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RIGOROUS THESIS

How Rewarding Is Technical Analysis? Evidence from Central and Eastern European Stock Markets

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

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Signature

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Content

Abstract

This thesis assesses whether technical analysis can generate substantial profits in Central and Eastern European stock markets with a special focus on the Prague Stock Exchange. It investigates a well established trend follower MACD as well as a counter-trend indicator stochastic oscillator and relative strength index and introduces test statistics and bootstrap methodology in order to explore the profitability of these technical trading rules. The empirical results suggest that rewards of technical analysis differ according to individual stock markets. Whereas both indicators considered are found to yield significantly positive returns especially in the Bucharest and Prague Stock Exchanges, but have no predictive power on the Frankfurt Stock Exchange. The findings raise a question about the efficiency of the less developed stock markets.

Keywords: Bootstrap; Efficiency; Central and Eastern European stock markets; MACD; Relative Strength Index; Stochastic oscillator; Technical analysis

JEL classification: G12, G14, G15

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Abstrakt

Tato práce se zabývá výnosností technické analýzy na středoevropských a východoevropských akciových trzích se zaměřením především na pražskou burzu. Použitím statistických testů a bootstrap metody testuje, zda nákupní a prodejní signály generované technickými indikátory MACD, stochastik a index relativní síly vedou k významným výnosům. Výsledky ukazují, že výnosnost technické analýzy se značně liší mezi jednotlivými akciovými trhy. Zatímco oba uvažované technické indikátory byly úspěšné především na pražské a bukurešťské burze, jejich výnosnost na frankfurtské burze byla zamítnuta. Výsledky vznášejí otázku ohledně efektivnosti rozvíjejících se akciových trhů.

Klíčová slova: bootstrap; efektivnost; index relativní síly; MACD; stochastik; středoevropské a východoevropské akciové trhy; technická analýza

JEL klasifikace: G12, G14, G15

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1. Introduction

The disputable issue of technical analysis profitability has attracted the attention of both academics and investors for decades. This thesis contributes to the ongoing discussion by an investigation of the technical analysis profitability on Central and Eastern European stock markets. Knowledge of the degree of the technical analysis profitability would have enormous practical implications for traders because they could decide to which extend it is advisable to rely on technical analysis when making investment decisions.

Technical analysis aims at predicting future asset prices with the use of their historical prices. Therefore, it is argued that the use of technical indicators cannot yield significantly positive returns as the indicators are based on the past performance. According to the theory of efficient markets (Fama, 1970), asset prices should reflect all available information. In consequence, it means that returns in excess of average market returns cannot be achieved through exploiting historical prices, which are publicly available. However, this theory has been challenged both empirically and theoretically and faced criticism especially from behavioral economists.

In fact, an abundance of traders are convinced that the availability of all information is not appreciatively significant to a successful trading strategy. That is, the stock price is sluggish to adjust. During the period in which the price adjusts, the trend can be identified owing to technical analysis. Hence, it is also the sluggish adjustment of stock prices to all available information and non-synchronous trading which might allow technical analysis to be successful.

In addition, technical analysis is widely used among traders. Literature provides us with compelling evidence supporting this statement[2]. Also, most information

[2] Smidt (1965b) finds that over half of the respondents among amateur traders in US commodity futures markets use technical analysis in form of charts. More recently, Billingsley and Chance (1996) find that about 60 % of commodity trading advisors rely heavily or exclusively on computer-guided technical trading systems. The evidence suggests that the use of technical analysis spread over the past decades. Frankel and Froot (1990) noted that traders as well as analysts do include technical analysis in order to try to forecast the market. Lui and Mole (1998) reveal that more than 85% of foreign exchange dealers surveyed in Hong Kong rely on both fundamental and technical analyses for

services, databases and trading platforms provide detailed, comprehensive, and up-to-date technical analysis information. All major brokerage firms publish technical commentary and teams of stock exchange members often rely heavily on technical analysis. Consequently, the wide use of technical analysis can lead to self-fulfilling expectations. For instance, if a lot of traders watch closely technical analysis and buy the asset after a buy signal is issued, the asset price is pushed up. As a result, the trend identified by technical indicators is reinforced regardless of whether it was initiated by random or fundamental factors. Therefore, the possible profitability of technical analysis does not stem from the dependency of prices on previous values but from self-fulfilling expectations of its users.

This thesis examines whether positive returns can be generated with the use of technical analysis. The most common technical indicators are considered and test statistics are introduced to test whether the buy and sell signals yield significantly positive returns. Technical analysis has been shown to yield different rewards in different markets. This study deals with stock markets since broad literature has already been written for foreign exchange markets. There are many studies devoted to the profitability of technical analysis on western European and the US stock markets. Recently and studies have been published concerning Asian stock markets. However, there have been very few attempts to explore the profitability of technical analysis on Central and Eastern European stock markets. Thus, this paper deals with the following hypothesis:

Technical analysis can yield significantly positive returns on Central and Eastern European stock markets.

The special is focus is devoted to the Prague Stock Exchange which is elaborated more into detail than the other stock exchanges.

The thesis is organized as follows. The next section gives a brief review of the existing literature on the topic of technical analysis profitability. It shows that there is no discernable consensus over the role of technical analysis in signaling market entry and exit. The following part discusses the data used in this paper as well as the stock

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predicting future rate movements at different time horizons. They conclude that there exists a skew towards reliance on technical analysis as opposed to fundamental analysis at shorter horizons.

markets. Seven stock markets considered in this thesis include Austrian, Czech, German, Hungarian, Polish, Romanian and Ukrainian stock market and all of them are introduced in term of their development. Section 3 is devoted to the technical indicators of our interest. It discusses concepts of the most common technical indicators such as MACD, stochastic oscillator and relative strength index and their calculations. The exact methodology is then elaborated upon. In order to examine the hypothesis of this thesis, two approaches were used. Both bootstrap techniques and conventional test statistics are introduced to test whether the buy and sell signals yield significantly positive returns. The computations were performed in software Excel, OxMetrics and Matlab. Empirical results are contained in Section 5, followed by some concluding comments and comparison of the results obtained for all stock markets of interest in the last section.

This thesis is based on the previous Master Thesis "Profitability of Technical Analysis: Evidence from Central and Eastern European stock markets". However, this thesis is expanded in two ways. Firstly, it includes more technical indicators and therefore provides a broader perspective on the actual profitability of technical analysis. Secondly, Reports on Master Thesis were taken into account which resulted into inclusion of more relevant literature and more precise definitions of technical indicators which are better supported by literature.

2. Literature Overview

A considerable amount of literature has been published on technical analysis. Even so, there is no discernable consensus over its role. Since the work by Friedman (1953) and Fama (1970), opinions on the role of technical analysis as a forecasting mechanism are very controversial. There are a number of studies that conclude that technical analysis is not useful. Nevertheless, there is also strong evidence that simple forms of technical analysis do bring forecasting power. This section briefly discusses the most influential studies on this topic.

Several research papers highlight the usefulness of technical analysis. This method has been a subject of criticism predominately from academics (Malkiel, 1982, 2003). The theoretical rejection of technical analysis is often based on the theory of efficient markets. Fama (1970) defines an efficient market: 'A market in which prices always "fully reflect" available information is called efficient'. Later on, Jensen (1978) defines an efficient market in the following way: 'A market is efficient with respect to information is set θ_t if it is impossible to make economic profits by trading on the basis of information set θ_tθt '. As a matter of fact, the Efficient Market Hypothesis exists in three forms (Jensen, 1978):

1. The "Weak" form of the Efficient Market Hypothesis asserts that all historical prices and data are fully reflected in securities prices.

2. The "Semistrong" form states that all publicly available information is fully reflected in securities prices.

3. The "Strong" form suggests that all information including insider information is fully reflected in securities prices.

In other words, technical analysis should not provide its users with any significant positive returns when the Efficient Market Hypothesis is valid in any of its forms.

Nonetheless, the Efficient Market Hypothesis has been challenged and we can observe increasing number of its attacks especially in the past decade. As Malkiel

(2003) points out, the intellectual dominance of the efficient market hypothesis had become far less universal by the start of the twenty-first century as many economists began to believe that stock prices are at least partially predictable. Criticism has arrived particularly from economists believing in the role of psychological mechanisms or behavioral elements on financial markets. For example, Shiller (2000) describes the rise in the US stock markets during the late 1990s as the consequence of psychological contagion. The behavioral economists offered another explanation for partial predictability of securities returns: a tendency to under react to new information. For instance, DeBondt and Thaler (1995), argue that investors are subject to waves of optimism and pessimism and hence prices deviate systematically from their fundamental values. Such findings are is consistent with the behavioral decision theory of Kahneman and Tversky (1981).

There are relevant studies that directly investigate the efficiency of Central European stock markets. They do not offer compelling results. For instance, Vošvrda, Filácek and Kapicka (1998) suggest the weak form Efficient Market Hypothesis does not apply to the Prague Stock Exchange in the period of 1995-1997. On the contrary, Filer and Hanousek (1996) could not reject the hypothesis that equity market returns are random in the Czech Republic, Hungary, Poland and Slovakia. Also Diviš and Teplý (2005) could not reject the weak form hypothesis of Central European capital markets. In his recent study, Malenko (2008) who deals concretely with MACD indicator and the relative strength index, finds out that these indicators can yield returns if their parameters are optimized. However, Malenko finds no profitability of non-optimized indicators.

Many especially earlier studies concluded that technical analysis is useless (Alexander, 1961, Levy, 1967, Van Horne and Parker 1967, 1968, Ackemann and Keller, 1977, Bohan, 1981, Brush and Boles, 1983, Jacobs and Levy, 1988). They argue that such a method of market entry and exit timing cannot provide us with better returns than a simple buy and hold strategy. Most of filter testing on the U.S. stock market actually concluded that filter rules do not generate superior returns. Some studies including those by Fama and Blume (1966), Jensen and Benington (1970) and Ball (1978) also considered transaction costs and concluded that returns can even be negative due to a higher number of trades in the comparison with buy and hold strategy.

The interest in profitability of technical analysis has been increasing in the last 15 years. Park and Irwin (2007) point out that more than half of all empirical studies conducted after 1960 were published after 1995 which may result from the publication of several seminal papers (e.g. Sweeney, 1986; Brock et al., 1992) between the mid-1980s and early 1990s, which, in contrast to earlier studies, found significant technical trading profits from the availability of cheaper computing power and the development of electronic price databases. Indeed, more recent studies suggest that technical analysis provides investors with superior returns in stock markets (Brock et al., 1992, Hudson et al., 1996, Gunasekarage and Power 2001). Also Chew, Manzur and Wong (2003) found that member firms of Singapore Stock Exchange tend to enjoy substantial profits by applying technical indicators. Taylor (2000) investigates a wide variety of US and UK stock indices and individual stock prices and proves the profitability of technical analysis up to a certain level of transaction costs. Lukac et al. (1988) found that a third of simulated trading systems on future markets yield statistically significant monthly portfolio net returns even after deducting transaction costs. Lukac and Brorsen (1990) reached a similar conclusion considering more trading systems and futures contracts and a longer sample period. Technical trading rules also proved to be profitable for some spot foreign exchange rates (Menkhoff and Schlumberger, 1995; Lee and Mathur, 1996a, 1996b; Maillet and Michel, 2000; Lee et al., 2001; Martin, 2001).

According to the study by Park and Irwin (2007), among a total of 95 studies written after 1988, 56 studies find positive results regarding technical trading strategies, 20 studies obtain negative results, and 19 studies indicate mixed results. All in all, the topic of technical analysis remains a controversial issue in literature.

3. Data and Stock Markets

This thesis is focused on the Central and Eastern European stock markets, namely Austrian, Czech, Hungarian, Polish, Romanian and Ukrainian. The German stock market is also considered as it serves as a benchmark. Since a special focus is devoted to the Prague Stock Exchange, this thesis examines also some of the stocks traded there, namely ČEZ, Erste Bank, Komerční banka and Telefonica O2. The data is used from Reuter's database. It consists of time series of daily stock market indices at closing time. Therefore, we have five time series. The paper covers the time period from June 1, 1993 up to April 30, 2010 with number of observations in the wide range depending on the availability of information for each index and stocks.

The daily values are used since a month or a week period is too long to capture the reactions of interest. On the other hand, it would be favorable to use intraday data. However, the number of observations in so called ultra-high frequency data sets can be enormous. That would make it difficult to cover a period longer than a year. In addition, non-negligible difficulties arise when trying to obtain intraday data, especially to the past further than a few months. Hence, using daily data is convenient to examine profitability of technical analysis. Using given time series, returns are calculated as daily changes in logarithms.

Individual stock markets are introduced and some of their crucial characteristics are presented in the remainder of this section. The special focus is devoted to the Prague Stock Exchange and the main four companies listed there.

3.1 Austria

The stock exchange in Austria - The Vienna Stock Exchange was founded in 1771 which classifies it as one of the world's oldest exchanges. It is a fully private company since 1999.

The development of the Vienna Stock Exchange is characterized by the index ATX in this study. The index includes the 20 largest companies listed there according to the capitalized free float and stock exchange trading volumes[3]. Our data set includes 4,293 values of index ATX which start on January 4, 1993 and end April 30, 2010.

Table 1: ATX index components

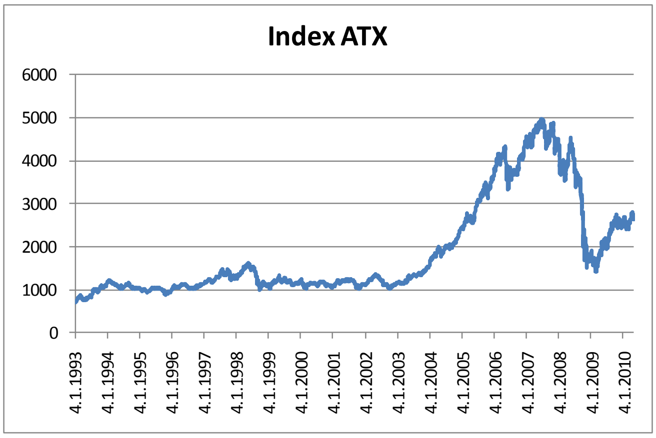
ATX index components	
Andritz	RHI
bwin	Schoeller-Bleckmann
EVN Group	Semperit
Erste Bank	Strabag
Flughafen Wien	Telekom Austria
Intercell	Verbund
Mayr-Melnhof Karton	voestalpine
Österreichische Post	Wiener Städtische
OMV	Wienerberger
Raiffeisen International	Zumtobel

Source: www.wienerborse.at

The Vienna Stock Exchange experienced a long period of a steady development between 1993 and 2003. Its rise became very pronounced afterwards and the ATX index multiplied its value 5 times in mere three years. That can be attributed to structural changes as well as opening of the formally communist countries in Central and Eastern Europe which helped the Vienna Stock Exchange to attract the interest of investors and hence grow significantly. In 2004, the Vienna Stock Exchange acquired about 13 % of the Budapest Stock Exchange. Acquisition of a stake of 81 % in the Ljubljana Stock Exchange and 93 % in the Prague Stock Exchange followed in 2008. The integration process culminated on September 17, 2009 which is the official starting date of the brand “CEE Stock Exchange Group”. The Vienna Stock Exchange did not experience any remarkable decline in the last 17 years but in 2007-2008 in association with the US credit crunch and consequential financial crisis.

[3] www.wienerborse.at

Figure 1: The Vienna Stock Exchange



Source: Reuters

3.2 The Czech Republic

Long efforts[4] to create a stock exchange were successful in Prague in 1871. Initially, the Prague exchange was known for trading commodities. The great boom of securities trade came after World War I. This period of prosperity was, however, interrupted by the arrival of World War II[5] and restoring of the Prague exchange was not achieved until 60 years later.

The Prague Stock Exchange (PSE, henceforth) was founded again in 1992 and trading with seven security issues was initiated on April 6, 1993. Trading took place only once a week in 1993 but the frequency of trading was gradually increasing and the PSE started operating every week day in September 1994. In the first months of its existence, there was extremely low liquidity. The turnover on the PSE rose due to the launching of 955 security issues from the 1st wave of voucher privatisation in June and July 1993. Other 674 security issues from the 2nd wave of voucher privatisation were launched on the market in 1995[6]. However, trading of these issues did not meet up the expectations. As soon as in 1997, 1,301 share issues were withdrawn from the free market for a lack of liquidity. Czech population was not accustomed to investing and the Czech capital markets remained largely under-

[4] dating back as far as to the Empress Maria Theresa
[5] www.pse.cz
[6] www.pse.cz

capitalized even after the reestablishment of the PSE and in spite of capital flows from foreign investors. The liquidity remained low for the subsequent years and there were no new successful issues.

The PSE did not revive sooner than in a new millennium. Initiation of trading in the 1st foreign share issue of Erste Bank took place in 2002. The PSE also became a full member of the Federation of European Securities Exchanges. Another important event was the 1st primary share issue of Zentiva in 2004 and ECM and Pegas Nonwovens in 2006. Initial public offering of AAA Auto was conducted in 2007 (together with VGP outside the System for Support of the Share and Bond Markets). Companies VIG and NWR followed in 2008. Prague Stock Exchange completed fifteen years of trading on April 6, 2008. Since the beginning of the trading, shares in the total of value of CZK 5.5 trillion have been sold[7].

After the successful stock issues mentioned above, the planned issues were postponed due to the crisis on financial markets. The period of drop in stock prices did not represent a good timing for companies to raise capital with the help of stock issues. Therefore, another issue - KIT digital - was launched as late as in January 2010 when stock markets were in process of recovering from a sharp decline and prospects of world economy were positive in the eyes of many investors. Currently, there are 14 companies listed on the PSE. They are summarized in the table below.

The types of trades available on the PSE at the time being are automatic trades (either in auction or continual regime), System for Support of the Share and Bond Markets (SPAD) trades and block trades[8]. The SPAD is the most liquid component of the PSE. As a matter of fact, considering total trade value structure, 81.3 % was done within SPAD system, whereas 16.9 % was conducted via auction system and mere 1.8 % in block trades in April 2010. Thus, we focus on this segment in this study. The reason for its superior liquidity is that prices are continually identified by the market makers who are responsible for the sufficient liquidity. A market maker is a member of the PSE and has concluded a contract to act as the market maker for selected

[7] www.pse.cz
[8] A block trade means a transaction concluded outside of the PSE trading system

issues of share titles[9].

The PSE uses a method of trading based on electronic processing of orders and instructions and the security price is quoted on the basis of the offer and demand of the security addressed to an unidentified group of people in automatic trading and trading with the participation of market makers[10]. In order to cover risks from settlement of trades with securities, all members of the PSE are obliged to participate in creation of the Exchange Guarantee Fund[11].

Table 2: PX index components

PX index components	
AAA	NWR
CETV	Orco
ČEZ	Pegas Nonwovens
ECM	Philip Morris ČR
Erste Group Bank	Telefónica O2 C.R.
KITD	Unipetrol
Komerční banka	VIG

Source: www.pse.cz

In order to represent the stock movements on the PSE the index PX is used. Index PX 50, introduced in 1994, was used to represent the movements on the exchange and originally it covered 50 companies listed on the PSE. Another index used on the PSE – PX-D – covered all the stocks traded in the SPAD system in order to represent only the most liquid segment of the PSE. By the time these two indices became so close that they merged into the index PX which was introduced in 2006[12].

