

ESTONIAN ENTREPRENEURSHIP UNIVERSITY OF APPLIED SCIENCES

Financial Management

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**A LOOK ON QUANTIFIED TRADING WITH EUR/USD THROUGH
EXCEL BACKTESTING EMULATION**

Bachelor Thesis

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Tallinn 2019

RESÜMEE

Antud lõputöö eesmärgiks oli luua simulatsioon, mis võimaldaks süstemaatilistel kauplejatel leida tootlikud intervallid libisevate keskmiste paaridele ristumisstrateegias läbi testimise FOREX-i paaride ajaloolise, kvantitatiivse info põhjal. Üks ajaraamistik oli kolme kuu jagu ehk 19996 5-minutilist hinnabaarist ning kokku testiti seitse perioodi ajavahemikus 02.01.2017-09.11.2018 mis oli kokku 139972 5-minutilist hinnabaari. Lisaks annab antud lõputöö ülevaate printsiipidest mida kasutati simulatsiooni loomisel ning piirangutest, mis mõjutavad tulemit ja annab võrdluse ka erinevatest libisevatest keskmistest mida antud simulatsioonis on võimalik testida. See raamistik testib libisevate keskmiste paaride ristumispunkte kui osta ja müü signaale, mis on suhtelised FOREX-i paari hinna indeksi suhtes ja muude muutujate suhtes. Testi tulem annab informatsiooni valitud libisevate keskmiste efektiivsuse kohta võimalikus ajaraamistikus ning kui hästi see töötaks kohandatud, reaalses kauplemisskeskkonnas kui algoritm mida süstemaatiline kaupleja tahab kasutada.

Eeltestimine on eluliselt oluline enamikele kauplejatele kes soovivad vältida kaotusi mis on põhjustatud mittetestitud tegudest ja otsustest turul. Laiemas mõõtnes antud raamistikku võib iseloomustada ka kui testimis tööriista, mis keskendub libisevatele keskmistele, mis on vaieldavalt kõige rohkem kasutatud tehniliste indikaatorite seas mida kauplejad kasutavad. Võimsama raudvaraga ja Python-iga on võimalik antud raamistikku edasi arendada ja kombineerida sarnaste funktsioonidega nagu „*Goal Seek*“, et saavutada optimeeritud tootlikkus. Lisaks, muud tehnilise analüüsi indikaatorite perekonnad, nagu näiteks „*Relative Strength Index*“, on võimalik kombineerida antud raamistikuga, et vältida perioode kus on vähe hinna liikuvust.

Läbi testi analüüsi autor leidis, et libisevate keskmiste ristumisstrateegia on väga tundlik muutustele sisendis ja sellega peab olema väga täpne, et saavutada kasumlikku tulemit. Ühe punkti jagu muutust intervallis muudab tulemit kasumlikkuses 85% pealt 35% peale. Sama kehtib ka muutustes vertikaalses nihutajas. Kasumlikus olekus ristumisstrateegia võib kaotada rohkem tehinguid kui see võidab kuid efekt tekib võidetud pikemate trendide pealt ja olukorrast kus rohkem tehinguid võidetakse üksteise järel kui kaotatakse.

RESUME

The purpose of this Bachelor Thesis was to create a simulation that would allow systematic traders to find profitable intervals for moving average pairs in a crossover strategy through testing on quantified empirical data of FOREX pair prices. One timeframe was a three-month set made of 19996 5-minute price bars in total seven periods were tested between 02.01.2017-09.11.2018 which summed up to 139972 5-minute price bars. In addition, this thesis will give an overview of the principals used in developing of the framework, limitations that affect the results and give a comparison of different moving averages that can be tested in it. This framework tests the moving average pair crossover points as buy or sell signals relative to the FOREX pair price index and other variables. The result of the tests will provide information about the efficiency of a moving average pair in a timeframe and how well it would perform in an adjusted real trading environment as an algorithm used by the systematic trader.

Back-testing is vitally important to most traders to avoid losses caused by untested actions in the market. On a broader scale this framework can be characterized as a back-testing tool that focuses on moving averages that are arguably among the most used technical indicators used by traders. With more powerful hardware and Python this framework could be further developed and combined with “Goal Seek” function for profitability optimization purposes. Also, other technical analysis indicator families, such as relative strength index, could be combined with the framework to avoid timeframes with little price index movement.

Through test analysis the author found that the moving average crossover strategy is highly sensitive to change in inputs and must be finely tuned in order to be profitable. One-point difference in interval will result in change from 85% profit to 35%, the same applies to changes in the vertical shifters. In profitable state it loses more trades than it wins, however it benefits more from longer trends than shorter ones.

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INTRODUCTION

The financial markets have grown vastly during the last few decades and trading has moved from large paper filled halls into the internet providing people the opportunity to take part in trading from their home (Manic, 2017) Today every person, with access to the internet and some basic computer smarts, can trade in the financial markets and platform owners take full advantage of this. Most finance related questions looked up through Google search engine will get at least four advertisements in the listing to a platform of a broker. It can be said that the development of computers and internet has supported the emerging of trading stations that have adapted automatized trading systems that use algorithms to do majority of their trading in the financial markets, capable of doing millions of calculations in seconds (Manic, 2017) This puts the focus on technical analysis.

Technical analysis has become more and more popular among the public as well. It is fair to say that many day-traders today use at least one type of technical indicator. Moreover, some programmers have become algorithmic traders because of their understanding of programming languages and how to automatize trading strategies. Many platforms and tools provided by various brokers allow the use of customized algorithms and the use of trading bots such as Metatrader. However, it seems that back-testing which is vital for designing a profitable trading algorithm has remained, in large part, the obligation for the trader. Arguably, demo-accounts and stock chart pages could be considered as some form of back-testing that is available to the public, but these do not give accurate results for real trading environment because they do not account slippage, trade transaction costs and leverage.

The interest for the current subject of this thesis came from observation of the behaviour of moving averages on price charts. Could moving averages be used for a profitable trading strategy for systematic high-frequency trading, was the main question that arose from the observation. The aim of the BA thesis is to create/provide an emulation that would allow systematic traders to find profitable intervals for moving average pairs through testing on quantified empirical data of FOREX pair prices. Current thesis is divided into three chapters to give an overview of the subject to the reader. The first chapter focuses on the concepts of technical analysis and how it has evolved over the years. Second chapter focuses on actual data

used and various types of moving averages that are included in the tests. The author will also provide information about moving averages (KAMA) that can be included in future testing but currently are not tested. This chapter also gives a detailed overview on how the emulation was built to provide the reader the opportunity for further research and development. Third chapter focuses on the result analysis of original test (2017, February-April) and expands the testing into multiple timeframes (2017-2018). In this chapter the author will also give a short overview how the framework can be further improved and implemented for different purposes.

The results and the simulation itself will be added to the extras of the thesis for future development and use. The simulation will be on a memory stick separately in an Excel file because it is too large to be added directly into the thesis. This bachelor thesis is based on various Estonian and English academic and applied source materials.

1. CONCEPTS OF TECHNICAL ANALYSIS

1.1 History of Technical Analysis

First introduced to the financial markets in the late 1800's by Charles Henry Dow, the founder of the Wall Street Journal and creator of the Dow Industrial Average in May 1896 (The Editors of Encyclopaedia Britannica, 2018), technical analysis has evolved to a complex trading discipline that focuses on patterns of price movements and statistical trends through various tools to evaluate and identify trading opportunities. The editorials of Charles H. Dow in the Wall Street Journal became the basis of Dow Theory, developed years later by Dow's successor William Peter Hamilton and popularized in 1932 by Robert Rhea in the book "The Dow Theory" (Modell, & Lynngard, 2017). The Dow Theory was mainly focused on identifying long-term trends and reoccurring patterns in the stock markets (Modell, & Lynngard, 2017).

It is worth noting that during the same time another great contribution for modern technical analysis was a dissertation by French mathematician Louis Bachelier in his Phd thesis "The Theory of Speculation" (*Théorie de la spéculation*, published 1900), which introduced for the first time a mathematical model for a stochastic process which today is more widely known as the Brownian motion (Sewell, 2011). Bacheliers work was ahead of its time and his mathematical model for stochastic process was published five years before Einstein's Brownian motion (1905), which in financial markets is also known as the "Random Walk", has had its effect on a different approach to the markets. Perhaps best explained by Alexander Elder in his book "Trading for Living" (1993), quote "Random Walkers theorists claim that market prices change at random" and by extension, "Random walkers deny that memories of the past influence the behaviour of the present" (Elder, 1993, 74), which correlates with Bacheliers stochastic process mode.

Bachelier also deducted 65 years before Samuelson (1965) explained, "The mathematical expectation of the speculator is zero" (Sewell, 2011. p. 2.), efficient markets in terms of martingale (Sewell, 2011). Because of unfortunate events in life, the "novelty" of his material and drafting into the army as a private during World War I, Bacheliers work was not widely known and has been reintroduced to the public "quite recently" by Leonard J. Savage in 1955. However, the work of other named pioneers has contributed to the development of the Efficient Market Hypothesis or EMH through iterations of multiple researchers. Efficient Market

Hypothesis states that nobody can outperform the market because any price at any given moment incorporates all available information (Elder, 1993), and because traders actions in the market are information it is included in price development. However, most traders do not make correct assumptions, and by extension, decisions therefore this provides opportunity to exploit those decisions for traders who do make correct decisions (Elder, 1993).

A. Elder (2014) also brings out a third theory through, “Nature’s Law”, which directly opposes the “Random Walkers” stating that financial markets have a perfect order and move more like clockwork as it is in nature, which derives from its creator R. N. Elliot’s book “Nature’s Law” (1946). Nature’s Law’s applicability to the financial markets have been further explored by Robert Prechter in a book Elliot Wave Principle: Key to Stock Market Profits (1977) and multiple other published documents. Prechter’s publications provide an extensive overview on how the Elliot Waves could be implemented to the financial markets. Overall the Nature’s Law states that all markets act in cycles in different timeframes and all these cycles act in a predictable and measurable way. While Elders view (2014), “Nature's Law is the rallying cry of a clutch of mystics who oppose Random Walkers in the financial markets”, is critical of the Nature’s law, practitioners have successfully managed to match, with near hundred percent accuracy, historical price movements to wave patterns described in Prechters publications. However, the prediction of future price movements with the wave patterns is still an elusive task.

While all theories have some form of correlation with the markets, it almost seems as if all theories exhibit a similar flaw of trying to explain things in a “Unified way” and not “AS IS” thereby being subject to criticism. Most technical analysis practitioners use charts to get an indication of the opportunity to enter the market, while professional analysts, in addition to charts, use empirical data (Appendix 1.) which forms the charts as formation of subsequent values. The most used three types of charts are: Japanese Candlestick Chart (Figure 1), Bar Chart (Figure 2), Line Chart (Figure 3). Using charts could be useful when the goal is to get an indication for market entry or even a better visual in terms of pattern analysis, however, it is highly inaccurate when doing quantitative analysis.



Figure 1. Japanese Candlestick Chart

Source: (<http://www.livecharts.co.uk/historicaldata.php>)

EUR/USD 1h Candlestick 11. January 2019 - 12. January 2019. Each candlestick represents price change relative to a timeframe in this case each bar represents price movements for one hour. The body on each candlestick represents the distance between opening and closing prices on the red bars (bearish) opening price is on top and close on the bottom and for green bars (bullish) vice versa. In a classical view (black and white) the bearish bars are black and bullish bars are white. The wicks on top represent the highs and at the bottom the lows of each bar. Japanese were using the candlestick bars much earlier in rice markets than chartist appeared in America (Elder, 1993, 88). It is likely that Candlestick Bars were integrated by the chartists because during that time all printing presses were black and white, and candlesticks were easier to separate from each other, because of the existence of a body, than traditional bars (Figure 2.) for the reader.



