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Technical Analysis Profitability Across Different Classes of Assets

Bachelor's thesis

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Abstract

This thesis examines the profitability of popular technical trading rules across the four asset classes – equities, currencies, commodities, and cryptocurrencies – over the period 2014-2024. This work's contribution lies in a comprehensive analysis of the differences in performance of technical analysis on different asset classes, which were historically present in the empirical literature. The analysis was conducted with a valid framework robust to data-snooping bias using the Model Confidence Set procedure, incorporating risk and transaction costs on the universe of 2870 rules. The results obtained show significant risk-unadjusted outperformance of the buy-and-hold strategy but very insignificant risk-adjusted outperformance, suggesting that technical analysis may increase the returns only at the expense of greater risk exposure. It holds for both cases with and without transaction costs. Also, this translates into substantial differences across the asset classes in risk-unadjusted returns but not in risk-adjusted returns. The main reason is the decreased performance expressed by lower average returns of the optimally selected trading rules and their higher variability in the out-of-sample period across the instruments within asset classes. This evidence corresponds to and contributes to the empirical trend of increasing efficiency of financial markets, which holds even for those markets without efficient fundamental pricing models.

Keywords Asset class, commodity, cryptocurrency, equity, forex, indicator, profitability, technical analysis, technical rule, trading

Title Technical Analysis Profitability Across Different Classes of Assets

Abstrakt

Tato práce zkoumá ziskovost populárních technických obchodních pravidel na čtyřech třídách aktiv - akcie, měny, komodity a kryptoměny - v období 2014-2024. Přínos této práce spočívá v komplexní analýze rozdílů ve výkonnosti technické analýzy na různých třídách aktiv, které se historicky vyskytovaly v empirické literatuře. Analýza byla provedena metodou odolnou vůči data-snoopingu pomocí postupu Model Confidence Set, zahrnujícím riziko a transakční náklady na univerzu 2870 pravidel. Získané výsledky ukazují významnou výkonnost technických pravidel oproti strategii "buy-and-hold" bez očištění o riziko, ale velmi nevýznamnou výkonnost se zahrnutím rizika, což naznačuje, že technická analýza může zvyšovat výnosy pouze na úkor větší míry rizika. Platí to pro oba případy s transakčními náklady i bez nich. To se také projevuje v podstatných rozdílech mezi jednotlivými třídami aktiv ve výnosnosti neočištěném o riziko, ale nikoli ve výnosnosti jej zahrnujícím. Hlavním důvodem je snížená výkonnost vyjádřená nižšími průměrnými výnosy optimálně zvolených obchodních pravidel a jejich vyšší variabilitou v období out-of-sample napříč instrumenty v rámci tříd aktiv. Tyto výsledky odpovídají a přispívají k empirickému trendu rostoucí efektivity finančních trhů, který platí i pro trhy bez efektivních modelů fundamentálního oceňování.

Klíčová slova	Třída aktiv, komodita, kryptoměna, akcie, forex, indikátor, ziskovost, technická analýza, technické pravidlo, obchodování
Název práce	Ziskovost Technické Analýzy Napříč Různými Třídami Aktiv

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Acronyms

EMA Exponential Moving Average

EMH Efficient Market Hypothesis

FOREX Foreign Exchange

MA Moving Average

MACD Moving Average Convergence Divergence

MCS Model Confidence Set

RSI Relative Strength index

TA Technical Analysis

TRB Trading Range Breakout

Chapter 1

Introduction

Technical Analysis (TA) is a method of forecasting price movements of financial assets by analyzing statistical and visual trends and patterns in historical price and volume data. TA today remains one of the biggest controversial topics since the first academic attempts to prove its ability to show consistent profits (Cowles 3rd 1933). Park & Irwin (2007) study more than 100 papers on TA up to 2004 and show that approximately 63% of them support its predictive power. Relatively similar findings were noted by de Souza *et al.* (2018), where they looked at studies ranging from 1961 to 2016, indicating continuing uncertainty in the field.

TA is built on 3 assumptions defined by Murphy (1999):

1. Prices reflect market events.
2. Prices move in trends.
3. Historical prices tend to repeat.

The last two of those are the subjects of the biggest controversies stemming from the mainstream Efficient Market Hypothesis (EMH), according to which market prices must reflect all relevant information (especially historical prices). Contrary to this, other theoretical models were developed focusing on human mass psychology (Nison 1991) or, in other words, their animal spirit (Keynes 1936), which leave some place for TA. According to them, prices move in periods of over-optimistic and over-pessimistic swings, and the role of TA is to predict not the "true value" of an asset but what people think about it. This is the idea behind Keynes' beauty contest, which emphasizes the nature of the price formation process, which radically differs from the EMH.

The principle that allows TA to work is sometimes referred to as self-fulfilling prophecy. In other words, when enough market participants start relying on TA, it naturally obtains a greater role in the price formation process. Theoretically, this is known as the dominance of non-fundamental factors, upon which the models supporting TA are based. In support of this assumption, a number of survey studies, both modern and older, found widespread use of TA in various markets. For example, a relatively recent study of Menkhoff (2010) revealed that around 90% of fund managers use TA at least to some degree. Hence, it is reasonable to take these opponents of the EMH seriously. Especially given the advice of Fama (1970) not to take the EMH too literally and to study the profitability of TA directly to properly understand its value.

Hence, in this thesis, we are continuing the tradition of research examining TA profitability. To date, there is a lack of studies that directly address the comparison of TA profitability across different asset classes (Han *et al.* 2013, p. 1458). Most of the prior research focused on particular asset classes or specific regional markets. There we find evidence signaling potential differences across them. Allegedly, this stems from their differences in efficiency and the presence of widely recognized and efficient valuation models. However, due to different methodologies and examined time periods, it is hard to extrapolate the general conclusion. Our goal here is to test these propositions by directly studying the performance of simple technical trading rules on a range of asset classes. By this, we hope to arrive at a more consistent conclusion regarding the performance of different trading rules and the performance of TA across the asset classes.

More specifically, we examine 4 of them: equities, currencies, commodities, and cryptocurrencies. Due to their high liquidity and volatility, along with relatively low transaction costs, these are believed to be most suitable for the use of TA, which is confirmed by an extensive history of research. For each of those classes, 10 instruments were selected for the application of a moderately large universe of trading rules, totaling 2870 rules. The rules are selected from 4 larger families of trading rules: Moving Average (MA), Trading Range Breakout (TRB), Moving Average Convergence Divergence (MACD), and Relative Strength index (RSI). The analysis spans a 10-year period from 2014 to 2024.

Historically, the analysis of TA profitability suffered from various data-snooping biases. It was especially true for older studies before approximately 1990s (Park & Irwin 2007). These biases tended to overestimate the true performance of trading rules when the selection of trading rules and analysis of their performance was done using the same data set. The error of this approach was greatly summarized by Jensen & Benington (1970)[1]:

> ... given enough computer time, we are sure that we can find a mechanical trading rule which "works" on a table of *random numbers* – provided of course that we are allowed to test the rule on the *same* table of numbers which we used to discover the rule. We realize of course that the rule would prove useless on any other table of random numbers ...

Due to these concerns, we are employing various techniques of valid inference to avoid falling victim to data-snooping. Most importantly, we are implementing a statistical procedure that has not yet been extensively used in similar literature to assess the significance of trading rules' outperformance of the buy-and-hold (B&H) strategy. Namely, it is the Model Confidence Set (MCS) procedure developed by Hansen *et al.* (2011). It works in a relatively similar manner to the Reality Check (RC) test (White 2000) and the Superior Predictive Ability (SPA) test (Hansen 2005), which were extensively used in the literature on TA performance since the beginning of 2000s. In addition, we split the sample period into in-sample and out-of-sample periods, where the latter period is used to test the best-performing rules from the former period. Lastly, we acknowledge the potential effects of risk and transaction costs on trading performance.

Our main findings suggest significant differences in excess nominal (risk-unadjusted) returns across the asset classes of the applied trading rules. However, these rules tend to strongly increase the risk by increasing the variance of returns. As a consequence, we found no simple trading rule that statistically outperforms the buy-and-hold strategy when adjusted for risk. Hence, the differences between the asset classes are essentially illusory from the perspective of the risk-adjusted returns.

The rest of the thesis is organized as follows. Chapter 2 provides an overview of the existing literature on the fundamentals and application of TA and evidence of its profitability across discussed asset classes. Chapter 3 discusses the portfolio of instruments in each of the asset classes, outlines the set of trading rules applied, and summarizes the methodology used to test and compare the profitability of trading rules. Chapter 4 presents the empirical evidence. Chapter 5 concludes.

[1] Italic text is preserved as it appears in the original text.

Chapter 2

Literature Review

TA as a method of forecasting price movements and a trading tool has been popular for more than 100 years. Its modern origins emanate from the late 19^{th} and early 20^{th} centuries from the works of Charles H. Dow, who introduced his famous Dow theory (Park & Irwin 2004). In fact, the history of TA goes even further back to 18^{th}-century Japan, where various candlestick patterns were allegedly used to analyze the price movements of rice contracts (Nison 1991).

Since then, the popularity of TA increased substantially both among individual investors and professionals. Various surveys from the 1990s and 2000s indicated widespread use of TA in Foreign Exchange (FOREX) and futures markets (Taylor & Allen 1990; 1992; Oberlechner 2001; Gehrig & Menkhoff 2006; Menkhoff 2010); and equity markets (Hoffmann & Shefrin 2014). According to them, especially in the FOREX market the use of TA is dominant mainly for short horizons (less than 1 year). This is for the most part due to the inability of any exchange rate models based on fundamentals to forecast the rates over the short term (Menkhoff & Taylor 2007).[1] Other evidence revealed that more than 90% of market participants use TA techniques at least to some degree and most of them combine it with fundamental analysis and order flow techniques. Exclusive use of TA or FA is rare (less than 10%). Depending on the time horizon, the weight given to these techniques varies: order flow is preferred for very short-term, FA for very long-term, and TA for short- to medium-term.

In contrast to this evidence, academics have been mostly skeptical of TA. Since the 1960s the influential works of E. F. Fama and S. S. Alexander appeared to convince the academic world that the markets are at least weakly efficient and prices tend to follow random walk procedure (Fama 1970; Alexan-

[1] This could be regarded as one of the drivers of the popularity of TA, as will be seen especially in the case of cryptocurrencies.

der 1961). This implies that all prior information from prices and volume, which TA exploits, must already be incorporated into the current price. Consequently, it is impossible to generate excess returns by using any technical trading rule. Even though Fama himself recognized that in practice there could be instances of departure from efficient markets[2] and that technical trading rules may catch some nonlinear dependence in the prices, nonetheless, TA became, for many, a synonym for 'astrology' and 'magic'.

However, in order to properly understand the value of TA Fama (1970) suggested studying the profitability of technical rules directly. Hence, this has been a very active area of research since the 1960s. Even though many early studies (before the 1990s) suffered from significant methodological problems such as data-snooping bias, the exclusion of transaction costs, and risk management, modern studies have significantly improved in these areas. Park & Irwin (2007), as stated previously, found that 63% of these modern studies supported the predictive ability and profitability of TA (as compared to 26% suggesting that it is not profitable). These results and especially papers such as those written by Brock *et al.* (1992) and Sullivan *et al.* (1999) returned some credibility to TA.

During the period from the 1980s to at least the 2000s, there was a boom in the use of TA.[3] Smidt (1965a) surveyed amateur traders in the US commodity futures market and found that about 53% of respondents used TA at least to some degree. Later, that percentage was found to be over 90% for FOREX professionals (Taylor & Allen 1992; Group of Thirty 1985; Gehrig & Menkhoff 2006). At the same time, the academic interest in TA also surged. Park & Irwin (2004) found that about half of all empirical studies of technical trading rules from the 1960s were published in the short period from 1995 to 2004. This popularity led to the decreasing profitability of simple rules in most markets. It became mostly unprofitable on the United States (US) equity market and reduced excess returns on FOREX and futures markets (Park & Irwin 2004; 2007; Menkhoff & Taylor 2007). This led researchers to conclude that these markets became more efficient over time. On the other hand, studies focused on markets outside the US mostly continued to be profitable. This accords with the notion that many markets outside the US are more likely to be less

[2] For example, the case of bunching limit orders on specific prices such as round numbers or previous highest or lowest price.

[3] Interestingly, during the same period, techniques of fundamental analysis in practical use were losing ground to TA and order flow (Gehrig & Menkhoff 2006). One of the possible reasons may be their poor ability to forecast price developments in the short term.

efficient. Also, these trends agree with the Adaptive Market Hypothesis (Neely *et al.* 2009), which suggests that profitable trading strategies will be assimilated by the market participants, which will consequently reduce their profitability.

However, it should be noted that the profitability of technical trading rules is not stable over time and depends on the extent of volatility (Menkhoff & Taylor 2007; Han *et al.* 2013; Taylor 2014). Han *et al.* (2013) showed that for portfolios with higher volatility, technical trading rules are more profitable. Shynkevich (2012) found that TA techniques on small-cap and technology companies were more profitable during the 1995-2002 period, which was characterized by the Dot-com bubble, than during the period 2003-2010. This implies that investors potentially can still benefit from technical trading rules even in the US equity market if they manage to separate the periods of higher and lower volatility.

Along with many promising results of empirical studies and widespread use, there were some attempts at theoretical justification of TA against the EMH. These include noisy rational expectation models (Treynor & Ferguson 1985; Brown & Jennings 1989; Blume *et al.* 1994; Grossman & Stiglitz 1976; 1980) disequilibrium models (Beja & Goldman 1980), behavioral models (De Long *et al.* 1990; Shleifer & Summers 1990), herding models (Froot *et al.* 1992; Hong & Stein 1999), agent-based models (Schmidt 2002), and chaos theory (Clyde & Osler 1997). All these models aim to take advantage of various market imperfections observed in practice, the market power of certain groups of investors, and theories related to price formation. These imply that prices may adjust sluggishly to new information by either underreacting or overreacting. As a result, there appear potential unexploited opportunities to capture excess profits. The role of TA is to search for information about those opportunities. Further, we will provide a more detailed explanation for each model.

Noisy rational expectation models are developed on the basis of asymmetric information of market participants (Park & Irwin 2004). Information quality is a crucial determinant of this asymmetry. It is assumed that private information that investors receive is not always perfect and fully revealing. Noise and randomness in the quality of information imply that investors may misinterpret it. Hence, noise in information quality directly translates into noise in the price movements instead of sudden jumps, as the EMH would suggest. As information gradually diffuses among investors, markets are adjusting towards the equilibrium price. However, because this process takes time, there appear potential profitable trading opportunities. Those investors without private information can extract valuable insights about the quality of information of others by combining current prices with historical prices and volume as suggested by the model of Blume *et al.* (1994).

Disequilibrium, behavioral, herding, and agent-based models are developed based on the market power that certain groups in the market possess. Broadly speaking, all of them divide the market participants into two groups: arbitrageurs (so-called sophisticated investors or smart money) and noise traders (feedback traders) (Park & Irwin 2004). The former group is considered to have sufficient knowledge about market fundamentals to accurately price the assets, and the latter group relies on pseudo-information or noise derived from TA or other methods. In the case that the latter group possesses a certain degree of market power, they can significantly alter the behavior of prices. Usually, most traders are trend followers (Stewart 1949), which means that in the case of good news, the rise in prices will cause further growth, leading to overreaction. Arbitrageurs may attempt to bring the price back to its fundamental value, but they face the risk of additional good news, which may lead to even higher overreaction (De Long *et al.* 1990). Hence, an optimal strategy for them may be to mimic the behavior of noise traders (so-called bandwagoning), and by that, they are reducing their own risk exposure (DeLong *et al.* 1987). It implies that non-fundamentals play an important role in the price formation process and that with the sufficient market power of noise traders, TA becomes, to some extent, self-fulfilling.