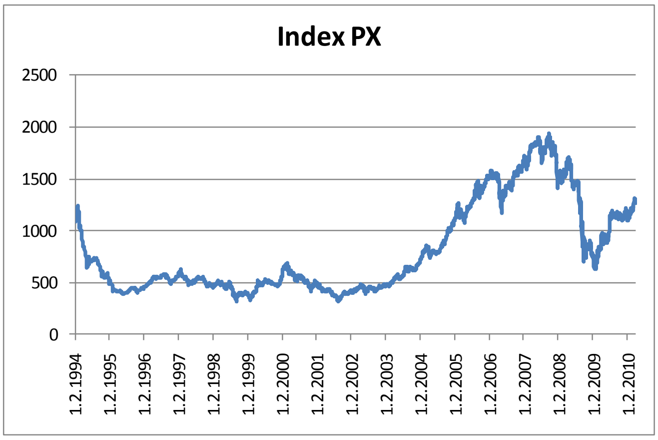
There are 3,981 observations for index PX starting February 1, 1994 and ending April 30, 2010. Every company out of the 14 listed (in April 2010) has a different weight in the index according to its market capitalization. Wiener Börse AG (the Vienna Stock Exchange) became the majority shareholder of the PSE with a

[9] www.pse.cz
[10] www.pse.cz
[11] Trading Rules of Association of the Prague Stock Exchange
[12] www.pse.cz

share of 92.7% as already discussed in the previous section.

The rise of the index PX was very steep, especially since 2004. Index PX reached its lowest value on October 8, 1998. Except for a decline in 2001, it experienced nearly continuous growth, reaching its highest value on October 29, 2007. Consequent turmoil on financial markets drew index PX down to less than a third of its highest value. Since February 2009 until April 2010, the index PX doubled its value as it has been gaining on the prospects of global recovery.

Figure 2: The Prague Stock Exchange



Source: Reuters

The remainder of this section introduces and examines the main components of the index PX. To be specific, four companies are further elaborated, namely ČEZ, Erste Bank, Komercni Banka and Telefonica O2. These four companies are chosen for three reasons.

Firstly, these four companies stand out owing to their market capitalization. Since July 2009, in the end of every month, the market capitalization of each of these companies has not declined below 100 billion CZK, whereas the capitalization of all other companies included in the index PX was below this threshold.

Consequently, the second reason is their weight in the index PX which actually stems from their capitalization. Taken all together, they account for as much as 80.1 % of the index PX in April 2010. In fact, the weight of neither of these companies in the index PX has decreased below 10 % in the last year. That classifies them as the main drivers of the index PX movements.

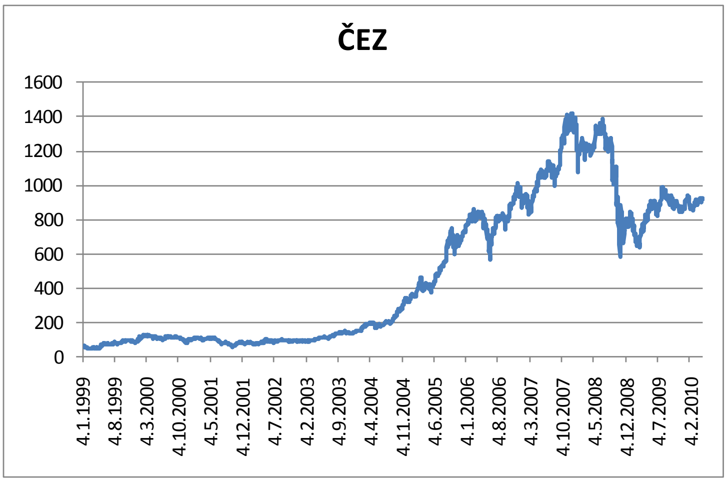
Last but not least, the data available had to be taken into account as well. As all these companies are traded on the PSE for the last 8 years, the time series available are long enough to allow testing the profitability of technical trading rules.

3.2.1 ČEZ

The publicly traded company ČEZ is the largest electricity producer in the Czech Republic. In 2003 it merged with several regional companies and ČEZ Group was founded. Having acquired distribution companies in Bulgaria and Romania as well as Polish and Bulgarian power plants, ČEZ Group has become a multinational enterprise comprising of over 90 Czech and foreign companies[13]. As for shareholders structure, 69.4 % of shares are held by Ministry of Finance of the Czech Republic and another 0.41 % by Ministry of Labour and Social Affairs (as in April 2010). The ČEZ company is regularly the most traded issue on the Prague Stock Exchange and its traded value exceeded 10.2 billion CZK in April 2010. Also, its market capitalization is the largest among all companies on the Prague Stock Exchange, having reached 497 billion CZK at the end of April 2010[14]. There are 2,842 values available for the stock price of the company ČEZ.

[13] www.cez.cz
[14] www.cez.cz

Figure 3: Stock price ČEZ in CZK



Source: Reuters

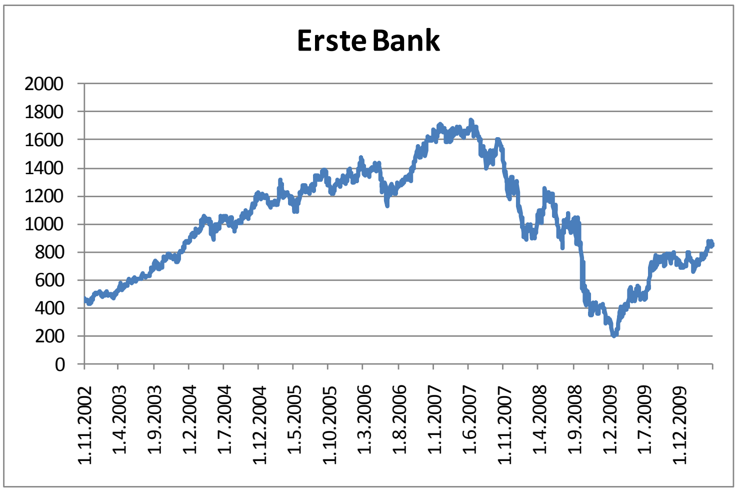
3.2.2 Erste Bank

Erste Group is a financial services provider in Central and Eastern Europe. It pertains to one of the largest in this area in terms of clients and total assets and it focuses on retail and SME banking. 43.9 % of shares are held by institutional investors and ERSTE Foundation owns a stake of more than 30 % in the capital of Erste Group[15]. The other two major shareholders are Criteria CaixaCorp and Capital Research.

The value 4.4 billion CZK was traded in April 2010 and the market capitalization reached 321 billion CZK at the end of the month which is the second largest on the PSE (after ČEZ company). Erste Bank entered the PSE in 2002.

15 www.erstegroup.com

Figure 4: Stock price Erste Bank in CZK

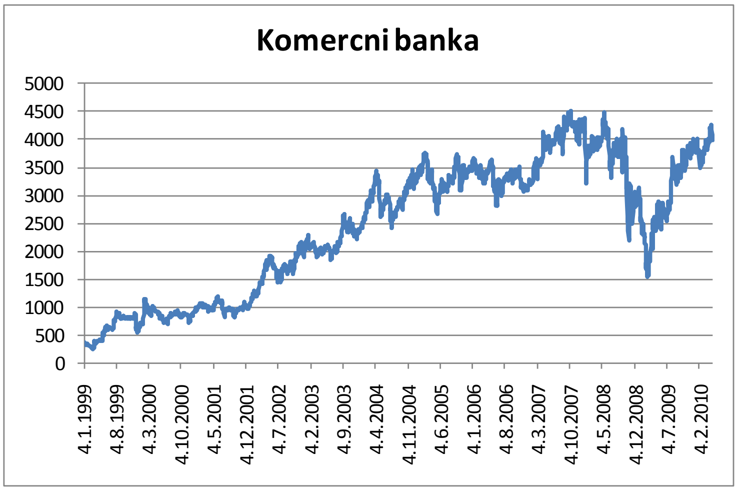


Source: Reuters

3.2.3 Komerční Banka

Komerční banka is a member of the Société Générale Group and provides services in retail, corporate and investment banking. Of the total share capital, Société Générale S.A. holds 60.35% as of 31 December 2009[16].

Figure 5: Stock price Komercni banka in CZK



Source: Reuters

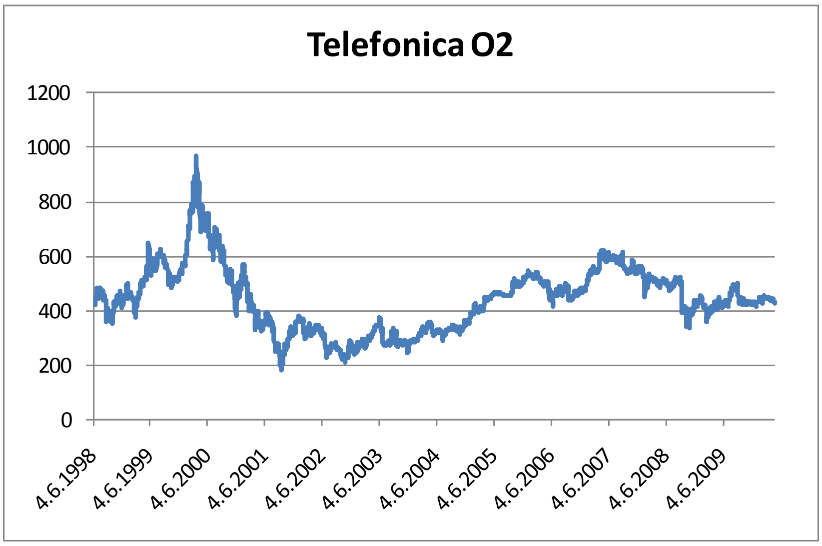
[16] www.kb.cz

The traded value in April 2010 was the second biggest in the SPAD system (after CEZ company) and reached 8.7 billion CZK. At the end of April 2010, the market capitalization was 152 billion CZK.

3.2.4 Telefonica O2

Telefónica O2 Czech Republic is a major integrated operator in the Czech Republic. Concerning ownership structure, 69.4 % of the shares is owned by Telefónica, S.A. The total trade value in April 2010 equaled 3.8 billion CZK. At the end of April 2010, its market capitalization was 137 billion CZK.

Figure 6: Stock price Telefonica O2 in CZK



Source: Reuters

3.3 Germany

The main German stock exchange is the Frankfurt Stock Exchange. Its long history goes back to the Middle Ages[17] and it is related to the important position of Frankfurt. Although some trades were transferred to Berlin later, the Frankfurt Stock

[17] http://deutsche-boerse.com

Exchange has remained the most remarkable German exchange. Nowadays it is a part of Deutsche Boerse AG.

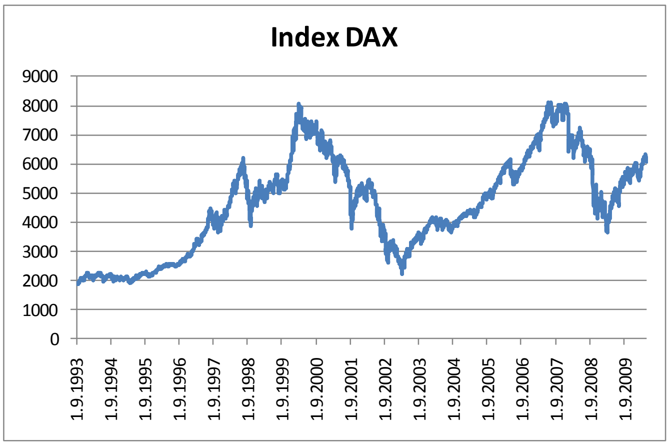
Table 3: DAX 30 index components

DAX 30 index components	
Adidas Salomon	Fresenius Medi
Allianz Ag	Henkel Hgaa Vz
BASF Ag	Infineon Tech
Bay Mot Werke	K+s Ag
Bayer Ag	Linde
Beiersdorf	Man Ag
Commerzbank Ag	Merck Kgaa
Daimler	Metro Ag
Deutsche Bank	Muench. Rueck
Deutsche Post	Rwe St A
Dt Boerse	Salzgitter
Dt Lufthansa	Sap Ag
Dt Telekom	Siemens
E.On	Thyssen Krupp
Fresenius Ag	Volkswagen VZ

Source: http://deutsche-boerse.com

The performance of the Frankfurt Stock Exchange is characterized by Deutscher Aktien-Index DAX 30. It is a Blue Chip stock market index which consists of the 30 major German companies traded there. The companies are chosen according to their market capitalization and liquidity. It is the index of a total yield which means that not only the stock performance but also the dividends distributed to shareholders are taken into account. The DAX was introduced in 1987 with 1000 as its original value. It is based on prices generated by the electronic Xetra system. We have 4217 observations for DAX 30 from September 1, 1993 until April 30, 2010.

Figure 7: The Frankfurt Stock Exchange



Source: Reuters

The German stock market demonstrated both remarkable falls and rises during the last 17 years. The decline was the case especially during the period between 2001 and 2003. It was the time of a deep fall of world stock markets which was initiated by the end of so called "dot com bubble" and 9/11 attacks.

However, for instance the already discussed Austrian and Czech stock markets were not influenced by this bear trend as much as developed markets were. Also, both the less developed markets discussed re-entried the growth period sooner than the German market. The index DAX 30 recouped from this decline as late as in 2007 when there was already another steep downtrend awaiting due to the financial crisis. Until April 2010, the index DAX 30 gained back about a half of its losses acquired due to the credit crunch.

3.4 Hungary

The ancestor of today's Budapest Stock Exchange (BSE) started its operation in 1864 and four years later after an acquisition of a centre of grain trade, Budapest Stock and Commodity Exchange was established[18].

Table 4: BUX index components

BUX index components	
Állami Nyomda	OTP Bank
econet.hu	PannErgy
Egis	Rába
FHB	Richter Gedeon
Fotex	Synergon
MOL	TVK
Magyar Telekom	

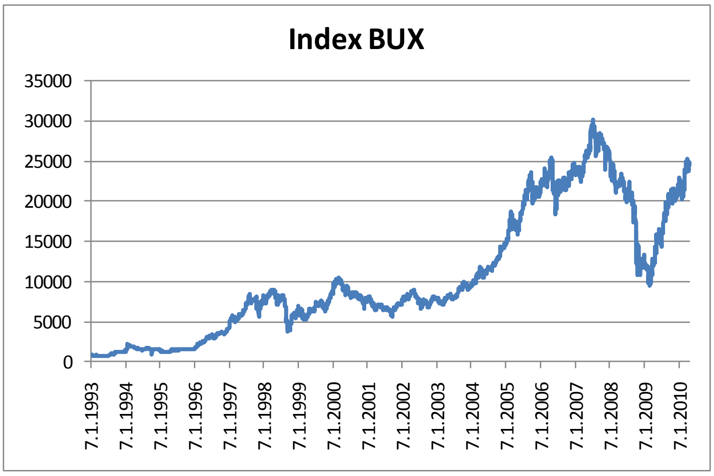
Source: www.bse.hu

The BUX index is the official index of blue-chip shares listed on the Budapest Stock Exchange. It is calculated according to the actual market prices of a basket of shares. The index is based on the shares with the biggest market value and turnover on the Budapest Stock Exchange.

The Budapest Stock Exchange experienced a growth trend from the beginning of our observation on January 7, 1993 until 2007. A noticeable decrease took place after credit crunch in 2007. However, the stocks included in the index boosted their gains in 2009. At the end of our period on April 30, 2010 the index BUX was only one fifth of its value lower than what was its highest value ever in 2007.

[18] www.bse.hu

Figure 8: The Budapest Stock Exchange



Source: Reuters

3.5 Poland

The most significant stock exchange in Poland as well as among the post-communist countries is the Warsaw Stock Exchange. The first Mercantile Exchange was founded in Warsaw in 1817 and the exchange began operating in its present form in 1991[19].

Table 5: WIG 20 index components

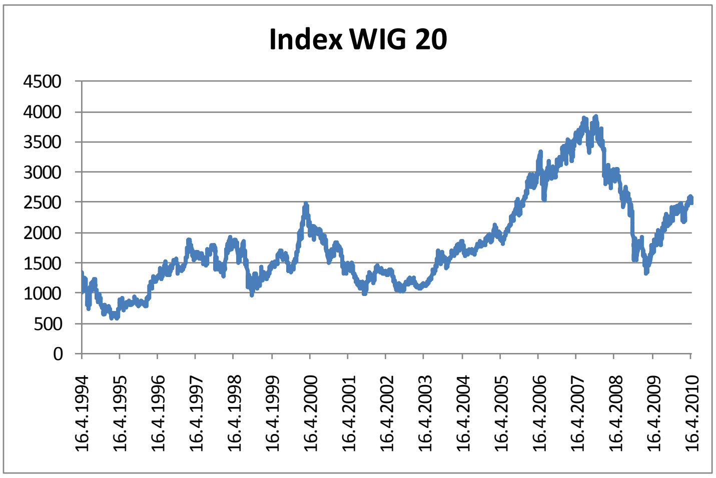
WIG 20 index components	
Pekao	BRE
PKOBP	PBG
KGHM	CEZ
PKN Orlen	TVN
TPSA	POLIMEXMS
ASSECOPOL	CERSANIT
BZWBK	CYFRPLSAT
GTC	Lotos
GETIN	AGORA
PGNIG	Bioton

Source: www.gpw.pl

[19] www.gpw.pl

While there are number of stock indices associated with the Warsaw Stock Exchange, the index used in this study is WIG 20. It covers the 20 biggest and most liquid companies traded on the exchange. The calculation of the index is based on their market capitalization. There are 3,984 values of WIG 20 from April 16, 1994 to April 30, 2010.

Figure 9: The Warsaw Stock Exchange



Source: Reuters

The performance of the Polish stock market was very similar to that of the Czech market during the last decade with the exception that the decrease in 2001-2003 lasted longer and was more pronounced. That may be attributed to the higher level of development which allowed a bigger bubble whereas the trading activity on the PSE was much lower.

3.6 Romania

The Romanian history records the establishment of the Bucharest Stock Exchange on the 1st of December 1882[20]. Similarly to other countries which

[20] www.bvb.ro

experienced the communist regime, the Bucharest Exchange was closed in 1945. It was reestablished again in 1995.

The Bucharest Stock Exchange saw a significant overall development in 1997, the progress which could have been noticed in the entire Romanian capital market. In September 1997 the first Bucharest Stock Exchange official index BET was launched as the reference index. The index BET is a free float weighted capitalization index of the most liquid 10 companies listed on the BVB regulated market[21]. Since the index was not introduced sooner than in 1997, the number of values available is 3,139 covering period from September 22, 1997 until April 30, 2010.

Table 6: BET index components

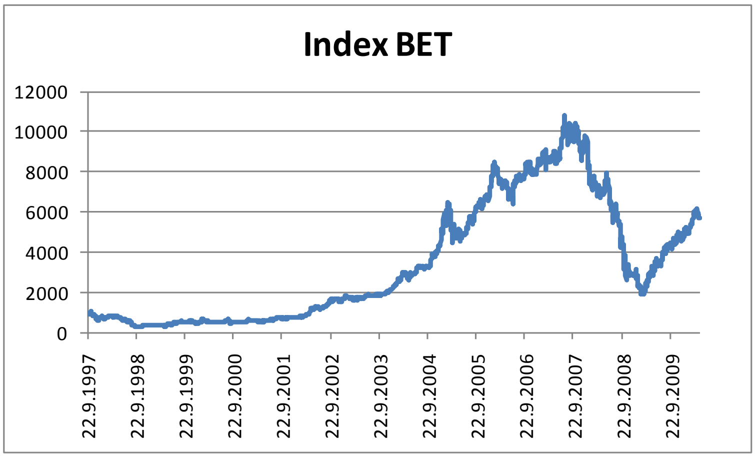
BET index components	
BANCA TRANSILVANIA S.A.	Biofarm S.A.
BRD - Groupe Societe Generale S.A.	CONDMAG S.A.
OMV PETROM S.A.	S.S.I.F. Broker S.A.
S.N.T.G.N. TRANSGAZ S.A.	Azomures S.A.
C.N.T.E.E. Transelectrica	Dafora SA

Source: www.bvb.ro

The index BET was not particularly influenced by the “dot com bubble” in 2001. Instead, it experienced a continuous rising trend with negligible temporary declines until 2007. In 2007 and 2008, the Romanian stocks were severely hit by the global crisis and the BET index fell down as much as to its one fifth. The BET index movements are extremely turbulent. The sharp fall alternated with a sharp rise and the index tripled its value in the subsequent year. In comparison with movements of the stock indices already discussed, the movements of the index BET are much more pronounced.