Figure 2. Bar Chart

Source: (<http://www.livecharts.co.uk/historicaldata.php>)

EUR/USD 1h Bar Chart 11. January 2019 - 12. January 2019. Much like the Japanese Candlestick Bars the upper line on the red bars (bearish) represents the opening price and the lower line represents the closing of a bar and on the green bars vice versa. The wicks represent the highs and lows.



Figure 3. Line Chart

Source: (<http://www.livecharts.co.uk/historicaldata.php>)

EUR/USD 1h Line Chart 11. January 2019 - 12. January 2019. The line chart gives less information than the other two chart types and mainly used to understand the direction of price movement and to see forming patterns more clearly. It is perhaps most common of the three chart types and publicly available online charts show the line based on closing prices (BID) by default, some however provide the option to turn it on the opening price (ASK).

EUR/USD 1h Empirical Data 11. January 2019 - 12. January 2019 (Appendix 1.). Empirical data can be used to back-test all types of technical analysis including quantified techniques and is also vital for most kinds of automatized trading. This data may sometimes include trading volumes which is important to test various oscillator tools in technical analysis. As seen here the empirical data matches the three types of charts and I have illustrated it with matching colours. Since the last bars have not formed yet the corresponding two data points are outlined with grey.

Modern technical analysis involves the prediction of future exchange rate movements from the analysis of past price movements using qualitative analysis e.g. recognizing certain patterns in the price chart or quantitative analysis (Menkhoff, & Taylor, 2006). Additionally, Relative Strength Index or RSI is a widely used tool which qualifies under oscillators, a family of technical indicators that measure the “overbought/oversold” of a price movement in an UP/Down direction (Menkhoff, & Taylor, 2006). While these are the most widely known, modern technical analysis has tens if not hundreds of various indicators and tools to fit a traders style, strategy and tactic. By 1985 (Yusupov, & Lux. 2007, 2) most professional traders were using some type of technical analysis in their trading techniques and the emerging of computers and internet vastly boosted the volumes of all types of trading. Technological advancements provided trading offices to develop methods for automated trading which contributed to the emergence of “High Frequency Trading” and broker firms created trading platforms to provide access to the markets for the public.

1.2 Applicable Markets and Limitations

Daily traders who use platforms for their traders experience two types of costs in the form of commissions and slippage (Elder, 2014). Nowadays there are tens if not hundreds various broker platforms that provide access to the markets and commissions are fixed costs for every

trade transaction implemented by the broker, therefore, they vary based on the platform that is used. Slippage occurs in both entering and exiting a trade and is the difference of the price in which trader enters or exits a trade and in which it gets filled and is a variable cost. Often the price in which an order gets filled is worse than the price that trader entered/exited and is caused by high volatility in markets (Elder, 2014). Volatility or standard deviation is the extent to which price tends to fluctuate within a certain period of time.

But the liquidity of commodities and many equity markets, can also affect slippage, since it is much smaller than for FX markets and are not large enough for efficiently handling bigger transactions. According to Gencay, Dacorogna, Muller, Picet & Olsen (2001, 33): “Large orders often cause considerable slippage with immediate price movements to the unfavourable direction”. Elder (1993) also describes examples of “common”, “volatility-based” and “criminal” slippages.

- Common slippage- Quote: “Broker may quote you 390.45 for June S&P 500. If you want to buy a contract at the market, you'll have to pay at least 390.50. If you want to sell at the market, you will receive 390.40 or less. Since each point is worth \$5, the 10-point spread between bid and ask transfers \$50 from your pocket to floor traders”. (Elder, 1993)
- Volatility-based slippage- Quote: “Slippage rises with market volatility. Floor traders can get away with more in fast-moving markets. When the market begins to run, slippage goes through the roof. When the S&P 500 rallies or drops, you can get hit with a 20 to 30-point slippage, and sometimes 100 points or more”. (Elder, 1993)
- Criminal slippage- Quote: “The third kind of slippage is caused by criminal activities of floor traders. They have many ways of stealing money from customers. Some put their bad trades into your account and keep good trades for themselves” (Elder, 1993).

All of these are categorized as negative slippage since the price where the order gets filled negative to profits, however, slippage can contribute to profits and that is categorized under positive slippage. While positive slippage exists, S. Bohn (2011) suggests that, “Market practitioners know that slippage is positive on average, and that the loss associated with the slippage can easily wipe out the expected gain of an investment strategy when trading too much”. It may be by mistake, but as seen in this statement there is some room for improvement in the mutual understanding between the public and academia on what is “positive slippage”

and what is “negative slippage”, since positive slippage in Investopedia, perhaps most commonly known financial education sources, defines “positive slippage” as slippage that contributes to the profits of an investor. Adding to Elders statement that slippage is caused by volatility in the market S. Bohn states that, “slippage is the direct consequence of the correlation between the supply and demand imbalance and the price change” (Figure 4).

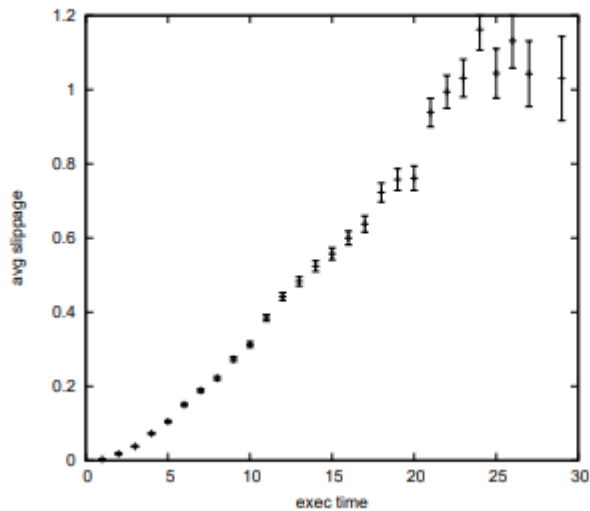


Figure 4. Average slippage as a function of the execution time [Bohn (2011)].

Because of the nature of many quantified trading algorithms, where the Buy/Sell orders are not controlled by the trader, the orders cannot be aimed into a period with low volatility, moreover, it might not be profitable in general according to Elder. Therefore, it is worth suspecting that most slippage will be negative, and it is highly unlikely that it will be positive, and that positive and negative slippage will result in no slippage by cancelling each other out. While the risk of unfavourable volatility always exists and same goes to the risk of fraud even in an online form, even the “common” slippage can have a devastating effect to a fully automated HFT trading strategy but more about this in the test result section of this thesis.

High Frequency Trading or HFT is most apparent in trading offices which use an array of algorithms and a variety of tools to trade hundreds or even thousands of times each day with a typical position holding period measured from milliseconds to minutes (Jones, 2013). If commodity markets and most equity markets might not be the best for individual HFT strategies or algorithmical trading due to slippage, that might not be the case for institutional traders who provide liquidity to the markets. Jones (2013) suggests that HFT, may have a positive effect to liquidity and potentially lower intermediate costs in the markets which could

make it easier for other automatized trading systems to operate in the markets. However, he also suggests that “The potential negative is that the speed of HFT could put other market participants at a disadvantage” (Jones, 2013). There could be various types of strategies how High Frequency Traders approach the market but the majority of HFT participants can be categorized under three types of strategies.

- First type is a formal or informal market-maker who provides liquidity to the market by aiming to buy at the bid price and sell at the ask price, thereby earning the bid-ask spread (Jones, 2013). While market makers can be an informal intermediary, they need a large size of securities to facilitate the purchases and sales. Most of them act inside large financial institutions, such as offices that make trades for banks, hedge funds or insurance companies. Often, they are a brokerage house that provides purchase and sale solutions for investors on order to keep financial markets liquid. These types of brokers can also be sub-categorized as a Dealing Desk (DD) broker who takes the “other side” of a client’s trade (Korcek, 2015) by providing clients the opportunity to trade at lower trading volumes and will earn profits when the client loses a trade. Being an intermediary, market makers control the market prices by offering fixed spreads for the client and often the exchange rates do not represent the Interbank rates (Korcek, 2015). These types of market maker practices are controlled by Securities and Exchange Commission (SEC) and by Financial Industry Regulatory Authority (FINRA).
- Second type of HFT can be categorized under Relative Value and Arbitrage Trading which can take many forms but a classical example of this is index arbitrage (Jones, C. M. 2013). “Arbitrage is the practice of identifying the price differential of the same entity in different platforms or markets and executing it” (Verma, 2010). SYP is ticker symbol for the largest exchange traded fund (ETF) that tracks the S&P 500 index, which is traded in Chicago on the Chicago Mercantile Exchange (Jones, 2013). While SYP is traded on nearly every equity trading venue in the U.S. as well as several foreign trading venues the two move almost one-to-one (Jones, 2013). “If the futures price goes up due to the arrival of buy orders, but the ETF price does not move up at the same instant, HFT would quickly buy SPY, sell S&P 500 futures contracts, and lock in a small profit on the price differential between the two instruments” (Jones, 2013). This requires extremely fast computers, network speed and location-strategic server placement that, through automatization, scan differences between the two entities and can do following transactions in milliseconds.

- Third type of HFT is directional trading where the HFT firm might base its strategy on order flow signals (Jones, 2013). This can cause substantial difficulties for a financial institution as suggested by C. M. Jones (2013) that, “if a large buy order executes at the prevailing ask price, an HFT strategy might infer that the order submitter has substantial positive information. The HFT might then respond by buying shares itself. If a large institutional trader is gradually purchasing shares of IBM, an HFT might be able to sniff this out by identifying a sequence of large buy orders over the space of several minutes. The HFT might purchase shares of IBM, driving the price up and increasing the price that the institutional trader must pay to buy IBM shares. In fact, the HFT might eventually realize its profit by selling its purchased IBM shares to the institutional trader.”

While these three categories are most commonly known, associated with trading institutions and can be associated with Quantitative Trading (QT), since many iterations of these three strategies have quantitative elements in them, it can be said that QT has become popular in FOREX amongst individual traders as well. Foreign exchange or FX market could be considered the largest market in the world with 5.1\$ trillion of daily turnover in April 2016 according to BIS (Bank For International Settlements. 2016) therefore adding to high liquidity which contributes to profitable framework of HFT. Many HFT strategies might not be profitable if slippage is involved in the trading costs and this is also relevant to individual traders who use QT strategies in the FOREX markets. If slippage is directly linked with volatility and is the difference between order on the platform and order filing, then it is linked with the nature of a broker and if the order would be directly processed then there would be little or no slippage. The development of trading systems has segmented brokers into two categories which was further reviewed by J. Korcek (2015), where one type of broker is the Dealing Desk (DD) broker and the other segment is No Deal Desk (NDD) broker (Figure 5). When in DD the broker takes the “other side” of the transaction for the client, NDD serves as the connecting element between the trader and the “other side”. No Deal Desk (NDD) brokers can be further divided into Straight Through Processing (STP) brokers and Electronic Communication Network (ECN).

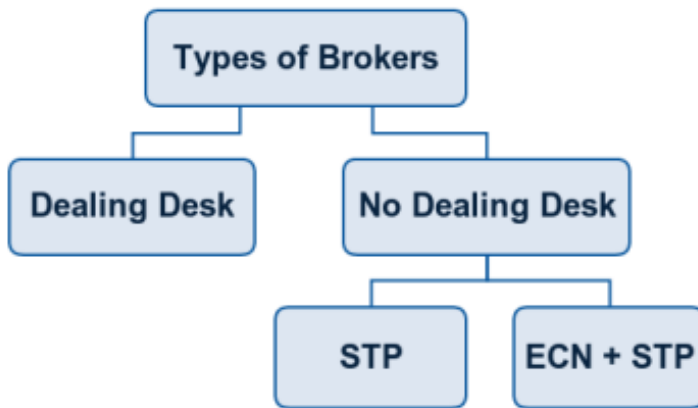


Figure 5. Types of brokers by J. Korcek (2015)

In contrast to Dealing Desk brokers, with Straight Through Processing, the transactions are fully computerized and processed immediately, without intervention of brokers in the “other side” and orders are automatically forwarded to the NDD STP brokers liquidity provider (Korcek, 2015). The liquidity providers could be banks, hedge funds, investment corporations or other brokers (Lien, 2018). Because the goal is to get the most accurate and most direct connection to the Interbank rates the best STP broker would be one that has a bank as a liquidity provider, since they have direct connection in the Interbank (Figure 6). STP broker also benefits from having multiple liquidity providers since it improves the fill rates for the clients (Lien, 2018). Today some of the biggest banks in the Interbank foreign exchange market are: JP Morgan & Chase (USA), Citicorp (USA), Deutsche Bank (Germany), HSBC (Asia).