Empirical evidence of the widespread use of TA supports the hypothesis that noise traders possess certain market power. During the 1980s, futures funds that relied heavily on TA were estimated to control an average of 23% of the open interest in 10 important futures markets (Brorsen & Irwin 1987). A survey of dealers in the London FOREX market by Taylor & Allen (1992) revealed that about 40% of respondents believed TA techniques are largely self-fulfilling. Other surveys of practitioners in FOREX markets found that psychology either dominated their decisions or at least played an important role in them (Taylor & Allen 1992; Gehrig & Menkhoff 2006; Oberlechner 2001; Menkhoff 2010).[4]

Finally, chaos theory suggests that prices may behave non-linearly and possess the behavior of deterministic chaos. The latter behavior is a type of non-linear behavior governed by strict economic laws that appears to be random, unpredictable, and highly sensitive to initial conditions. Many fundamental

[4]Interestingly, financial journalists tend to believe that rationality dominates their decisions more than psychology compared to dealers and traders. This may be due to their market role, as their purpose is to "rationalize" every market action (Oberlechner 2001).

models rely on linear equations to explain the market movements. However, there is little theoretical justification for assuming that the market system is governed by linear equations (Clyde & Osler 1997). Conversely, there is evidence of non-linearity (Savit 1989) and deterministic chaos in prices (Blank 1991). Fama (1970) claimed that TA may rely on non-linear dependence and, thus, produce excess profits. Clyde & Osler (1997) argues that graphical TA may be a crude method of non-linear forecasting. Their results indicate that graphical patterns such as head-and-shoulders tend to perform better on non-linear data than on random data. Lo *et al.* (2000) also found that charting patterns are informative when comparing the conditional distribution of returns with the conditional distribution on charting patterns. On the other hand, some studies indicated rather negative results of chart patterns application (Curcio *et al.* 1997).

2.1 Evidence on Equities

TA is a very popular method used in practice for equities. Initially, Dow theory was developed out of observations of stock prices and was first intended mainly for the stock market (Murphy 1999). Most empirical research on TA has been focused on the stock market and FOREX market throughout the 20th century (Park & Irwin 2004).

Unfortunately, there is a lack of survey research focused on the use of TA among professionals in the equity market. However, among individual stock investors, TA tends to play an important role as suggested by Lewellen *et al.* (1980) (US investors) and Hoffmann & Shefrin (2014) (Dutch investors). Their surveys indicated that 27% and 32% of respondents respectively use TA and 4% and 9% use TA exclusively.[5] Another of their findings indicated that the use of TA severely degrades the portfolio performance mainly due to high turnover, high concentration, high risk, and engagement in options trading. However, after the exclusion of "high derivative rollers"[6] from the sample, TA still did not improve portfolio performance but at least its costs were not statistically

[5] However, the use of fundamental analysis drastically differs across these studies. Lewellen *et al.* (1980) found that 65% of respondents were relying on it, whereas Hoffmann & Shefrin (2014) found only 20%. It may indicate that TA has become more popular and fundamental analysis less popular over time. However, this difference in preferences should be interpreted with caution as these studies considered different countries.

[6] The group mostly engaged in options trading that suffers the most from high turnover, high concentration, and high risk.

significant. One of the main reasons for these results are high transaction costs incurred by individuals (especially it holds for high derivative rollers with high turnover).

The empirical evidence of the profitability of TA on equities is mixed. On average, in the US market it yielded profits until the late 1980s and not thereafter, indicating that the US stock market became more efficient (Sullivan *et al.* 1999; Kwon & Kish 2002; Park & Irwin 2007)[7]. One of the most influential studies by Brock *et al.* (1992) showed that simple trading rules like MAs and TRBs significantly outperformed buy-and-hold strategy in the Dow Jones Industrial Average index in the period 1897-1986. Their results indicated that technical trading rules increased average return from 0.17% (buy-and-hold) to 0.8% over a 10-day period without transaction costs. These intriguing results could not be explained by popular models of price modeling (random walk, AR(1), GARCH-M, EGARCH), risk, and data-snooping (Sullivan *et al.* 1999). However, after the inclusion of transaction costs, these excessive profits largely disappeared (Bessembinder & Chan 1998). Similar results were found by Fama & Blume (1966), who tested filter rules and concluded that after the inclusion of transaction costs, profits disappeared.

Further research extended the reach by testing different indices. Kwon & Kish (2002) analyzed NYSE and NASDAQ indices in the same manner as Brock *et al.* (1992). The results for the NYSE and NASDAQ were mostly similar, indicating that around the 1990s, profits disappeared for the NYSE and weakened for the NASDAQ. Hsu & Kuan (2005) found similar results indicating that in the same period, there were no significantly profitable rules for mature markets (S&P500 and Dow Jones Industrial Average), but there were for younger markets (NASDAQ, Russell 2000) even after transaction costs. The best rule for NASDAQ increased average returns from 14.1% to 23.35% per year, and the best rule for Russell 2000 increased the returns from 8% to 28.9% per year. Marshall *et al.* (2009) studied individual stocks in the NYSE and NASDAQ indices and found similar results in the same period. Shynkevich (2012) showed that the performance of TA on small-cap and technology indices continued weakening in the period 1995-2002 and disappeared fully in the period 2003-2010.

[7] One of the possible reasons for this results is that during the earlier part of 20^{th} century information disclosure was significantly limited implying that investors could not rely solely on fundamental analysis (Brock *et al.* 1992).

2.2 Evidence on Foreign exchange

As was mentioned at the beginning of the chapter, TA is a widely used tool in the FOREX market, according to numerous survey studies. The main reason for this popularity is the lack of adequate fundamental models that would manage to predict the movements of exchange rates in the short-term period of less than 12 months. Moreover, compared to equities, the global FOREX market has a very high turnover of around $7.5 trillion per day (Bank for International Settlements 2022), which is considerably more than the stock market turnover. Other important factors include an almost exclusive presence of professionals in the market and significant reliance on short-term trading due to the market specifics (Menkhoff & Taylor 2007). Again, psychological factors tend to be considered as important for professionals, which implies that non-fundamental factors contribute to market price formation. Hence, from the theoretical standpoint, we may expect that TA performs better here than on equities.

Another factor that may explain TA profitability is the presence of a party, whose goal is not profit maximization, i.e. central bank. The interventions by central banks tend to increase the volatility of prices significantly, which may imply that TA rules become more profitable during these periods. In fact, Neely (1998) found that most of the profits occur during the periods of interventions. However, other studies questioned this result and suggested that profitability may be the highest before interventions (Menkhoff & Taylor 2007). This is due to the idea that TA may drive exchange rates away from their fundamental values, which will then be offset by the central bank "leaning against the wind".

Historical empirical studies tend to stress the usefulness and profitability of TA in FOREX. Most studies find that TA techniques were significantly profitable until the 1990s and continued to be after but with a decreasing trend (Sweeney 1986; Park & Irwin 2007; Menkhoff & Taylor 2007; Levich & Thomas III 1993)[8]. For big currency pairs such as USD/DM and USD/BP Papadamou & Tsopoglou (2001) concluded that during the 1990s technical rules stopped significantly outperforming the buy-and-hold strategy. Nonetheless, they still remained profitable, and most of the trading rules were nominally outperforming the buy-and-hold. Recent comprehensive research by Hsu *et al.* (2016) studied both mature and emerging currencies in the period of 1971 to 2015

[8] This indicated that after the beginning of generalized managed floating in 1973, FOREX was showing significant signs of inefficiency.

with a big universe of trading rules. They concluded that TA was significantly profitable after transaction costs for both types of currency pairs even after the 1990s. In agreement with other research, there is a negative trend in profitability over time, and emerging currencies tend to perform better. Moreover, neither risk premia nor market volatility and central bank interventions could explain these excess returns, according to the authors.

2.3 Evidence on Commodities

The commodities futures market is one of the most popular markets for users of TA along with the FOREX market (Park & Irwin 2004). For example, Brorsen & Irwin (1987) found that only 2 out of 21 large commodity fund managers did not use TA, and the extensive users of TA in futures possessed certain market power. This may be again due to the poor ability of fundamental models to forecast the prices in the short-term.

Concerning the empirical studies, most indicated rather positive results before the 1990s (Roberts 2005). For example, Lukac & Brorsen (1990) concluded that some of the trading rules were capable of outperforming the buy-and-hold strategy even after transaction costs. However, after 1990s the profits mostly disappeared (Roberts 2005; Yen & Hsu 2010). Yen & Hsu (2010) selected a universe of the most profitable rules in previous studies and tested it on the data from 1998 to 2007. The results were rather mixed depending on the testing procedure used. Superior predictive ability (SPA) test developed by Hansen (2005) yielded negative results, whereas the test based on the Sortino ratio managed to select some significant outperforming rules that mostly exploited volume information.

2.4 Evidence on Cryptocurrencies

The cryptocurrency market is one of the youngest markets, which appeared with the introduction of Bitcoin by Nakamoto (2008). Since then, it has been one of the most speculative, unregulated, concentrated, and volatile markets. First, concerning its speculative nature Detzel *et al.* (2018) wrote: "Bitcoin is no doubt one of the most speculative assets in the history of finance". It is full of over-optimistic investors hoping to quickly earn a fortune, and conversely, most professionals in finance have been avoiding cryptocurrencies at least until the introduction of the first Bitcoin exchange-traded funds in 2024 (U.S. Securities and Exchange Commission 2024). Second, regulatory concerns are significant for this market, and scrutiny is increasing over time. However, as of the time of writing this thesis, the regulatory framework remains far from being as consistent and comprehensive as it is in most other markets, both internationally and within individual states. Third, the cryptocurrency market has been significantly concentrated as Bitcoin alone corresponds to about half of the whole market capitalization, and the top 5 cryptocurrencies correspond to 75% of the market capitalization as of the time of writing this thesis. Fourth, the volatility is related to its speculative nature as, for example, $1 invested in Bitcoin on July 13, 2010 would become $1.218.689 by March 14, 2024.

Moreover, crypto-assets do not have any widely accepted fundamentals to which they could be related. For example, popular predictors of stock returns, such as VIX, Treasury bill rates, term spread, and default spread are not able to explain the price movements of Bitcoin (Detzel *et al.* 2018). Psychological factors are highly probable to have a significant impact on price movements. Detzel *et al.* (2018) showed that bitcoin prices were not following the random walk procedure before 2018. Hence, this market most probably possesses the best conditions for applying TA out of all asset classes. However, as in other assets, there is some evidence that it might be moving towards more efficiency (Resta *et al.* 2020; Svogun & Bazán-Palomino 2022).

In accordance with this, empirical evidence almost unanimously found significant excess returns after transaction costs, even for simple trading rules. Mostly, these come from avoiding periods of major drawdowns and staying in the market during major runs, which are very characteristic of Bitcoin and other cryptocurrencies (Detzel *et al.* 2018; Gerritsen *et al.* 2020; Resta *et al.* 2020; Svogun & Bazán-Palomino 2022). Detzel *et al.* (2018) obtained 0.2 – 0.6 higher Sharpe ratios by using simple trading rules compared to the buy-and-hold strategy in Bitcoin. The returns after the buy signal in their study were 11 – 58 times higher than after the rules that indicated short signals.

Chapter 3

Data and Methodology

3.1 Data

In this thesis, 4 asset classes were chosen for comparison: equities, FOREX, commodities, and cryptocurrencies. The motivation for choosing precisely these markets derives from a few reasons. First, they are one of the biggest and most empirically studied markets since the 1960s. Hence, it will be interesting to compare our results with the historical evidence in other studies and analyze whether our results agree with a theoretical background that may stem from earlier presumed levels of efficiency of each market. Second, these markets are of special interest to technical analysts since, as discussed in Chapter 2, the use of TA is widespread there. From a theoretical perspective, it may be a justification for denying the full market efficiency due to the potential role of non-fundamentals. Third, these markets possess characteristics that allow the effective use of TA, i.e., sufficient level of liquidity and volatility, along with relatively low transaction costs.

Based on each asset class, 10 assumed representative instruments were selected, each being among the most traded within its respective class. For equities, the following US indices were chosen: Dow Jones Industrial Average, Dow Jones Transportation Average, Dow Jones Utility Average, S&P 500, S&P 400, Vanguard Total Stock Market Index Fund ETF, NASDAQ Composite, Russell 2000, NYSE Composite, and NASDAQ Biotech.[1] For FOREX, the following currencies *paired with the US dollar* in the indirect or counter currency format (e.g. AUD/USD) are: Australian, Canadian, and Singapore dollars, Swiss franc, Czech crown, Euro, British pound, Japanese yen, South Korean won, and

[1]Tickers: DJI, DJT, DJU, GSPC, SP400, VTI, IXIC, RUT, NYA, NBI.

Mexican peso. Commodities futures are the following: Copper, Corn, Soybean, Soybean oil, Sugar, Wheat, Gold, Silver, Natural gas, and Oil.[2] Finally, cryptocurrencies are the following: Cardano, Bitcoin Cash, Binance Coin, Bitcoin, Doge Coin, Ethereum, Chainlink, Litecoin, Tron Coin, and Ripple.[3]

All the data on daily prices were extracted from the Yahoo Finance website.[4] The studied period ranges from 17.9.2014 to 29.2.2024. Due to data availability, the data on 8 cryptocurrencies out of 10 are from 9.11.2017 to 29.2.2024. This period is further divided into the in-sample (17.9.2014 — 28.2.2022) period covering approximately 8 years and the out-of-sample (1.3.2022 — 29.2.2024) period covering approximately 2 years for the purposes of avoiding data-snooping bias as will be described in detail in Section 3.3.

In this thesis, daily closing prices are used to compute the daily log-returns using the following formula:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3.1}$$

The returns for equity indices are calculated using closing prices adjusted for splits and dividends. The prices of commodities are assuming rolling over the contract every quarter of the year.

Transaction costs play an important part in the empirical research on the application of TA. According to Park & Irwin (2007), studies that omit the proper inclusion of transaction costs in the trading procedure may run into the risk of obtaining returns that are in no way realistic. Hence, the alleged profitability may be illusory. As was mentioned in Chapter 2, one of the most famous examples of this is the study by Bessembinder & Chan (1998) that revealed extraordinary profits in the Dow Jones index obtained by Brock *et al.* (1992) to be non-existent after the transaction costs were taken into account. However, the discussion about the extent of transaction cost applied to different markets is to some extent speculative as there are some uncertain factors at any given point in time contributing to it, e.g. bid-and-ask spread. This led researchers to use different estimates of transaction costs. For example, Bessembinder & Chan (1998) computed one-way break-even costs to be 0.39%

[2]These commodities are traded in different exchanges: Copper, Gold, and Silver in COMEX; Corn, Soybean, Soybean oil and Wheat in CBOT; Sugar in ICE Futures; Natural gas and Oil in NY Mercantile.

