all-day trading possibilities, the majority of active traders see the E-Mini contracts as the perfect tool for trading for the index (Investopedia, *E-mini S&P 500: Definition, Trading, and Example)*. Moreover, the mix of these exact factors were behind why they were employed by Sarao on the 6$^{th}$ of May 2010 to distort the market. They are both strong and simple to exchange (Melloy, 2015).

On the other side of the notorious Flash Crash there was the SPDR S&P 500 ETF Trust, also famous as the SPY, which is considered to be one of the major funds which has as its objective the tracking of the Standard & Poor's 500 Index. The stocks which are comprised within are chosen by a special committee which is based on industry, liquidity, and the size of the market. The SPY was first launched in 1993 and at the time had solely $6.53 million in assets. After a difficult start and various problems looking for finding investors, in just three years it raised to a staggering $1 billion worth of assets under management. Since ETF shares are traded in a way which is close to the one of stocks, investors and traders can purchase and sell SPY via their broker during the day, which includes their short selling (SSGA, *SPDR S&P 500 ETF Trust;* Mitchell, 2023*)*.

## APPENDIX II - Flash Boys: A Wall Street Revolt

The concept that algorithmic and high frequency traders were employing velocity to take benefits from normal investors was taken into consideration by the world for the first time when, in 2014, the author Michael Lewis published his novel *"Flash Boys: A Wall Street Revolt"*. A vicissitude that follows the story of the ex RBC electronic traders Ronan Ryan and Brad Katsuyama as they start to become conscious of the fact the automation of the financial market has paved the way for new "predators" which employed velocity and algorithms to beat and jump ahead of more obsolete and traditional institutions. The publishing of this novel stressed the significance of momentum in trading and rose the quantity of focus spent to how it might be employed to gain benefits of the inexperienced common investor.

The book narrates the story of market manipulation and latency arbitrage, starting with the introduction of *Spread Networks*, a firm that with the price of $300 million set up a super-low latency fiber optic cable linking New Jersey and Chicago. By means of high-speed connections, either with the help of entrance to feeds of proprietary data or co-locations, High Frequency and Algorithmic Traders were indicted for profiting by unaware investors from retail and common institutions, by means of data assembled on the public markets at a quicker speed or by using access to the private dark pools[24] of various banks. The book reports that in 2011 about 11% of the overall trades in the stock market were happening off-market, with many of these trades happening in dark pools (Smith, 2022).

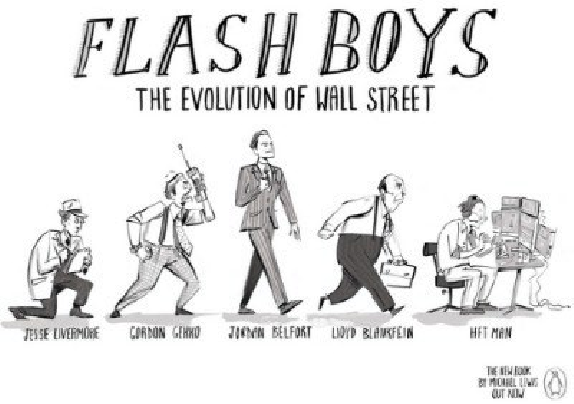


*Figure 16 "If we thought Wall Street was about alpha males standing in trading pits hollering at each other, think again. That world is dead".*
*- Michael Lewis, The Flash Boys.*

On Reg NMS in the United States, both Ryan and Katsuyama founded their claims that the market was continuously manipulated. Reg NMS was introduced by the SEC, the Securities and Exchanges Commission, in the United States in 2007, motivated by

[24] A private securities exchange in which investors, typically large financial institutions, are able to make trades anonymously.

accusations averse to participants in 2004. The broker is needed in order to fetch the best price for the investor in the National Best Bid and Offer (NBBO) which means that the broker firstly has to buy any quantity of that specific stock is accessible at the best price. To congregate the picture of the National Bid and Offer, exchanges generated Securities Information Processors, or SIPs, which are feeds of consolidated data which include all ask and bid quotes from each trading head office, nevertheless, the IEX founders reported that the system provided an escape clause to those companies which were disposed to construct magnified SIPs close to the systems of the exchanges to gather quicker the information.