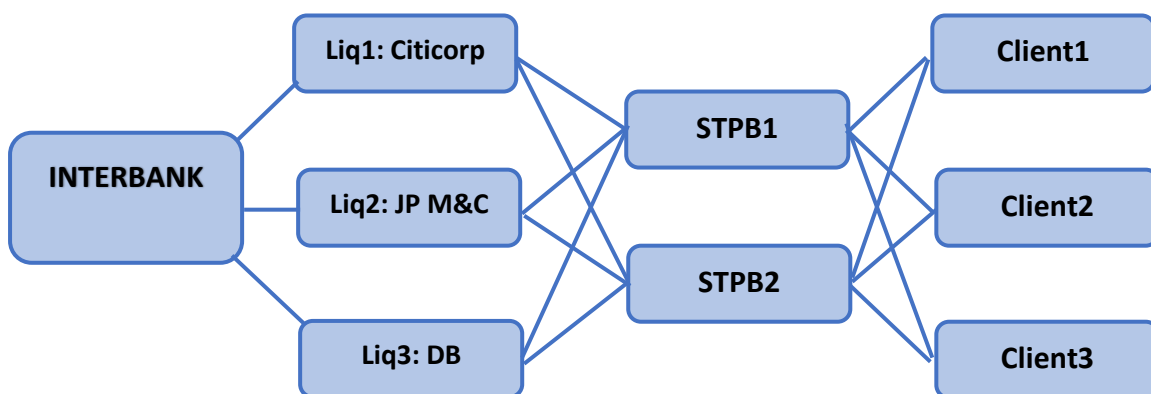


Figure 6. STP Illustration (made by the author of this thesis)

If slippage is caused through the combination of volatility and the brokers “reaction speed” then in the case of STP it might not exist at all. While the prices are usually variable with an

STP broker they correlate much more with the Interbank rates (Korcek, 2015). Supposedly, STP brokers do not go against the client's trades, but rather apply a fixed markup (automatically) to the spread that is received from the liquidity provider by applying the markup to the quoted bid/ask price before revealing it to the client on its electronic platform (Korcek, 2015). While STP could be considered perhaps the most suitable framework for applying the QT algorithm that can be developed from the back-testing (market emulation) that this thesis focuses on, the subject of STP is still relatively new and more theoretical and empirical studies are needed to provide further proof of feasibility.

While similar by initiative, automatizing transaction processes to lower transaction and labour costs, Electronic Communication Network (ECN) differs from STP by its transparency (Korcek, 2015). Unlike the STP NDD broker, where the other side is taken by brokers liquidity providers, the other side of the ECN is taken by various entities such as hedge funds, banks, mutual funds and other brokers (Korcek, 2015). A trader using an ECN broker would almost always be aware of who is on the other side of the transaction and the broker by nature is best described as Direct Access Trading because it connects various trading institutions with each other. The consequence of bypassing liquidity providers results in much bigger transactions, meaning that buying/selling in small amounts such as 100€ is simply not possible since the other side would not accept offers in that size (Korcek, 2015). Minimum deposits with an ECN broker are in the range of 50000€-100000€ (Korcek, 2015). While this could be suitable for some types of HFT, for example ones that are not dependent on liquidity, it most likely is not for the moving average type of QT that is the focus of this thesis.

2. METHODOLOGY AND DATA

2.1 Moving Averages

In contrast to the “Brownian motion” and “Random walk” where the past prices do not have any relevance to determining future prices and future prices are relative to the present price, traditional technical analysts believe that past price movements have many important indicators for future price movements. It can be said that Charles H. Dow was the first financial analyst to interpret the bigger picture and studied the ups and downs of a stock and deduced that all markets move in ups and downs creating “highs” and “lows”. Through traders favouring “highs” and “lows” create sequences of “higher highs” and “lower lows” that creates trends. While the core principle of technical analysis practitioners is that prices move in trends and that future trends can be uncovered in a timely manner, prices fluctuate and due to the fluctuations, simple concepts can be difficult to implement to take profit from “riding” a trend (Modell, & Lynngard, 2017). To cancel out the “noise” from price fluctuations, practitioners can apply a Moving Average (MA) that “smooths” the price fluctuations and identify a trend.

The development of Moving Average can be traced back to the year of 1901, although the technical analysis existed far before that and the name was applied later (McClellan Financial Publications. 2009). The Moving Average is categorised by statisticians into the family of tools called “Time Series Analysis” (McClellan Financial Publications. 2009). Both the academia and technical analysis practitioners have contributed into developing variations of the MA and creating a family of various MA-s. While there are many MA-s, the scope of this thesis and the tests include:

- Simple Moving Average (SMA)
- Exponential Moving Average (EMA)
- Double Exponential Moving Average (DEMA)
- Triple Moving Average (TEMA)

One of the reasons for the development of different moving averages could be that all moving averages are in a “lag”. The tests that will be discussed in more depth later in this thesis, and with some of the new iterations of MA-s there is the attempt to mitigate that “lag”. Most notable moving averages that are not included in the tests are:

- Hull Moving Average (HMA)
- Kaufmans Adaptive Moving Average (KAMA)

The reason for excluding HMA and KAMA were both the complexity and newness of the two moving averages but also the technical feasibility for testing in Excel.

Simple Moving Average (SMA) is the simplest moving average of the family of stochastic indicators and is the unweighted mean of an array of subsequent values. A simple example of this for an n-number of periods is:

$$1. \text{SMA}_n = (a_1 + a_2 + \dots + a_n) / n$$

When the following SMA (n+1) position value is calculated then the first value of array (a) drops out and a new value at the end of the array (a) is added and the calculation is as follows:

$$2. \text{SMA}_{n+1} = (a_{1+1} + a_{2+1} + \dots + a_{n+1}) / n$$

Exponential Moving Average (EMA), also known as the Exponentially Weighted Moving Average (EWMA) is a weighted moving average that places more weight, or importance, on the recent prices. Unlike SMA, the calculation of EMA must have a seed value (Q) and a multiplier (P). Since the first value in an array of EMA-s cannot be an EMA, because of the seed value (Q), many practitioners use SMA as the first value. An example of this for an n-number of periods is:

- $P_n = [2 / (n + 1)]$

If n was 10 then the multiplier would be:

- $P_{10} = [2 / (10 + 1)] = 0.1818$

In an array the first three values would be calculated as follows:

- $Q_{n-1} = (a_1 + a_2 + \dots + a_n) / n$
- $\text{EMA}_n = (a_n - Q_{n-1}) * P + Q_{n-1}$
- $\text{EMA}_{n+1} = (a_{n+1} - \text{EMA}_n) * P + \text{EMA}_n$

Double Exponential Moving Average (DEMA) is a more intensive weighted moving average that, by its name, gives double the amount of weight/importance of EMA to the recent prices. Much like EMA it needs seed value but in this case is dependent on EMA and requires EMA to first be calculated, so the values of DEMAs are somewhat also dependent on EMAs seed value (Q) and multiplier (P). In an array an example of this calculation would be:

Multiplier:

- $P_n = [2/(n+1)]$

Seed value:

- $Q_{n-1} = (a_1+a_2+\dots a_n)/n$

EMA array:

- $EMA_n = (a_n - Q_{n-1}) * P + Q_{n-1}$
- $EMA_{n+1} = (a_n - EMA_n) * P + EMA_n$

DEMA array:

- $DEMA_n = (2 * EMA_n - (Q_{n-1} + P * (EMA_n - Q_{n-1})))$
- $DEMA_{n+1} = (2 * EMA_{n+1} - (EMA_n + P * (EMA_{n+1} - EMA_n)))$

Triple Exponential Moving Average (TEMA) is even more intensive on the weight on the recent prices than DEMA and is perhaps the most mathematically complex of the four moving averages. In an array an example of this calculation would be:

Multiplier:

- $P_n = [2/(n+1)]$

Seed value:

- $Q_{n-1} = (a_1+a_2+\dots a_n)/n$

EMA array:

- $EMA_n = (a_n - Q_{n-1}) * P + Q_{n-1}$
- $EMA_{n+1} = (a_n - EMA_n) * P + EMA_n$

TEMA array:

- $(3*EMA_n) - (3*(Q_{n-1}+P_n*(EMA_n - Q_{n-1}))) + (Q_{n-1}+P_n*((Q_{n-1}+P_n*(EMA_n - Q_{n-1})) - Q_{n-1}))$
- $(3*EMA_{n+1}) - (3*(EMA_n + P_n*(EMA_{n+1} - EMA_n))) + (EMA_n + P_n*((EMA_n + P_n * (EMA_{n+1} - EMA_n)) - EMA_n))$

There are perhaps other iterations by academia of even more intense weighted moving averages (QEMA or Quadruple Exponential Moving Average) since by nature the intensiveness of such moving averages are infinite, however in financial markets there might not be much practical use for more intense weighted moving averages since, while they do bring the MA value closer to the price index, every following iteration smooths the “noise” less. While SMA was not included, an example of the intensiveness comparison can be viewed from the chart below (Figure 7.).



Figure 7. EUR/USD TEMA, DEMA, EMA (taken from tradingview.com)

While the Kaufman Adaptive Moving Average developed by Perry Kaufman (Kaufman, P. 2013) in 1972 is not in the scope of the testing in this thesis it could provide interesting results. KAMA is an intelligent moving average that is responsive to both trend and volatility (Stockcharts.com. 2017). Developed from EMA, it follows the price closely and simultaneously smooths out the “noise”. While EMA has two variables, seed values (Q) and multiplier (P), KAMA has three variables: Efficiency Ratio (ER), Fastest smoothing constant (FSC), Slowest smoothing constant (SSC). Much like EMA, KAMA also needs a seed value (Q) which could be SMA, EMA, DEMA or TEMA for the first value in an array of KAMA-s. An example of KAMA (10;2;30) would be:

Where:

- 10 is the number of periods for the efficiency ratio ER (variable)

- 2 is the number of periods for the fastest smoothing constant or FSC (variable)
- 30 is the number of periods for the slowest smoothing constant or SSC (variable)

To calculate ER, one would need to calculate Change (CH) and Volatility (V), where Volatility (V) is the sum of absolute value of last ten price changes. If 10 for ER were something else, V would be the sum of absolute value of that amount of price changes.

- $ER = CH/V$
- $CH = ABS(a_n - a_{n-9})$
- $V = ABS((a_n - a_{n-1}) + (a_{n-1} - a_{n-2}) + \dots + (a_{n-8} - a_{n-9}))$
- $SC = [ER \times (FSC - SSC) + SSC] \times [ER \times (FSC - SSC) + SSC]$
- $SC = [ER \times (2/(2+1) - 2/(30+1)) + 2/(30+1)] \times [ER \times (2/(2+1) - 2/(30+1)) + 2/(30+1)]$

And now it is possible to do the calculation of KAMA on an array:

- $Q_{n-1} = (a_1 + a_2 + \dots + a_n)/n$
- $KAMA_n = Q_{n-1} + SC \times (a_n - Q_{n-1})$
- $KAMA_{n+1} = KAMA_n + SC \times (a_{n+1} - KAMA_n)$



Figure 8. Price Index, SMA and KAMA comparison (taken from forexkarma.com)

There is a comparison of 20-day SMA and KAMA and provides a good visual example that KAMA is sharper and more sensitive than SMA while also being smoother than TEMA. While KAMA, TEMA and DEMA derive from EMA, the Hull Moving Average (HMA), developed

by Alan Hull, is a multiple iteration combination of Weighted Moving Average, which puts more weight on the earlier prices from the array of closing prices. Most public educative sources provide a very optimistic visual in terms of the correlation, smoothing and reactivity of the HMA relative to the current price index, however, through a deeper look into the calculation of the HMA, based on how it is calculated, real results are much different. To calculate HMA the trader should know how to calculate Weighted Moving Average. Moreover, many sources on calculating HMA could have better explanations on the steps to calculate it. An example of an HMA could be as follows:

- Define your HMA period (n) and calculate the WMA with that period
- $WMA_n = (a_1 * n) + (a_2 * (n-1)) + \dots + (a_n * (n-(n-1))) / (n + (n-1) + (n-2) + \dots + (n-(n-1)))$
- Calculate WMA with n/2 periods if period was 16 then now it is 8
- Calculate $2 * WMA(n/2) - WMA(n)$
- Calculate square root of (n) which in the case of 16 would be 4. The results of $(2 * WMA(n/2) - WMA(n))$ will be the (a) for the new WMA calculation which is the HMA.