[3]Tickers: ADA, BCH, BNB, BTC, DOGE, ETH, LINK, LTC, TRX, XRP. All come from CoinMarketCap website.

[4]https://finance.yahoo.com/

Ticker	N	Mean	Median	σ	Skewness	Kurtosis	D-stat.	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$	$\rho(5)$
EQUITIES												
In-sample												
DJI	1874	0.00036	0.00060	0.01163	-1.06	24.74	0.1241**	-0.1505*	0.1293	0.0048	-0.0876	0.0444
DJT	1874	0.00030	0.00074	0.01423	-0.52	11.33	0.0748**	-0.0856	0.0924	-0.0106	-0.0715	0.0435
DJU	1874	0.00028	0.00100	0.01235	-0.31	20.17	0.0837**	-0.0870	0.0759	-0.0764	-0.1315*	0.1022
GSPC	1874	0.00042	0.00067	0.01132	-0.99	20.07	0.1248**	-0.1609*	0.1086	0.0073	-0.0899	0.0354
SP400	1874	0.00033	0.00067	0.01302	-1.31	19.98	0.0972**	-0.0986	0.1518*	-0.0073	-0.0861	0.0603
VTI	1874	0.00048	0.00072	0.01135	-1.01	18.56	0.1207**	-0.1362*	0.1136	0.0136	-0.0876	0.0346
IXIC	1874	0.00059	0.00114	0.01294	-0.86	11.78	0.1063**	-0.1454**	0.0762	0.0066	-0.0494	0.0218
RUT	1874	0.00031	0.00083	0.01441	-1.21	15.15	0.0812**	-0.1097*	0.1481*	-0.0049	-0.0625	0.0633
NYA	1874	0.00021	0.00058	0.01107	-1.31	22.53	0.1167**	-0.1145	0.1386	0.0046	-0.0957	0.0599
NBI	1874	0.00018	0.00079	0.01618	-0.20	2.82	0.0472**	-0.0638	0.0228	0.0265	-0.0186	0.0206
Out-of-sample												
DJI	502	0.00028	0.00041	0.00991	-0.22	1.59	0.0536	0.0041	-0.0202	-0.0182	-0.0068	0.0213
DJT	502	0.00007	0.00002	0.01546	-0.26	1.64	0.0500	0.0788	-0.0760	-0.0024	-0.0302	0.0145
DJU	502	-0.00023	0.00026	0.01233	-0.17	1.07	0.0461	0.0010	0.0057	0.0778	0.0230	-0.0246
GSPC	502	0.00030	0.00008	0.01190	-0.17	1.62	0.0536	0.0009	-0.0439	-0.0204	-0.0046	0.0093
SP400	502	0.00016	0.00016	0.01356	-0.08	0.88	0.0366	0.0042	-0.0481	0.0067	-0.0388	0.0009
VTI	502	0.00033	0.00041	0.01224	-0.17	1.50	0.0452	0.0088	-0.0437	-0.0191	-0.0116	0.0030
IXIC	502	0.00031	0.00031	0.01561	-0.11	1.19	0.0438	-0.0161	-0.0421	-0.0357	-0.0014	0.0177
RUT	502	0.00001	0.00010	0.01516	0.00	0.57	0.0276	-0.0019	-0.0458	-0.0089	-0.0411	-0.0246
NYA	502	0.00015	0.00014	0.01056	-0.14	1.28	0.0451	0.0377	-0.0316	0.0136	-0.0161	-0.0114
NBI	502	0.00020	0.00096	0.01449	-0.09	0.55	0.0359	-0.0071	-0.0127	-0.0776	-0.0481	-0.0287
CURRENCIES												
In-sample												
AUD	1939	-0.00012	0	0.00617	-0.13	1.39	0.0363*	-0.0155	0.0353	0.0115	-0.0101	0.0018
CAD	1939	-0.00008	-0.00023	0.00481	0.07	2.64	0.0468**	-0.0123	-0.0145	-0.0029	-0.0031	-0.0327
CHF	1939	0	-0.00021	0.00624	11.62	326.84	0.0965**	0.0027	-0.0484	0.0011	0.0521*	-0.0418
CZK	1939	-0.00002	-0.00003	0.00587	-0.23	2.88	0.0437**	-0.0021	0.0383	0.0429	-0.0149	0.0021
EUR	1939	-0.00008	-0.00007	0.00499	-0.07	3	0.0388**	-0.0262	0.0027	0.0014	-0.0155	0.0152
GBP	1939	-0.00010	-0.00010	0.00584	-1.35	19.60	0.0552**	0.0349	0.0323	-0.0412	0.0236	-0.0331
JPY	1939	-0.00004	-0.00012	0.00515	0.07	3.75	0.0512**	-0.0115	0.0311	-0.0001	0.0367	-0.0861**
KRW	1939	-0.00008	0	0.00544	-0.10	2.19	0.0601**	-0.0975**	-0.0091	0.0033	-0.0377	-0.0198
MXN	1941	-0.00023	0.00002	0.00821	-0.98	8.24	0.0540**	0.0253	-0.0027	-0.0073	-0.0357	-0.0086
SGD	1939	-0.00004	0.00006	0.0031	0.06	1.70	0.0417**	-0.0218	-0.0238	0.0082	0.0152	-0.0251
Out-of-sample												
AUD	522	-0.00019	-0.00010	0.00742	0.06	0.50	0.0312	-0.0284	-0.0925	-0.0353	0.0689	-0.0185
CAD	522	-0.00012	-0.00010	0.00434	0.10	0.73	0.0507	-0.0018	-0.0582	-0.0609	0.0920	-0.0321
CHF	522	0.00010	-0.00055	0.00534	0.63	2.13	0.0662*	0.1028*	-0.0399	-0.0333	0.0656	0.0313
CZK	522	-0.00009	-0.00011	0.00673	0.15	0.78	0.0477	0.0597	-0.1107*	0.0172	0.0461	-0.0516
EUR	522	-0.00006	-0.00002	0.00542	0.07	0.67	0.0427	0.0218	-0.0587	-0.0428	0.0292	0.0052
GBP	522	-0.00010	-0.00017	0.00653	-0.22	4.69	0.0599*	0.0235	-0.0709	0.0081	-0.0789	-0.0066
JPY	522	-0.00051	-0.00094	0.00685	0.53	2.91	0.0722**	0.0170	-0.0700	-0.0363	0.0330	0.0608
KRW	522	-0.00021	-0.00128	0.00666	0.53	1.58	0.0900**	-0.0438	-0.0325	-0.0512	0.0372	0.0700
MXN	522	0.00035	0.00097	0.00666	-0.66	1.85	0.0835**	-0.0201	0.0072	-0.0274	0.0089	-0.0086
SGD	522	0.00002	-0.00001	0.00308	0.24	1.06	0.0370	0.0445	-0.0541	-0.0236	0.1081*	0.0198
COMMODITIES												
In-sample												
Copper	1871	0.00019	0	0.01340	-0.07	1.48	0.0433**	-0.0508	-0.0124	0.0059	-0.0094	-0.0048
Corn	1870	0.00038	0.00067	0.01570	-0.94	13.26	0.0557**	0.0134	-0.0076	-0.0154	-0.0410	0.0103
Soybean	1872	0.00027	0.00053	0.01248	-0.19	3.37	0.0469**	-0.0402	0.0399	-0.0310	-0.0244	-0.0359
Soybean oil	1872	0.00042	0	0.01410	-0.12	2.04	0.0360*	0.0229	0.0229	-0.0281	-0.0383	-0.0088
Sugar	1872	0.00014	-0.00052	0.01857	0.33	1.90	0.0351*	0.0259	0.0032	0.0146	-0.0126	0.0008
Wheat	1872	0.00033	0	0.01788	0.28	1.17	0.0341*	-0.0013	-0.0175	0.0241	-0.0184	-0.0167
Gold	1871	0.00023	0.00035	0.00933	-0.07	4.55	0.0745**	-0.0238	0.0001	0.0243	-0.0332	-0.0409
Silver	1871	0.00014	0.00031	0.01798	-0.72	7.04	0.0913**	-0.0518	0.0606	0.0149	-0.0466	-0.0331
Natural gas	1872	0.00005	0	0.03461	0.47	13.26	0.0731**	-0.0894	-0.0410	-0.0117	0.0225	-0.0822*
Oil	1870	0.00033	0.00132	0.03073	0.16	23.75	0.0971**	-0.0168	-0.0028	-0.0855	0.0309	0.0540
Out-of-sample												
Copper	503	-0.00029	-0.00033	0.01497	0.09	1.67	0.0332	0.0418	-0.0912	0.0375	-0.0007	0.0275
Corn	502	-0.0010	-0.00075	0.01952	-2.23	20.26	0.0918**	-0.0601	-0.0252	0.1357	-0.0089	-0.1192
Soybean	502	-0.00075	0.00038	0.01536	-1.09	7.43	0.0493	0.0307	-0.0499	-0.0449	-0.1293*	-0.0248
Soybean oil	502	-0.00097	-0.00031	0.02197	-0.41	1.18	0.0525	0.1124*	-0.0572	-0.0913*	-0.0532	0.0250
Sugar	504	0.00045	0.00088	0.0169	-0.53	1.87	0.0451*	-0.0018	-0.0300	0.0406	-0.0428	0.0666
Wheat	502	-0.00094	-0.00236	0.02701	0.77	6.45	0.0629*	-0.0298	-0.0486	-0.0756	-0.1047*	-0.1451*
Gold	504	0.00015	0.00011	0.00886	0.14	1.01	0.0546	-0.0649	-0.0332	0.0634	0.0778	0.0958*
Silver	502	-0.00014	-0.00134	0.01795	0.54	1.92	0.0516	0.0191	0.0294	0.0103	0.0300	0.0019
Natural gas	504	-0.00171	0.00044	0.04977	-0.35	0.66	0.0324	-0.0685	-0.0025	0.0805	-0.0374	-0.0050
Oil	504	-0.00040	0.00219	0.02618	-0.41	1.38	0.0483	0.0289	-0.0923	-0.0927	0.0390	-0.1037

Note: D-statistic (D-stat.) is test statistics for the Kolmogorov-Smirnov test, $\rho(i)$ is the estimated autocorrelation at lag i. ** and * indicate, respectively, 1% and 5% significance for a two-tailed test. The significance of $\rho(i)$ was estimated using heteroskedasticity-consistent robust standard errors.

Table 3.1: Summary statistics of daily returns.

Ticker	N	Mean	Median	σ	Skewness	Kurtosis	D-stat.	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$	$\rho(5)$
CRYPTOCURRENCIES												
In-sample												
ADA	1571	0.00216	0.00057	0.07047	2.02	23.77	0.1040**	-0.0210	0.1292*	0.0628*	0.0307	-0.008
BCH	1571	-0.00042	-0.00111	0.06733	0.05	10.61	0.1055**	-0.0370	0.0330	0.0334	0.0348	-0.0177
BNB	1571	0.00337	0.00112	0.06198	0.4	13.85	0.0989**	0.0010	0.0719	-0.0072	-0.0088	-0.0456
BTC	2720	0.00167	0.00199	0.03922	-0.77	11.12	0.10331**	-0.0210	0.0016	0.0135	0.0154	0.0067
DOGE	1571	0.00289	-0.00080	0.08178	4.93	83.67	0.1806**	0.0398	-0.0509	0.1180**	-0.0089	-0.0275
ETH	1571	0.0014	0.00154	0.0524	-0.98	10.21	0.0864**	-0.0441	0.0571*	0.0139	0.0453	0
LINK	1571	0.00268	0.00084	0.07393	-0.06	6.84	0.0631**	-0.0661	0.0347	0.0405	0.0416	-0.0096
LTC	2720	0.00114	-0.00022	0.05688	0.11	12.91	0.1104**	-0.0088	-0.0109	0.0117	0.0573*	-0.0229
TRX	1571	0.00208	0.00146	0.07466	1.9	23.34	0.1218**	0.0268	0.1003	0.0978	-0.0065	0.0273
XRP	1571	0.00081	-0.00091	0.06688	0.85	15.66	0.1375**	0.0110	0.0404	0.0019	0.0418	0.0146
Out-of-sample												
ADA	730	-0.00052	-0.00049	0.04075	0.04	4.23	0.0786**	-0.0748	0.0302	0.0291	0.0060	-0.0049
BCH	730	-0.00017	-0.00003	0.04169	0.82	7.70	0.1018**	-0.0411	0.0631	0.1028	-0.0477	-0.0020
BNB	730	0.00005	0.00097	0.03018	-0.98	7.25	0.1060**	-0.1131*	0.0670	0.0399	-0.0145	0.0105
BTC	730	0.00048	-0.00034	0.02798	-0.56	5.33	0.1057**	-0.0102	0.0793	0.0455	-0.0169	0.0067
DOGE	730	-0.00017	0.00015	0.04522	0.45	10.42	0.0963**	-0.0937	0.1145	0.0718	-0.0101	-0.0181
ETH	730	0.00019	-0.00010	0.03515	-0.44	5.1	0.0995**	-0.0373	0.0416	0.0640	-0.0329	0.0124
LINK	730	0.00033	0.00152	0.04441	-0.3	2.78	0.0557*	-0.0335	0	0.0226	-0.0673	-0.0334
LTC	730	-0.00048	0.00078	0.03854	-0.17	5.19	0.0834**	-0.0349	-0.0085	-0.0477	-0.0349	-0.0050
TRX	730	0.00113	0.00208	0.02844	-0.42	10.46	0.1123**	-0.2192*	0.0532	0.0454	-0.0286	-0.0776
XRP	730	-0.00039	-0.00003	0.04116	3.16	46.36	0.1166**	-0.1521**	0.0132	0.0384	-0.0133	-0.0244

Note: D-statistic (D-stat.) is test statistics for the Kolmogorov-Smirnov test, $\rho(i)$ is the estimated autocorrelation at lag i. ** and * indicate, respectively, 1% and 5% significance for a two-tailed test. The significance of $\rho(i)$ was estimated using heteroskedasticity-consistent standard errors.

Table 3.2: Summary statistics of daily returns (continued).

which they considered rather small compared to the actual costs at the time. On the other hand, other studies in the equity market tended to put it somewhere between 0.1% and 0.25% one-way (Sweeney 1986; Shynkevich 2012). Here, we are using the following one-way transaction costs: 0.25% for equities as considered to be moderate according to Shynkevich (2012); for FOREX 0.03% following Papadamou & Tsopoglou (2001) and Hsu *et al.* (2016); for commodities 0.015% following the upper estimate used by Yen & Hsu (2010); for cryptocurrencies 0.1% following maximum Binance standard fee.

Tables 3.1 and 3.2 show summary statistics for each of the instruments considered for the in-sample and the out-of-sample periods. For the former we have 1571 - 2720 observations, and for the latter 502 - 730 observations of daily returns depending on the instrument and asset class. Other statistics show the distribution characteristics: mean, median, standard deviation, skewness, kurtosis, the Kolmogorov-Smirnov normality test statistic (D-stat.), and autoregression coefficients up to the 5$^{\text{th}}$ lag. Importantly, from these tables, we can see that there are quite significant distinctions in return distributions, mainly between the asset classes. These are mostly differences in mean returns and their variances as proxies of risk and different levels of autocorrelation as proxies of weak market efficiency. We may suspect that these differences will be contributing to the differences in technical trading rules' performance at least without adjusting for risk.