[21] www.bvb.ro

Figure 10: The Bucharest Stock Exchange



Source: Reuters

3.7 Ukraine

There are two main stock exchanges in Ukraine. For the purpose of this study, the PFTS Stock Exchange was chosen as a representative because the PFTS index is often used as a benchmark of the development of Ukrainian equity markets. The name "PFTS" stands for the abbreviation of its Ukrainian name. The PFTS Stock Exchange is acting as an organizer of securities trading since 1997[22].

Table 7: PFTS index components

PFTS index components	
Alchevsk Metallurgical Plant	Mariupol Heavy Machinebuilding Plant
Avdiivka Cokery Plant	INTERPIPE Nizhnedneprovsky Tube Rolling Plant
Azovstal Iron and Steel Works	Poltava Ore Mining and Processing Plant
Raiffeisen Bank Aval	Sumy Frunze Machine Building Plant
Centrenergo	Stirol
Dniproenergo	Ukrnafta
Donbasenergo	Ukrsotsbank
Enakievo Metallurgical Plant	Ukrtelecom
Krukivsky Carriage Works	Yasynivka Cokery Plant
Motor Sich	Zakhidenergo

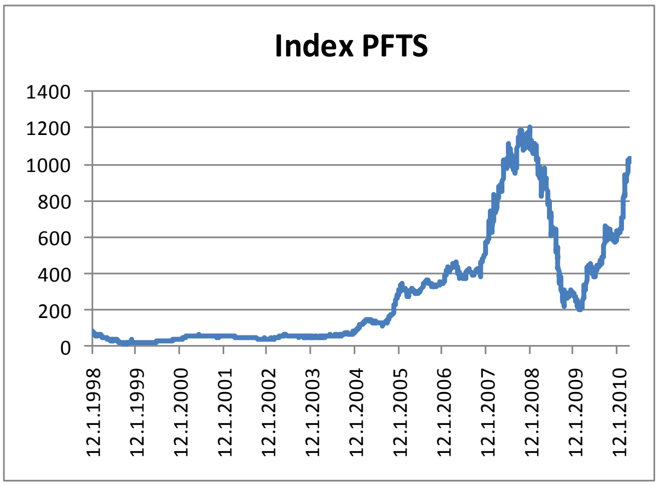
Source: www.pfts.com

[22] www.pfts.com

In a consequence, there are 2,920 observations available starting October 3, 1997 and ending April 30, 2010.

The PFTS index is the major and the oldest indicator of Ukrainian capital market and is a capital-weighted price index of the 20 major and most liquid Ukrainian equities traded at the PFTS Stock Exchange.

Figure 11: The Ukrainian Stock Exchange



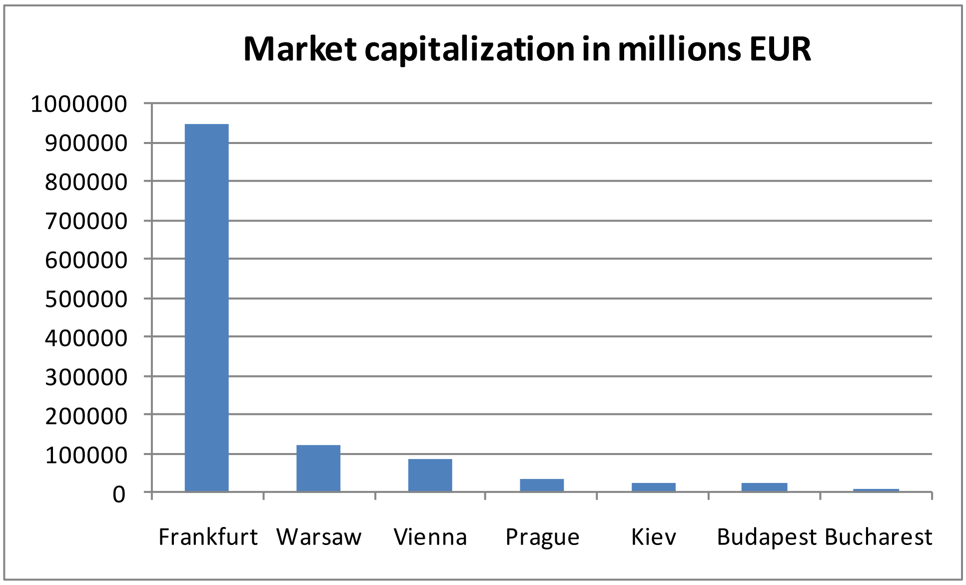
Source: Reuters

We can observe a very dramatic development of the index PFTS. It reached more than a sextuple of its original value in only the 3-year period between 2004 and 2007. However, its fall in the subsequent year due to the credit crunch was also breathtaking: the index PFTS fell to less than a quarter of its original value within mere 9 months. And again, in the last year and a half, the index almost recovered from its sharp drop and is approaching its highest levels again. Undoubtedly, enormous volatility of the Ukrainian stock market represents a risky as well as attractive opportunities for some investors.

3.8 Comparison

The stock markets considered in this study differ appreciably in terms of history, development and size. The figure 7 shows that market capitalization of the Frankfurt Exchange is the highest by far. As for market capitalization of CEE stock exchanges, the Warsaw Stock Exchange stands out. Its capitalization is by 43.6 % higher than that of the Vienna Stock Exchange and as much as more than ten times higher than the capitalization of the Bucharest Stock Exchange at the end of April 2010.

Figure 12: Market capitalization (all market segments) at the end of April 2010 in millions EUR

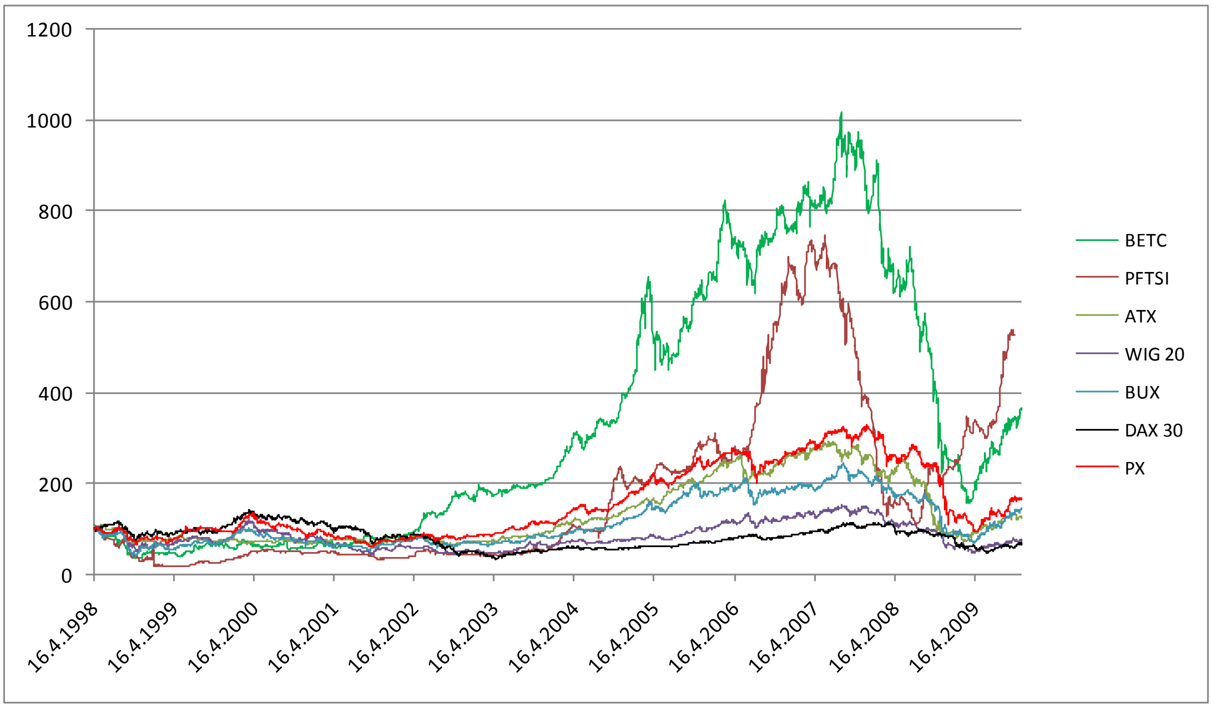


Source: www.fese.be and www.pfts.com

Consequently, the performances of individual stock indices differ as well. However, some common characteristics of the CEE stock markets performance can be found. The CEE stock markets of our interest were not dramatically hit by the crush of so called dot com bubble on stock markets in 2001. These markets fully revived later. A remarkable increase of the CEE stock indices can be observed between 2003 and 2007. The rise in this period is much more pronounced for the CEE stock markets than for the German stock market. It can be attributed to gradual structural changes on the CEE exchanges, new stock issues, slowly changing mentality towards investing of local investors as well as increased involvement of foreign investors. While the CEE stock markets seem very attractive to many speculators, they are still perceived as less developed and not so well established and riskier in comparison with their western European or US counterparts. As such, the CEE stock markets were massively left after the credit crunch. All observed stock markets experienced a period of sharp decline due to the credit crunch in 2008 and the fall was much more pronounced for the CEE markets than for the German one. The opposite was true in 2009 when the financial markets started to reach recovery.

This is especially true for the Romanian and Ukrainian stock markets. These two markets show a high volatility and the most pronounced rise and fall periods among the CEE stock markets considered.

Figure 13: Standardized indices values



Source: Calculations based on Reuters data

To conclude, the CEE stock markets are still considered to be so called emerging markets in the eyes of many investors. Especially the stock markets of Romania and Ukraine provide investors with high returns as well as high risks as steep rise alternates with deep fall. Some investors search there for higher returns stemming from economic convergence to more developed countries and productivity increase. This statement is easily proved by an increased interest of investors in these markets when the overall mood on financial markets as well as future prospects is positive which drives the mean returns higher. On the other hand, when the outlook of global economy is gloomy and aversion to risk increases, a rapid exit from these markets is observed due to the expected higher riskiness of these stock markets. In turn, volatility of these markets exceeds levels common on more developed markets, which inflicts more turbulent development in general. These conclusions are summarized in terms of descriptive statistics in the table below. Hence, the Central and Eastern European stock markets have been the subject of substantial recent interest of investors.

Table 8: Descriptive Statistics for Indices

	ATX	BET	BUX	DAX 30	PX	WIG 20	PFTS
Standard deviation	1145.3	2992.1	7821.3	1681.2	444.4	750.2	311.1
Average	1876.7	3371.3	10502.7	4618.2	808.9	1816.4	269.0
Minimum	712.1	281.2	717.8	1852.8	316.0	577.9	16.5
Maximum	4981.9	10813.6	30118.1	8105.7	1936.9	3917.9	1208.6
Median	1244.9	2066.7	7961.6	4699.3	566.7	1647.9	74.3
Average deviation	936.9	2605.4	6525.3	1414.6	380.5	585.8	247.8

Source: Author´s calculations

4. Technical Indicators

This chapter introduces technical analysis and individual indicators which are used in this study to represent a technical approach.

To begin with, methods used to analyze and attempt to predict assets values fall into two broad categories. The first approach is called a fundamental analysis and it explores asset's characteristics in order to decide if there are any fundamentally underlaid reasons for the price to move up or down. On the other hand, another approach – technical analysis – does not concern itself with asset's characteristics but solely with price movements instead. It tries to identify the trend which is followed by the asset price. The reasons for price movements are not the question since it is the profitability what matters.

Nonetheless, there have been attempts to theoretically explain why technical analysis may work. As it was already mentioned in Introduction of this study, common explanations include especially possible inefficiency of the stock markets, self-fulfilling expectations, sluggish adjustments of prices and non-synchronous reporting of prices. The last reasons are particularly relevant in case of stock indices. Indeed, the adjustment of index values is only partial because of non-synchronous trading of its component securities. That implies that the measured next day return can be biased in the same direction as the prior day price change. Scholes and Williams (1977) find that measurement errors due to non-synchronous reporting of prices induce spurious positive autocorrelation in portfolio. Consequently, the technical trading rules could exploit positive serial dependence.

To sum up, technical analysis is generally perceived as a method trying to predict future asset price through its past development regardless of the underlying reasons. Pring (2002) provides a more specific definition:

"The technical approach to investment is essentially a reflection of the idea that prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces. The art of

technical analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed.”

There are numerous types of technical analysis. Although technical analysis includes also visual chart patterns, this paper as well as the vast majority of academic research is limited to techniques which can be expressed in a mathematical form. We focus on the commonly used indicators MACD , stochastic and relative strength index. The first mentioned indicator is so called trend follower whereas the others pertain to the group of so called counter-trend indicators. They were chosen owing to their wide use which is illustrated by their involvement in most trading platforms.

4.1 The Concept of MACD

The first indicator used in this study is so called MACD. This commonly used abbreviation stands for Moving Average Convergence / Divergence. This technical indicator was created by Gerald Appel in the late 1970s. Since it is based on moving averages of closing prices, MACD is inherently a lagging, trend following indicator.

The heart of the MACD is the difference between two moving averages. A faster moving average of closing prices reflects shorter term market trends whereas a slower one longer term trends. The difference between a fast and slow moving average is then compared to its own average which is called a signal line. Consequently, the indicator shows expectations of investors. When it is positive and moreover getting up the signal line, it is bullish as it shows that current expectations are more bullish than previous expectations and vice versa.

There are several ways how to compute the MACD. This thesis follows the approach suggested by Gerald (1999). Two main decisions have to be made concerning the length of period of interest and a type of moving average used.

Firstly, a type of moving average has to be chosen. A simple moving average uses the same weights on all values taken into account. It has a strong momentum and lacks flexibility to price changes due to its construction. Therefore, exponential moving average is used more commonly to identify trends. It considers all values in time series but puts more weight on recent price development than on the older one. In fact, the weight for the oldest price observation approaches zero in its limit. Therefore, exponential moving average (EMA) is more flexible and it follows the price development more precisely. The degree of weighting decrease is expressed as a constant smoothing factor. A higher smoothing factor discounts older observations faster. Exponential moving averages reduce the lag by applying more weight to recent prices. The weighting applied to the most recent price depends on the number of periods in the moving average. Having calculated the smoothing constants we use them to update the exponential moving averages for each new piece of data. To calculate N-day exponential moving averages the smoothing constant is 2/(N+1). These formulas are recursive, so it does not tell where to start. A simple approximation is to use the earliest four price values as the earliest exponential moving average reading. Following this procedure introduces a small error, but after a few weeks' of data that error becomes negligible.

Secondly, we discuss parameters which define the period which is taken into account. The set of periods for the averages can be varied. The usual set of parameters is written as 12,26,9 for the fast EMA, slow EMA and signal line periods respectively. These parameters were originally published by Gerald Appel and are used in predefined packages until now. Therefore, the same set of parameters is used in this study as well.

$$EMA_t = EMA_{t-1} - K * EMA_{t-1} + C_t * K$$

Where:

EMA_t…exponential moving average of the price at time t

K …smoothing constant

$$K = \frac{2}{N+1}$$

N…number of periods

$N = 12$…for faster moving average, let us donate $EMA_t(12)$

$N = 26$…for slower moving average, let us donate $EMA_t(26)$

C_t…closing price at time t

MACD can be now calculated by subtracting a 26-day exponential moving average of a security's price from a 12-day moving average of its price. The following formula is suggested by Gerald (1999) as well as numerous websites[23].

$$MACD_t(12{,}26) = EMA_t(12) - EMA_t(26)$$

The signal line, which is another EMA of the MACD values themselves. A signal line (or trigger line) is calculated as average of MACD itself. The period for this is 9 days.

$$Signal\ line = EMA_{t-1} - K * EMA_{t-1} + C_t * K$$

EMA_t…exponential moving average of the MACD at time t

$$N = 9$$

4.1.1 Determination of Buy and Sell Signals

Positive MACD indicates that the 12-day EMA is above the 26-day EMA. In such a case, current expectations are more bullish than previous expectations. Moreover, the rising MACD indicates that the difference in expectations is getting more pronounced. In other words, current expectations are becoming more bullish relatively to previous expectations. On the contrary, the market climate is most unfavorable when MACD is falling and below zero, signifying that shorter term market trends are weaker than longer term trends. For the sake of preciseness and expliciteness, comparison to the signal line was introduced. Consequently, the usual trading rule is signal line crossing.

[23] See http://stockcharts.com

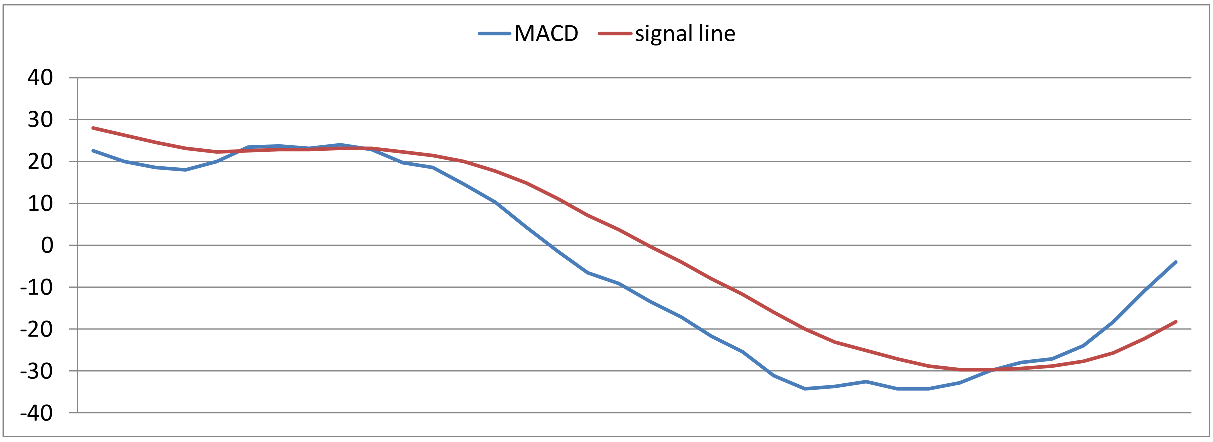
The buy signal is generated when the MACD crosses up through the signal line.

All days which follow an issue of the buy signal are referred to as buy days, henceforth, before the sell signal is issued.

The sell signal is generated when the MACD crosses down through the signal line.

All days which follow an issue of the sell signal are referred to as sell days, henceforth, before the buy signal is issued.