With the same period, 16, I did an example of this calculation and made it into a chart (Figure 9.) which resulted as follows.

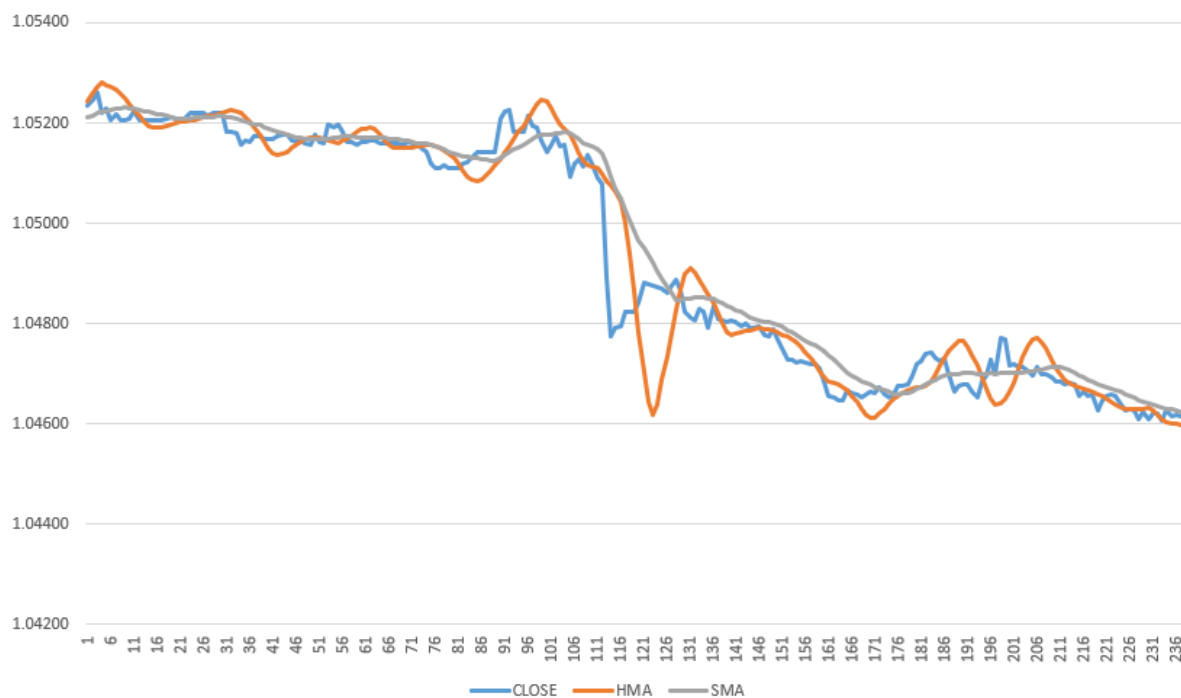


Figure 9. Price Index, HMA and SMA comparison on EUR/USD (made by the author)

While there is good correlation, smoothing and reactivity between the price index and HMA the “lag” is still present and is considerably worse more than with TEMA or DEMA. HMA follows a logical mistake in terms of “lag”. WMA-s and iterations must be calculated before HMA can be calculated and real values of the 16 period HMA start from position 19 when they should start from position 4 since the square root of 16 is 4. The reason, possibly, why most public sources show HMA without “lag” could be that the calculated results have been shifted from position 19 to position 4 leaving the last 15 positions of current data empty and all educational charts show historical data not the current one. Whatever the case could be it is not suitable for the current focus of this thesis but does bring out a good visual of “lag” which is discussed further in the following sub-chapters.

2.2 Used Data

The original goal was to create an emulation of the financial market electronic platform and to find the optimal values for the strategy variables through the Excel “Goal Seek” function and to see if the strategy can be profitable through multiple timeframes. This required a sufficient quantity of historical market data. With the growth of trading opportunity availability to the public, online trading has become more popular among the public but the availability of empirical market data has become more difficult. Most pages either provide the support services of charts and data through paid subscription or for some fee. Some sources like Yahoo finance or Google stocks, that can provide free empirical data, have information that is too vague or does not go back long enough. Because the author wanted to test the moving averages in higher frequencies, timeframe for price bars was important. The most suitable source for empirical data turned out to be LiveCharts.co.uk where it was possible to get adjusted empirical data. Because high liquidity was a factor for a suitable market for QT the decision fell in favour of EUR/USD, which is the most traded FX pair. Originally, the author adjusted the prices for 5-minute price bars for the last two years which resulted in a 140000-position list. However, with first few calculations and adjustments in Excel, the authors hardware did not efficiently manage the computing. Therefore, the list had to be divided into 19996 position sections which handled a bit better. The emulation is divided into five functional sections. Many functions seen in the emulation were done with the guidance of Excel educational videos from a YouTube channel Excellsfun (Girvin, 2016) that has hundreds of Excel dedicated videos from beginner to advanced level. The emulation is attached to this thesis on a portable memory stick as an extra.

First section, with the dimensions A8:U20004, focuses on the calculation of SMA, EMA, DEMA and TEMA. The first row 8 is reserved for the headlines. Columns D to I are for facilitating the empirical data taken from LiveCarts.co.uk, but it must be adjusted in another sheet, where the data (.csv) is adjusted into emulation suitable columns and the volatility (column) is removed. Column C gives ID to the bar of the price, which are just consecutive numbers (1,2, ...19996). Column J is reserved for the “shorter” MA1 and column K for the “longer” MA2, which are taken from columns L to S. Column L is reserved for the “shorter” SMA1 and column M for the “longer” SMA2, which have the following functions at their relative position (RP) to closing price.

- SMA1 (length 19 RP 19): =IF(C27>=\$R\$5;AVERAGE(OFFSET(I27;0;0;-\$R\$5;1));"")
- SMA2 (length 90 RP 90): =IF(C98>=\$S\$5;AVERAGE(OFFSET(I98;0;0;-\$S\$5;1));"")

Column R is reserved for the “shorter” EMA1 and column S is reserved for the “longer” EMA2, which have following functions at their RP-s to closing price.

- EMA1 (length 19 RP 19): =IF(C27>=\$R\$5;(R26+\$R\$7*(I27-R26));\$Q\$3)
- EMA2 (length 90 RP 90): =IF(C27>=\$S\$5;(S26+\$S\$7*(I27-S26));\$Q\$5)

Column P is reserved for the “shorter” DEMA1 and column Q is reserved for the “longer” DEMA2 which have following functions at their RP-s to closing price and EMA values.

- DEMA1 (length 19 RP 19): =IF(C27>=\$R\$5;2*R27-(R26+\$R\$7*(R27-R26));"")
- DEMA2 (length 90 RP 90): =IF(C98>=\$S\$5;2*S98-(S97+\$S\$7*(S98-S97));"")

Column N is reserved for the “shorter” TEMA1 and column P is reserved for the “longer” TEMA2 which have following functions at their RP-s to closing price and DEMA values.

- TEMA1 (length 19 RP 19): =IF(C27>=\$R\$5;(3*R27)-(3*(R26+\$R\$7*(R27-R26)))+(R26+\$R\$7*((R26+\$R\$7*(R27-R26))-R26));"")
- TEMA2 (length 90 RP 90): =IF(C98>=\$S\$5;(3*S98)-(3*(S97+\$S\$7*(S98-S97)))+(S97+\$S\$7*((S97+\$S\$7*(S98-S97))-S97));"")

Column J and K are reserved for the “shorter” and “longer” MA-s that take use the values of SMA, EMA, DEMA, TEMA based on preference. These change if variables at section three are changed. Column J (MA1) and K (MA2) have following functions.

- MA1 (RP19)
=IF(C27>=\$R\$5;IFS(\$O\$3="TEMA1";N27;\$O\$3="DEMA1";P27;\$O\$3="EMA1";R27;\$O\$3="SMA1";L27)+\$R\$3;"")
- MA2 (RP90) =M98-\$S\$3

Column B is reserved for the BUY/SELL signals that happen when MA1 and MA2 cross and give a “signal” where two simultaneous actions must happen BUY/Close Sell or SELL/Close Buy with a following function in Excel.

- Signal (RP316):
=IF(AND(J323<K323;J324>K324);"BUY,CloseSell";IF(AND(J323>K323;J324<K324);"SELL,CloseBuy";""))

Column A is reserved for the UniqueID which would be better described as Unique Signal because it ties the Signal (column B) to the ID (column C) and therefore to the closing price in the series of consecutive data. This is important to compact the calculated data at the second section which is the analytical part that translates into trades. Column A has the following function in Excel.

- UniqueID (RP316):
=IF(AND(B324="BUY,CloseSell");CONCATENATE(B324;C324);IF(AND(B324="SELL,CloseBuy");CONCATENATE(B324;C324);""))

All these functions must be copied in the range of 10 to 19996 in their columns to provide the quantified data for the next section. Column T and U are reserved for experimentation with the MA-s since the MA functions in the table itself should not be changed.

Second section, with dimensions of V8:AO2504, compacts the results of the signals into consecutive values automatically. Row 8 is left for the headings. With current MA intervals (19; 90) the actual table reaches the row 399 but it is important to leave room for other values if the intervals are changed. Surprisingly, Excel had no easy way to compact the values automatically and pivot tables were not suitable for the calculations that followed. Here, winning and losing trades are calculated, various costs and leverage are added to the trades.

Column V is reserved for UniqueID values that are compacted into consecutive values and those are taken from column A. Various videos from Excellfun (33) helped a lot and it took many days to get the function right. Column V has the following function.

- UniqueID (RP10):

$$=IF(ROWS(\$V\$9:V10)>COUNTA(\$A\$9:\$A\$20108);"";INDEX(\$A\$9:\$A\$20108;AGGREGATE(15;6;(ROW(\$A\$9:\$A\$20108)-ROW(\$A\$9)+1)/(\$A\$9:\$A\$20108<>"");ROWS(\$V\$9:V10))))$$

Column W is reserved for the “signal” and serves as control function for column V through observation eg. if UniqueID is BUY,CloseSell316 the control signal next to it (at column W) should be BUY,CloseSell. Column W has the following function.

- Signal (RP10): =VLOOKUP(V10;A10:M20108;2;FALSE)

Columns X to AD show the corresponding: TIME, OPEN, HIGH, LOW, CLOSE, MA1, MA2 to the UniqueID from section one. Functions for the X to AB columns are.

- Time (RP9): =VLOOKUP(V9;A9:M20108;4;FALSE)
- Open (RP9): =VLOOKUP(V9;A9:M20108;6;FALSE)
- High (RP9): =VLOOKUP(V9;A9:M20108;7;FALSE)
- Low (RP9): =VLOOKUP(V9;A9:M20108;8;FALSE)
- Close (RP9): =VLOOKUP(V9;A9:M20108;9;FALSE)
- MA1 (RP9): =VLOOKUP(V9;A9:M20108;10;FALSE)
- MA2 (RP9): =VLOOKUP(V9;A9:M20108;11;FALSE)

Column AE is reserved for the values of price change between two “signals” and this was the reason why the UniqueID-s had to be compacted, because the positions signals change, and Excel does not track changes in that way or at least the author could not find a simpler way to make the price change calculations adapt to “signal” position changes. Column AE has the following function and cell AE9 is blank.