The important characteristic that most instruments share is their significant deviation from the normal distribution. Mostly, we are witnessing slight negative skewness and high leptokurtosis (value higher than 3) indicating thick tails. It is most visible in the case of the Swiss franc, where the kurtosis value is above 300. This is captured by the Kolmogorov-Smirnov test, which indicates significant deviations from the normal distribution of most of the instruments. Some important exceptions to this are equities, currencies, and commodities in the out-of-sample period for which there is significantly less evidence to reject the normality (for equities there is no significant D-statistic at all). This is mostly due to a significant decrease in kurtosis, where all the returns became even slightly platykurtic.

It is worth noting that the out-of-sample period for most currencies and commodities was a period of recession, which is indicated by negative mean returns for both of them and slightly higher volatility for commodities. For cryptocurrencies, the out-of-sample period significantly decreased the mean returns and their volatility.

Concerning the autocorrelation coefficients, we are witnessing mostly insignificant results for all the instruments *at 5% level*. However, there are some occurrences of significant coefficients for equities in the in-sample period (7 out of 10 contain at least 1 significant coefficient), for commodities in the out-of-sample period (4 out of 10 contain at least 1 significant coefficient) and for cryptocurrencies in both periods (4 out of 10 in the in-sample and 3 out of 10 in the out-of-sample periods contain at least 1 significant coefficient).[5]

As noted by Shynkevich (2012), positive autocorrelation is associated with the ability of trend-chasing trading rules to generate superior returns due to the rejection of random-walk behavior. In our sample, only 11 (5 in cryptocurrencies) out of 26 significant coefficients are positive. Hence, it casts some doubt that simple trading rules on most instruments will be superior over the buy-and-hold strategy. Moreover, there are some signs of dynamics in the significance of the autocorrelation coefficients. The most important dynamics are in equities, where in the out-of-sample period, significant coefficients disappear completely, and in cryptocurrencies, where 5 significant coefficients in the in-sample period reduce to 3 in the out-of-sample period. Interestingly, in commodities, this trend is reversed, as there is only 1 significant coefficient in the in-sample period and 6 in the out-of-sample period. This observation sug-

[5]Some of the coefficients were significant at the 10% level, but we resorted to omitting indicating it since all of them were nominally very small.

gests the possibility that markets for equities and cryptocurrencies may have become more efficient over the sample period[6], whereas commodities probably happened to become less efficient.[7]

3.2 Trading Rules

In this thesis, a moderately large universe of trading rules based on historical prices is examined. In total, 4 families of those rules are chosen, which are often examined in related literature (Shynkevich 2012; Brock *et al.* 1992; Papadamou & Tsopoglou 2001; Yen & Hsu 2010). These are Moving Average (MA), Trading Range Breakout (TRB), Moving Average Convergence Divergence (MACD), and Relative Strength Index (RSI) rules. The first 3 are so-called trend-following rules, which try to identify the beginning of a trend and ride on it. The last one is a trend reversal rule that tries to anticipate the trend reversal by betting against the current trend.[8] To all the rules the same procedure of opening a position is applied. Namely, when a signal appears, the position is opened with a price equal to the closing price of that same day. It means that a hypothetical trader opens a position right before the market closes. In our case, all the instruments are believed to be sufficiently liquid to perform such an operation.

By selecting different combinations of the relevant parameters for constructing trading strategies we obtain the universe of trading rules. In total, we have *2870* rules (See Appendix A for the specification of parameters and calculations of the total number of rules for each family). Next, the description of each rule follows.

Moving Average (MA) rules are one of the most popular and most studied trading rules. They generate a trade signal based on the relation between short and long MAs, which are the averages of the price of a financial instrument over a certain period of time. The short MA is defined with a smaller parameter determining the length of the period, whereas the long is defined with a larger

[6] This supports the theoretical notion that markets become increasingly efficient over time, a trend that is widely observed empirically (Park & Irwin 2007; Kwon & Kish 2002; Resta *et al.* 2020).

[7] The out-of-sample period almost fully overlaps with the beginning of the war between Russia and Ukraine and the end of COVID-19 pandemic, events that significantly influenced the market for commodities worldwide. Possibly, these and other geopolitical and economic issues could have contributed to an observed potential decrease in efficiency.

[8] It is worth noting that the TRB rule may fall in both of those categories and indicate both trend continuations and trend reversals depending on the context.

parameter. Here, we are using the Exponential Moving Average (EMA) instead of the Simple Moving Average (SMA) because it gives more weight to recent time periods, making it more responsive to changes in prices. It is calculated using the following formula:

$$\mathrm{EMA}_t = \frac{2}{n+1} \cdot p_t + \left(1 - \frac{2}{n+1}\right) \cdot \mathrm{EMA}_{t-1} \tag{3.2}$$

Where p_t is the price at time t, $\frac{2}{n+1}$ is the smoothing parameter in which n is the number of time periods.

A buy signal is generated when a short EMA crosses a long EMA from below, indicating the beginning of an up-trend. A sell (short) signal is generated when a short EMA crosses a long EMA from above, indicating the beginning of a down-trend. Moreover, we consider two different variants of MA strategy – Variable length Moving Average (VMA) and Fixed length Moving Average (FMA). The former suggests holding a position until the opposite signal occurs, e.g. holding a buy position until a sell signal occurs and a short position is opened. The latter suggests holding a position for a fixed number of days after the signal occurs unless the opposite signal appears in the meantime. To reduce the number of false ("whiplash") signals, we also apply a percentage band strategy, which implies opening a position only when the price moves in the desired direction (up for a buy signal and down for a sell signal) by a fixed percentage from the initial price. In total, we have *1000* MA rules.

Trading Range Breakout (TRB) is another highly used rule that relies on the so-called channels in which prices tend to oscillate for certain periods of time. A channel is defined by a support level line at the bottom and a resistance level line at the top. It is assumed that breaking out of the channel initiates a larger price move in the same direction. A channel is formed when the highest price over the period of fixed length is within a pre-specified percentage from the lowest price over the same period, not including the current price. Here, we are also applying bands and fixed holding periods. In total, we have *1200* TRB rules.

Moving Average Convergence Divergence (MACD) is a very popular indicator developed by Appel (2005) in the 1970s. It measures the momentum in price movement as an indicator of trend strength. Its calculation is divided into two parts. The first part calculates the MACD line using the following formula:

$$\mathrm{MACD}_t = \mathrm{EMA}_t{}^{\mathrm{short}} - \mathrm{EMA}_t{}^{\mathrm{long}} \tag{3.3}$$

The second part uses MACD line and its EMA which is called the Signal Line (SL) to calculate the MACD Histogram (MACDH) with the following formula:

$$\mathrm{MACDH}_t = \mathrm{MACD}_t - \mathrm{SL}_t \tag{3.4}$$

At this point it takes 3 parameters which define $\mathrm{EMA}_t{}^{\mathrm{short}}$, $\mathrm{EMA}_t{}^{\mathrm{long}}$ and SL_t, where again the long EMA must have higher parameter than the short EMA.

The logic of this indicator is that when the price begins to move in a certain direction, the MACD line moves accordingly and crosses the signal line (its EMA), indicating the start of the trend. The buy signal is generated when MACD histogram becomes positive. The sell (short) signal is generated when MACD histogram becomes negative. Here, we also apply fixed and variable holding periods. In total, we have *420* MACD rules.

The Relative Strength Index (RSI) was developed by Wilder (1978). It is a widely used momentum oscillator that falls into a different category of trading rules than all previously described rules. It is a reversal indicator that tries to bet against the trend in order to anticipate its reversal. RSI is designed as a function that oscillates between 0 and 100. It is calculated in the following way:

$$\mathrm{RSI}_t = 100 - \frac{100}{1 + \mathrm{RS}_t} \tag{3.5}$$

Where RS_t is the Relative Strength, defined as the average of n days' up closes divided by the average of n days' down closes. Here, we are expressing them using EMAs:

$$\mathrm{RS}_t = \frac{\mathrm{EMA}_t{}^{\mathrm{up}}}{\mathrm{EMA}_t{}^{\mathrm{down}}} \tag{3.6}$$

Where $\mathrm{EMA}_t{}^{\mathrm{up}}$ represents the Exponential Moving Average of gains over n periods, and $\mathrm{EMA}_t{}^{\mathrm{down}}$ represents the Exponential Moving Average of losses over n periods.

When the value of the function is closer to 100 it implies that RS_t is high, which in turn means that the prices have been rising quickly over the last n periods. It indicates that an instrument may be overbought at the moment. Conversely, if it is closer to 0 an instrument is considered to be oversold. Setting some entry threshold (ET) at the bottom and the top for RSI_t will indicate when the position needs to be opened. Here, an ET, which needs to be less than 50, will indicate opening a long position, and a different threshold $100 -$

ET will indicate opening a short position. Again, we are using fixed and variable holding periods for this strategy, where variable length is defined by RSI_t staying above the threshold for long positions and below the threshold for short positions. In total, we have *250* RSI rules.

3.3 Methodology

Testing the predictive abilities of technical trading rules historically has been prone to data snooping biases (Park & Irwin 2007). Data snooping occurs when the performance of multiple trading rules is examined using the same data set (Shynkevich 2012). It may be that some of those are profitable simply due to luck. For example, the popularity of MA rules during the 20^{th} century may have stemmed from the fact that it just happened to be profitable at that time. Here we are following Park & Irwin (2007), who broadly outlined necessary conditions for valid inference of studying technical trading rules:

Conditions for valid inference according to Park & Irwin (2007):

1. Testing of sufficiently many trading rules.
2. Incorporation of transaction costs and risk.
3. Parameter optimization and out-of-sample verification.
4. Statistical testing.

These conditions intend to make the study more realistic, akin to the actual trading experience. The first condition allows us to see the actual merits of TA by showing the performance of many rules instead of a small selected sample. The second one considers the realism of generated profits, as no trading incurs 0 trading costs. Further, it checks whether potential increased profits are not a result of higher risk exposure. The third is the main instrumental approach to deal with data snooping bias. In essence, trading rules and their parameters are chosen based on their performance in the in-sample period and afterwards evaluated in the out-of-sample period. This is similar to evaluating any prediction model. In this scenario a trader does not know in advance which trading strategy to choose with its specific parameters. Hence, evaluating trading rules based on their performance in the in-sample period would be mistaken. Finally, the last condition checks whether the realized profits are actually statistically different from the benchmark model (buy-and-hold).

In this thesis we are following the wave of research where the testing of the universe of trading rules is conducted using popular statistical techniques such as Reality Check (RC) developed by White (2000) or Superior Predictive Ability (SPA) developed by Hansen (2005). In essence, these methods check whether the best model is statistically different from a benchmark while taking into consideration the dependencies between the rules tested. Specifically, the composite null hypothesis states that the best trading rule from the universe of rules performs no better than the benchmark:

$$H_0 : \boldsymbol{\mu} \leq \mathbf{0} \tag{3.7}$$

Where $\boldsymbol{\mu} \equiv (\mu_1, \ldots, \mu_m)'$ is the vector of excess performances of m trading rules over the benchmark. This allows for the selection and parameter optimization of rules in the in-sample period with subsequent evaluation in the out-of-sample period.

Even though the SPA test, which was designed to overcome some drawbacks of the RC test, is sufficient to check whether some models in the universe outperform the benchmark, there is a bit more modern technique offering several advantages — Model Confidence Set (MCS) procedure. It was developed by Hansen *et al.* (2011) for the purposes of model selection. It consists of a sequence of tests to determine the set of "superior" models. This procedure can perform the same task as the SPA test by observing whether a benchmark is present in the set of "superior" models. Additionally, it allows for model selection for which the SPA test is not suited since it only tests whether there is a better model than a benchmark, but it says nothing about this better model and whether it is suited to be used. MCS makes all the models benchmarks and compares them with each other. To some extent, we can look at it as a series of "SPA tests". Finally, unlike MCS, which involves equalities, SPA uses composite null hypothesis with multiple inequalities, creating a nuisance parameter problem that induces some additional loss of power (Hansen *et al.* 2011).

MCS procedure estimates the set of "superior models" $\widehat{\mathbf{M}}^*$ with a given confidence level α from the collection of models $\mathbf{M}^0$. The process of winnowing models from $\mathbf{M}^0$ is based on an equivalence test, δ_M, and an elimination rule, e_M. At each iteration when δ_M is rejected, which means that there are better and worse models, e_M is used to eliminate the worst model from the set $\mathbf{M} \subseteq$

$\mathbf{M}^0$. This iteration continues until δ_M is not rejected and resulting $\mathbf{M}$ will constitute $\widehat{\mathbf{M}}^*$.

The procedure is calculated for an arbitrary loss function. In our case we are using $L_{t,k} = -r_{t,k}$ for k$^{\text{th}}$ trading rule as a loss function following Hansen (2005, p. 366-367). From this the relative performance measure $d_{ij,t}$ is calculated for trading strategies i and j:

$$d_{ij,t} = L_{i,t} - L_{j,t}, , \quad i, j \in M^0, \quad i \neq j \tag{3.8}$$

This relative performance variable is assumed to be strictly stationary for all i and j. In our case, it means that the relative performance of all trading strategies is strictly stationary across time. Since we are using popular trading rules that were established long before the examined period, it is reasonable to assume that their relative performances over the sample period covering only 10 years do not change significantly, making $d_{ij,t}$ stationary for all i and j.

The hypotheses for δ_M are formulated in the following way[9]:

$$\begin{aligned} H_{0,M} &: \mu_i = 0 \quad \text{for all } i \in M \\ H_{A,M} &: \mu_i \neq 0 \quad \text{for some } i \in M \end{aligned} \tag{3.9}$$

Where $\mu_i = \mathbb{E}[(m-1)^{-1} \sum_{j \in M} d_{ij,t}]$. The following t-statistic is then constructed which is used in the test statistic:

$$t_i = \frac{\overline{d}_i}{\sqrt{\widehat{var}(\overline{d}_i)}} \tag{3.10}$$

Where $\overline{d}_i$ is the average of $d_{ij,t}$ across time and $\widehat{var}(\overline{d}_i)$ is a bootstrapped estimate of $var(\overline{d}_i)$ using block-bootstrap with block length p which is equal to the maximum number of significant parameters obtained by fitting an AR(p) process on all of the d_i terms (Bernardi & Catania 2018). Finally, the test statistic for testing the hypotheses in (3.9) is constructed in the following way:

$$T_M = \max_{i \in M} t_i \tag{3.11}$$

Where t_i is defined in equation (3.10). Again, block-bootstrap is used to estimate the distribution of T_M in a similar fashion as it was used to estimate $var(\overline{d}_i)$ in (3.10). In our testing we will be using the number of bootstrap re-

[9]The following is one of the two variations for the test which are essentially equivalent according to Hansen *et al.* (2011). The second keeps two model (i and j) notation instead of aggregating them.

samples $B = 2000$. It is worth noting that due to the construction of the test statistic, it takes into account the risk associated with trading rules. Hence, measuring risk is already incorporated into the testing procedure.

The elimination rule e_M is used to eliminate the worst model at each iteration when δ_M is rejected. It is defined in the following manner:

$$e_M = \arg\max_{i \in M} t_i \tag{3.12}$$

Where t_i is defined in (3.10). This rule eliminates the model which contributes the most to the test statistic.