**What happened next?**

While the first glimpse into the secrets that were hiding beneath the functioning of the financial markets, the release of the book has had an important and everlasting impression on how some market users decided to execute trades and has pushed regulators to spend a major focus on few practices. There is no doubt on how the book had a big cultural impact on the biggest US asset managers, since it made them realize that the tools that they were increasingly using, such as electronic trading, were not as efficient and as good as they thought. The 2010 Flash Crash instituted improved controls for risk, improved evaluation of the electronic functions and improved systems that had been embraced in a smaller scale by the major asset managers. Similar to the recent execution on $LUNA[25], the case spread light on feasible frailties of the industry, like the constitution of unfavourable loops of feedback caused by the feeble link of markets that are into pieces and exchanges that came into view as a result of the institution of Reg NMS in the middle of the 2000s (Smith, 2022).

A numerous number of legal cases simultaneously appeared supported by the claims beamed in the novel, which included examinations from the SEC into the dark pools of large payers such as Barclays and Credit Suisse. At the end, nevertheless, the fault fell on the exchanges since they permitted the supposed behaviour to happen in the first place. In 2014, just after a month the novel had been published, five lawsuits were filed which in due course became just one against the indicted trading exchanges.

[25] In May 2022, the stablecoin TerraUSD fell to US$0.10. This was supposed to be pegged to the US dollar via a complex algorithmic relationship with its support coin Luna. The loss of the peg resulted in Luna falling to almost zero, down from its high of $119.51.

The case, which was later renowned the *Flash Boys Case*, protracted by investors from big institutions stated that the venues, which included BATS Global Markets, NYSE, and Nasdaq, generated an environment that was favourable to Algorithmic and High Frequency Traders that placed the other investors in a position of weakness. Co-location resources were among the supposedly favouritisms, that enabled companies to generate an improved and quicker representation of the financial market. These resolutions that were based on latency, were thought for the improvement the velocity at which companies could grasp their hand on relevant information and move in and move out of transactions on exchanges, which made possible for them to gain advantage over other investors and generate revenue from the minuscule gap in time when they were quiet to data and information which the remaining part of the market was not aware of. The case was exposed in 2015 based on the fact that the status to which exchanges benefit, protects them from receiving lawsuits for damages (Smith, 2022). Nevertheless, it was later proved in 2017 that they had no such privileges. Only eight years later, in March 2022, the Federal Court declared that the investors could not demonstrate that they had been subject to some sort of harm that the exchanges gave to them. Proprietary products and co-location are given as an offer to every institution, with previous approval by the SEC. As a matter of fact, the buy-side interconnects the venues through brokers and one of the first questions which they are often interested in is whether their algorithms connect to feeds of proprietary data.
The scandal narrated on High Frequency and Algo Trading is only the last proof that the insiders of the stock market have always preferred benefits from improved and quicker information and data. However, fiction is necessary in order to make sure that the market does not fall into the fate of being over-regulated. Lewis goes one step ahead of this: he makes us understand that he believes regulators cannot do very much, hence he suggests how the market might adjust by itself (Ross, 2014). The author has written an efficient manifesto, however, when debating the "commercial heroism" of the founders of IEX, he wraps up by cleaning up the myth of the financial market as a mechanism that self-corrects. Left to its own plots and taking from the constant technological innovations in the financial scenario, the market will clean itself up and go back to its gracious state where all the market participants have a fair shot at beating each other. As stated by this scenario, the defeat of regulatory authorities is already written.

In conclusion, according to Lewis, if the overexcitement around Flash Boys aids a huge disastrous event automatically triggered by the Algorithmic and High-Frequency Trading machines, then it will have done some righteousness.

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