- Change (RP10) =(AB9-AB10)/AB9

Column AF is reserved for the values of slippage, which currently is just a fixed number 0.0005. Column AG is reserved for the values of change with slippage and currently function is done without slippage, until a better quantification of slippage is done. Column AF has the following function and cell AF9 is blank.

- Change with slippage (RP10) =(AB9-AB10)/AB9

Column AH calculates the WON/LOST trades based on “change” relative to the “signal” and column AI should include the slippage into the calculations but currently both are the same

because calculations are without slippage. Column AI has the following function and cell AI9 is blank.

- WON/LOST with slippage (RP10):
=IF(AND(W10="BUY,CloseSell";AG10>0);"WON";IF(AND(W10="SELL,CloseBuy";AG10<0);"WON";"LOST"))

Columns AJ and AK are reserved for experimentation with slippage to compare with other results. Column AN is reserved for state of current equity on account. Column AN has the following function and cell AN9 equals AN5 (section four).

- Equity (RP10) =AL10+AN9

Column AL is reserved for PROFIT/LOSS of current trade based on “change” and lots “in trade”. Column AL has the following function and cell AL9 gives an error.

- PROFIT/LOSS (RP10)
=IF(AND(W10="BUY,CloseSell");(AM9*AG10);IF(AND(W10="SELL,CloseBuy");(AM9*(-AG10));""))

Column AM is reserved for leveraged equity in trade and heading is named Equity in Trade. It takes variables from both section two and section four. Column AM has the following function.

- Equity in Trade (RP9): =AN9*\$AN\$6*\$AN\$7

Column AO is reserved for equity calculations where fixed transaction costs have been discounted. Cell AQ6 has the fixed transaction cost that is changeable. I tested with various fixed transaction costs (4.95€, 10.95€, 15.95€) and it had little effect on average profitability of the QT strategy. Column AO has the following function and cell AO9 is blank.

- EquityWithTradeOpeningCost (RP10): =AN10-\$AQ\$7

Section three has dimensions of O2 to S7 and is for the variables that MA-s in section one use. This test was done keeping the QT trading and algorithm writing in mind and has some things that can be written into a code, but the author has not seen that with DD brokers. Cell O2 and P2 are reserved for headings (MA1 and MA2) and O3 and P3 was supposed to be a text box where one could write MA references (TEMA, DEMA, EMA or SMA). While it works for O3 the same did not work for P3 so in section one MA2 has to be manually

referenced. Cells Q2 and Q4 are reserved for headings (Seed 1 and Seed 2) and the seed values in cells Q3 and Q5 change automatically when other variables in this section are changed. They change the seed values required by EMA calculations and therefore by DEMA and TEMA. They have the following functions (after entering the functions into Excel you must press the Ctrl+Shift+Enter to get the curly brackets for the multicell array formula).

- Seed 1 $\{=INDEX(L9:L20004;MATCH(TRUE;L9:L20004<>"";0))\}$
- Seed 2 $\{=INDEX(M9:M20004;MATCH(TRUE;M9:M20004<>"";0))\}$

Cells R2 and S2 are reserved for headings (Shifter1 and Shifter2) and R3 and S3 are for values. These are particularly interesting since they are not available with DD brokers but can be added to an algorithm. They shift the MA-s in a vertical direction and must be in opposite direction from each other. In that case the MA1 and MA2 crossover points on the MA-s curve move closer to the closing price. These values are changeable and MA-s at section one includes these in the calculation. Cells R4 and S4 are reserved for headings (Period 1 and Period 2) and R5 and S5 for values. Changing the values on R5 changes MA1 (SMA1, EMA1, DEMA1 and TEMA1) intervals in section one and the automatic values in section three. Changing the values on S5 changes MA2 (SMA2, EMA2, DEMA2 and TEMA2) intervals in section one and the automatic values in section three. Cells R6 and S6 are reserved for headings (Alpha1 and Alpha2) and cells R7 and S7 have the Alpha values which are the multipliers required by EMA1 and EMA2. Cells R7 and S7 have the following functions.

- Alpha1: $=2/(\$R\$5+1)$
- Alpha2: $=2/(\$S\$5+1)$

The fourth section, with dimensions AM5 to AN7, contains the variable inputs for used in section two. Cells AM5 to AM7 are reserved for headings (Total Start Equity, Amount Invested, Leverage) and AN5 to AN7 contain the values which influence the results in section two and therefore in section five. Cell AN5 can be any amount of cash, AN6 can be a number between 0 and 1, AN7 is leverage can be a round number between 1 and 1000.

The fifth section, with dimensions of AQ12 to AR37, sums up the results of the emulation and is the basis for the analysis for the next chapter. Column AQ is reserved for the headings and column AR is for the formulas.

- Cell AR 15 $=AN7$ shows the leverage for the current strategy.

- Cells AR 16 =O3 and AR 14 (=P3) show which MA-s are currently used under MA1 and MA2.
- Cell AR 17: =COUNTIFS(W9:W605;"SELL,CloseBuy";AI9:AI605;"LOST") shows how many trades were LOST with current intervals.
- Cell AR 18: =COUNTIFS(W9:W605;"BUY,CloseSell";AI9:AI605;"Won") shows how many trades were WON with current intervals.
- Cell AR 19: =(-
(AVERAGEIFS(AG10:AG605;W10:W605;"SELL,CloseBUY";AI10:AI605;"LOST"
))) shows the average value of all LOST BUY trades.
- Cell AR 20: =(-
(AVERAGEIFS(AG10:AG605;W10:W605;"SELL,CloseBUY";AI10:AI605;"WON")
) shows the average value of all WON BUY trades.
- Cell AR 21:
=AVERAGEIFS(AG10:AG605;W10:W605;"BUY,CloseSell";AI10:AI605;"LOST")
shows the average value of all LOST SELL trades.
- Cell AR 22:
=AVERAGEIFS(AG10:AG605;W10:W605;"BUY,CloseSell";AI10:AI605;"WON")
shows the average value of all WON SELL trades.
- Cell AR 23: =(AR15*AR19)+(AR16*AR20)+(AR17*AR21)+(AR18*AR22) shows the total profitability of all trades within the timeframe and is perhaps the most important indicator of the test.
- Cell AR 24:
=AVERAGEIFS(AL10:AL605;W10:W605;"SELL,CloseBUY";AI10:AI605;"LOST"
) shows the average value of LOST BUY trades in money.
- Cell AR 25:
=AVERAGEIFS(AL10:AL605;W10:W605;"SELL,CloseBUY";AI10:AI605;"WON"
) shows the average value of WON BUY trades in money.
- Cell AR 26:
=AVERAGEIFS(AL10:AL605;W10:W605;"BUY,CloseSELL";AI10:AI605;"LOST"
) shows the average value of LOST SELL trades in money.
- Cell AR 27:
=AVERAGEIFS(AL10:AL605;W10:W605;"BUY,CloseSELL";AI10:AI605;"WON"
) shows the average value of WON SELL trades in money.

- Cell AR 28: $=AR15*AR24+AR16*AR25+AR17*AR26+AR18*AR27$ shows the amount of profit by the end of the period.’
- Cell AR 29: $=(AR28/AN9)$ shows the amount of profit by the end of the period in percentage and is perhaps the second most important indicator in the sum-up.
- Cell AR 30: $(- (MAXIFS(AG10:AG605;W10:W605;"SELL,CloseBUY";AI10:AI605;"LOST")))$ shows the maximum BUY trade LOST.
- Cell AR 31: $(- (MINIFS(AG10:AG605;W10:W605;"SELL,CloseBUY";AI10:AI605;"WON")))$ shows the maximum BUY trade WON.
- Cell AR 32: $(- (MINIFS(AG10:AG605;W10:W605;"SELL,CloseBUY";AI10:AI605;"LOST")))$ shows the minimum BUY trade LOST
- Cell AR 33: $(- (MAXIFS(AG10:AG605;W10:W605;"SELL,CloseBUY";AI10:AI605;"WON")))$ shows the minimum BUY trade WON
- Cell AR 34: $=MINIFS(AG10:AG605;W10:W605;"BUY,CloseSell";AI10:AI605;"LOST")$ shows the maximum SELL trade LOST.
- Cell AR 35: $=MAXIFS(AG10:AG605;W10:W605;"BUY,CloseSell";AI10:AI605;"WON")$ shows the maximum SELL trade WON.
- Cell AR 36: $=MAXIFS(AG10:AG605;W10:W605;"BUY,CloseSell";AI10:AI605;"LOST")$ shows the minimum SELL trade LOST.
- Cell AR 37: $=MINIFS(AG10:AG605;W10:W605;"BUY,CloseSell";AI10:AI605;"WON")$ shows the minimum SELL trade WON.

In the current emulation, there are six variables that affect the MA-s and three variables that affect their combinations. Combining the “Goal Seek” with variables in section three and four to search for the maximum value at cell AR23 would result in self-optimizing the strategy. However, because the Excel and my current hardware is insufficient to calculate “Goal Seek” this will be a subject for future developments. It is likely that the values in section three and

four should have ranges, otherwise “Goal Seek” search can come up with results that are not applicable to actual markets. Section five also sums up the results from testing that were in the scope of this thesis, which is the subject of the following chapter.

3. DATA ANALYSIS

3.1 In and Out sample testing

The emulation was built by observing the electronic platforms of FOREX markets and the principles implemented in them and the profitable results for the first timeframe were achieved through trial and error. During this thesis the author tested both with and without slippage with EUR/USD market of three-month periods through the years of 2017 and 2018 (Table 1.) with 1996 five-minute Japanese Candlesticks per timeframe. The reason why this thesis focuses heavily on slippage is because in this type of QT strategy slippage influences the results of the tests by a substantial amount. While positive results were without slippage and resulted in 85% profit by the end of the period the same strategy with slippage (negative 0.0001) included resulted in -35% by the end of the period, however both tests had fixed transaction costs included which did not have this effect on the end results.

Table 1. Timeframes

Data A	02.01.2017-07.04.2017
Data B	07.04.2017-13.07.2017
Data C	13.07.2017-18.10.2017
Data D	18.10.2017-25.01.2018
Data E	25.01.2018-02.05.2018
Data F	02.05.2018-07.08.2018
Data G	07.08.2018-09.11.2018

Source: Compiled by the author

The emulation was built around Data A. First creating the SMA formulas and section two and the other moving averages were added later with the other sections. After multiple tries, mistakes and iterations the profitable MA pair for Data A was 19 and 90. Section five (Table 2.) was added to the emulation after finding the profitable MA intervals to find out other relevant results. From the results it is visible that with Data A the all the winning trades against all the losing trades resulted in 3.798% profitability and by the end of the period growth of equity was 85% and at its peak (during the period) the growth was over 300% where the latter was during a period where successful trades were much more frequent than losing trades.

Table 2. Data A results from section five (name/value)

Leverage	300
MA1	TEMA1
MA2	SMA2
BuyTradesLost	148
BuyTradesWon	47
SellTradesLost	138
SellTradesWon	57
AVGBuyTradeLost(%)	-0.065%
AVGBuyTradeWon(%)	0.259%
AVGSELLTradeLost(%)	-0.073%
AVGSELLTradeWon(%)	0.199%
TOTAL(Profit/Loss(%))	3.798%
AVGBuyTradeLost(InTrade)	-46.83
AVGBuyTradeWon(InTrade)	161.31
AVGSELLTradeLost(InTrade)	-53.49
AVGSELLTradeWon(InTrade)	133.06
TOTALProfit(InTrade)	852.33
TOTALProfit(InTrade(%))	85%
MAXBuyLost	-0.255%
MAXBuyWon	0.942%
MINBuyLost	0.000%
MINBuyWon	0.005%
MAXSellLost	-0.361%
MAXSellWon	0.621%
MINSellLost	-0.0009%
MINSellWon	0.0028%

Source: Compiled by the author

This strategy appears to follow the 20/80 rule meaning that 20% of trades account for 80% of the profits where the winning trades have more weight than the losing ones. This can be seen from the AVGBuy, AVGSell WON vs AVGBuy, AVGSell LOST where the average winning trades are significantly higher than the losing ones. However, while testing the other timeframes from Table 1. with the same variables from Table 3. the emulation came up with interesting results (Table 4.).