As a result of this procedure, we also get the p-values for each trading strategy. The p-value for model k indicates the significance level α at which k is part of $\widehat{\mathbf{M}}^*$. Hence, a higher p-value indicates a better model, while a lower p-value indicates a worse model. We will be interested mostly in its value for the buy-and-hold strategy.

In total, we perform **160** MCS procedures, which are comprised of the in-sample and out-of-sample periods for both scenarios with and without transaction costs. Due to calculation constraints and lack of a sufficient number of observations, we are not conducting the MCS procedures with the whole universe of trading rules. Instead, in the in-sample period 50 best rules are selected from the whole universe of trading rules based on their Sortino ratios to be used in the MCS. Sharpe ratio could be used instead, but we believe the Sortino ratio, in this case, is a better risk-adjusted measure of performance since it punishes only the downward volatility and omits the upward volatility. In the case of users of TA, upward volatility perhaps may even be considered more favorable. It is calculated in the following manner:

$$\text{Sortino Ratio} = \frac{\text{Mean returns} - \text{Mean risk-free rate}}{\text{Standard deviation of negative returns}} \tag{3.13}$$

As the risk-free rate, we are considering the average of 3-month US treasury yield over the sample period, which is equal to 0.0056% per day (1.4% annually). Further, the same 50 rules are evaluated in the out-of-sample period. We are reporting the scenarios with and without transaction costs for illustrational purposes.

Chapter 4

Empirical Results

4.1 General results without transaction costs

First, the case without transaction costs is examined on both the in-sample and the out-of-sample periods. The main results are depicted in Tables 4.1 and 4.2. There, for each of the instruments we report the best trading rule measured by the Sortino ratio in the in-sample period with its average annualized excess return over the buy-and-hold strategy. The following formula is used to calculate the average annualized excess return:

$$\bar{r}_i^{\mathrm{e}} = (1 + \bar{r}_i - \bar{r}_{\mathrm{B\&H}})^n - 1 \tag{4.1}$$

Where $\bar{r}_i$ is the average daily return of a trading rule i, $\bar{r}_{\mathrm{B\&H}}$ is the average daily return of the buy-and-hold strategy, and n is the number of days in a year[1].

Similarly, the average annualized excess return and the average daily Sortino ratio increase over all the rules selected for the MCS procedure are reported. The number of rules selected for the MCS procedure is reported in the column "Rules for MCS", which is mostly equal to 50, as discussed in Chapter 3.[2] These statistics will be more informative of the overall performance of the universe of trading rules compared to just one best rule. Also, by comparing the average excess returns (risk-unadjusted returns) with the average Sortino ratio increase (risk-adjusted returns), we will be able to assess the common hypothesis that

[1]For equities, currencies, and commodities the standard 252 days are used, and for cryptocurrencies it is 365 days since they are traded constantly.

[2]This number differs for some instruments due to limitations of the MCS procedure. In the case where numerous very similar models are included, the procedure no longer works. Trading rules that had similar average returns were removed, except one.

TA may increase the returns but only at the expense of greater risk exposure, which was discussed for example in Park & Irwin (2007). *We find this hypothesis to be mostly true for most of the cases in our data where trading rules increased the risk-unadjusted returns.*

Lastly, we report the p-values of the buy-and-hold strategy, which come from the MCS procedure discussed in Chapter 3. They indicate the significance level at which the buy-and-hold strategy is part of the MCS. In other words, this figure shows the statistical significance of risk-adjusted outperformance of trading rules over the buy-and-hold strategy. *In our case, we find that the selected trading rules on all the instruments in each category and in each scenario did not manage to significantly outperform the buy-and-hold strategy.*

Ticker	Best trading rule	Excess return (%)	Avg. excess return (%)	Avg. Sortino ratio increase	% Outperforming rules	Rules for MCS	$p_{B\&H}$
EQUITIES:							
DJI	MACD_10_100_10_5days	-1.82	-4.42	-0.01 (-40.7%)	0.47	49	1
DJT	MACD_10_30_10_10days	8.03	2.76	0.01 (78.5%)	15.53	50	1
DJU	MACD_10_100_40_25days	0.69	-2.44	-0.01 (-32.2%)	1.06	49	1
GSPC	Buy-and-hold	0	-5.51	-0.01 (-47%)	0	49	1
SP400	MACD_10_30_10_10days	-1.07	-2.64	-0.01 (-27.2%)	0.99	49	1
VTI	Buy-and-hold	0	-4.45	-0.01 (-35.6%)	0	49	1
IXIC	Buy-and-hold	0	-6.42	-0.01 (-38.1%)	0	49	1
RUT	MACD_10_20_20_10days	0.72	-0.86	0 (1.2%)	6.23	49	1
NYA	TRB_175_0.15_10days_0.01band	0.41	-1.62	0 (-28.6%)	1.92	49	1
NBI	MA_5_30_5days	14.92	9.06	0.02 (321.1%)	36.2	50	1
AVERAGE:		**2.19**	**-1.65**	**0.00**	**6.24**		**1**
CURRENCIES:							
AUD	MA_5_100_50days_0.005band	4.51	3.3	0.02 (83.1%)	43.43	50	0.999
CAD	MACD_30_50_40_50days	4.95	2.96	0.03 (90.6%)	38.94	50	1
CHF	RSI_25_40/60	2.15	0.64	0.01 (68.7%)	8.27	50	1
CZK	MACD_30_50_50	4.71	2.52	0.02 (151.1%)	33.33	50	1
EUR	RSI_15_40/60	3.4	2.18	0.02 (78.2%)	34.78	50	0.997
GBP	MACD_100_200_20	6.75	5.19	0.03 (140.8%)	62.74	50	0.88
JPY	TRB_50_0.1_50days	3.06	1.93	0.02 (85%)	25.33	50	1
KRW	RSI_10_40/60	6.23	2.62	0.02 (85.6%)	35.52	50	0.971
MXN	MACD_30_100_20_50days	12.65	9.5	0.04 (137.2%)	75.29	50	0.969
SGD	MACD_100_200_20_50days	2.17	1.34	0.02 (71.2%)	35.27	50	1
AVERAGE:		**5.06**	**3.38**	**0.02**	**39.29**		**0.982**
COMMODITIES:							
Copper	RSI_10_40/60_5days	4.35	0.47	0 (20.1%)	5.41	49	1
Corn	MACD_20_100_20	4.3	0.43	0 (13.7%)	7.25	49	1
Soybean	MACD_30_100_50	11.97	2.39	0.01 (52%)	12.26	50	1
Soybean oil	MACD_50_150_50	5.68	-1.4	0 (-14.3%)	2.17	49	1
Sugar	MACD_20_200_20_50days	9.93	5.01	0.01 (215.1%)	18.36	50	1
Wheat	RSI_10_30/70_5days	6.05	-1.17	0 (-24.8%)	1.9	49	1
Gold	MACD_20_30_20_50days	0.59	-3.07	-0.01 (-65%)	0.22	49	1
Silver	MACD_10_50_40	3.9	-1.54	0 (-19%)	2.92	49	1
Natural gas	RSI_10_30/70	20.35	6.79	0.01 (4331.6%)	12.85	50	1
Oil	MACD_20_50_20_50days	29.77	18.95	0.03 (2212.4%)	42.53	50	1
AVERAGE:		**9.69**	**2.69**	**0.01**	**10.59**		**1**
CRYPTOCURRENCIES:							
ADA	MA_15_40	250.91	195.34	0.06 (166.8%)	47.36	50	0.66
BCH	MACD_10_20_40	376.03	243.2	0.07 (713.7%)	83.02	49	0.785
BNB	MACD_20_150_40	122.68	82.39	0.04 (66%)	28.53	50	0.959
BTC	MACD_10_20_20	23.76	9.02	0.01 (28.2%)	14.76	50	1
DOGE	MA_5_30_50days_0.01band	149.71	64.14	0.02 (47.4%)	15.23	50	0.99
ETH	TRB_10_0.2_50days_0.02band	184.13	101.85	0.04 (176%)	42.93	50	0.8
LINK	MACD_10_150_20_50days	32.53	6.13	0.01 (20.5%)	9.06	49	1
LTC	MACD_10_20_40	85.02	36.47	0.02 (84%)	26.1	50	0.999
TRX	MACD_20_50_20_50days	192.81	123.07	0.04 (143.3%)	65.04	50	0.867
XRP	MACD_10_100_10_25days	413.29	222.43	0.06 (487.4%)	59.25	50	0.549
AVERAGE:		**183.09**	**108.40**	**0.04**	**39.13**		**0.861**

Note: Best trading rule is measured by the Sortino ratio. The names of the rules are described in Appendix A. *Excess return* is the average annualized excess return over the B&H strategy of the best rule. *Avg. excess return* is the average annualized excess return over the B&H strategy of all the rules selected for the MCS procedure. *Avg. Sortino ratio increase* is the average increase of the daily Sortino ratio over the B&H strategy of all the rules selected for the MCS procedure (percentage increase in brackets). *% Outperforming rules* is the percentage of rules that outperform the B&H strategy in the whole universe of rules measured by the Sortino ratio. *Rules for the MCS* is the number of rules that are used in the MCS procedure. $p_{B\&H}$ is the MCS p-value of the B&H strategy.

Table 4.1: Performance of trading strategies during the in-sample period from September 17, 2014, to February 28, 2022, *excluding transaction costs.*

These statistics, among other things, are intended to measure the consistency and significance of TA returns and the presence of differences in their performance for each asset class. These factors are of prime interest in this thesis. Also, they allow us to check for the potential differences in performance between each family of trading rules. This might be of interest, although it is not the primary focus of the thesis. *Overall, we find little evidence of significant consistency and differences of risk-adjusted returns across the asset classes.*

One noticeable observation stemming from Tables 4.1 and 4.2 is the relative consistency of excess returns, percentages of outperforming rules, and the p-values within the asset classes. For both in-sample and out-of-sample periods,

Ticker	In-sample best trading rule	Excess return (%)	Avg. excess return (%)	Avg. Sortino ratio increase	% Outperforming rules	Rules for MCS	$p_{B\&H}$
EQUITIES:							
DJI	MACD_10_100_10_5days	-7.51	-5.76	-0.02 (-71.4%)	16.88	48	1
DJT	MACD_10_30_10_10days	-3.39	6.12	0.02 (703.5%)	32.73	45	1
DJU	MACD_10_100_40_25days	30.80	16.23	0.06 (88.3%)	60.69	48	0.985
GSPC	Buy-and-hold	0	-9.99	-0.04 (-187.6%)	21.86	42	1
SP400	MACD_10_30_10_10days	-9.10	0.63	0.01 (63.4%)	35.16	47	1
VTI	Buy-and-hold	0	-11.59	-0.04 (-176.5%)	21.69	49	1
IXIC	Buy-and-hold	0	-1.09	0 (-0.8%)	39.07	43	1
RUT	MACD_10_20_20_10days	4.71	-2.18	-0.01 (-1428.6%)	52.2	42	1
NYA	TRB_175_0.15_10days_0.01band	-5.83	-4.37	-0.03 (-247.2%)	30.67	39	1
NBI	MA_5_30_5days	-4.11	-7.17	-0.01 (-127.5%)	15.49	50	1
AVERAGE:		**0.56**	**-1.92**	**-0.01**	**32.64**		**0.998**
CURRENCIES:							
AUD	MA_5_100_50days_0.005band	7.15	3.54	0.01 (62%)	67.08	50	1
CAD	MACD_30_50_40_50days	-2.38	0.37	-0.01 (-218.1%)	57.22	47	1
CHF	RSI_25_40/60	0.10	-2.6	-0.03 (-490.7%)	19.52	46	1
CZK	MACD_30_50_50	-1.1	2.6	0.01 (66.8%)	87.26	46	1
EUR	RSI_15_40/60	2.08	1.58	0.01 (57.8%)	76.71	46	1
GBP	MACD_100_200_20	14.09	5.12	0.03 (129.2%)	91.07	47	1
JPY	TRB_50_0.1_50days	27.06	21.68	0.13 (165%)	99.89	48	0.501
KRW	RSI_10_40/60	3.74	6.52	0.03 (82.2%)	94.73	46	0.999
MXN	MACD_30_100_20_50days	-19.65	-11.14	-0.08 (-210.8%)	0.61	48	1
SGD	MACD_100_200_20_50days	-0.5	0.67	0.02 (120.5%)	51.8	50	1
AVERAGE:		**3.06**	**2.83**	**0.01**	**64.59**		**0.95**
COMMODITIES:							
Copper	RSI_10_40/60_5days	4.45	-1.66	-0.01 (-234.5%)	61.89	47	1
Corn	MACD_20_100_20	35.27	34.48	0.07 (122.4%)	96.78	46	0.979
Soybean	MACD_30_100_50	21.97	19.35	0.04 (-115.8%)	92.54	48	0.981
Soybean oil	MACD_50_150_50	42.88	58.06	0.08 (86.4%)	95.51	43	0.803
Sugar	MACD_20_200_20_50days	-20.30	-16.45	-0.04 (-180%)	3.59	45	1
Wheat	RSI_10_30/70_5days	22.72	22.89	0.02 (65.8%)	92.69	47	0.998
Gold	MACD_20_30_20_50days	-5.63	-2.07	0.02 (458.3%)	39.08	48	1
Silver	MACD_10_50_40	-14.38	1.6	0.01 (68.5%)	40.1	47	1
Natural gas	RSI_10_30/70	53.05	56.77	0.04 (98.3%)	98.61	34	0.985
Oil	MACD_20_50_20_50days	13.88	-9.11	-0.03 (-330.1%)	64.78	46	1
AVERAGE:		**15.39**	**16.39**	**0.02**	**68.56**		**0.975**
CRYPTOCURRENCIES:							
ADA	MA_15_40	155.49	103.75	0.05 (130.6%)	94.98	47	0.973
BCH	MACD_10_20_40	-9.26	11.26	0.01 (20.2%)	62.24	45	1
BNB	MACD_20_150_40	197.07	34.3	0.03 (1000%)	72.66	50	1
BTC	MACD_10_20_20	21.43	12.98	0.02 (161%)	55.96	50	1
DOGE	MA_5_30_50days_0.01band	155.57	21.66	0.01 (1.3%)	61.86	47	1
ETH	TRB_10_0.2_50days_0.02band	23.48	8.02	0 (162.5%)	64.27	49	1
LINK	MACD_10_150_20_50days	97.44	15.73	0.02 (315.6%)	41.78	47	1
LTC	MACD_10_20_40	20.2	-8.4	-0.01 (-276.9%)	45.43	50	1
TRX	MACD_20_50_20_50days	38.75	-42.64	-0.06 (-187.7%)	0.99	48	1
XRP	MACD_10_100_10_25days	114.98	66.34	0.05 (165.5%)	58.29	50	0.997
AVERAGE:		**81.52**	**22.3**	**0.01**	**55.85**		**0.997**

Note: Best in-sample trading rule is the best trading rule in the in-sample period measured by the Sortino ratio. The names of the rules are described in Appendix A. *Excess return* is the average annualized excess return over the B&H strategy of the best in-sample rule. *Avg. excess return* is the average annualized excess return over the B&H strategy of all the rules selected for the MCS procedure in the in-sample period. *Avg. Sortino ratio increase* is the average increase of the daily Sortino ratio over the B&H strategy of all the rules selected for the MCS procedure in the in-sample period (percentage increase in brackets). *% Outperforming rules* is the percentage of rules that outperform the B&H strategy in the whole universe of rules measured by the Sortino ratio. *Rules for the MCS* is the number of rules that are used in the MCS procedure. $p_{B\&H}$ is the MCS p-value of the B&H strategy.