Figure 14: MACD buy and sell signals



Source: Author´s calculations

4.2 The Concept of Stochastic

Stochastic Oscillator was developed by George C. Lane in the late 1950s. It is a momentum indicator that shows the location of the close relative to the high-low range over a predefined number of periods. The underlying idea is that in a bullish market the high are located closer to close values. The opposite is true for a bear market. Since the asset price tends to decrease, the lowest values are located near the close values. Hence, stochastic oscillator follows the speed or the momentum of prices instead of volume or prices themselves. Investors who use this indicator hope to benefit from the fact that the momentum changes direction before price. The oscillator's range is bound between 0 and 100. Following this, the oscillator can be used in two ways. Firstly, it is supposed to be useful for identifying overbought and oversold levels. Secondly, it can be used to identify bullish and bearish divergences to anticipate the change in price direction. This technical indicator is used especially when the trend of the market is flat. When the asset is steeply rising or falling, its signal may not be so reliable.

As outlined above, stochastic represents the relative distance between low or high and close. It consists of two lines which are expressed in the following formulas stemming from Lane (1984):

$$\%K = \frac{(Close - Lowest\ Low)}{(Highest\ High - Lowest\ Low)} * 100$$

Where:
$Close$…Current close value of the index
$Lowest\ Low$…the lowest value reached by the index over the look-back period
$Highest\ High$… the highest value reached by the index over the look-back period

The other line exploited in the stochastic oscillator is a three day simple moving average (SMA) of the line above[24].

Once again, the question is how long period should be used. There are more possibilities which are commonly used. This study concerns two ways. Firstly, 14 periods are used which translates into 14 days in our case. The settings for the other line are 3 days as already discussed above. Secondly, 5 periods (5 days) are used to compute the line, then 3-period is used to smooth this line and the resulting line is smoothed once again with another 3-day simple moving average. To summarize, we consider stochastic (14, 3) and stochastic (5, 3, 3).

4.2.1. Determination of Buy and Sell Signals

Both buy and sell signal are issued in a very similar way to what was determined for the MACD indicator. In fact, the % D line serves as a signal line for stochastic oscillator. Again, signals take place when the lines cross.

[24] See http://stockcharts.com

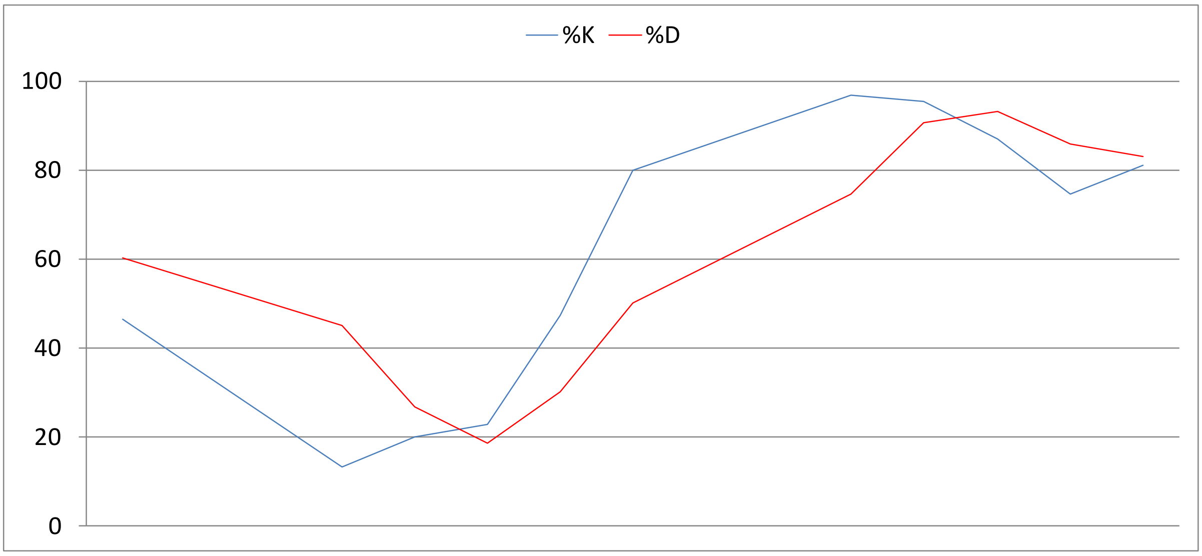
The buy signal is generated when the faster % K line crosses up through the % D line.

All days which follow an issue of the buy signal are referred to as buy days, henceforth, before the sell signal is issued.

The sell signal is generated when the % K line crosses down through the % D line.

All days which follow an issue of the sell signal are referred to as sell days, henceforth, before the buy signal is issued.

Figure 15: Stochastic Oscillator buy and sell signals



Source: Author´s calculations

4.3 The Concept of Relative Strength Index

The Relative Strength Index was developed by J. W. Wilder in 1970s. It is classified as a momentum oscillator with the aim to measure the speed and change of price movements.

The idea underlying the relative strength index is that when the price moves up rapidly, at some point the market is considered overbought. Likewise, when price falls down rapidly, at some point the market is considered oversold. When the market is considered overbought or oversold, the opposite movement can be expected. The relative strength index reveals a relationship between an average gain and average loss over a certain period. This way, the indicator tries to identify when the market is so called overbought or oversold.

The standard period suggested by Wilder (1978) to compute the relative strength index is 14 days. This setting can be lowered to increase sensitivity or raised to decrease sensitivity. The shorter the period is, the more likely the relative strength index is to indicate oversold or overbought levels.

The relative strength index is calculated according to the following formula[25]:

$$RSI = 100 - \frac{100}{1 + RS}$$

$$RS = \frac{\text{Average Gain}}{\text{Average Loss}}$$

Where:

Average Gain … Sum of Gains over the past 14 periods / 14
Average Loss … Sum of Losses over the past 14 periods / 14

Wilder (1978) introduced levels 30 and 70 to indicate oversold and overbought market. In fact, these values are not binding. Investors can use any values depending on the frequency of their trades. Apparently, the smaller range between the chosen values, the more signal the relative strength index generates. This thesis considers values 30 and 70 as originally introduced by Wilder (1978).

[25] stockcharts.com

4.3.1. Determination of Buy and Sell Signals

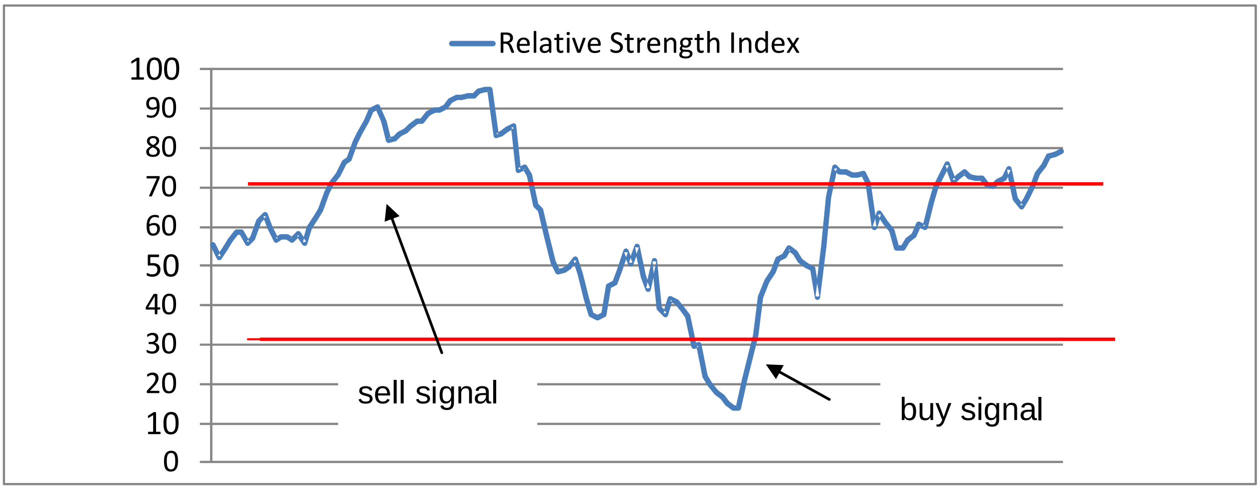
The buy signal is generated when the market is considered oversold, that is when the relative strength index falls below 30.

All days which follow an issue of the buy signal are referred to as buy days, henceforth, before the sell signal is issued.

The sell signal is generated when the market is considered overbought, that is when the relative strength index rises over 70.

All days which follow an issue of the sell signal are referred to as sell days, henceforth, before the buy signal is issued.

Figure 16: Relative Strength Index buy and sell signals



Source: Author´s calculations

5. Methodology

First of all, the problem of a danger of data snooping bias has to be addressed in order to assess the profitability of technical analysis. Whereas research on technical analysis before 1990s limited itself to exploring a small number of trading systems, more recent studies search over a large number of trading rules.

On one hand, detecting ex-post profitable trading rules and conducting parameter optimization facilitates a possible discovery of rewarding patterns. This strategy is employed by some of the reality check (Sullivan et al., 1999), genetic programming (Allen and Karjalainen, 1999) and non-linear (Gençay, 1998) studies.

On the other hand, testing a huge number of trading rules across a large data set can lead to misleading conclusions. Spurious patterns can be detected when trading strategies are both discovered and tested in the same data set. That is, there is a high chance that a profitable rule will be detected by pure luck and the rule will not yield excessive returns when put into practice[26].

Furthermore, such an approach is of limited practical use. Abundance of individual investors is unlikely to conduct their own research on ex-post profitable trading rules and rather rely on technical trading rules provided together with their trading platforms. In consequence, it is more useful for our purposes to assess the profitability of well known technical indicators.

For this reason and to avoid troubles associated with data snooping, this study does not search for trading rules proved to be profitable in the past but set the trading rules together with all the parameters in advance instead as already discussed in the previous chapter.

[26] Some studies try to mitigate this problem by introducing out-of-sample verification.

5.1 Statistical Tests

To test the profitability of technical indicators of our interest, conventional statistical tests are used. Technical indicators provide us with buy and sell signals and we compute the returns of stock indices. In order to obtain a comprehensive answer to the question of technical analysis profitability, the following hypotheses are formulated:

1. The returns are significantly larger/ smaller than zero.

If technical analysis is profitable, we expect returns on days when a buy signal is issued to be larger than zero and returns on days when a sell signal is issued to be smaller than zero.

2. The returns on buy and sell days differ appreciably.

We verify the previous results by comparing returns on buy and sell days. They should significantly differ if technical analysis is useful.

3. The returns on buy and sell days exceed returns on a buy and hold strategy.

Finally, we compare returns obtained owing to technical analysis to a standard buy and hold strategy.

Thus, we report the mean daily returns earned during buy and sell periods and test the hypotheses stated below. The hypotheses of this thesis are the alternative hypotheses to those that we test. In other words, if we cannot reject the null hypotheses formulated in this section, we cannot find any evidence on technical analysis profitability. The statistical tests are based on the calculations suggested by Anděl (1985). Considering the size of our samples, critical values corresponding to a normal distribution were used instead of those corresponding to a student distribution. The critical values z_{α} are, 1.282, 1.645 and 2.326 (for levels of significance α 10 %, 5 % and 1 %, respectively). Their negative equivalents are used when needed. For two tailed distribution related to the second hypothesis the values 1.645, 1.96, 2.576 (for levels of significance 10 %, 5 % and 1 %, respectively) were used.

Hence, for the α level of significance, if the resulting T> z_{α}, we will reject H_0.

The hypotheses tested are the following:

1. Difference from zero

We compare the mean daily returns earned during buy or sell periods with corresponding t-statistics. The procedure for testing is as stated below.

a)

$$H_0: \overline{X_1} = 0$$

$$H_A: \overline{X_1} > 0$$

$$t = \frac{\overline{X_1}}{\frac{s_1}{\sqrt{n_1}}}$$

Where:

$\overline{X_1}$…the mean return on “buy days”
s_1…the standard error estimated from the “buy days” sample
n_1…a number of returns on “buy days”

b)

$$H_0: \overline{X_2} = 0$$

$$H_A: \overline{X_2} < 0$$

$$t = \frac{\overline{X_2}}{\frac{s_2}{\sqrt{n_2}}}$$

Where:

$\overline{X_2}$…the mean return on "sell days"

s_2…the standard error estimated from the "sell days" sample

n_2…a number of returns on "sell days"

2. Equality of the mean daily returns on buy days with the mean daily returns on sell days

We compare the mean daily returns earned during buy and sell periods with corresponding t-statistics following two-tailed distribution. These returns do not differ under the null hypothesis.

$$H_0: \overline{X_1} - \overline{X_2} = 0$$

$$H_A: \overline{X_1} - \overline{X_2} \neq 0$$

$$t = \frac{\overline{X_1} - \overline{X_2}}{\left(\sqrt{\frac{{s_1}^2}{n_1} + \frac{{s_2}^2}{n_2}}\right)}$$

3. Equality of the respective returns with unconditional mean daily returns.

We test whether the respective returns are equal to the unconditional mean daily returns with corresponding t-statistics. Under the null hypothesis, the returns earned owing to technical trading rules on buy days do not differ significantly from returns earned according to a buy and hold strategy.

$$H_0: \overline{X_1} - \bar{X} = 0$$

$$H_A: \overline{X_1} - \bar{X} \neq 0$$

$$t = \frac{\overline{X_1} - \bar{X}}{\frac{s_1}{\sqrt{n_1}}}$$

Where:

$\bar{X}$…the unconditional mean daily returns

s…the standard error estimated from the entire sample

In this investigation there is a source for difficulties in terms of dealing with mean daily returns. It can be argued that computations based on mean daily returns are inapposite since investors are unlikely to hold an asset only for a single day. Consequently, the mean daily returns are difficult to interpret in term of an investment decision. However, it is impossible to determine the exact timing of market entry and exit which renders the method based on mean daily returns the most suitable. In addition, this method has been extensively utilized until today[27].

5.2 Verification: Bootstrap

A source of uncertainty in the method used above is returns distribution. Conventional t-statistics assume normal returns distributions. Numerous studies (James, 1968; Peterson and Leuthold, 1982; Bird, 1985; Sweeney, 1986) assume that returns are normally distributed and use Z- or t-tests to measure statistical significance. It has become a common practice that normality is assumed especially when dealing with large data sets. Given the amplitude of our samples we can assume normality convergence owing to the central limit theorem (Rice 1995).

Nonetheless, these assumptions might be invalid according to some studies. As Taylor (1985) points out, distribution of the returns under the null hypothesis of an efficient market cannot be assumed to be normal because it is not known. The invalidity of the assumption of normal distribution is verified by Lukac and Brorsen (1990). They found that returns are positively skewed and leptokurtic. In such a case, applying conventional statistical tests to trading rule returns renders irrelevant.

Normality tests of our time series returns are reported in the following table. As can be seen, the normality can be rejected for all time series and therefore does not

[27] See Bessembinder and Chan (1995), Chew et al. (2003), Hudson et al. (1996)

characterize our data. In turn, we do not fully rely on the convergence to normality in spite of the fact that many researchers do so.

Table 9: Normality tests

Nomality test		
Index returns	Statistic	P-value
ATX	4055.8	0.0000**
BET	1223.5	0.0000**
BUX	92135	0.0000**
DAX 30	1407	0.0000**
PX	4355.2	0.0000**
WIG 20	955.64	0.0000**
PFTS	54362	0.0000**

Source: Author´s calculations

Therefore, as far as the first question is concerned, we introduce also another methodology. Bootstrap methodology is used to address the possible problem of non-normality of returns. Testing statistical significance in this way can assure that our previous results are robust. Consequently, resulting statistics are not compared to critical values assuming normal distribution but bootstrap confidence intervals are constructed instead.

The procedure is as follows. We report mean daily returns on buy days as well as on sell days. We resample the data to obtain a bootstrap resample. This procedure is repeated 100 000 times and it allows us to substitute an unknown distribution of returns by an empirical one:

$$F \to \hat{F}$$

Once we get an empirical bootstrap distribution, we derive bootstrap confidence intervals for the purpose of hypothesis testing.

6. Empirical Results

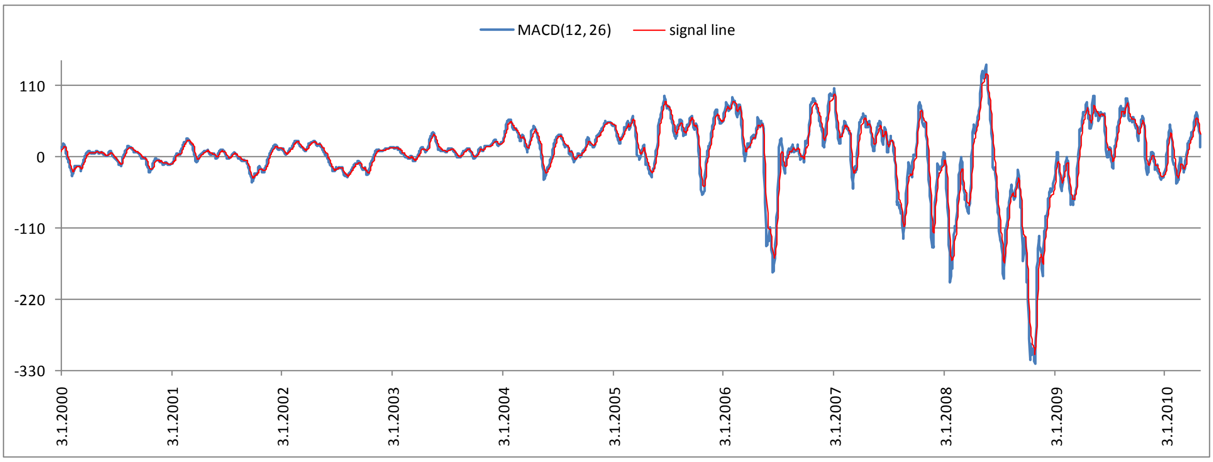
The empirical results are described and discussed in this section. Firstly, results for MACD indicator are reported. Secondly, results obtained for profitability of stochastic oscillator are presented. Results are compared both in terms of individual markets and in terms of both technical indicators at the end of this chapter.

6.1 Statistical Tests for the MACD Indicator

6.1.1 Austria

In line with the rising market, the mean return of daily returns of ATX index is positive and equal to 0.03 % which is approximately 8 % at an annual rate. MACD also indicated more buy days than sell days during the period. The mean returns on the respective days are of the expected sign. That is, the mean return on buy days is positive and the mean return on sell days is negative as one would expect if signals issued by technical indicators made sense.