Table 3. Variables used in the test of Data A (name/value)

MA1 and MA 2	TEMA and SMA
Shifter 1 and Shifter 2	-0.00002 and -0.00015
Period 1 and Period 2	19 and 90
Total Starting Equity	1000
Amount invested	0.1
Leverage	300

Source: (made by the author)

Results from Data B showed that the losing trades against winning trades were -1.8746% and by the end of the period resulted in -68.68% loss, meaning that the same variables might not bring profit if applied to other future periods, because it was likely optimized for the current period and that trend developments in timeframes are not the same. Results from Data C, D, E, F and G (Table 4.) can be seen from the table below and the full overview can be seen from the appendix.

Table 4. Profitability results in section five with Table 3 variables with Data C, D, E, F and G (name/value)

Data C TOTAL(profit/loss) % and TOTALProfit%	0.706% and -28.04%
Data D TOTAL(profit/loss) % and TOTALProfit%	-2.071% and -66.34%
Data E TOTAL(profit/loss) % and TOTALProfit%	-4.483% and -84.52%
Data F TOTAL(profit/loss) % and TOTALProfit%	-0.161% and -43.43%
Data G TOTAL(profit/loss) % and TOTALProfit%	-2.356% and -71.06%

Source: (made by the author)

One of the interesting things that the testing results show is that the winning trades against losing trades % can be in fact positive yet there can exist loss at the end of the period as seen from the results of Data C. Also using the Shifter as a variable increased the profitability of the results on Data A. The shifter is a number that moves the MA-s vertically and should always be opposite in the MA1 and MA2 functions from each other. When the Shifters are applied then the crossover points, in various locations, on the MA-s move closer to the closing price. While with Data A the shifters were as seen in the variables table (Table 3.) and resulted in 3.798% for the winning against losing and 85% by the end of the period, without them (shifter=0) the same variables resulted in 0.789% for the winning against losing and -32% by the end of the period.

The other interesting thing that the results show is that the winning trades against losing trades are not necessarily correlating with the losses by the end of the period. When looking at Data B results the TOTAL(profit/loss) % was -1.8746% and the TOTALProfit% was -68.68% and

in Data D it was -2.071% and -66.34%. If it were in correlation then the TOTALProfit% absolute value in Data D results could be higher than in Data B because the TOTAL(profit/loss)% in Data D is higher than in Data B. This shows that the trend developments in one timeframe do not necessarily follow the same rules as the other periods. This, in turn, proposes a new challenge for the “Goal Seek” function. If the timeframe periods are different, in trend development, what is their mutual similarity, and would that result in a profitable % in the losing trades against winning trades by testing the timeframes simultaneously for the same MA pair intervals and other variables. If those intervals would result in a profitable MA pair, then that could increase the likeliness of the following periods being profitable as well.

3.2 Further Developments

The proof to the fact that all MA-s are in a lag was obtained during the testing when by mistake the author entered the MA1(19) to a position that was 4 bars shorter than the actual moving average length. While this (Table 5.) may seem like something extremely positive it still counts as “seeing into the future” because the last four positions in MA1 have no values, which means that deals cannot be made in real time with these settings. Current results were achieved with Data A but these settings were also tested with Data B which also resulted in absurdly high profitability of TOTAL(Profit/Loss)% 22.957% and TOTALProfit(InTrade)% 54565%. While Data B is lower, in profitability, than Data A it shows that this could be profitable trough other timeframes as well in comparison to the original testing.

Table 5. No lag results

Leverage	300
MA1	SMA1
MA2	TEMA2
BuyTradesLost	58
BuyTradesWon	89
SellTradesLost	56
SellTradesWon	91
AVGBuyTradeLost(%)	-0.043%
AVGBuyTradeWon(%)	0.186%
AVGSELLTradeLost(%)	-0.052%
AVGSELLTradeWon(%)	0.173%
TOTAL(Profit/Loss(%))	26.857%
AVGBuyTradeLost(InTrade)	-5501.07
AVGBuyTradeWon(InTrade)	11453.58
AVGSELLTradeLost(InTrade)	-5351.92
AVGSELLTradeWon(InTrade)	14362.43
TOTALProfit(InTrade)	1707579.91
TOTALProfit(InTrade(%))	170758%
MAXBuyLost	-0.138%
MAXBuyWon	1.081%
MINBuyLost	0.000%
MINBuyWon	0.001%
MAXSellLost	-0.211%
MAXSellWon	0.843%
MINSellLost	-0.0009%
MINSellWon	0.0009%

Source: Compiled by the author

However, AI, known for its ability to learn, could be one potential candidate for generating the missing four values based on trial and error. For example, it could generate values into the positions, based on previous data and MA data, and another program tells the AI if the generated values are CORRECT or NOT based on the actual moving average values. By both the academia and the practitioners, some efforts to include AI into the financial markets are already being explored with the Intelligent Moving Average (Marques, N. C., & Gomez, C. 2010) that in the financial markets should decide between different moving averages on which MA is most suitable for the current situation simultaneously smoothing and mitigating the lag. Attempts on including machine learning for SMA Crossover strategies for the financial markets have also been explored regarding by J. I. Larsen (2010). However, the author suspects that being 50% correct from all the values generated would not result in $TOTAL(Profit/Loss)\% = 26.857\% * 0.5 = 13.428\%$ but being, for example, 70% accurate (near exact) and 30% exact could, meaning that closer values to the actual MA future values are more important than being 50% correct and 50% random.



Figure 10. No Lag Graph position 1-1441

Source: Compiled by the author

On a purely basic observation (Figure 10) MA1 (orange), mostly, crosses MA2(90) (grey) when the MA1(19) line is straight and not in a curve so if the four values were just an extension (calculated results) of the current MA1 it could also bring interesting results as a test. For the next closing price, the first extension would be corrected by the new MA1 value, three of the following extension values would be recalculated and a new extension value would take the last position. While both the AI and the extension may have high potential in providing good results for the tests both need to be confirmed through further development and research.

The more intensive moving averages (EMA, DEMA, TEMA) could occupy the last positions of the MA1(19). While EMA uses the previous EMA value in the current EMA value calculation it could use the SMA value. This would also affect the following DEMA and TEMA values. Small iterations (changes in Bold) would have to be made to the EMA formula.

- EMA using previous EMA: =IF(C27>=\$R\$5;(R26+\$R\$7*(I27-R26));\$Q\$3)
- EMA using current SMA instead of previous EMA:
=IF(C27>=\$R\$5;(L27+\$R\$7*(I27-L27));\$Q\$3)

This by nature is an additional type of MA for the tests and provides additional opportunity for testing let's call it Adaptive Triple Exponential Moving Average (ATEMA). While the

goal was for the EMA, DEMA and TEMA to occupy the last three positions of the MA1 the results of section five (Table 6.) were more like the original test (Table 2.) than the No Lag (Table 5.) results.

Table 6. MA1 = ATEMA section five results

Leverage	300
MA1	TEMA1
MA2	TEMA2
BuyTradesLost	224
BuyTradesWon	74
SellTradesLost	205
SellTradesWon	93
AVGBuyTradeLost(%)	-0.041%
AVGBuyTradeWon(%)	0.160%
AVGSELLTradeLost(%)	-0.050%
AVGSELLTradeWon(%)	0.121%
TOTAL(Profit/Loss(%))	3.683%
AVGBuyTradeLost(InTrade)	-28.00
AVGBuyTradeWon(InTrade)	95.33
AVGSELLTradeLost(InTrade)	-33.97
AVGSELLTradeWon(InTrade)	75.24
TOTALProfit(InTrade)	815.56
TOTALProfit(InTrade(%))	82%
MAXBuyLost	-0.268%
MAXBuyWon	1.001%
MINBuyLost	0.000%
MINBuyWon	0.002%
MAXSellLost	-0.296%
MAXSellWon	0.805%
MINSellLost	0.0000%
MINSellWon	0.0009%

Source: Compiled by the author

The latter may be because MA1 is formed after the last position (ATEMA) in the line of MA1 and therefore is not SMA as seen in the No Lag (Table 5. No lag results). When the TOTALProfit(InTrade)% and TOTAL(Profit/Loss)% is similar to the original test results (Table 2. Section five results) the ATEMA test has 34.56% more trades, which could be because the first one has SMA2 as MA2 instead of TEMA2. While the latter is like the original test results, MAXBuyWon (1.001%) is like the No Lag results (1.081%) the same can be said about MAXSellWon (0.805%) in comparison to No Lag (0.843%). ATEMA was also tested on Data B, which in comparison to original testing on Data B proved to more profitable with TOTALProfit(InTrade)% of -34% and TOTAL(Profit/Loss)% of 0.572% while the original on Data B had TOTALProfit(InTrade)% of -64% and TOTAL(Profit/Loss)% -1.8746%. Other results (Table 7. Data C, D, E, F, G section five ATEMA) on Data sets C, D, E, F, G, at times, showed more favourable indications.

Table 7. Profitability results in section five with Table 3 variables while MA1=ATEMA with Data C, D, E, F and G (name/value)

Data C TOTAL(profit/loss) % and TOTALProfit%	0.188% and -27.24% (better)
Data D TOTAL(profit/loss) % and TOTALProfit%	-2.670% and -68.95% (worse)
Data E TOTAL(profit/loss) % and TOTALProfit%	-4.999% and -84.77% (worse)
Data F TOTAL(profit/loss) % and TOTALProfit%	-2.316% and -68.49% (worse)
Data G TOTAL(profit/loss) % and TOTALProfit%	1.447% and -9.27% (significantly better)

Source: Compiled by the author

The reason why section five results have multiple different averages about the analysis is so that various further analysis could be done, and hidden information could be uncovered easily. This strategy's profitability could be further explored through calculating the profitability of BUY and SELL signals within the timeframes (Table 8. BUY and SELL for original and ATEMA comparison). In real time it would not be hard to write an algorithm that only does BUY signals or SELL signals instead of both. For the original (Table 2. Section five results) the calculations would be following.

- Original BUY signal profitability: $\text{BuyTradesWon} * \text{AVGBuyTradeWon\%} + \text{BuyTradesLost} * \text{AVGBuyTradeLost} \Rightarrow 47 * 0.259\% + 148 * (-0.065\%) = 12.173\% - 9.62\% = 2.553\%$
- Original SELL signal profitability: $\text{SellTradesWon} * \text{AVGSellTradeWon} + \text{SellTradesLost} * \text{AVGSellTradeLost} \Rightarrow 57 * 0.199\% + 138 * (-0.073\%) = 11.343 - 10.074 = 1.269\%$

These values can show the BUY or SELL bias of the MA crossover (Table 12. MA crossover BUY/SELL bias comparison between original and ATEMA) settings between timeframes and can provide further information about using BUY or SELL signals if periods in timeframes have similar negative or positive through multiple years.