Table 4.2: Performance of trading strategies during the out-of-sample period from March 1, 2022, to February 29, 2024, *excluding transaction costs.*

the excess returns keep almost the same order: equities have the smallest average excess return, where the values tend to be negative or close to zero, followed by currencies ($\sim 3-5\%$), commodities ($\sim 3-16\%$), and, lastly, cryptocurrencies with a markedly higher magnitude of excess returns ($\sim 22-180\%$).[3] However, this order is not present if we consider the Sortino ratios, although at first glance, some consistency is still present. For example, here, the values for equities tend to stay negative, and for cryptocurrencies, they tend to stay positive for the vast majority of instruments. Interestingly, if we look at the whole universe of rules, then the consistency of the percentage of outperforming trading rules based on the Sortino ratio is rather high. For both the in-sample and out-of-sample periods for each of the instruments within an asset class, the percentage tends to stay in some particular range, which, surprisingly, increases from the in-sample to the out-of-sample periods for all the asset classes. This could be due to a temporary decrease in the Sortino ratio of the buy-and-hold strategy, whereas it is likely that trading rules managed to stay out of the market in times of significant drawdowns, which in turn decreased the returns less.

It is worth noting that the consistency in excess returns and Sortino ratios decreases for the out-of-sample period. We see there a higher variability between the instruments within the asset classes. For example, Figure 4.1, depicting the box plots of the average Sortino ratio increase for the in-sample and out-of-sample periods, shows that for all the asset classes, except cryptocurrencies, the variability increases significantly.

The potential reason for this increase is likely to come from the fact that the performance of the trading rules selected in the in-sample period is greatly reduced in the out-of-sample period. Figure 4.2 depicts the dynamics of average excess returns for all the asset classes. For all the classes except commodities the reduction is present, especially it is great for cryptocurrencies, where it decreases by approximately 80% from 108.4% to 22.3%. Surprisingly, it is reversed for the commodities, and excess returns increase 5 times from 2.69% to 16.39%. As mentioned in Chapter 3, this could be caused by a decreased

[3]We see no clear connection between these returns and the extent of (positive) autocorrelation of returns. On the one hand, with regard to cryptocurrencies, the number of significant coefficients seems to be related to their high profitability. Similarly, the increase of returns of commodities in the out-of-sample period corresponds with the increase in the number of (positive) autocorrelation coefficients. However, we see that the returns are also increasing for those instruments without significant coefficients. Also, the number of significant coefficients in equities does not translate into their profitability. Hence, the causal relationship is, at maximum, very vague.

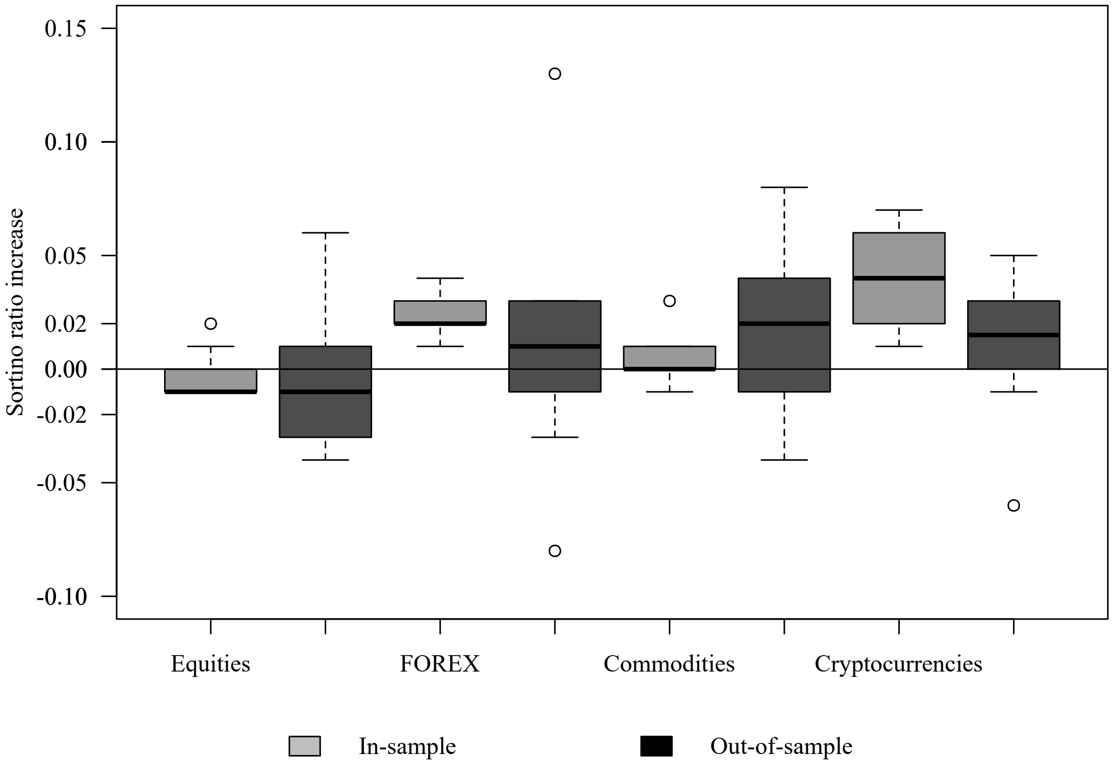

Figure 4.1: Box plots of average Sortino ratio increase by the asset class *excluding transaction costs.*

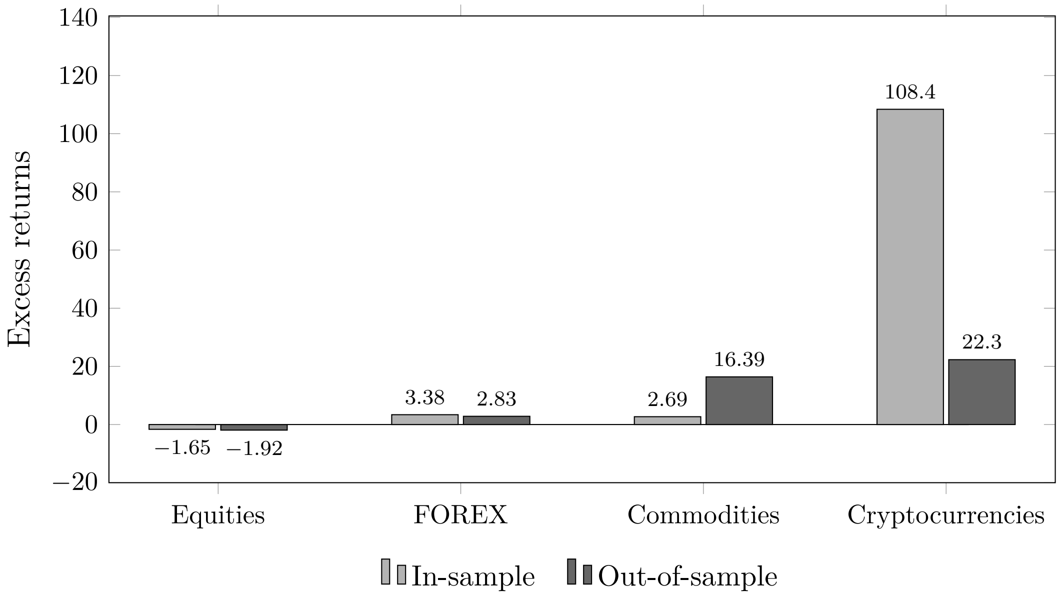

Figure 4.2: Average of excess returns by the asset class *excluding transaction costs.*

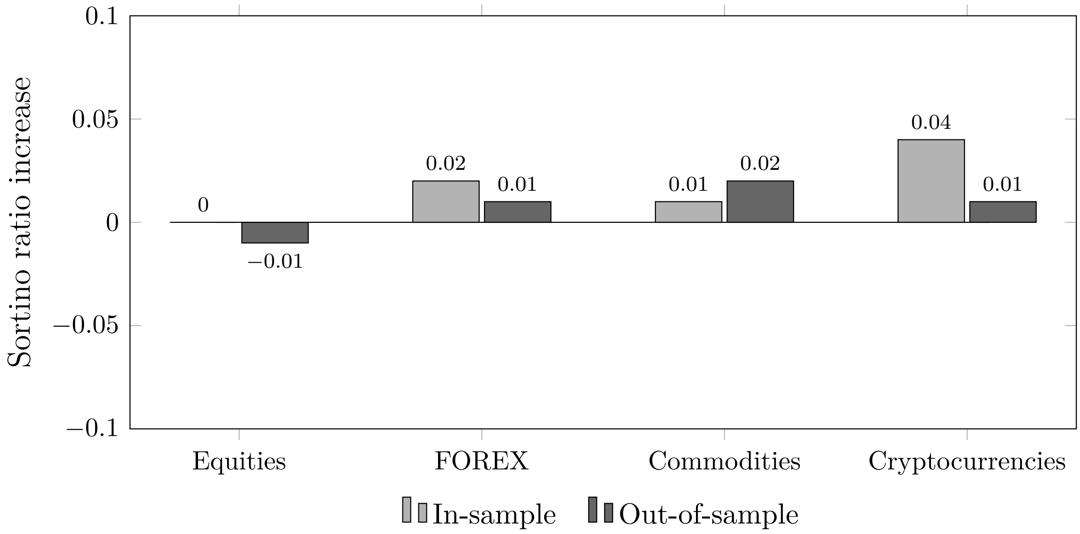

Figure 4.3: Average of Sortino ratio increase by the asset class *excluding transaction costs*.

efficiency of the commodity market, which was captured by the increase in the number of significant autocorrelation coefficients in the out-of-sample period.

A similar conclusion could also be drawn by looking at Figures 4.3 and 4.1, which depict the returns adjusted for risk using the Sortino ratios. Here again, all classes except commodities experience a decline, which is roughly comparable to a decrease in excess returns. Thus, it might be the case that the risk did not change significantly from the in-sample period by applying the same rules in the out-of-sample period. Here, by risk, we understand the variation in returns of a trading rule. As noted before, the performance of trading rules possesses an increased variation across the instruments in the out-of-sample period, which could also be conceived as a form of risk, though of a different nature.

With respect to the differences in performance between the asset classes, we see some significant changes in average excess returns across them for both the in-sample and out-of-sample periods. In Figure 4.2, we see that this change may reach not only a few percentage points but also tens of percentage points in the case of cryptocurrencies. However, some of those differences could be caused by the differences in the risk of the underlying instruments. Surely, our four examined asset classes differ in risk profiles, as was discussed in Chapter 3. We saw that in our sample, currencies generally had the smallest variance of returns, followed by equities, commodities, and finally, cryptocurrencies, whose riskiness is notorious. By looking at risk-adjusted figures in Figure 4.1, we see that the differences become less pronounced. Even though in the in-sample period, there is a semblance of certain differences due to low variation across the instruments, they largely disappear if we look at the out-of-sample period. The variations increase, and thus, box plots are significantly overlapping there, meaning that TA can hardly claim any substantial differences in results across the asset classes.

Moreover, for both the periods and all the instruments we reject the hypothesis that the trading rules outperform the buy-and-hold strategy. The p-values for most of the instruments across the asset classes are around 1, meaning that it is almost certain that the trading rules do not outperform the buy-and-hold strategy. Only some cryptocurrencies in the in-sample period and the Japanese yen in the out-of-sample period show smaller p-values closer to 0.5. However, even those do not constitute any meaningful confidence level to reject the null hypothesis of equal performance. Hence, there is even more evidence to reject any differences in performance among the asset classes.

This evidence supports the hypothesis mentioned before that TA may increase returns but only at the expense of higher-risk exposure. Thus, even though rough returns may seem to be significantly increased with the use of TA, in fact, they bear a higher inherent risk. Also, the results are in line with the general trend in research suggesting decreasing performance of technical trading rules over time. It could have been expected that the use of TA on such highly traded instruments would not produce any surprisingly positive results except for cryptocurrencies. Even though cryptocurrencies show the highest potential to generate significant excess returns, it is the case that even they are not able to outperform the buy-and-hold strategy if we account for risk.

This finding is against most of the previous evidence of applying TA to cryptocurrencies that showed substantially increased profits. This rather unexpected result could also be related to a significant increase in cryptocurrency market efficiency in the out-of-sample period as the performance there decreases substantially compared to the in-sample period. As mentioned in Chapter 2 there were some signs of this improvement before. Hence, this result is not totally unexpected. Considering other asset classes, our conclusions are mostly in line with the existing research. Given that already since the 1990s, the performance of TA on equities, currencies, and commodities was weakened, and the trend towards greater efficiency was established, it is fair to conclude that, during our sample, these markets possessed an expected level of efficiency.

Lastly, it is interesting to look at the best rules for each of the instruments.

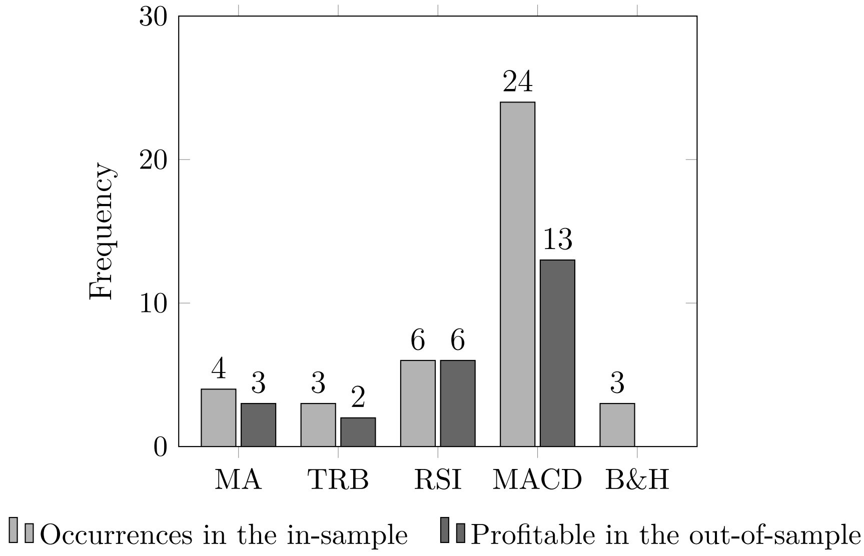

Figure 4.4: Frequency of the in-sample best trading rules by the trading strategy *excluding transaction costs*.

Figure 4.4 shows the frequency of occurrence of rules from different families as the best rules in the in-sample period and whether they remained nominally profitable in the out-of-sample period. It seems that MACD rules are by far the most promising family of rules as they are clearly dominating all other families. However, almost half of those rules stopped being profitable further in the out-of-sample period, which is the highest decrease among all the families. Interestingly, the second most successful family is RSI, which equally occurs only in currencies and commodities. These are the asset classes where the prices tend to oscillate in some particular range for a prolonged period of time without any long-term trends. Theoretically, these conditions are the best for using RSI rules since, according to the logic of this indicator, it makes sense to bet against the trend if the price tends to reach some particular high or low. Hence, *it may be worth considering the state of the market and the type of instrument for the choice of trading rules*. Especially so, given that, in our case, all RSI rules remained nominally profitable in the out-of-sample period.