Figure 14: MACD for the index ATX



Source: Author´s calculations

Table 10: MACD statistics for daily returns of ATX

Statistics for daily returns of the index ATX		
Number of daily returns	4293	
Mean return of daily returns	0.030%	
Standard deviation of daily returns	0.013	
	Buy days	**Sell days**
Number of days	2241	2042
Mean return	0.065%	-0.007%
Standard deviation	0.012	0.015
T statistics		
1/ Equality to 0	2.61**	-0.21
2/ Difference between buy and sell returns	1.71	
3/ Comparison to a buy and hold strategy	1.41	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

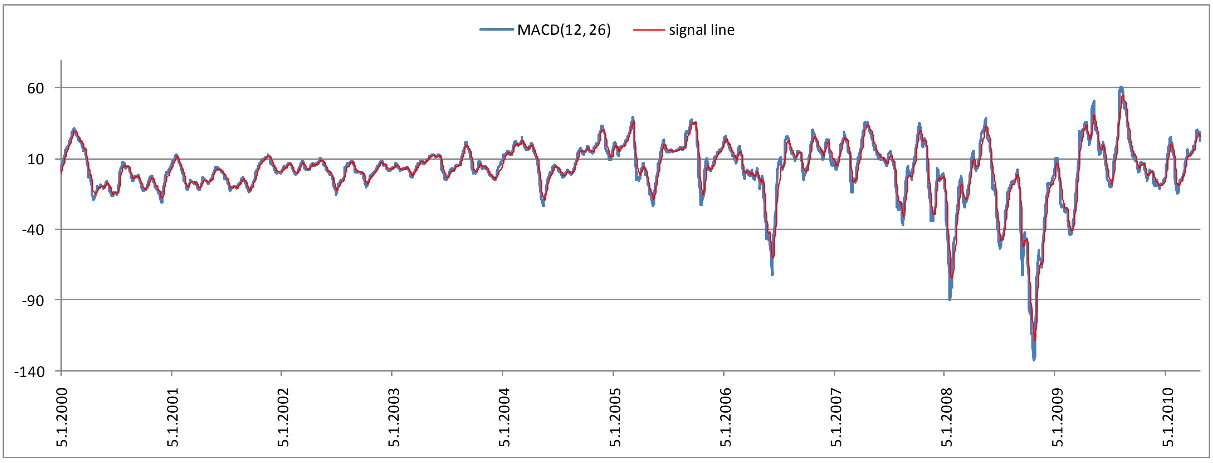
Source: Author´s calculations

As far as the three questions of our interest are concerned, we obtained the following results. We cannot reject that returns on buy and sell days are equal as well as that they do not yield significantly different returns than a buy and hold strategy. We cannot reject that returns on sell days are zero either. The only promising significant result we found out is for returns on buy days. Returns obtained on buy days are significantly larger than zero even at 1 % significance level.

6.1.2 The Czech Republic

We have a time series consisting of 3,981 values out of which 52 % are determined by the MACD indicator to be sell days. The mean return over the whole sample is merely 0.004 % which translates into 1 % annually.

Figure 15: MACD for the index PX



Source: Author´s calculations

As can be seen from the table below, mean returns on buy/sell days are both of expected sign and markedly bigger/smaller than in the case of the Vienna Stock Exchange. Also the t-statistics are not only of the correct sign but also provide us with much more promising results.

Table 11: MACD statistics for daily returns of PX

Statistics for daily returns of the index PX		
Number of daily returns	3981	
Mean return of daily returns	0.004%	
Standard deviation of daily returns	0.015	
	Buy days	**Sell days**
Number of days	2057	1913
Mean return	0.092%	-0.094%
Standard deviation	0.013	0.016
T statistics		
1/ Equality to 0	3.27**	-2.52**
2/ Difference between buy and sell returns	3.98**	
3/ Comparison to a buy and hold strategy	3.13**	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

Actually, all statistics are significant on 1 % significance level. In other words, we can reject equality to zero for both sell and buy days returns, equality of buy and sell days mean returns and equality to a buy and hold strategy. The MACD indicator seems to prove itself profitable on the Prague Stock Exchange in the period of our interest. It brings us to the investigation of the main individual constituents of the index PX.

6.1.2.1 ČEZ

There are 2,842 observations available to explore the profitability of the MACD indicator on ČEZ stock price. The daily mean return of the ČEZ stock prices is 0.095 % which is 26.8 % annually.

Mean returns on sell days are irrelevant at the first sight. They do not have the expected sign and neither does the corresponding t-statistic. On the other hand, we can reject equality to zero for mean returns on buy days on 1 % significance level. The rest of the results is not compelling. We cannot reject the null hypotheses neither for the second question nor for the third question of our interest.

Table 12: MACD statistics for daily returns of ČEZ stock price

Statistics for daily returns of ČEZ		
Number of daily returns	2842	
Mean return of daily returns	0.095%	
Standard deviation of daily returns	0.022	
	Buy days	**Sell days**
Number of days	1434	1398
Mean return	0.159%	0.037%
Standard deviation	0.021	0.023
T statistics		
1/ Equality to 0	2.90**	0.60
2/ Difference between buy and sell returns	1.48	
3/ Comparison to a buy and hold strategy	1.17	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.1.2.2 Erste Bank

Due to the fact that stocks of the Erste Bank were issued on the PSE in 2002, there are only 1,882 values of close prices. The daily mean return is 0.032 % which translates into 8.4 % on annual basis.

The mean returns on both buy and sell days have the sign which is expected if technical indicator was useful. However, none of the t-statistics provides us with any significant results. In fact, no null hypothesis can be rejected. Hence, the MACD indicator failed in yielding any significant returns for the Erste Bank stocks in the tested period.

Table 13: MACD statistics for daily returns of Erste Bank stock price

Statistics for daily returns of Erste Bank		
Number of daily returns	1882	
Mean return of daily returns	0.032%	
Standard deviation of daily returns	0.026	
	Buy days	**Sell days**
Number of days	936	936
Mean return	0.082%	-0.016%
Standard deviation	0.025	0.028
T statistics		
1/ Equality to 0	1.02	-0.17
2/ Difference between buy and sell returns	0.80	
3/ Comparison to a buy and hold strategy	0.62	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.1.2.3 Komerční banka

There are 2,849 observations of close prices of Komerční banka stocks. Mean daily return is 0.087 % and that is 24.3 % annually. The MACD indicated more buy days than sell days. Mean returns on both buy and sell days are of the expected signs. Moreover, our results indicate that the difference from zero on buy days is significant on 1 % significance level. In addition, we can reject null hypotheses for both the second and third question on 5 % significance level. In other words, we reject equality of mean returns on buy and sell days and equality of mean returns on buy days to those associated with a buy and hold strategy.

Table 14: MACD statistics for daily returns of Komerční banka stock price

Statistics for daily returns of Komerční banka		
Number of daily returns	2849	
Mean return of daily returns	0.087%	
Standard deviation of daily returns	0.025	
	Buy days	**Sell days**
Number of days	1443	1396
Mean return	0.201%	-0.026%
Standard deviation	0.023	0.026
T statistics		
1/ Equality to 0	3.27**	-0.38
2/ Difference between buy and sell returns	2.45*	
3/ Comparison to a buy and hold strategy	1.85*	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.1.2.4 Telefonica O2

The time series of Telefonica O2 stock prices at closing time consist of 3,080 values. It is the only time series considered that has a negative mean return, to be specific, -0.001 % which is -0.21 % on annual basis. However, the MACD indicated slightly more buy days.

Mean return on buy days is positive and mean return on sell days is negative which is what one would expect if the indicator was useful in generating buy signals. However, the obtained t-statistics are too low to suggest any significance in our results. Consequently, null hypotheses cannot be rejected. The MACD indicator renders irrelevant for predicting the price of Telefonica O2 in the tested period.

Table 15: MACD statistics for daily returns of Telefonica O2 stock price

Statistics for daily returns of Telefonica O2		
Number of daily returns	2995	
Mean return of daily returns	-0.001%	
Standard deviation of daily returns	0.022	
	Buy days	**Sell days**
Number of days	1498	1487
Mean return	0.012%	-0.012%
Standard deviation	0.020	0.023
T statistics		
1/ Equality to 0	0.23	-0.20
2/ Difference between buy and sell returns	0.30	
3/ Comparison to a buy and hold strategy	0.25	

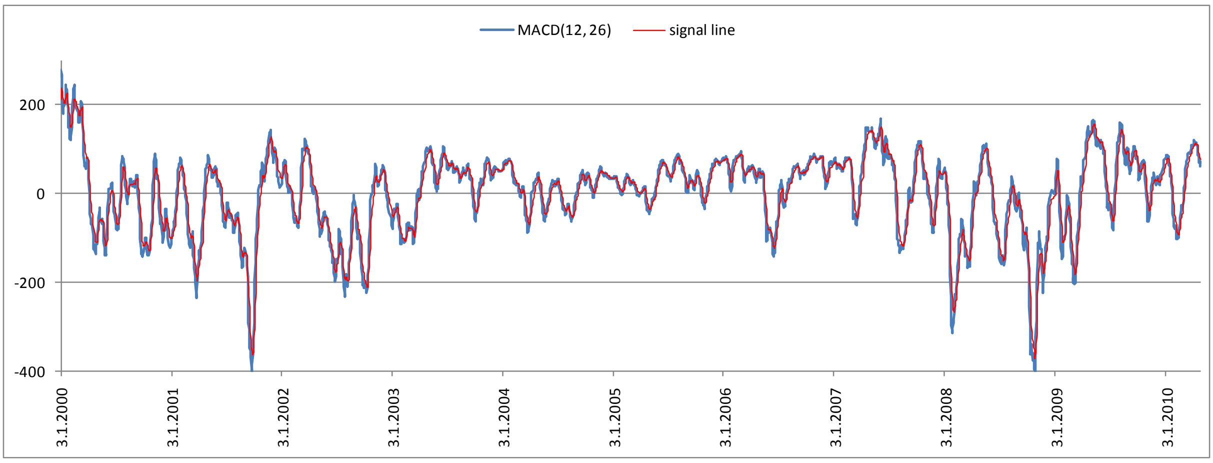
Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.1.3 Germany

The mean return of DAX 30 returns is only slightly lower than that of ATX returns. It reaches 0.028 % which is 7 % at annual basis.

Figure 16: MACD for the index DAX 30



Source: Author´s calculations

It is apparent at the first sight that our results are very poor. They are summarizes in the following table. First of all, mean return on sell days is not even of the correct sign. Although the MACD issued a sell signal, mean returns were positive on average. Consequently, t-statistics for sell days are of wrong sign as well.

Table 16: MACD statistics for daily returns of DAX 30

Statistics for daily returns of the index DAX 30		
Number of daily returns	4217	
Mean return of daily returns	0.028%	
Standard deviation of daily returns	0.015	
	Buy days	**Sell days**
Number of days	2163	2044
Mean return	0.016%	0.041%
Standard deviation	0.014	0.017
T statistics		
1/ Equality to 0	0.55	1.09
2/ Difference between buy and sell returns	-0.52	
3/ Comparison to a buy and hold strategy	-0.39	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

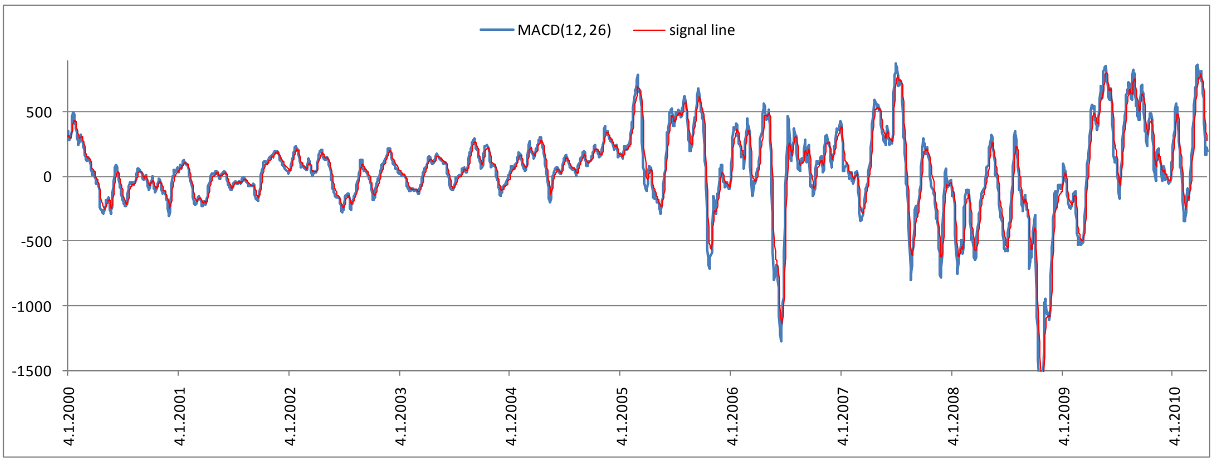
Source: Author´s calculations

Moreover, also t-statistic for comparison of buy days returns and a buy and hold strategy is not of the correct sign. Statistic for equality of buy days returns to zero is of the expected sign indeed, however, we cannot reject this equality even on 10 % significance level. All in all, results derived from exploration of DAX 30 index do not support the idea of the MACD profitability.

6.1.4 Hungary

The mean return of the BUX index daily returns is higher than mean returns of the previous two indices. It reaches 0.08 % on a daily basis and 21 % on an annual basis.

Figure 17: MACD for the index BUX



Source: Author´s calculations

From the following table we can see that once again, the mean return on sell days is not of the expected sign as was the case of the DAX 30 index. Nonetheless, the empirical results are still more promising. In fact, the sign is not what we expect only for the mean return on sell days.

Table 17: MACD statistics for daily returns of BUX

Statistics for daily returns of the index BUX		
Number of daily returns	4331	
Mean return of daily returns	0.077%	
Standard deviation of daily returns	0.022	
	Buy days	**Sell days**
Number of days	2168	2153
Mean return	0.129%	0.029%
Standard deviation	0.021	0.023
T statistics		
1/ Equality to 0	2.87**	0.58
2/ Difference between buy and sell returns	1.49	
3/ Comparison to a buy and hold strategy	1.15	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

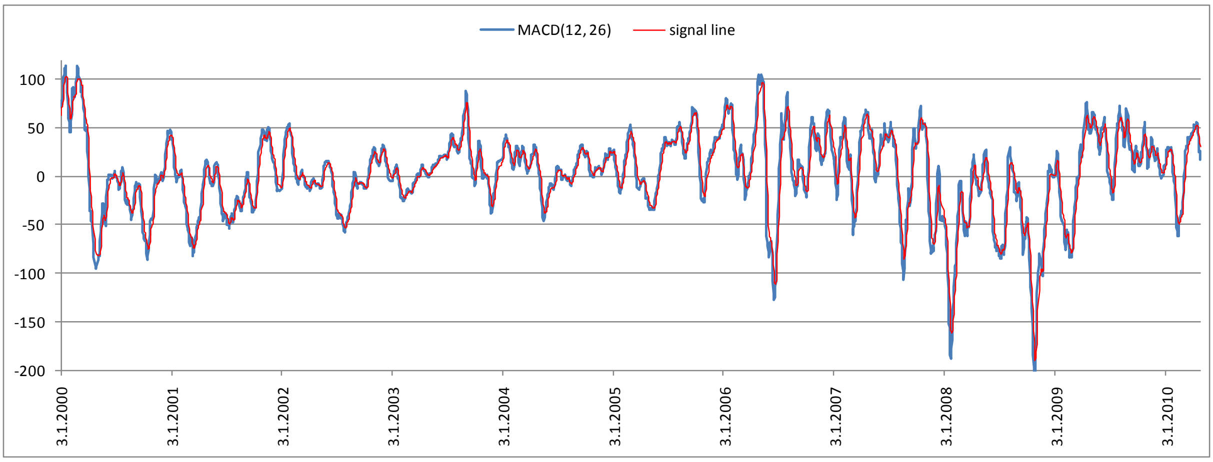
Source: Author´s calculations

Even though, we cannot reject most of the null hypothesis even on 10 % significance level. The only convincing result is that for the difference of mean returns on buy days from zero. Those returns are different from zero on 1 % significance level. Hence, although the results are more encouraging than those for the index DAX 30, we find only one significant result supporting the idea of the MACD profitability.

6.1.5 Poland

The data for the index WIG 20 consist of 3,984 observations. The daily mean return equals 0.022 %. That is 5.7 % on annualized basis.

Figure 18: MACD for the index WIG 20



Source: Author´s calculations

It can be seen from the results in the following table that mean returns on buy days are positive and mean returns on sell days are negative as we expect them to be. However, we can reject equality to zero only for buy days returns. We also reject that mean returns on buy and sell days are the same. Both null hypotheses can be rejected on 5 % significance level.

Table 1817: MACD statistics for daily returns of WIG 20

Statistics for daily returns of the index WIG 20		
Number of daily returns	3984	
Mean return of daily returns	0.022%	
Standard deviation of daily returns	0.020	
	Buy days	**Sell days**
Number of days	2056	1918
Mean return	0.090%	-0.049%
Standard deviation	0.019	0.021
T statistics		
1/ Equality to 0	2.17*	-1.02
2/ Difference between buy and sell returns	2.18*	
3/ Comparison to a buy and hold strategy	1.63	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

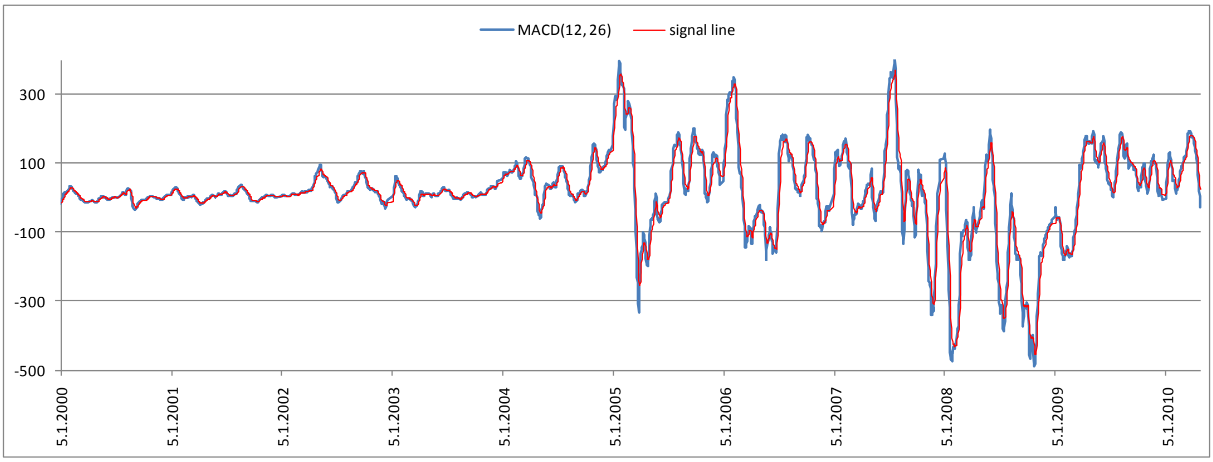
To sum up, the results obtained for the index WIG 20 are mixed similarly to results for the index BUX. In general, those results are not particularly compelling, especially in comparison with the results obtained for the index PX.

6.1.6 Romania

The mean return over the observed period consisting of 3,139 observations is 0.058 % on daily basis. The annualized mean return is 15.6 %.

The MACD indicator issued more buy signals than sell signals and mean returns on both buy and sell days have the expected sign. However, we cannot reject that mean returns on sell days are equal to zero.

Figure 19: MACD for the index BET



Source: Author´s calculations

On the contrary, we reject equality of mean returns on buy days to zero as well as equality of mean returns on buy days to those on sell days on 1 % significance level. Also, the equality of mean returns on buy days can be rejected on the same significance level.

Moreover, our results suggest that the mean returns on buy days exceed returns gained owing to a standard buy and hold strategy. The null hypothesis of our third question can be rejected on 1 % significance level as well. Hence, the findings support the hypothesis of technical analysis profitability for the index BET.