Table 12. MA crossover BUY/SELL bias comparison between original and ATEMA

Data A	BUY (original): 2.553% BUY(ATEMA): 2.656%	SELL (original): 1.269% SELL (ATEMA): 1.003%
Data B	BUY (original): 2.615% BUY(ATEMA): 3.862%	SELL (original): -4.576% SELL (ATEMA): -3.275%
Data C	BUY (original): 1.906% BUY(ATEMA): 2.350%	SELL (original): -1.223% SELL (ATEMA): -2.161%
Data D	BUY (original): 1.602% BUY(ATEMA): -0.022%	SELL (original): -3.529% SELL (ATEMA): -2.590%
Data E	BUY (original): -3.869% BUY(ATEMA): -2.756%	SELL (original): -0.534% SELL (ATEMA): -2.271%
Data F	BUY (original): -1.924% BUY(ATEMA): -2.784%	SELL (original): 1.751% SELL (ATEMA): 0.592%
Data G	BUY (original): -2.310% BUY(ATEMA): 0.035%	SELL (original): -0.088% SELL (ATEMA): 1.435%

Source: Compiled by the author

As seen from the original testing with MA crossover TEMA1(19) and SMA2(90) BUY signals performed significantly better than SELL signals for Data sets A, B, C, D and roughly during the turn of the year, with Data sets E, F and G, SELL signals started performing better than BUY signals. It would be interesting to find out if there is some consistency in this yearly turn when more years would be involved. If so, this signal change on the yearly turn would not be difficult to include into the algorithm. The same applies, somewhat, to the ATEMA tests. Moreover, when the original test on Data sets B, C, D, E, F and G were not profitable, using only BUY signal on Data sets B, C and D would turn them profitable and using SELL signal on Data sets E, F and G would turn them somewhat profitable or less costly. As seen from the No Lag test (Table 5. No Lag results) the growth of the TOTAL(Profit/Loss)% can exponentially increase TOTALProfit(InTrade)%, therefore decreasing the amount of losing trades and/or less profitable can have significant impact on the overall profitability of the results. Moreover, in the simultaneous testing of multiple timeframes with “Goal Seek” positive values of the BUY/SELL bias can be set as the goal instead of the TOTAL(Profit/Loss)% and the TOTALProfit(InTrade)% as suggested earlier. This probably would provide more flexibility to the calculations.

The last option how to improve the profitability of the tests and by extension the trading strategy is to remove the signals during flats that seem to happen during the timeframes. While some sources suggest that the best times for trading are 7.00 pm.- 11.00 am. UK time and therefore 9.00 pm. – 1.00 pm Tallinn (Rodriguez, 2014. 14. February), however, better way to get rid of (reoccurring) flats would be by locating them through multiple years. This can have notable impact on the section five results and by extension on the profitability of the settings. It is highly likely that this, with currently not removed flats, accounts to a large proportion of the BuyTradesLost and SellTradesLost (Table 6. ATEMA section five results). This is because with longer flats the MA-s start to clutter together and then start doing small trades that add up and move in unfavourable directions because the MA-s are not able to adapt to such small changes profitably. This is even worse in real time because the Fixed Transaction Costs are used every time when these small trades are opened and closed.

CONCLUSION

Motivated by the continuous interest towards trading the primary goal of my bachelor thesis was to further explore the potential of quantified trading and technical analysis. While options were open to write about other subjects, quantified trading was appealing for me because it mostly functions on technical analysis which by nature does not include my emotional leanings in a trading environment and can be automated. This thesis revolves around my own Excel market emulation that focuses on moving averages and their potential for gains in crossover strategies. The emulation itself was built to be used by algorithmical traders for finding suitable setting for moving average crossover strategy and further research and development.

First chapter focuses on various theories developed over decades that have influenced modern technical analysis with a heavier focus on the theories, such as “Random Walk”, “Dow Theory” and “Nature’s Law”, that laid the groundwork for technical analysis discussed in later chapters. It also introduces the basics of charting, technical analysis, the difference between chart based technical analysis and quantified technical analysis and what are the benefits of using quantified technical analysis. The second part of the first chapter looks on the development of various markets and views through their limitations, applicable markets for quantified trading strategies. While most suitable markets for quantified trading is FOREX it is also reflected that stock exchange could facilitate some HFT and QT strategies as well, but in later chapters I focused on FOREX EUR/USD market to explore in greater depth the quantified specifics of the market.

Second chapter takes into scope the various moving averages, SMA, EMA, DEMA, TEMA, that will be further explored in a crossover strategy in quantified trading emulation. While HMA and KAMA are left out of scope of testing in the following chapters its qualities are explored, and the reader of this thesis can test those moving averages in the emulation as well. Also, it is noted in this chapter that there are various other iterations of MA-s that can be explored and used in this emulation, one of which is explored in greater depth in the following chapters. This subchapter also brings out the differences between the MA-s that are in the scope. Second subchapter of this chapter focuses on the data that was used during the empirical part of the testing and explains in explicit detail how the emulation was built and what each

formula does, giving the reader the opportunity to replicate the emulation and the results explored in the following chapters.

The first subchapter of the third chapter focuses on the analysis of the original tests around which the emulation was built and introduces seven timeframes consisting of 19996 five-minute Japanese Candlestick Bars. It also points out which variables are changeable in the multivariable equations that determine the profitability of the emulation. The author also introduces a variable (the shifter) that can, within the emulation, move the crossover points in all crossovers, to a profitable direction in some crossovers. The lag of the moving average is also explored here, and suggestions are presented for further research and development for MA value generation. The second subchapter of the third chapter introduces a new moving average, ATEMA, and explores in even greater depth the results of the tests done through the seven timeframes. It is explained here that the goal is a consistently profitable setting that could be integrated into real-time trading. The variables are the crossover MA-s (SMA, EMA, DEMA, TEMA and ATEMA), their intervals, the shifter, starting equity, percentage invested and leverage. Further testing suggests that EUR/USD market is BUY/SELL signal biased and this type of bias turning could occur every year. Moreover, it is also suggested that the “Goal Seek” could be used search the correct variables for highest positive values exploiting the BUY/SELL bias.

While this thesis explored in depth how moving averages behave in a quantified trading method, it also provided a tool for further testing and raised questions for developing better tools that can answer them. I suspect that profitable algorithms for MA crossover QT can be developed through the theoretical groundwork explored here and developing the tools required to answer the questions, raised during this thesis, is a great driver for master studies of the financial field or programming.

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APPENDIX

Appendix 1. Empirical data Example.

Local	time	Open	High	Low	Close
11.01.2019	00:00:00.000	1.14994	1.15003	1.14964	1.14973
11.01.2019	01:00:00.000	1.14973	1.15082	1.14961	1.15081
11.01.2019	02:00:00.000	1.15082	1.1517	1.15058	1.15113
11.01.2019	03:00:00.000	1.15113	1.15227	1.1507	1.15177
11.01.2019	04:00:00.000	1.15177	1.15249	1.15133	1.15218
11.01.2019	05:00:00.000	1.15218	1.15277	1.15186	1.15248
11.01.2019	06:00:00.000	1.15248	1.153	1.15225	1.15289
11.01.2019	07:00:00.000	1.1529	1.15308	1.15217	1.15253
11.01.2019	08:00:00.000	1.15253	1.15291	1.15171	1.15227
11.01.2019	09:00:00.000	1.15226	1.1532	1.15216	1.15261
11.01.2019	10:00:00.000	1.1526	1.153	1.15173	1.15291
11.01.2019	11:00:00.000	1.15293	1.15295	1.15164	1.15196
11.01.2019	12:00:00.000	1.15197	1.15403	1.15155	1.15345
11.01.2019	13:00:00.000	1.15345	1.15346	1.15188	1.15318
11.01.2019	14:00:00.000	1.15319	1.15364	1.15221	1.15278
11.01.2019	15:00:00.000	1.15279	1.15356	1.152	1.15265
11.01.2019	16:00:00.000	1.15265	1.15269	1.1458	1.14701
11.01.2019	17:00:00.000	1.14698	1.14811	1.14618	1.14773
11.01.2019	18:00:00.000	1.14774	1.14794	1.14646	1.14781
11.01.2019	19:00:00.000	1.14781	1.14858	1.14776	1.14823
11.01.2019	20:00:00.000	1.14823	1.14837	1.14695	1.14708
11.01.2019	21:00:00.000	1.14707	1.14729	1.1463	1.1465
11.01.2019	22:00:00.000	1.14651	1.14654	1.1458	1.14626
11.01.2019	23:00:00.000	1.14626	1.14692	1.14601	1.14656
12.01.2019	00:00:00.000	1.14656	1.14656	1.14656	1.14656

Source: (<http://www.livecharts.co.uk/historicaldata.php>)

Appendix 2. Data A results from 02.01.2017-07.04.2017 with Table 3. variables

Leverage	300
MA1	TEMA1
MA2	SMA2
BuyTradesLost	148
BuyTradesWon	47
SellTradesLost	138
SellTradesWon	57
AVGBuyTradeLost(%)	-0.065%
AVGBuyTradeWon(%)	0.259%
AVGSELLTradeLost(%)	-0.073%
AVGSELLTradeWon(%)	0.199%
TOTAL(Profit/Loss(%))	3.798%
AVGBuyTradeLost(InTrade)	-46.83
AVGBuyTradeWon(InTrade)	161.31
AVGSELLTradeLost(InTrade)	-53.49
AVGSELLTradeWon(InTrade)	133.06
TOTALProfit(InTrade)	852.33
TOTALProfit(InTrade(%))	85%
MAXBuyLost	-0.255%
MAXBuyWon	0.942%
MINBuyLost	0.000%
MINBuyWon	0.005%
MAXSellLost	-0.361%
MAXSellWon	0.621%
MINSellLost	-0.0009%
MINSellWon	0.0028%

Source: Compiled by the author

Appendix 3. Data B results from 07.02.2017-13.07.2017 with Table 3. variables

Leverage	300
MA1	TEMA1
MA2	SMA2
BuyTradesLost	167
BuyTradesWon	53
SellTradesLost	176
SellTradesWon	44
AVGBuyTradeLost(%)	-0.064%
AVGBuyTradeWon(%)	0.251%
AVGSELLTradeLost(%)	-0.071%
AVGSELLTradeWon(%)	0.180%
TOTAL(Profit/Loss(%))	-1.846%
AVGBuyTradeLost(InTrade)	-30.87
AVGBuyTradeWon(InTrade)	119.89
AVGSELLTradeLost(InTrade)	-35.61
AVGSELLTradeWon(InTrade)	86.31
TOTALProfit(InTrade)	-1270.53
TOTALProfit(InTrade(%))	-69%
MAXBuyLost	-0.655%
MAXBuyWon	1.307%
MINBuyLost	0.000%
MINBuyWon	0.001%
MAXSellLost	-0.778%
MAXSellWon	0.536%
MINSellLost	-0.0009%
MINSellWon	0.0009%

Source: Compiled by the author

Appendix 4. Data C results from 13.07.2017-18.10.2017 with Table 3. variables

Leverage	300
MA1	TEMA1
MA2	SMA2
BuyTradesLost	159
BuyTradesWon	55
SellTradesLost	176
SellTradesWon	39
AVGBuyTradeLost(%)	-0.061%
AVGBuyTradeWon(%)	0.211%
AVGSELLTradeLost(%)	-0.067%
AVGSELLTradeWon(%)	0.271%
TOTAL(Profit/Loss(%))	0.706%
AVGBuyTradeLost(InTrade)	-29.32
AVGBuyTradeWon(InTrade)	94.52
AVGSELLTradeLost(InTrade)	-32.60
AVGSELLTradeWon(InTrade)	120.03
TOTALProfit(InTrade)	-518.67
TOTALProfit(InTrade(%))	-28%
MAXBuyLost	-0.471%
MAXBuyWon	1.071%
MINBuyLost	-0.002%
MINBuyWon	0.002%
MAXSellLost	-0.469%
MAXSellWon	0.812%
MINSellLost	0.0000%
MINSellWon	0.0008%

Source: Compiled by the author

Appendix 5. Data D results from 18.10.2017-25.01.2018 with Table 3 variables.