4.2 Transaction costs

This section examines the effects of incorporating transaction costs into the trading procedure. Since the previous section's results did not show many promising results in favor of TA, we would expect them to worsen even more here. In fact, we find that this is indeed the case. The precise amounts of transaction costs for each asset class can be found in Chapter 3.[4] The main results are depicted in Tables 4.3 and 4.4.

With respect to the consistency of results within the asset classes we see a quite similar picture as before. In Figure 4.5 there is an analogous order in terms of excess returns: equities are performing the worst, followed by currencies, commodities, and cryptocurrencies with the best performance. Transaction costs here resulted in a decrease equal to a few percentage points compared to the previous section for all asset classes except commodities, for which the

Ticker	Best trading rule	Excess return (%)	Avg. excess return (%)	Avg. Sortino ratio increase	% Outperforming rules	Rules for MCS	$p_{B\&H}$
EQUITIES:							
DJI	Buy-and-hold	0	-5.96	-0.02 (-74.3%)	0	49	1
DJT	MACD_10_30_10_10days	0.52	-2.43	0 (-12.3%)	2.48	49	1
DJU	Buy-and-hold	0	-4.28	-0.01 (-72.5%)	0	49	1
GSPC	Buy-and-hold	0	-6.48	-0.02 (-63.1%)	0	49	1
SP400	Buy-and-hold	0	-3.81	-0.01 (-52.5%)	0	49	1
VTI	Buy-and-hold	0	-5.23	-0.01 (-45%)	0	49	1
IXIC	Buy-and-hold	0	-7.38	-0.02 (-50.2%)	0	49	1
RUT	TRB_100_0.2_10days_0.02band	0.49	-1.84	0 (-21.4%)	1.19	49	1
NYA	TRB_175_0.15_10days_0.01band	-0.06	-2.41	-0.01 (-56%)	0.19	49	1
NBI	MA_5_30_5days	10.89	5.55	0.01 (194.2%)	22.61	50	1
AVERAGE:		**1.18**	**-3.43**	**-0.01**	**2.65**		**1**
CURRENCIES:							
AUD	MA_5_100_50days_0.005band	4.32	3.06	0.02 (79.3%)	40.08	50	0.998
CAD	MACD_30_50_40_50days	4.63	2.52	0.02 (80.8%)	34.03	50	1
CHF	RSI_25_40/60	1.49	0.29	0 (56.9%)	5.49	49	1
CZK	MACD_30_50_50	4.37	2.24	0.02 (121.5%)	30.88	50	1
EUR	MA_20_250_50days_0.005band	2.93	1.91	0.02 (73.3%)	30.26	50	0.999
GBP	MACD_100_200_20	6.6	5.07	0.03 (135%)	58.75	50	0.903
JPY	TRB_50_0.1_50days	2.9	1.82	0.01 (82%)	21.94	50	1
KRW	RSI_10_40/60	4.71	2.19	0.02 (77%)	30.82	50	0.997
MXN	MACD_30_100_20_50days	12.21	9.16	0.04 (128.9%)	73.9	50	0.97
SGD	MACD_100_200_20_50days	2.01	1.22	0.02 (68.5%)	30.04	50	1
AVERAGE:		**4.62**	**2.95**	**0.02**	**35.62**		**0.987**
COMMODITIES:							
Copper	RSI_10_40/60_5days	3.64	0.45	0 (17.6%)	5.02	49	1
Corn	MACD_50_150_40	4.26	0.18	0 (11.1%)	6.49	49	1
Soybean	MACD_30_100_50	11.84	2.36	0.01 (51.8%)	12.34	50	1
Soybean oil	MACD_50_150_50	5.61	-1.45	0 (-14.6%)	2.2	49	1
Sugar	MACD_20_200_20_50days	9.71	4.86	0.01 (209.3%)	17.98	50	1
Wheat	RSI_10_30/70_5days	5.58	-1.33	0 (-26.8%)	1.58	49	1
Gold	MACD_20_30_20_50days	0.3	-3.35	-0.01 (-71.2%)	0.21	49	1
Silver	MA_5_200_5days_0.001band	1.48	-1.55	0 (-19.6%)	2.99	49	1
Natural gas	RSI_10_30/70	19.8	6.48	0.01 (4254.2%)	12.24	50	1
Oil	MACD_20_50_20_50days	29.46	19.13	0.03 (2214.9%)	42.21	50	1
AVERAGE:		**9.17**	**2.58**	**0.01**	**10.33**		**1**
CRYPTOCURRENCIES:							
ADA	MA_15_40	247.46	190.05	0.05 (163.9%)	46.75	50	0.736
BCH	MACD_10_20_40	361.10	237.95	0.07 (696.1%)	81.42	49	0.763
BNB	MACD_20_150_40	120	82.4	0.04 (65.7%)	28.47	50	0.928
BTC	MACD_10_20_20	19.13	6.79	0.01 (24.1%)	12.99	50	1
DOGE	MA_5_30_50days_0.01band	145.82	62.11	0.02 (45.4%)	13.88	50	0.998
ETH	TRB_10_0.2_50days_0.02band	175.44	96.73	0.04 (172.2%)	42.59	50	0.83
LINK	MACD_10_150_20_50days	28.96	2.34	0.01 (16%)	7.95	49	1
LTC	MACD_10_20_40	78.64	36.18	0.02 (81.4%)	24.57	50	0.999
TRX	MACD_20_50_20_50days	187.15	112.69	0.04 (135.1%)	65.98	50	0.886
XRP	MACD_10_100_10_25days	397.33	212.03	0.06 (473.9%)	58.75	50	0.514
AVERAGE:		**176.1**	**103.93**	**0.04**	**38.34**		**0.865**

Note: Best trading rule is measured by the Sortino ratio. The names of the rules are described in Appendix A. *Excess return* is the average annualized excess return over the B&H strategy of the best rule. *Avg. excess return* is the average annualized excess return over the B&H strategy of all the rules selected for the MCS procedure. *Avg. Sortino ratio increase* is the average increase of the daily Sortino ratio over the B&H strategy of all the rules selected for the MCS procedure (percentage increase in brackets). *% Outperforming rules* is the percentage of rules that outperform the B&H strategy in the whole universe of rules measured by the Sortino ratio. *Rules for the MCS* is the number of rules that are used in the MCS procedure. $p_{B\&H}$ is the MCS p-value of the B&H strategy.

Table 4.3: Performance of trading strategies during the in-sample period from September 17, 2014, to February 28, 2022, *including transaction costs.*

[4]It is certainly possible to consider transaction costs different from those used here. However, these would not change the results significantly, given the already poor performance without them.

excess returns decreased to a much smaller extent. This is related to two facts: small transaction costs and the occasion that among the 50 best rules there are more rules with higher parameters, which generated a smaller number of signals, decreasing the effect of transaction costs.

With respect to the Sortino ratios, we contemplate essentially similar results, especially if we compare Figures 4.6 and 4.3.[5] The only difference is a relatively more significant decrease in average Sortino ratios for equities compared to other asset classes. In terms of the volatility of results, we see a

Ticker	In-sample best trading rule	Excess return (%)	Avg. excess return (%)	Avg. Sortino ratio increase	% Outperforming rules	Rules for MCS	$p_{B\&H}$
EQUITIES:							
DJI	Buy-and-hold	0	-7.75	-0.02 (-79.6%)	7.41	48	1
DJT	MACD_10_30_10_10days	-6.35	1.93	0.01 (401.6%)	25.14	45	1
DJU	Buy-and-hold	0	11.89	0.05 (26.4%)	53.71	48	1
GSPC	Buy-and-hold	0	-13.48	-0.06 (-247%)	14.69	42	1
SP400	Buy-and-hold	0	-3.76	-0.01 (-83.1%)	26.07	47	1
VTI	Buy-and-hold	0	-14.97	-0.05 (-220.3%)	13.6	49	1
IXIC	Buy-and-hold	0	-1.49	0 (-18.1%)	29.68	43	1
RUT	TRB_100_0.2_10days_0.02band	0.43	-4.87	-0.02 (-3096.4%)	45.49	42	1
NYA	TRB_175_0.15_10days_0.01band	-4.2	-7.37	-0.05 (-420.1%)	19.22	39	1
NBI	MA_5_30_5days	-11.95	-9.97	-0.03 (-263.3%)	9.16	50	1
AVERAGE:		**-2.21**	**-4.98**	**-0.02**	**24.42**		**1**
CURRENCIES:							
AUD	MA_5_100_50days_0.005band	10.56	4.24	0.02 (71.2%)	65.85	50	1
CAD	MACD_30_50_40_50days	-0.44	-0.42	-0.02 (-250.8%)	54.89	47	1
CHF	RSI_25_40/60	-0.42	-2.49	-0.03 (-448.1%)	18.14	46	1
CZK	MACD_30_50_50	0.26	2.01	0.01 (62%)	84.42	46	1
EUR	MA_20_250_50days_0.005band	-1.02	1.49	0 (53.9%)	74.37	46	1
GBP	MACD_100_200_20	14.46	5.07	0.03 (131.9%)	89.59	47	1
JPY	TRB_50_0.1_50days	32.63	21.6	0.13 (148.4%)	99.88	50	0.517
KRW	RSI_10_40/60	4.36	5.42	0.03 (74.7%)	94.7	46	1
MXN	MACD_30_100_20_50days	-15.8	-11.61	-0.07 (-199.7%)	0.45	48	1
SGD	MACD_100_200_20_50days	0.7	0.27	0.02 (161.8%)	46.94	50	1
AVERAGE:		**4.53**	**2.56**	**0.01**	**62.92**		**0.952**
COMMODITIES:							
Copper	RSI_10_40/60_5days	8.82	-2.84	-0.01 (-226.7%)	61.24	47	1
Corn	MACD_50_150_40	19.43	33.37	0.06 (98.2%)	96.66	46	1
Soybean	MACD_30_100_50	29.65	19.49	0.05 (90%)	91.75	48	1
Soybean oil	MACD_50_150_50	63.99	57.91	0.08 (267.4%)	95.99	48	0.600
Sugar	MACD_20_200_20_50days	-15.88	-16.03	-0.03 (-154.1%)	4.07	45	1
Wheat	RSI_10_30/70_5days	29.69	22.84	0.02 (67.5%)	92.81	47	1
Gold	MACD_20_30_20_50days	-3.67	-2.2	0 (1.7%)	36.53	48	1
Silver	MA_5_200_5days_0.001band	10.74	1.93	0.01 (65%)	39.64	47	1
Natural gas	RSI_10_30/70	92.12	56.71	0.03 (81.6%)	98.44	34	1
Oil	MACD_20_50_20_50days	-3.41	-8.86	-0.03 (-331%)	62.66	46	1
AVERAGE:		**23.15**	**16.23**	**0.02**	**67.98**		**0.96**
CRYPTOCURRENCIES:							
ADA	MA_15_40	132.63	103.7	0.05 (138.2%)	94.46	46	0.993
BCH	MACD_10_20_40	-13.00	4.04	0 (89.4%)	57.83	46	1
BNB	MACD_20_150_40	41.11	32.45	0.03 (915.6%)	70.02	49	1
BTC	MACD_10_20_20	-2.17	12	0.02 (156.4%)	54.11	47	1
DOGE	MA_5_30_50days_0.01band	88.9	18.62	0.01 (25.3%)	60.66	47	1
ETH	TRB_10_0.2_50days_0.02band	-5.99	4.35	0 (129.7%)	62.37	48	1
LINK	MACD_10_150_20_50days	23.34	11.84	0.01 (205.2%)	40.1	49	1
LTC	MACD_10_20_40	10.27	-8.99	-0.01 (-278.6%)	45.06	50	1
TRX	MACD_20_50_20_50days	-43.77	-44.95	-0.07 (-193.5%)	0.78	50	1
XRP	MACD_10_100_10_25days	112.55	59.04	0.05 (164.8%)	57.56	50	0.999
AVERAGE:		**34.39**	**19.21**	**0.01**	**54.3**		**0.999**

Note: Best in-sample trading rule is the best trading rule in the in-sample period measured by the Sortino ratio. The names of the rules are described in Appendix A. *Excess return* is the average annualized excess return over the B&H strategy of the best in-sample rule . *Avg. excess return* is the average annualized excess return over the B&H strategy of all the rules selected for the MCS procedure in the in-sample period. *Avg. Sortino ratio increase* is the average increase of the daily Sortino ratio over the B&H strategy of all the rules selected for the MCS procedure in the in-sample period (percentage increase in brackets). *% Outperforming rules* is the percentage of rules that outperform the B&H strategy in the whole universe of rules measured by the Sortino ratio. *Rules for the MCS* is the number of rules that are used in the MCS procedure. $p_{B\&H}$ is the MCS p-value of the B&H strategy.

Table 4.4: Performance of trading strategies during the out-of-sample period from March 1, 2022, to February 29, 2024, *including transaction costs.*

[5] The numbers in the figures are very similar due to rounding.