Table 19: MACD statistics for daily returns of BET

Statistics for daily returns of the index BET		
Number of daily returns	3139	
Mean return of daily returns	0.058%	
Standard deviation of daily returns	0.019	
	Buy days	**Sell days**
Number of days	1605	1523
Mean return	0.175%	-0.062%
Standard deviation	0.018	0.020
T statistics		
1/ Equality to 0	3.92**	-1.21
2/ Difference between buy and sell returns	3.49**	
3/ Comparison to a buy and hold strategy	2.63**	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

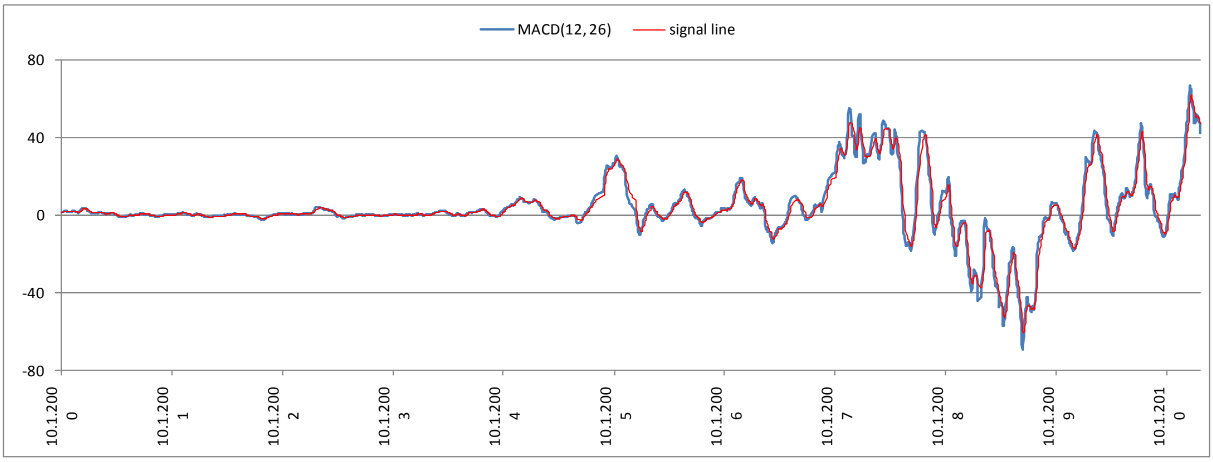
Source: Author´s calculations

6.1.7 Ukraine

The 2,918 daily values of the index PFTS have the mean value 0.079 % which is 21.8 % annually. That is the highest mean return among all stock indices which are considered in this thesis. Correspondingly, the MACD indicator issued more buy signals in the given period.

The daily mean returns on buy days are positive and they are negative on sell days as expected. The results are similar to those obtained for the index BET with the exception of lower statistics obtained. In other words, results for the index PFTS are slightly less compelling.

Figure 20: MACD for the index PFTS



Source: Author´s calculations

Whereas we cannot reject that mean returns on sell days are equal to zero, we can reject this equality for mean returns on buy days on 1 % significance level. Also, mean returns on buy and sell days differ significantly (on 1 % significance level again) according to our results. Last but not least, equality of mean returns on buy days to returns earned owing to a buy and hold strategy is rejected on 5 % significance level.

Table 2018: MACD statistics for daily returns of PFTS

Statistics for daily returns of the index PFTS		
Number of daily returns	2918	
Mean return of daily returns	0.079%	
Standard deviation of daily returns	0.028	
	Buy days	**Sell days**
Number of days	1550	1357
Mean return	0.219%	-0.073%
Standard deviation	0.032	0.023
T statistics		
1/ Equality to 0	2.71**	-1.15
2/ Difference between buy and sell returns	2.84**	
3/ Comparison to a buy and hold strategy	1.74*	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

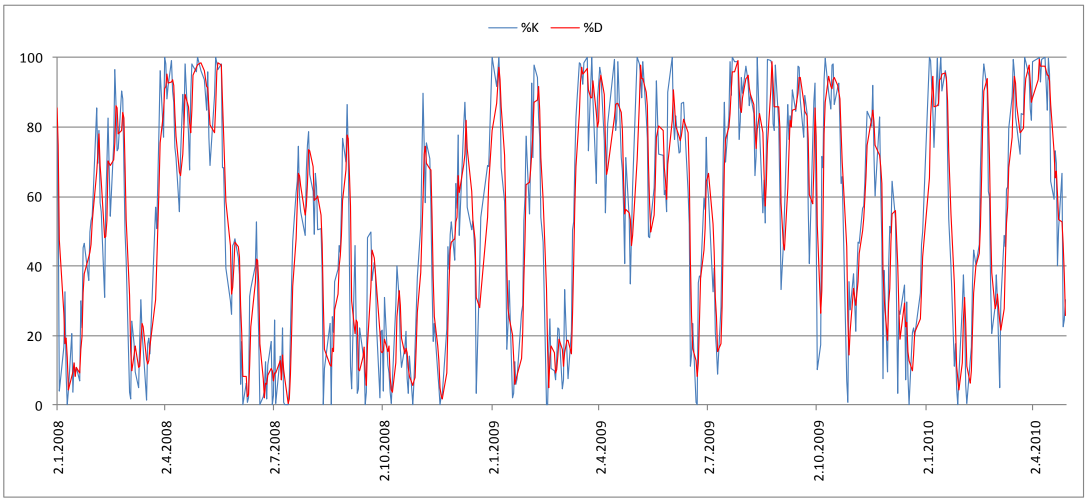
6.2 Statistical Tests for the Stochastic Oscillator

We discuss results of statistical tests on profitability of stochastic oscillator on Central and Eastern European stock markets in this section. Due to the data limitation, observations available are at most cases fewer than in the previous section. That is because values of daily high and low are required in order to compute values of stochastic oscillator. However, these values were not available for such a long period for which close values are available. Accordingly, profitability of signals issued by stochastic oscillator is tested on a smaller sample. Number of available observations is stated in a table corresponding with each index. Unfortunately, as far as index PFTS is concerned, values needed were available only from March 2010. Therefore, the sample is too small and statistics obtained for the index PFTS should be treated with caution. In addition, values needed were not available for the individual PX constituents.

6.2.1 Austria

Our data to test profitability of stochastic oscillator consist of 2,581 observations.

Figure 21: Stochastic (14,3) for the index ATX



Source: Author´s calculations

This time there is a slightly bigger amount of sell days unlike when we were testing the profitability of the MACD indicator over a longer period of time. The annualized mean return is 2.2 %.

All results are of the expected sign as can be seen from the preceding table. Concerning our first question, we can reject equality to zero for mean returns on buy days for both set of parameters on 1 % significance level, whereas we cannot reject it at all for sell days. Equality of mean returns on buy and sell days is rejected for both sets of parameters, while results suggest that mean returns on buy days exceed those gained due to a buy and hold strategy only for a set (14, 3).

Table 21: Stochastic statistics for daily returns of the index ATX

Statistics for daily returns of the index ATX					
Number of daily returns	4276				
Mean return of daily returns	0.029%				
Standard deviation of daily returns	0.010				
Stochastic (14,3)			**Stochastic (5,3,3)**		
	Buy days	**Sell days**		**Buy days**	**Sell days**
Number of days	2176	2100	Number of days	2158	2118
Mean return	0.097%	-0.041%	Mean return	0.076%	-0.018%
Standard deviation	0.013	0.014	Standard deviation	0.013	0.014
T statistics			**T statistics**		
1/ Equality to 0	3.43**	-1.38	1/ Equality to 0	2.63**	-0.62
2/ Difference between buy and sell returns	3.36**		2/ Difference between buy and sell returns	2.28*	
3/ Comparison to a buy and hold strategy	2.40**		3/ Comparison to a buy and hold strategy	1.62	

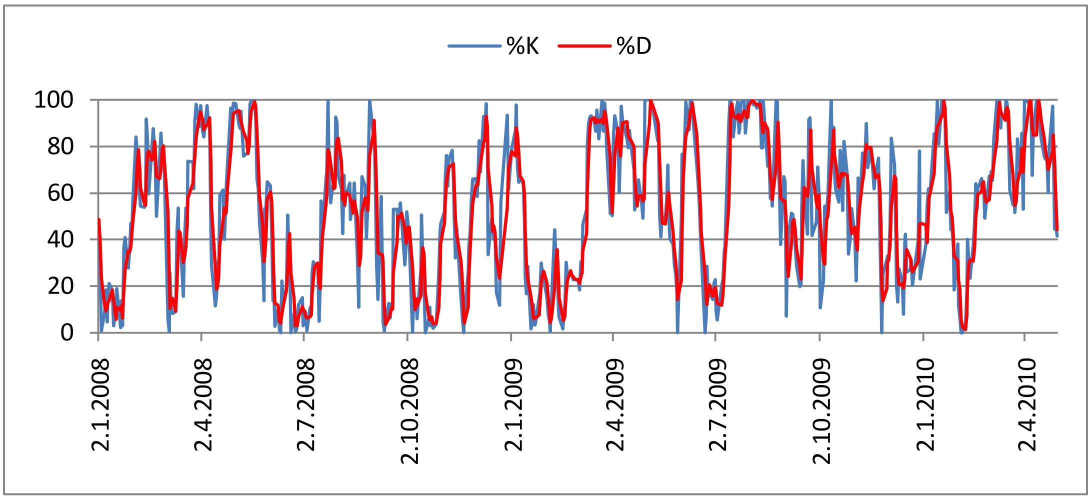
Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.2.2 The Czech Republic

We have 2,580 observations of PX index values available to test whether stochastic oscillator is profitable. There are more buy days than sell days and the overall mean return is 5 % on the annual basis.

Figure 22: Stochastic (14,3) for the index PX



Source: Author´s calculations

Results received after investigation of the index PX are not unanimous and further elaboration is needed.

Firstly, we consider t-statistics for stochastic oscillator (14, 3). We can reject all the hypotheses tested except for the equality of mean returns on sell days to zero but the corresponding significance levels vary. Buy and sell days returns are not equal on 1 % significance level as well as mean returns on buy days to zero. Equality of mean returns on buy days to a buy and hold strategy can be rejected on 5 % significance level.

As for stochastic oscillator (5, 3, 3), the equality of buy and sell days mean returns can be rejected on 5 % significance level. We reject equality of buy days returns to zero and to a buy and hold strategy on 5 % significance level. On the contrary, equality of sell days mean returns to zero cannot be rejected. Although levels of significance on which we can reject the tested hypotheses differ appreciably, the results altogether show that following signals issued by the stochastic oscillator yielded significantly positive returns for buy days.

Table 22: Stochastic statistics for daily returns of the index PX

Statistics for daily returns of the index PX					
Number of daily returns	2533				
Mean return of daily returns	0.024%				
Standard deviation of daily returns	0.016				
Stochastic (14,3)			**Stochastic (5,3,3)**		
	Buy days	**Sell days**		**Buy days**	**Sell days**
Number of days	1286	1247	Number of days	1294	1239
Mean return	0.112%	-0.067%	Mean return	0.098%	-0.053%
Standard deviation	0.015	0.017	Standard deviation	0.016	0.016
T statistics			**T statistics**		
1/ Equality to 0	2.71**	-1.40	1/ Equality to 0	2.23*	-1.16
2/ Difference between buy and sell returns	2.84**		2/ Difference between buy and sell returns	2.39*	
3/ Comparison to a buy and hold strategy	2.12*		3/ Comparison to a buy and hold strategy	1.68*	

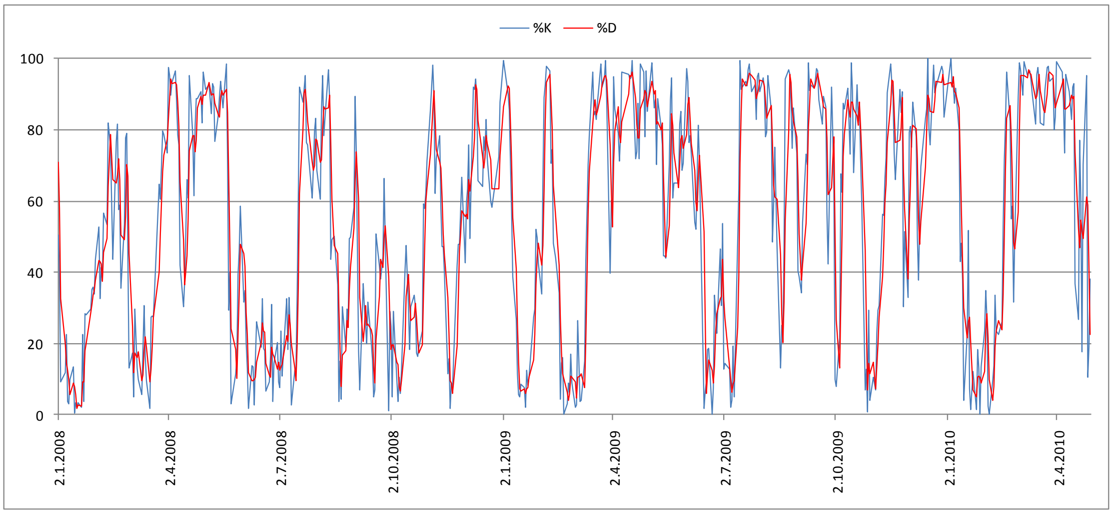
Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.2.3 Germany

There are 2,592 values of index DAX 30 with a mean annual return of 5.7 %. The number of buy days exceeds the number of sell days by 7 % for stochastic oscillator (14, 3) and by 5 % for stochastic oscillator (5, 3, 3).

Figure 23: Stochastic (14,3) for the index DAX 30



Source: Author´s calculations

Similarly to statistics for the MACD indicator on the index DAX 30, our results are far from being convincing. In fact, we cannot reject any null hypothesis. Stochastic oscillators failed to be profitable for the index DAX 30.

Table 23: Stochastic statistics for daily returns of the index DAX 30

Statistics for daily returns of the index DAX 30					
Number of daily returns	4139				
Mean return of daily returns	0.025%				
Standard deviation of daily returns	0.015				
Stochastic (14,3)			**Stochastic (5,3,3)**		
	Buy days	**Sell days**		**Buy days**	**Sell days**
Number of days	2151	1976	Number of days	2143	1984
Mean return	0.036%	0.013%	Mean return	0.034%	0.014%
Standard deviation	0.015	0.015	Standard deviation	0.015	0.016
T statistics			**T statistics**		
1/ Equality to 0	1.07	0.36	1/ Equality to 0	1.04	0.41
2/ Difference between buy and sell returns	0.48		2/ Difference between buy and sell returns	0.41	
3/ Comparison to a buy and hold strategy	0.33		3/ Comparison to a buy and hold strategy	0.29	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

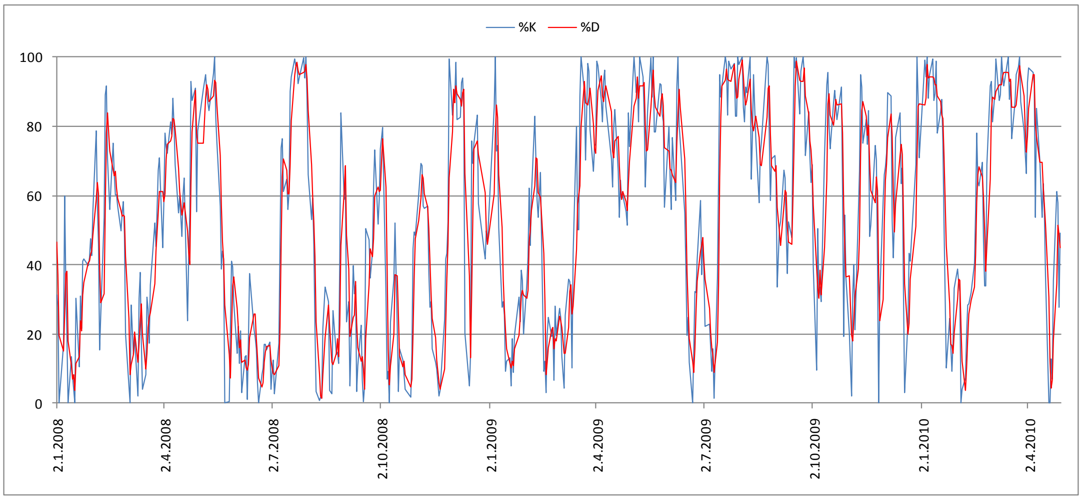
Source: Author´s calculations

6.2.4 Hungary

The number of index BUX values available to explore stochastic oscillator is 2,592. The mean return is 15.4 % on annualized basis. Buy days prevail for stochastic oscillator with both sets of parameters.

In terms of significance, the findings are completely the same for both the stochastic oscillator (14, 3) and the stochastic oscillator (5, 3, 3).

Figure 24: Stochastic (14,3) for the index BUX



Source: Author´s calculations

Equality to zero can be rejected on 1 % significance level for both buy days mean returns and sell days mean returns, equality of mean returns on buy days to a buy and hold strategy mean returns is also rejected on 1 % significance. We also reject that returns on buy and sell days are the same (on 1 % significance level).

Table 24: Stochastic statistics for daily returns of the index BUX

Statistics for daily returns of the index BUX					
Number of daily returns			3263		
Mean return of daily returns			0.044%		
Standard deviation of daily returns			0.019		
Stochastic (14,3)			**Stochastic (5,3,3)**		
	Buy days	**Sell days**		**Buy days**	**Sell days**
Number of days	1643	1608	Number of days	1649	1602
Mean return	0.151%	-0.065%	Mean return	0.145%	-0.059%
Standard deviation	0.019	0.020	Standard deviation	0.018	0.021
T statistics			**T statistics**		
1/ Equality to 0	3.30**	-1.32	1/ Equality to 0	3.36**	-1.14
2/ Difference between buy and sell returns	3.22**		2/ Difference between buy and sell returns	3.03**	
3/ Comparison to a buy and hold strategy	2.33**		3/ Comparison to a buy and hold strategy	2.33**	

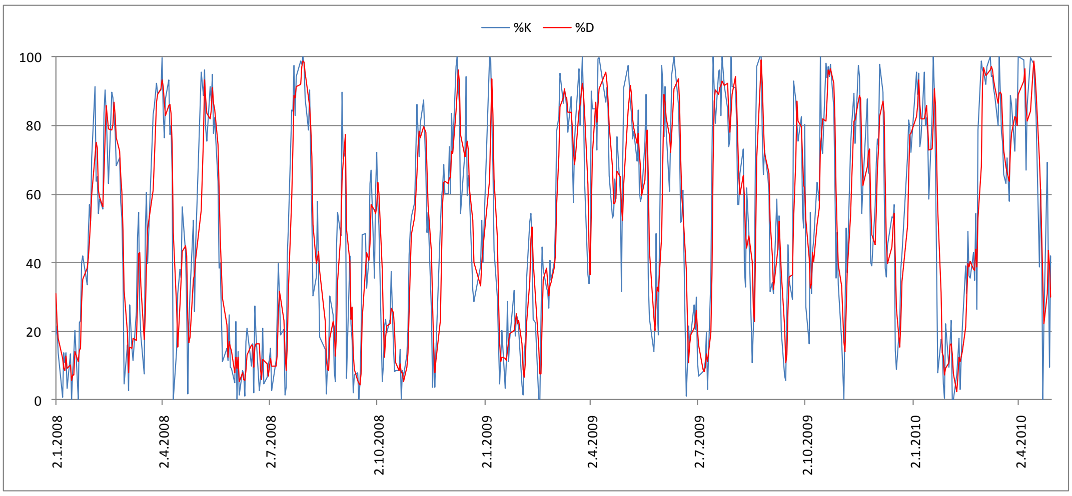
Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.2.5 Poland

We have 2,592 observations for WIG 20 index to compute stochastic oscillator. Majority of signals issued indicate sell days. The sign of mean returns and of all t-statistics are of the expected direction.

Figure 25: Stochastic (14,3) for the index WIG 20



Source: Author´s calculations

However, the results are not convincing although all the signs are “correct”. The situation is the same as for the index DAX 30. None of the null hypotheses can be rejected. In other words, no evidence on stochastic oscillator profitability for the index WIG 20 is found.