Leverage	300
MA1	TEMA1
MA2	SMA2
BuyTradesLost	169
BuyTradesWon	57
SellTradesLost	187
SellTradesWon	39
AVGBuyTradeLost(%)	-0.060%
AVGBuyTradeWon(%)	0.206%
AVGSELLTradeLost(%)	-0.061%
AVGSELLTradeWon(%)	0.202%
TOTAL(Profit/Loss(%))	-2.071%
AVGBuyTradeLost(InTrade)	-7.72
AVGBuyTradeWon(InTrade)	19.84
AVGSELLTradeLost(InTrade)	-7.91
AVGSELLTradeWon(InTrade)	25.38
TOTALProfit(InTrade)	-663.45
TOTALProfit(InTrade(%))	-66%
MAXBuyLost	-0.574%
MAXBuyWon	0.918%
MINBuyLost	0.000%
MINBuyWon	0.002%
MAXSellLost	-0.379%
MAXSellWon	1.527%
MINSellLost	-0.0017%
MINSellWon	0.0033%

Source: Compiled by the author

Appendix 5. Data E results from 25.01.2018-02.05.2018 with Table 3 variables.

Leverage	300
MA1	TEMA1
MA2	SMA2
BuyTradesLost	175
BuyTradesWon	46
SellTradesLost	174
SellTradesWon	47
AVGBuyTradeLost(%)	-0.071%
AVGBuyTradeWon(%)	0.186%
AVGSELLTradeLost(%)	-0.076%
AVGSELLTradeWon(%)	0.270%
TOTAL(Profit/Loss(%))	-4.483%
AVGBuyTradeLost(InTrade)	-9.69
AVGBuyTradeWon(InTrade)	25.30
AVGSELLTradeLost(InTrade)	-10.45
AVGSELLTradeWon(InTrade)	32.03
TOTALProfit(InTrade)	-845.24
TOTALProfit(InTrade(%))	-85%
MAXBuyLost	-0.400%
MAXBuyWon	0.655%
MINBuyLost	0.000%
MINBuyWon	0.001%
MAXSellLost	-0.409%
MAXSellWon	0.897%
MINSellLost	-0.001%
MINSellWon	0.007%

Source: Compiled by the author

Appendix 6. Data F results from 02.05.2018-07.08.2018 with Table 3 variables.

Leverage	300
MA1	TEMA1
MA2	SMA2
BuyTradesLost	157
BuyTradesWon	55
SellTradesLost	163
SellTradesWon	50
AVGBuyTradeLost(%)	-0.062%
AVGBuyTradeWon(%)	0.142%
AVGSELLTradeLost(%)	-0.073%
AVGSELLTradeWon(%)	0.273%
TOTAL(Profit/Loss(%))	-0.161%
AVGBuyTradeLost(InTrade)	-13.05
AVGBuyTradeWon(InTrade)	25.97
AVGSELLTradeLost(InTrade)	-14.96
AVGSELLTradeWon(InTrade)	52.50
TOTALProfit(InTrade)	-434.25
TOTALProfit(InTrade(%))	-43%
MAXBuyLost	-0.445%
MAXBuyWon	0.627%
MINBuyLost	0.000%
MINBuyWon	0.001%
MAXSellLost	-0.403%
MAXSellWon	1.682%
MINSellLost	0.000%
MINSellWon	0.013%

Source: Compiled by the author

Appendix 7. Data G results from 07.08.2018-09.11.2018 with Table 3 variables.

Leverage	300
MA1	TEMA1
MA2	SMA2
BuyTradesLost	186
BuyTradesWon	42
SellTradesLost	178
SellTradesWon	50
AVGBuyTradeLost(%)	-0.063%
AVGBuyTradeWon(%)	0.224%
AVGSELLTradeLost(%)	-0.071%
AVGSELLTradeWon(%)	0.251%
TOTAL(Profit/Loss(%))	-2.356%
AVGBuyTradeLost(InTrade)	-13.82
AVGBuyTradeWon(InTrade)	47.86
AVGSELLTradeLost(InTrade)	-15.91
AVGSELLTradeWon(InTrade)	53.62
TOTALProfit(InTrade)	-710.59
TOTALProfit(InTrade(%))	-71%
MAXBuyLost	-0.237%
MAXBuyWon	0.855%
MINBuyLost	-0.002%
MINBuyWon	0.005%
MAXSellLost	-0.322%
MAXSellWon	1.031%
MINSellLost	-0.002%
MINSellWon	0.003%

Source: Compiled by the author

Appendix 8. Data A results from 02.01.2017-07.04.2018 with Table 3 variables with MA1=ATEMA.

Leverage	300
MA1	TEMA1
MA2	TEMA2
BuyTradesLost	224
BuyTradesWon	74
SellTradesLost	205
SellTradesWon	93
AVGBuyTradeLost(%)	-0.041%
AVGBuyTradeWon(%)	0.160%
AVGSELLTradeLost(%)	-0.050%
AVGSELLTradeWon(%)	0.121%
TOTAL(Profit/Loss(%))	3.683%
AVGBuyTradeLost(InTrade)	-28.00
AVGBuyTradeWon(InTrade)	95.33
AVGSELLTradeLost(InTrade)	-33.97
AVGSELLTradeWon(InTrade)	75.24
TOTALProfit(InTrade)	815.56
TOTALProfit(InTrade(%))	82%
MAXBuyLost	-0.268%
MAXBuyWon	1.001%
MINBuyLost	0.000%
MINBuyWon	0.002%
MAXSellLost	-0.296%
MAXSellWon	0.805%
MINSellLost	0.0000%
MINSellWon	0.0009%

Source: Compiled by the author

Appendix 9. Data B results from 07.04.2017-13.07.2018 with Table 3 variables with MA1=ATEMA.

Leverage	300
MA1	TEMA1
MA2	TEMA2
BuyTradesLost	218
BuyTradesWon	80
SellTradesLost	223
SellTradesWon	75
AVGBuyTradeLost(%)	-0.041%
AVGBuyTradeWon(%)	0.160%
AVGSELLTradeLost(%)	-0.050%
AVGSELLTradeWon(%)	0.105%
TOTAL(Profit/Loss(%))	0.572%
AVGBuyTradeLost(InTrade)	-18.28
AVGBuyTradeWon(InTrade)	66.41
AVGSELLTradeLost(InTrade)	-22.27
AVGSELLTradeWon(InTrade)	44.27
TOTALProfit(InTrade)	-316.43
TOTALProfit(InTrade(%))	-32%
MAXBuyLost	-0.592%
MAXBuyWon	1.354%
MINBuyLost	0.000%
MINBuyWon	0.001%
MAXSellLost	-0.778%
MAXSellWon	0.583%
MINSellLost	0.0000%
MINSellWon	0.0009%

Source: Compiled by the author

Appendix 10. Data C results from 13.07.2017-18.10.2018 with Table 3 variables with MA1=ATEMA.

Leverage	300
MA1	TEMA1
MA2	TEMA2
BuyTradesLost	210
BuyTradesWon	88
SellTradesLost	231
SellTradesWon	67
AVGBuyTradeLost(%)	-0.037%
AVGBuyTradeWon(%)	0.115%
AVGSELLTradeLost(%)	-0.043%
AVGSELLTradeWon(%)	0.116%
TOTAL(Profit/Loss(%))	0.188%
AVGBuyTradeLost(InTrade)	-12.84
AVGBuyTradeWon(InTrade)	37.72
AVGSELLTradeLost(InTrade)	-14.83
AVGSELLTradeWon(InTrade)	37.76
TOTALProfit(InTrade)	-272.43
TOTALProfit(InTrade(%))	-27%
MAXBuyLost	-0.431%
MAXBuyWon	0.716%
MINBuyLost	0.000%
MINBuyWon	0.001%
MAXSellLost	-0.360%
MAXSellWon	0.770%
MINSellLost	0.0000%
MINSellWon	0.0008%

Source: Compiled by the author

Appendix 11. Data D results from 18.10.2017-25.01.2018 with Table 3 variables with MA1=ATEMA.

Leverage	300
MA1	TEMA1
MA2	TEMA2
BuyTradesLost	218
BuyTradesWon	80
SellTradesLost	226
SellTradesWon	72
AVGBuyTradeLost(%)	-0.039%
AVGBuyTradeWon(%)	0.106%
AVGSELLTradeLost(%)	-0.043%
AVGSELLTradeWon(%)	0.099%
TOTAL(Profit/Loss(%))	-2.670%
AVGBuyTradeLost(InTrade)	-6.12
AVGBuyTradeWon(InTrade)	12.99
AVGSELLTradeLost(InTrade)	-6.70
AVGSELLTradeWon(InTrade)	15.54
TOTALProfit(InTrade)	-689.52
TOTALProfit(InTrade(%))	-68.95%
MAXBuyLost	-0.217%
MAXBuyWon	0.943%
MINBuyLost	0.000%
MINBuyWon	0.001%
MAXSellLost	-0.276%
MAXSellWon	1.888%
MINSellLost	0.0000%
MINSellWon	0.0008%

Source: Compiled by the author

Appendix 12. Data E results from 25.01.2017-02.05.2018 with Table 3 variables with MA1=ATEMA.

Leverage	300
MA1	TEMA1
MA2	TEMA2
BuyTradesLost	224
BuyTradesWon	74
SellTradesLost	235
SellTradesWon	63
AVGBuyTradeLost(%)	-0.046%
AVGBuyTradeWon(%)	0.102%
AVGSELLTradeLost(%)	-0.048%
AVGSELLTradeWon(%)	0.143%
TOTAL(Profit/Loss(%))	-4.999%
AVGBuyTradeLost(InTrade)	-5.08
AVGBuyTradeWon(InTrade)	9.27
AVGSELLTradeLost(InTrade)	-5.17
AVGSELLTradeWon(InTrade)	13.00
TOTALProfit(InTrade)	-847.69
TOTALProfit(InTrade(%))	-84.77%
MAXBuyLost	-0.430%
MAXBuyWon	0.743%
MINBuyLost	0.000%
MINBuyWon	0.001%
MAXSellLost	-0.395%
MAXSellWon	0.800%
MINSellLost	0.0000%
MINSellWon	0.0008%

Source: Compiled by the author

Appendix 13. Data F results from 02.05.2017-07.08.2018 with Table 3 variables with MA1=ATEMA.

Leverage	300
MA1	TEMA1
MA2	TEMA2
BuyTradesLost	208
BuyTradesWon	90
SellTradesLost	222
SellTradesWon	76
AVGBuyTradeLost(%)	-0.048%
AVGBuyTradeWon(%)	0.080%
AVGSELLTradeLost(%)	-0.048%
AVGSELLTradeWon(%)	0.148%
TOTAL(Profit/Loss(%))	-2.318%
AVGBuyTradeLost(InTrade)	-6.70
AVGBuyTradeWon(InTrade)	9.37
AVGSELLTradeLost(InTrade)	-6.43
AVGSELLTradeWon(InTrade)	16.98
TOTALProfit(InTrade)	-684.91
TOTALProfit(InTrade(%))	-68.49%
MAXBuyLost	-0.535%
MAXBuyWon	1.031%
MINBuyLost	0.000%
MINBuyWon	0.001%
MAXSellLost	-0.386%
MAXSellWon	1.521%
MINSellLost	0.0000%
MINSellWon	0.0008%

Source: Compiled by the author

Appendix 14. Data G results from 07.08.2017-09.11.2018 with Table 3 variables with MA1=ATEMA.

Leverage	300
MA1	TEMA1
MA2	TEMA2
BuyTradesLost	221
BuyTradesWon	77
SellTradesLost	219
SellTradesWon	79
AVGBuyTradeLost(%)	-0.042%
AVGBuyTradeWon(%)	0.121%
AVGSELLTradeLost(%)	-0.049%
AVGSELLTradeWon(%)	0.154%
TOTAL(Profit/Loss(%))	1.447%
AVGBuyTradeLost(InTrade)	-12.03
AVGBuyTradeWon(InTrade)	29.78
AVGSELLTradeLost(InTrade)	-13.76
AVGSELLTradeWon(InTrade)	41.58
TOTALProfit(InTrade)	-92.69
TOTALProfit(InTrade(%))	-9.27%
MAXBuyLost	-0.262%
MAXBuyWon	0.800%
MINBuyLost	0.000%
MINBuyWon	0.001%
MAXSellLost	-0.239%
MAXSellWon	1.790%
MINSellLost	0.0000%
MINSellWon	0.0009%

Source: Compiled by the author