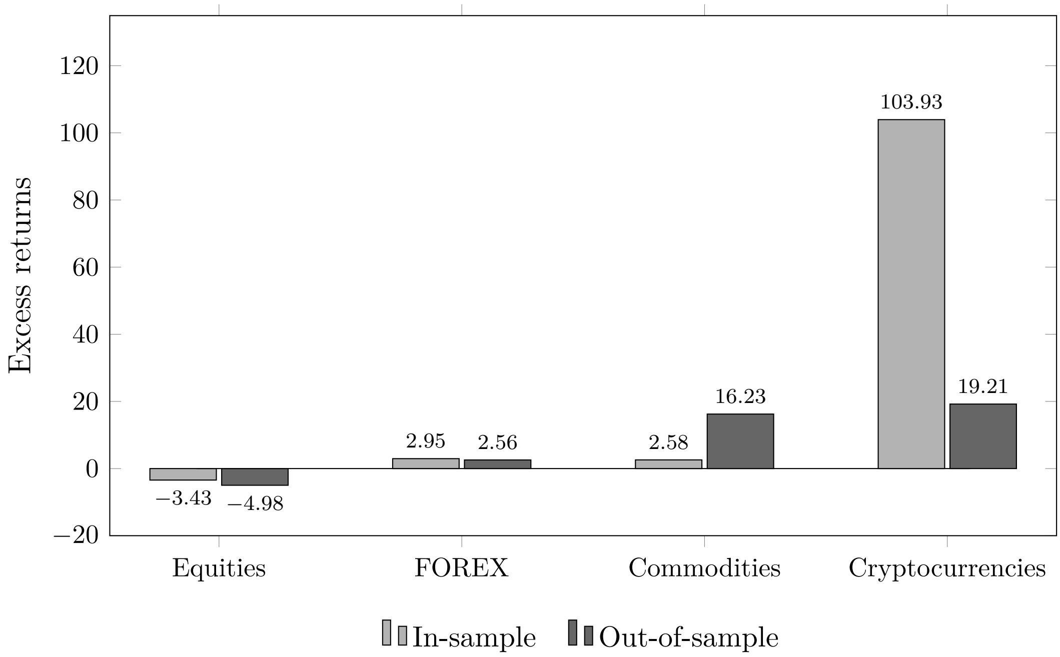

Figure 4.5: Average of excess returns by the asset class *including transaction costs.*

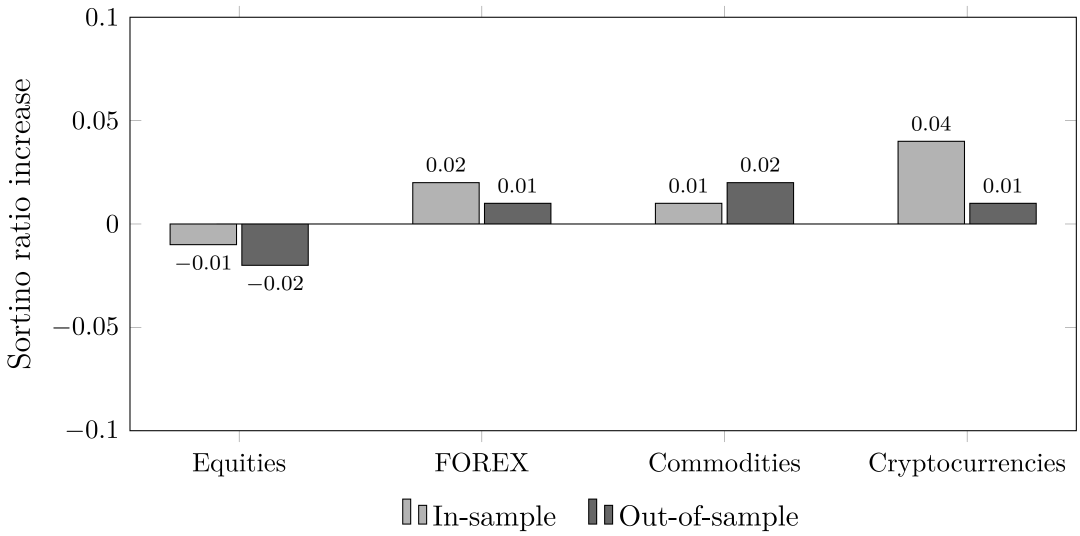

Figure 4.6: Average of Sortino ratio increase by the asset class *including transaction costs.*

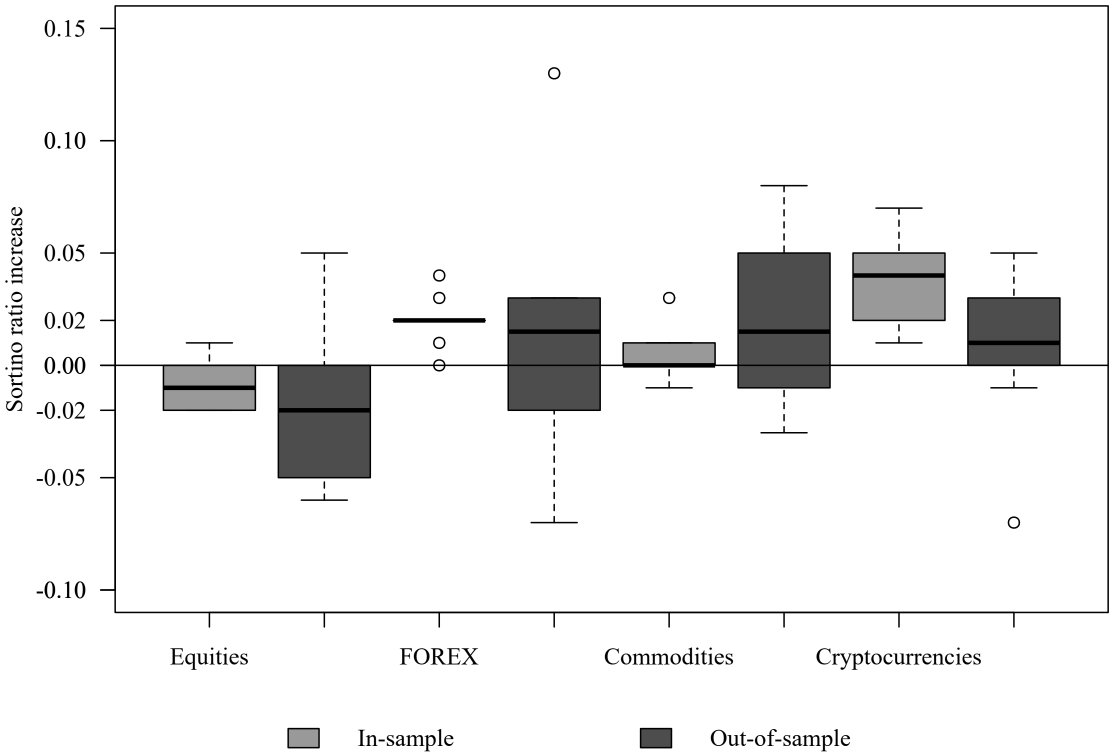

Figure 4.7: Box plots of average Sortino ratio increase by the asset class *including transaction costs.*

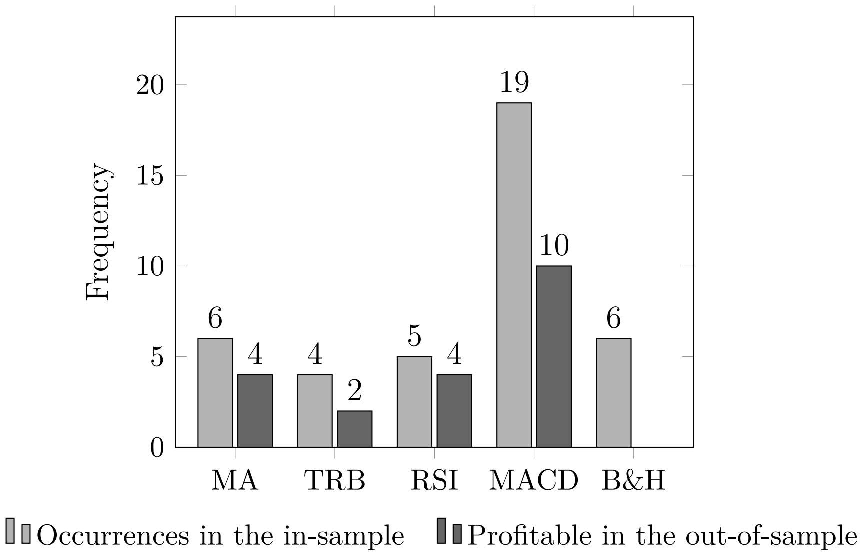

Figure 4.8: Frequency of the in-sample best trading rules by the trading strategy *including transaction costs.*

small deterioration in some instances due to transaction costs according to Figure 4.7. Hence, it only worsens the consistency within the asset classes. It is natural that worse consistency within the asset classes will translate into a more blurred difference between them. In this instance, the box plots in Figure 4.7 show even greater overlap compared to the scenario without transaction costs. We see now that even some small differences in the in-sample period without transaction costs are largely erased if the transaction costs are taken into account. *Hence, it could be concluded that in the realistic setup, which most traders experience, there were no significant differences in risk-adjusted returns across the asset classes, at least for the period and instruments examined in this thesis.*

Lastly, we can check how transaction costs affected the distribution of best rules in Figure 4.8. The most noticeable change is that the frequency of occurrence of the buy-and-hold strategy is doubled from 3 to 6 compared to the case without transaction costs. This effectively makes the buy-and-hold strategy the second-best "trading" strategy along with MA rules. Interestingly, all of those occur exclusively within the equities, which highlights the fact that equities are probably the worst asset class to which one could apply TA. This agrees with the theory and previous research evidence on its market efficiency as discussed in Chapter 2. Also, it is still the case that MACD rules dominate all others, however, to a lesser degree. The number of occurrences decreased from 24 to 19 and the number of profitable MACD rules also decreased from 13 to 10. On the other hand, there is a slight increase in the MA and TRB rules occurrence. The reason for this could lie in the fact that the best MACD rules tend to generate many signals, which, however, decreases the returns if transaction costs are taken into account. Hence, some of those were probably substituted by MA and TRB rules.

Chapter 5

Conclusion

This thesis examines the performance of TA trading rules across 4 asset classes (equities, currencies, commodities, and cryptocurrencies) over the period from 2014 to 2024. We defined a moderately large universe of rules consisting of a total of 2870 rules from 4 larger and generally considered families of rules: Moving Average (MA), Trading Range Breakout (TRB), Moving Average Convergence Divergence (MACD), and Relative Strength Index (RSI). The testing procedure involved splitting the full sample period into the in-sample and the out-of-sample periods and conducting Model Confidence Set (MCS) procedures developed by Hansen *et al.* (2011) to test the significance of trading rules' outperformance of the buy-and-hold strategy.

With regard to the risk-unadjusted returns, we saw that the trading rules generally managed to increase the returns by *a few percentage points* ($\sim 2-3\%$) for currencies (in-sample and out-of-sample) and commodities (in-sample), and by *tens of percentage points* ($\sim 15 - 100\%$) for commodities (out-of-sample) and cryptocurrencies (in-sample and out-of-sample) *per year*. We found that these results are, to some extent, associated with the significance of positive autocorrelation of returns. However, there is no clear causal effect in our case.

On the contrary, further analysis showed that these returns were mostly accompanied by increased risk exposure. By considering the Sortino ratios of the trading rules, we saw these increases strongly downcasted, indicating higher downward volatility of returns. Moreover, the best trading rules in the in-sample period, as expected, tended to perform worse in the out-of-sample, and the volatility of their returns was increased across all the asset classes. Hence, according to the MCS procedure, we found strong evidence that the trading rules studied *did not outperform the buy-and-hold strategy* on all 40 financial instruments examined when the risk was accounted for, both with and without transaction cost and on both the in-sample and the out-of-sample periods.

Comparing our results with the existing evidence shows some interesting features of the dynamics of market efficiency of these asset classes. With respect to equities, currencies, and commodities, they are in line with the general theoretical notion and empirical trend of increasing efficiency. Since the end of the last century, the performance of TA has been steadily decreasing, suggesting the presence and persistency of this trend. During the 1990s and 2000s, big equity indices stopped being profitable with the application of TA, and the profitability of most currencies and commodities was severely degraded. Our results confirmed the continuation of the trend, indicating that currencies and commodities have largely ceased to be profitable using TA over the past decade. With respect to cryptocurrencies, our results, to some extent, are contrary to the recent observations, suggesting significantly high profitability when applying TA. We found that the increased profits did not bear the same proportion of risk as the buy-and-hold strategy, making them, in essence, illusory. However, this result is not fully unexpected since it is highly probable that the market has moved towards greater efficiency over the last decade. Recent research showed the possibility and signs of this happening.

Our main contribution is the study of the differences in the performance of technical trading rules across the asset classes. By this, we address the lack of comprehensive studies in the field. Considering the nominal returns, we see significant differences between the asset classes. Also, we found some evidence of the differences in *risk-adjusted* returns in the in-sample period without transaction costs. On average, equities tend to perform the worst, with mostly negative results, and cryptocurrencies the best, with almost exclusively positive results. However, the out-of-sample period reveals a more blurred picture due to significantly increased volatility within the asset classes. Furthermore, by incorporating the transaction costs of moderate size the differences become practically of no account. *Thus, we question the possibility of performance differences in risk-adjusted returns of simple trading rules across the studied asset classes.* This conclusion may be useful to many traders and other market participants trying to implement the techniques of TA out of the impression of presumed market efficiencies of different asset classes. We encourage readers to avoid falling victim to omitting the risk factor from the trading strategy and following only the nominal returns.

Finally, we acknowledge the limitations of this study and hope further research will overcome them. First, the sample period examined is rather short compared to other papers. Covering a larger time interval will lead to more consistent results and could possibly reveal some other interesting features of the relationship between TA and the asset classes. Second, the universe of trading rules could be enlarged by incorporating a larger number of parameters and other families of rules (especially those using the volume information). Including more complex rules and strategies such as those described in Hsu & Kuan (2005) could lead to better results, which in turn could increase the gap between the asset classes. Third, more instruments for each asset class and other asset classes could be examined. This will lead to more consistent results and allow to thoroughly test for the differences in performance. Also, including instruments suspected of lower efficiency could significantly change the results. Since our examined assets are among those most traded, we may suspect that they are more efficient than others.

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Appendix A

Description of trading rules

The following factors were taken into consideration for the selection parameters for the trading rules:

1. Consistency with other research.
2. The idea of the rules is preserved.
3. The rules generate enough signals.
4. The scope of parameters covers different investing horizons.
5. The difference in parameters is big enough to create a difference in the actual signals.
6. Optimization of calculation time.

A.1 Moving average rules (MA)

Table format: MA_n_short_n_long_$c$days_$b$band
n_short – number of days for a short moving average,
n_long – number of days for a long moving average,
m – number of long-short combinations,
c – number of days a position is held unless the opposite signal occurs,
b – fixed percentage band for opening a signal

n_short = 5, 10, 15, 20 (4 values),
n_long = 30, 40, 50, 75, 100, 125, 150, 175, 200, 250 (10 values),
$m = n\_short * n\_long = 4 * 10 = 40$,
c = VMA: till the opposite signal occurs, FMA: 5, 10, 25, 50 (5 values),

$b = 0$, 0.001, 0.005, 0.01, 0,02 (5 values),
Total number of rules $= m * c * b = 40 * 5 * 5 =$ **1000**

A.2 Trading range breakout (TRB)

Table format: TRB_n_x_$c$days_$b$band
n – number of days for calculating the trading range,
x – difference between a high price and a low price as a percentage of the low price required to form a channel,
c – number of days a position is held unless the opposite signal occurs,
b – fixed percentage band for opening a signal

$n = 10$, 25, 50, 75, 100, 125, 150, 175, 200, 250 (10 values),
$x = 0.01$, 0.02, 0.05, 0.1, 0.15, 0.2 (6 values),
$c = 5$, 10, 25, 50 (4 values),
$b = 0$, 0.001, 0.005, 0.01, 0,02 (5 values),
Total number of rules $= n * x * c * b = 10 * 6 * 4 * 5 =$ **1200**

A.3 Moving average convergence divergence (MACD)

Table format: MACD_n_$short$_n_$long$_s_$c$days
n – number of days for calculating the moving averages for MACD line,
m – number of combinations of parameters for calculating the moving averages for MACD line,
s – number of days for calculating the signal line,
c – number of days a position is held unless the opposite signal occurs

$n = 10$, 20, 30, 50, 100, 150, 200 (7 values),
$m = n * (n - 1)/2 = 7 * 6/2 = 21$
$s = 10$, 20, 40, 50 (4 values),
$c = 5$, 10, 25, 50, till the opposite signal occurs (5 values),
Total number of rules $= m * s * c = 21 * 4 * 5 =$ **420**

A.4 Relative strength index (RSI)

Table format: RSI_n_ET_$c$days
n – number of days for calculating the moving average,
ET – combinations of thresholds for opening a position,
c – number of days a position is held unless the opposite signal occurs

$n = 10, 15, 25, 30, 40, 50, 75, 100, 150, 200$ (10 values),
$ET = 40/60, 30/70, 20/80, 10/90, 5/95$ (5 combinations),
$c = 5, 10, 25, 50$, till the opposite signal occurs (5 values),
Total number of rules $= n * ET * c = 10 * 5 * 5 =$ **250**