Table 19:Stochastic statistics for daily returns of the index WIG 20

Statistics for daily returns of the index WIG 20					
Number of daily returns	3314				
Mean return of daily returns	0.009%				
Standard deviation of daily returns	0.019				
Stochastic (14,3)			**Stochastic (5,3,3)**		
	Buy days	**Sell days**		**Buy days**	**Sell days**
Number of days	1609	1693	Number of days	1643	1659
Mean return	0.029%	-0.010%	Mean return	0.068%	-0.048%
Standard deviation	0.019	0.019	Standard deviation	0.019	0.019
T statistics			**T statistics**		
1/ Equality to 0	0.63	-0.20	1/ Equality to 0	1.48	-1.02
2/ Difference between buy and sell returns	0.59		2/ Difference between buy and sell returns	1.76	
3/ Comparison to a buy and hold strategy	0.43		3/ Comparison to a buy and hold strategy	1.27	

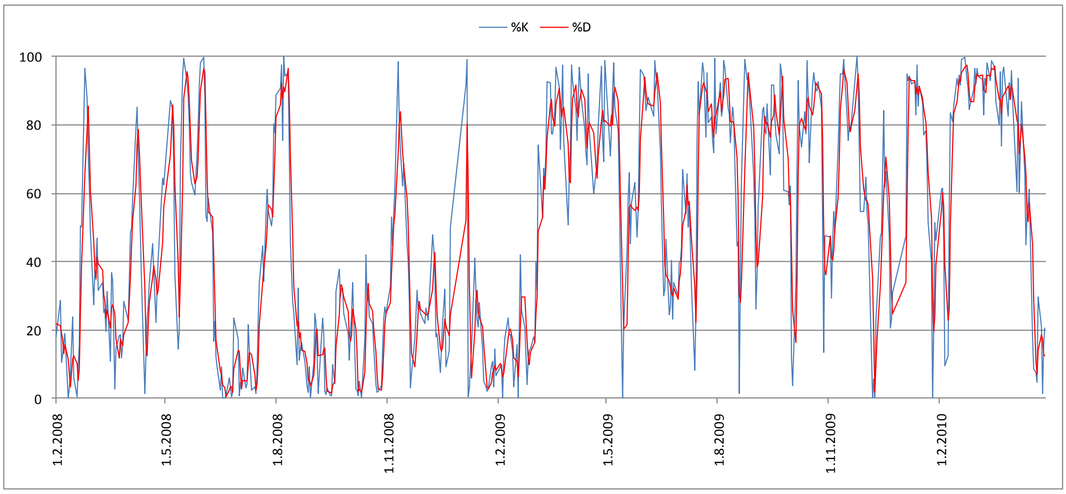
Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.2.6 Romania

There are 3,134 observations available for the BET index. Mean returns on both buy and sell days are of the expected sign.

Figure 26: Stochastic (14,3) for the index BET



Source: Author´s calculations

Results obtained for the index BET strongly support the hypothesis of this study. We can observe statistical significance of results for all three questions raised.

Not only can we reject null hypothesis in the first and the second question, but also profits gained on buy days from stochastic oscillator signals with any of the parameter sets significantly exceed a standard buy and hold strategy.

Table 26: Stochastic statistics for daily returns of the index BET

Statistics for daily returns of the index BET					
Number of daily returns	3134				
Mean return of daily returns	0.055%				
Standard deviation of daily returns	0.019				
Stochastic (14,3)			**Stochastic (5,3,3)**		
	Buy days	**Sell days**		**Buy days**	**Sell days**
Number of days	1534	1588	Number of days	1559	1563
Mean return	0.315%	-0.196%	Mean return	0.278%	-0.168%
Standard deviation	0.019	0.019	Standard deviation	0.019	0.019
T statistics			**T statistics**		
1/ Equality to 0	6.58**	-4.15**	1/ Equality to 0	5.88**	-3.50**
2/ Difference between buy and sell returns	7.60**		2/ Difference between buy and sell returns	6.62**	
3/ Comparison to a buy and hold strategy	5.44**		3/ Comparison to a buy and hold strategy	4.72**	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

All in all, all results strongly suggest that using the stochastic oscillator to generate market entry and exit signals on the Bucharest Stock Exchange was rewarding in the period tested.

6.2.7 Ukraine

Since stochastic oscillator calculation requires not only close values but also high and low daily values of the index there are only 72 values available for the index PFTS. Therefore, the results are very questionable.

Figure 27: Stochastic (14,3) for the index PFTS

Source: Author´s calculations

Half of the results obtained for the index PFTS is significant on 5 % significance level. However, due to the lack of observations, these results cannot be fully trusted.

Table 27: Stochastic statistics for daily returns of the index PFTS

Statistics for daily returns of the index PFTS

Number of daily returns	72
Mean return of daily returns	-0.385%
Standard deviation of daily returns	0.033

Stochastic (14,3)	**Buy days**	**Sell days**	**Stochastic (5,3,3)**	**Buy days**	**Sell days**
Number of days	31	29	Number of days	30	30
Mean return	0.263%	-1.077%	Mean return	0.613%	-1.383%
Standard deviation	0.034	0.031	Standard deviation	0.025	0.037
T statistics			**T statistics**		
1/ Equality to 0	0.43	-1.88*	1/ Equality to 0	1.33	-2.07*
2/ Difference between buy and sell returns	1.61		2/ Difference between buy and sell returns	2.46*	
3/ Comparison to a buy and hold strategy	1.07		3/ Comparison to a buy and hold strategy	2.17*	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.3 Statistical Tests for the Relative Strength Index

This section presents empirical results obtained while testing the profitability of the relative strength index by the conventional statistical tests.

6.3.1 Austria

Similar to the previously tested technical indicators, the relative strength index indicated more buy days than sell days in the given period. Our results have the expected sign.

Equality to zero can be rejected on 1 % significance level for buy days mean return and equality of mean returns on buy days to a buy and hold strategy mean returns is also rejected on 1 % significance. We also reject that returns on buy and sell days are the same (on 1 % significance level). On the contrary, we cannot reject equality of sell days mean returns to zero.

Table 28: Relative strength index statistics for daily returns of the index ATX

Statistics for daily returns of ATX		
Number of daily returns	4293	
Mean return of daily returns	0,030%	
Standard deviation of daily returns	0,013	
	Buy days	**Sell days**
Number of days	2279	2003
Mean return	0,086%	-0,032%
Standard deviation	0,009	0,017
T statistics		
1/ Equality to 0	4.49**	-0,85
2/ Difference between buy and sell returns	2.76**	
3/ Comparison to a buy and hold strategy	2.93**	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.3.2 The Czech Republic

As for the index PX, the tests for the relative strength index provide us with results which strongly suggest that the use of the technical indicator is rewarding. Mean return on buy days equals almost 0.1 % and the mean return on sell days opposite. Again, buy days prevail.

The results are pretty much the same as those obtained while testing the MACD. All null hypotheses can be rejected on 1 % significance level. Hence, using the relative strength index proved to be profitable in the period of our interest.

Table 29: Relative strength index statistics for daily returns of the index PX

Statistics for daily returns of PX		
Number of daily returns	3981	
Mean return of daily returns	0,004%	
Standard deviation of daily returns	0,015	
	Buy days	**Sell days**
Number of days	2171	1784
Mean return	0,095%	-0,099%
Standard deviation	0,012	0,017
T statistics		
1/ Equality to 0	3.78**	-2.42**
2/ Difference between buy and sell returns	4.04**	
3/ Comparison to a buy and hold strategy	3.63**	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.3.3 Germany

Mean returns of the index DAX 30 have the expected signs on both buy and sell days. Unlike for the previous indices, for the index DAX 30 there are more sell days than buy days.

Nevertheless, the relative strength index is the most successful technical indicator on the Frankfurt Stock Exchange out of all tested indicators according to our results. Equality to zero can be rejected on 1 % significance level for buy days mean returns. While we cannot reject equality to zero of sell days mean returns, we reject null hypotheses stated in the second and third question of our interest on 5 % significance level.

Table 30: Relative strength index statistics for daily returns of the index DAX 30

Statistics for daily returns of DAX 30		
Number of daily returns	4217	
Mean return of daily returns	0,028%	
Standard deviation of daily returns	0,015	
	Buy days	**Sell days**
Number of days	2016	2190
Mean return	0,078%	-0,018%
Standard deviation	0,011	0,018
T statistics		
1/ Equality to 0	3.17**	-0,46
2/ Difference between buy and sell returns	2.08*	
3/ Comparison to a buy and hold strategy	2.05*	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.3.4 Hungary

The relative strength index indicated more buy days than sell days for the index BUX. Mean returns as well as the test statistics have the expected sign.

The profitability of the relative strength index for the index BUX is the same as that of the stochastic oscillator (with both sets of parameters) according to our results. Again, while we cannot reject equality to zero for sell days mean returns, the equality to zero can be rejected on 1 % significance level for buy days mean returns. Equality of mean returns on buy days to a buy and hold strategy mean returns is also rejected on 1 % significance. We reject that returns on buy and sell days are the same (on 1 % significance level) as well.

Table 31: Relative strength index statistics for daily returns of the index BUX

Statistics for daily returns of BUX		
Number of daily returns	4332	
Mean return of daily returns	0,077%	
Standard deviation of daily returns	0,022	
	Buy days	**Sell days**
Number of days	2236	2085
Mean return	0,178%	-0,028%
Standard deviation	0,016	0,027
T statistics		
1/ Equality to 0	5.38**	-0,47
2/ Difference between buy and sell returns	3.02**	
3/ Comparison to a buy and hold strategy	3.05**	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.3.5 Poland

The relative strength index suggested more buy than sell days for the index WIG 20. Similarly to the other indices, the sign of mean returns on buy and sell days are as expected.

The relative strength index was again more successful in indicating buy days than sell days. While we can reject equality of buy days mean returns on 1 % significance level, we cannot reject it at all for sell days. Buy and sell days mean returns equality was rejected on 5 % significance level. On the contrary, we cannot reject the equality of buy days mean returns and returns earned owing to a simple buy and hold strategy.

Table 32: Relative strength index statistics for daily returns of the index WIG 20

Statistics for daily returns of WIG 20		
Number of daily returns	3984	
Mean return of daily returns	0,022%	
Standard deviation of daily returns	0,020	
	Buy days	**Sell days**
Number of days	2354	1619
Mean return	0,090%	-0,069%
Standard deviation	0,017	0,024
T statistics		
1/ Equality to 0	2.59**	-1,17
2/ Difference between buy and sell returns	2.32*	
3/ Comparison to a buy and hold strategy	1,95	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.3.6 Romania

As for the index BET, the tests for the relative strength index provide us with results which suggest that the use of the technical indicator is rewarding. Mean return on buy days equals almost 0.2 % and the mean return on sell days almost -0.14 %. Again, buy days prevail.

Equality to zero can be rejected on 1 % significance level for buy days mean return and equality of mean returns on buy days to a buy and hold strategy mean returns is also rejected on 1 % significance. We also reject that returns on buy and sell days are the same (on 5 % significance level). On the contrary, we cannot reject equality of sell days mean returns to zero.

Table 33: Relative strength index statistics for daily returns of the index BET

Statistics for daily returns of BET		
Number of daily returns	2989	
Mean return of daily returns	0,045%	
Standard deviation of daily returns	0,036	
	Buy days	**Sell days**
Number of days	1743	1219
Mean return	0,186%	-0,137%
Standard deviation	0,014	0,053
T statistics		
1/ Equality to 0	5.55**	-0.9
2/ Difference between buy and sell returns	2.07*	
3/ Comparison to a buy and hold strategy	4.20**	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.3.7 Ukraine

The relative strength index suggested more sell than buy days for the index PFTS. Contrary to all the other indices, the sign of mean returns on buy and sell days are not as expected.

Equality to zero can be rejected on 5 % significance level for buy days mean return and equality of mean returns on buy days to a buy and hold strategy mean returns is also rejected on 5 % significance. However, there are so few available observations that results for the index PFTS are not trustworthy.

Table 34: Relative strength index statistics for daily returns of the index PFTS

Statistics for daily returns of PFTS		
Number of daily returns	83	
Mean return of daily returns	0,013%	
Standard deviation of daily returns	0,031	
	Buy days	**Sell days**
Number of days	19	37
Mean return	-0,958%	-0,085%
Standard deviation	0,025	0,037
T statistics		
1/ Equality to 0	-1,66*	-0,14
2/ Difference between buy and sell returns	-1,03	
3/ Comparison to a buy and hold strategy	-1,68*	

Note: * denotes the result is significant on 5 % significance level, ** denotes the result is significant on 1 % significance level

Source: Author´s calculations

6.4 Bootstrap results

As already discussed in the previous chapter, we use also bootstrap methodology to assure that our results are robust. We obtain quantiles of bootstrap distribution which are presented in the following table.

With the help of these bootstrap results we can assess the first question of our interest again.

Table 35: Bootstrap confidence intervals

Bootstrap confidence intervals			
1%	5%	95%	99%
all values *10^-3			
Index ATX			
-0.506	-0.347	0.423	0.581
Index BET			
-0.509	-0.348	0.422	0.584
Index BUX			
-0.503	-0.345	0.424	0.582
Index DAX 30			
-0.508	-0.348	0.421	0.580
Index PX			
-0.507	-0.347	0.427	0.581
Index PFTS			
-0.509	-0.348	0.423	0.585
Index WIG 20			
-0.506	-0.347	0.425	0.584

Source: Author´s calculations

6.4.1 MACD

At most cases, bootstrap results provide us with completely the same results as t-statistics.

We can reject that buy returns are equal to zero for the indices ATX and BUX on 1 % significance level, whereas their mean sell returns equality to zero cannot be rejected. As for index DAX, none of the null hypothesis can be rejected. Concerning the PX index, we strongly reject equality to zero for both sell and buy mean returns. As far as index BUX is concerned, buy returns are significantly larger than zero on the 1 % significance level.

However, bootstrap results slightly differ concerning the rest of the indices. Whereas t-statistics could not reject equality to zero for mean returns on sell days for the indices BET and PFTS, bootstrap results can reject it. We can also reject equality to zero on 5 % significance level for sell returns and on 1 % significance level for buy signal of the WIG 20 index while t-statistics reject equality to zero for mean returns on buy days only on 5 % significance level and it could not reject it for mean returns on sell days at all.

To conclude, we can see that results obtained with the use of bootstrap methodology roughly correspond with our previous results but they tend to be slightly more prone to support the hypothesis of technical analysis profitability for certain indices.

6.4.2 Stochastic

Bootstrap results show that equality to zero can be rejected for both buy and sell days returns on 1 % significance level for the index BET, the index BUX and the index PX considering both sets of parameters. The same results are obtained for the index PFTS, however, those results must be treated with caution as already discussed.

As for the index DAX 30, we cannot reject the equality of sell days mean returns to zero once again.

As far as the index ATX is concerned, we reject equality of buy days mean returns to zero on 1 % significance level for both sets of parameters. Equality of sell days mean returns to zero can be rejected on 5 % significance level for stochastic oscillator (14, 3) but cannot be rejected at all for the set of parameters (5, 3, 3).

Lastly, we reject equality of buy days mean returns of the index WIG 20 to zero on 1 % significance level for the set of parameters (5, 3, 3), whereas we cannot reject any other null hypothesis.

6.4.3 Relative Strength Index

Considering the relative strength index, the bootstrap results obtained for the indices ATX, DAX 30 and PX are completely the same as those obtained by the conventional test statistics. Differences occur only when we consider some hypotheses about the profitability of the relative strength index for the indices BUX and WIG 20.

As for the index BUX, bootstrap results do not suggest that mean returns on buy days are significantly different from zero unlike conventional tests. Results for equality of sell days mean returns are the same via both techniques.

Concerning the index WIG 20, equality of buy days mean returns to zero is rejected on 1 % significance level which is the same result as the one obtained by test statistics. However, the results differ on sell days. Whereas conventional tests suggest that we cannot reject equality of those mean returns to zero, bootstrap results reject it on 1 % significance level.

Generally, bootstrap results tend to be more inclined to support profitability of the technical indicators than the conventional statistical tests. The comparison is provided in the following table.

Table 36: Comparison of T-statistics and Bootstrap Results

T-statistics	ATX	BET	BUX	DAX 30	PX	PFTS	WIG 20
MACD							
1/ Equality to 0							
buy days	1%	1%	1%	cannot reject	1%	1%	5%
sell days	cannot reject	cannot reject	cannot reject	cannot reject	1%	cannot reject	cannot reject
Stochastic Oscillator (14,3)							
1/ Equality to 0							
buy days	1%	1%	1%	cannot reject	1%	cannot reject	cannot reject
sell days	cannot reject	1%	cannot reject	cannot reject	cannot reject	5%	cannot reject
Stochastic Oscillator (5,3,3)							
1/ Equality to 0							
buy days	1%	1%	1%	cannot reject	5%	cannot reject	cannot reject
sell days	cannot reject	1%	cannot reject	cannot reject	cannot reject	5%	cannot reject
Relative Strenght Index							
1/ Equality to 0							
buy days	1%	1%	1%	1%	1%	5%	1%
sell days	cannot reject	cannot reject	cannot reject	cannot reject	1%	cannot reject	cannot reject
Bootstrap results							
MACD							
1/ Equality to 0							
buy days	1%	1%	1%	cannot reject	1%	1%	1%
sell days	cannot reject	1%	cannot reject	cannot reject	1%	1%	5%
Stochastic Oscillator (14,3)							
1/ Equality to 0							
buy days	1%	1%	1%	cannot reject	1%	1%	cannot reject
sell days	5%	1%	1%	cannot reject	1%	1%	cannot reject
Stochastic Oscillator (5,3,3)							
1/ Equality to 0							
buy days	1%	1%	1%	cannot reject	1%	1%	1%
sell days	cannot reject	1%	1%	cannot reject	1%	1%	cannot reject
Relative Strenght Index							
1/ Equality to 0							
buy days	1%	1%	1%	1%	1%	1%	1%
sell days	cannot reject	1%	cannot reject	cannot reject	1%	cannot reject	1%

Source: Author´s calculations

6.4 Comparison

The empirical analysis conducted in this thesis provides us with mixed results.

The findings suggest that the MACD indicator brings forecasting power especially on the stock exchanges in Bucharest, Kiev and Prague. The stochastic oscillator proves to be profitable also on the exchanges mentioned above besides Kiev.

The results most supporting the idea that technical analysis does yield significantly positive returns were obtained for the MACD indicator, the relative strength index as well as stochastic oscillator with both sets of parameters on the Prague Stock Exchange by both t-statistics and bootstrap methodology. We reject almost all tested hypotheses.

Concerning individual components of the index PX, results differ remarkably. Whereas the MACD indicator does not yield any significantly positive results for Erste Bank and Telefonica O2, the results for Komerční banka suggest that the MACD indicator was successful in predicting its stock price in the given period. Results for ČEZ are mixed. The findings show that in spite of the fact that the MACD indicator proved to be successful in predicting the index PX movements in the given period, it does not necessarily mean that it was successful concerning all stock issues involved.

On the contrary to the suggested profitability on the two stock markets mentioned, there is no evidence that technical indicators of our interest are useful concerning the Frankfurt Stock Exchange. Actually, we cannot reject any of our tested null hypotheses for the index DAX 30 which suggest irrelevance of technical analysis on the Frankfurt Stock Exchange. Similarly, the technical trading rules of our interest do not bring much predictive power on the Warsaw Stock Exchange. Results for both the Budapest Stock Exchange and the Vienna Stock Exchange are mixed.

In general, more compelling results were obtained for buy days. In other words, we are more likely to reject stated null hypotheses about equality to zero for mean returns on buy days than for those on sell days. This conclusion suggests that buy signals issued by the MACD indicator, the relative strength index and the stochastic oscillator are more reliable than sell signals and can potentially lead to higher yields for investors.

Table 37: Summary of T-statistics

MACD	ATX	BET	BUX	DAX 30	PX	PFTS	WIG 20
1/ Equality to 0							
buy days	1%	1%	1%	cannot reject	1%	1%	5%
sell days	cannot reject	cannot reject	cannot reject	cannot reject	1%	cannot reject	cannot reject
2/ Difference between buy and sell returns	10%	1%	cannot reject	cannot reject	1%	1%	5%
3/ Equality to a buy and hold strategy							
buy days	cannot reject	1%	cannot reject	cannot reject	1%	5%	cannot reject
Stochastic Oscillator (14,3)							
1/ Equality to 0							
buy days	1%	1%	1%	cannot reject	1%	cannot reject	cannot reject
sell days	cannot reject	1%	cannot reject	cannot reject	cannot reject	5%	cannot reject
2/ Difference between buy and sell returns	1%	1%	1%	cannot reject	1%	cannot reject	cannot reject
3/ Equality to a buy and hold strategy							
buy days	1%	1%	1%	cannot reject	5%	cannot reject	cannot reject
Stochastic Oscillator (5,3,3)							
1/ Equality to 0							
buy days	1%	1%	1%	cannot reject	5%	cannot reject	cannot reject
sell days	cannot reject	1%	cannot reject	cannot reject	cannot reject	5%	cannot reject
2/ Difference between buy and sell returns	5%		1%	cannot reject	5%	5%	10%
3/ Equality to a buy and hold strategy							
buy days	cannot reject	1%	1%	cannot reject	5%	5%	cannot reject
Relative Strenght Index							
1/ Equality to 0							
buy days	1%	1%	1%	1%	1%	5%	1%
sell days	cannot reject	cannot reject	cannot reject	cannot reject	1%	cannot reject	cannot reject
2/ Difference between buy and sell returns	1%	5%	1%	5%	1%	cannot reject	5%
3/ Equality to a buy and hold strategy							
buy days	1%	1%	1%	5%	1%	5%	cannot reject

Source: Author´s calculations

Our empirical results suggest that technical indicators might be more useful on less developed markets (such as the Prague Stock Exchange) as opposed to more developed markets (such as the Frankfurt Stock Exchange).

More evidence on profitability of technical analysis on less developed markets might have been found for several reasons. The example of the Prague Stock Exchange is elaborated. First of all, the Prague Stock Exchange is characterized by relatively low volume and thin trading. This may be due to the institutional structure which may imply a lower informational efficiency. Some less developed stock markets are dominated by a few large companies. For example, an energetic company CEZ accounts for a quarter of index PX in its weight. Moreover, the ownership of this company has always been concentrated in the hands of Czech government and only about a third of stocks constitutes free float. In addition, the incidence of insider trading might be relatively high. It can be the low liquidity supported by institutional structure that results into lower efficiency which can be in turn exploited by technical analysis.

Park and Irwin (2007) summarize results of 48 studies which were written after 1988. These studies were focused on profitability of technical analysis on stock markets. Their results as well as the methods used to answer the question of interest are indicated in the following table. The method used in this study would classify as a standard method according to the given criteria and our results would expand the category with mixed results.

Table 38: Results of studies on TA profitability on stock markets

	Number of studies		
returns to TA:	**Positive**	**Mixed**	**Negative**
Standard method	2	2	2
Model-based bootstrap	7	4	3
Reality check	0	1	1
Genetic programming	2	1	3
Non-linear	3	2	0
Chart patterns	4	1	1
Others	8	1	10
Total	**26**	**12**	**20**

Source: Park and Irwin (2007)

7. Conclusion

This thesis concerns the issue of profitability of technical analysis on Central and Eastern European stock markets. The aim of the thesis is to determine how successful technical trading rules are in determining timing of stock market entry and exit. It states the main hypothesis: technical analysis can yield significantly positive returns on Central and Eastern European stock markets.

After the introduction to the topic, the thesis summarizes the most influential literature on the technical analysis profitability. The seven Central and Eastern European stock markets used in this dissertation are then described as well as technical indicators such as the MACD, stochastic oscillator and relative strength index. The dissertation turns to methodology and empirical results afterwards. Using conventional statistical tests as well as bootstrap techniques it is found that rewards of technical analysis differ according to individual markets and various technical indicators. Therefore, it is not possible to explicitly reject or not the hypothesis of this thesis.

The most remarkable results were obtained for the Frankfurt Stock Exchange (namely index DAX 30) and the Bucharest Stock Exchange (index BET) as well as the Prague Stock Exchange (index PX). Whereas there is hardly any evidence on profitability of technical analysis on the Frankfurt Stock Exchange, technical indicators of our interest proved to be highly successful on the Bucharest and Prague Stock Exchange. Specifically, the MACD indicator and the stochastic oscillator with set of parameters (14, 3) and (5, 3, 3) yielded significantly positive results for the index PX in period starting February 1, 1994 (March 3, 2000, respectively) and ending April 30, 2010 as well as for the index BET in period starting September 22, 1997 and ending April 30, 2010. This varation of profitability can be explained in terms of increased efficiency, higher liquidity and higher levels of development in the Frankfurt Stock Exchange, rendering technical analysis irrelevant.

Consequently, the results suggest that technical trading rules are more successful on emerging markets. This conclusion is in line with findings by

Bessembinder and Chan (1995) who report that trading rules are more successful in predicting stock price movements in the emerging markets of Malaysia, Thailand and Taiwan than in the more developed markets of Japan and Hong Kong, and Korea. Such findings might be leveraged into investment decisions of traders. The findings of this study challenge some conclusions of the previous research. Diviš and Teplý (2004) find that current prices on Central European stock markets are likely to reflect all available information which means that the use of technical analysis cannot yield any significant returns.

There are several contributions of this study to the issue of technical analysis in terms of both methodology used and markets considered. First of all, it does not search for technical trading rules already proved to be profitable unlike many other studies on the topic. Also, our results are not averaged across more markets and more trading rules. Although an averaging strategy may help to explore profitability on the parts of academics, the practical use of such an approach is very limited for investors. Last but not least, this study contributes to the investigation of whether following technical trading rules on Central European stock markets is rewarding. Practical implications for investors suggest increased attention to the signals issued by technical indicators on the less developed stock markets, whereas the use of the technical trading rules on developed stock exchanges such as the Frankfurt Stock Exchange was not rewarding according to our results.

The main suggestion for further research is inclusion of transaction costs. In fact, transaction costs may significantly decrease returns gained owing to technical analysis since investors need to enter and exit stock markets more often. In consequence, if transaction costs reach a certain level, they eliminate potential positive returns of technical analysis. In addition, analysis of technical indicators profitability over time would reveal whether its usefulness is increasing (e.g. owing to its increasing popularity among traders) or decreasing (e.g. due to increasing efficiency of the markets) and therefore suggest expected future prospects of technical analysis profitability.

Bibliography

Alexander, S.S. (1961) Price movements in speculative markets: trends or random walks. Industrial Management Review 2: 7–26.

Allen, F. and Karjalainen, R. (1999) Using genetic algorithms to find technical trading rules. Journal of Financial Economics 51: 245–271.

Appel, G. (1999) Technical Analysis Power Tools for Active Investors. Financial Times Prentice Hall. pp. 166

Ball, R., 1978, Filter Rules: Interpretation of Market Efficiency, Experimental Problem and Australian Experience, Accounting Education, November, 1-7.

Bessembinder, H. and Chan, K. (1995) The profitability of technical trading rules in the Asian stock markets. Pacific-Basin Finance Journal 3: 257–284.

Billingsley, R.S. and Chance, D.M. (1996) Benefits and limitations of diversification among commodity trading advisors. Journal of Portfolio Management 23: 65–80.

Bird, P.J.W.N. (1985) The weak form efficiency of the London Metal Exchange. Applied Economics 17: 571–587.

Chew, B-K., Wong,W-K., Manzur, M. (2003) How rewarding is technical analysis? Evidence from Singapore stock market. Applied Financial Economics. Volume 13, Pages: 543-551

Brock, W., Lakonishock, J. and LeBaron, B. (1992) Simple technical trading rules and the stochastic properties of stock returns. Journal of Finance 47: 1731–1764.

DeBondt, Werner F. M. and Thaler, R. (1995). Does the Stock Market Overreact? Journal of Finance, 40, 793-805.

Diviš, K., Teplý, P. (2005) Information Efficiency of Central Europe Stock Exchanges. Czech Journal of Economics and Finance. Volume 55, Issue 9 -10, Pages 471-482.

Fama, E.F. (1970) Efficient capital markets: a review of theory and empirical work. Journal of Finance 25: 383–417.

Fama, E.F. and Blume, M.E. (1966) Filter rules and stock market trading. Journal of Business 39: 226–241.

Filer, Randall K. and Jan Hanousek. 1996. The Extent of Efficiency in Central European Equity Markets. Working Paper no. 104. Prague: CERGE-EI.

Frankel and Froot (1990)

Frankel, J. A., and K. A. Froot (1990), Chartists, fundamentalists and the demand for dollars, in Courakis, A. S., and M. P. Taylor (eds.) (1990), Private Behaviour and Government Policy in Interdependent Economies. Oxford: Oxford University Press, 73-126.

Friedman, M., 1953, The Case for Flexible Exchange Rate, in Essays in Positive

Economics, Chicago, University of Chicago Press.

Gençay, R. (1998a) Optimization of technical trading strategies and the profitability in

security markets. Economic Letters 59: 249–254.

Gunasekarage, A. and Power, D.M. (2001) The profitability of moving average trading rules in South Asian stock markets. Emerging Markets Review 2: 17–33.

Hrušová, I. (2010) Profitability of Technical Analysis: Evidence from Central and Eastern European stock markets. Charles University in Prague.

Hudson, R., Dempsey, M. and Keasey, K. (1996) A note on the weak form efficiency of capital markets: the application of simple technical trading rules to UK stock prices

– 1935 to 1964. Journal of Banking and Finance 20: 1121–1132.

James, F.E. (1968) Monthly moving averages – an effective investment tool? Journal of Financial and Quantitative Analysis September, 315–326.

Jensen, M.C. (1978) Some anomalous evidence regarding market efficiency. Journal of Financial Economics 6: 95–101.

Jensen, M.C. and Benington, G.A. (1970) Random walks and technical theories: some additional evidence. Journal of Finance 25: 469–482.

Kahneman, D. and Tversky, A. (1981) The framing of decisions and the psychology of choice. Science, 211, 453–458.

Laštovička,R., Marcinčin, A. and Mejstřík, M. (1994) Privatization and Opening the Capital Market in the Czech and Slovak Republics. CERGE-EI Working Paper Series No. 54, April 1, 1994.

LeBeau, C. and D.W. Lucas, 1992, Technical Traders Guide to Computer

Analysis of the Futures Market, Business One Irwin, Richard D. Irwin, Inc.

Lee, C.I. and Mathur, I. (1996a) Trading rule profits in European currency spot cross-rates. Journal of Banking and Finance 20: 949–962.

Lee, C.I. and Mathur, I. (1996b) A comprehensive look at the efficiency of technical trading rules applied to cross-rates. European Journal of Finance 2: 389–411.

Lee, C.I., Gleason, K.C. and Mathur, I. (2001) Trading rule profits in Latin American

currency spot rates. International Review of Financial Analysis 10: 135–156.

Levy, R.A. (1967a) Random walks: reality or myth. Financial Analysts Journal 23: 69–77.

Levy, R.A. (1967b) Relative strength as a criterion for investment selection. Journal of Finance 22: 595–610.

Lo, A.W., Mamaysky H. and Wang, J. 2000. Foundations of technical analysis:

computational algorithms, statistical inference, and empirical implementation.

Journal of Finance, 55: 1705-1764.

Yu-Hon Luia, and David Mole (1998) The use of fundamental and technical analyses by foreign exchange dealers: Hong Kong evidence. Journal of International Money and Finance Volume 17, Issue 3, 1 June 1998, Pages 535-545

Lukac, L.P. and Brorsen, B.W. (1990) A comprehensive test of futures market disequilibrium. Financial Review 25: 593–622.

Lukac, L.P., Brorsen, B.W. and Irwin, S.H. (1988) A test of futures market disequilibrium using twelve different technical trading systems. Applied Economics 20: 623–639.

Maillet, B. and Michel, T. (2000) Further insights on the puzzle of technical analysis

profitability. European Journal of Finance 6: 196–224.

Malenko, J., (2008) "Předpovídání trendu na akciových trzích za použití genetických algoritmů", Univerzita Karlova, Fakulta sociálních věd, Institut ekonomických studií, Praha.

Malkiel, B.G. (1982) Winning Investment Strategies. New York: W.W. Norton.

Malkiel, B.G. (2003) The Efficient Market Hypothesis and Its Critics. Princeton University. CEPS Working Paper No. 91. April 2003.

Martin, A.D. (2001) Technical trading rules in the spot foreign exchange markets of developing countries. Journal of Multinational Financial Management 11: 59–68.

Menkhoff, L. and Schlumberger, M. (1995) Persistent profitability of technical analysis on foreign exchange markets? Banca Nazionale del Lavoro Quarterly Review 193: 189–216.

Cheol-Ho Park, Scott H. Irwin (2007) What do we know about the profitability of technical analysis? Journal of Economic Surveys Volume 21 Issue 4, Pages 786 – 826, Published Online: 11 Jul 2007

Peterson, P.E. and Leuthold, R.M. (1982) Using mechanical trading systems to evaluate the weak form efficiency of futures markets. Southern Journal of Agricultural Economics 14: 147–152.

Pring, M.J. (2002) Technical Analysis Explained. New York: McGraw-Hill.

Rice, John (1995), Mathematical Statistics and Data Analysis (Second ed.), Duxbury Press, ISBN 0-534-20934-3

Scholes, M. and J. Williams (1977) Estimating betas from nonsynchronous data, Journal of Financial Economics 5, 309-327.

Shiller, R. J. (2000) Irrational Exuberance, Princeton: Princeton University Press.

Smidt, S. (1965b) Amateur Speculators. Ithaca, NY: Graduate School of Business and Public Administration, Cornell University.

Sullivan, R., Timmermann, A. and White, H. (1999) Data snooping, technical trading rule performance, and the bootstrap. Journal of Finance 54: 1647–1691.

Sweeny, R.J. (1986) Beating the foreign exchange market. Journal of Finance 41: 163–182.

Taylor, S.J. (1985) The behaviour of futures prices over time. Applied Economics 17: 713–734.

Taylor, S.J. (2000) Stock index and price dynamics in the UK and the US: new evidence from a trading rule and statistical analysis. European Journal of Finance 6: 39–69.

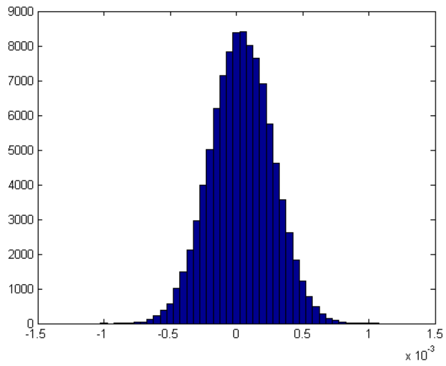
Van Horne, J.C. and Parker, G.G.C. (1967) The random-walk theory: an empirical test. Financial Analysts Journal 23: 87–92.

Van Horne, J.C. and Parker, G.G.C. (1968) Technical trading rules: a comment. Financial Analysts Journal 24: 128–132.

Vošvrda, M., Filácek, J. and Kapicka, M. (1998) The Efficient Market Hypothesis Testing on the Prague Stock Exchange. Bulletin of the Czech Econometric Society 5:55-67.

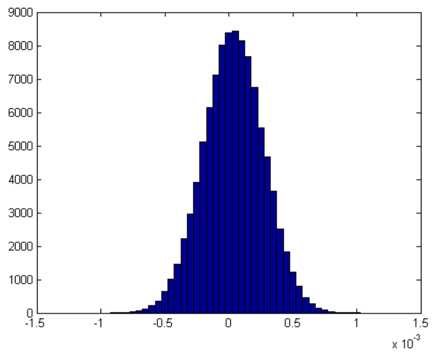
Appendix

Figure A 1: Bootstrap distribution ATX



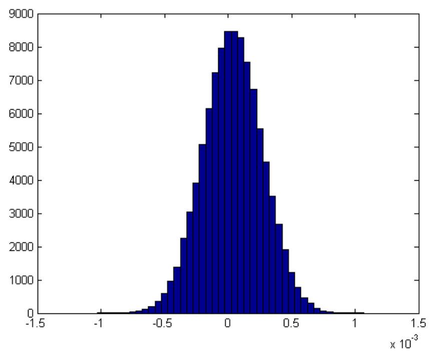
Source: Author´s calculations

Figure A 2: Bootstrap distribution BET



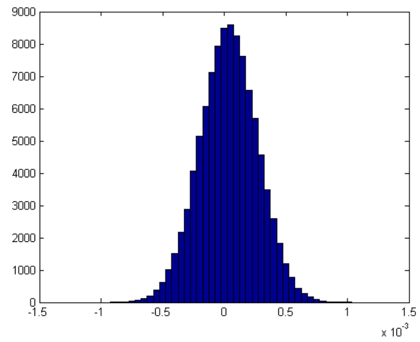
Source: Author´s calculations

Figure A 3: Bootstrap distribution BUX



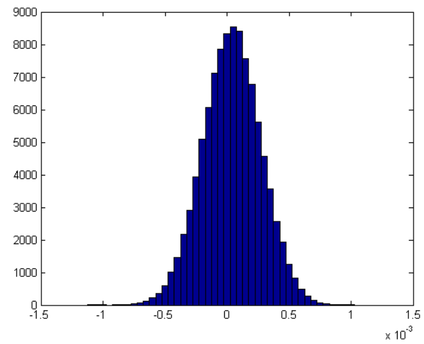
Source: Author´s calculations

Figure A 4: Bootstrap distribution DAX 30



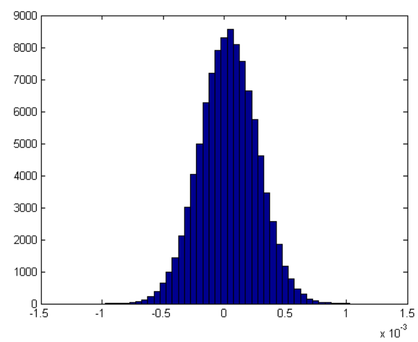
Source: Author´s calculations

Figure A 5: Bootstrap distribution PX



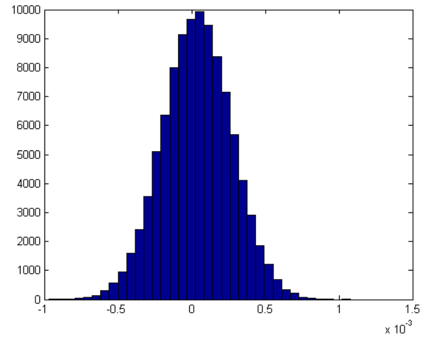
Source: Author´s calculations

Figure A 6: Bootstrap distribution PFTS



Source: Author´s calculations

Figure A 7: Bootstrap distribution WIG 20



Source: Author´s calculations