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FACULTY OF SOCIAL SCIENCES

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Does the choice of method of forecast of index stock returns  
and the choice of investment strategy depend on index's  
industry affiliation?

*Bachelor thesis*

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## Abstract

The purpose of this thesis is to analyze and reveal if there is any dependence of index stock return valuation method on index's industry affiliation. The question about profitable strategy to react to valuation method's forecasts is also investigated. I focus on three methods of valuation: technical analysis, time series forecast and combination of rules from both technical and time series forecast rules, and test them on 10 Dow Jones Industrial Indices. Double-or-out strategy is compared to buy-and-hold strategy by estimation of its excess return.

I found no dependence of choice of method on index's industry affiliation. However, the double-or-out strategy was proved to outperform buy-and-hold strategy in all of the industries.

## Keywords

Stock Valuation Methods, Trend Prediction Analyses, Technical analysis, Fundamental analysis, Methods of valuation, Time series forecast, Double-or-out strategy

## JEL Classification

G11 G12 G14 G17 C22 C51 C52 C55 C58

## **Declaration of Authorship**

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

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Prague, July 31, 2015

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Signature

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# Project of Bachelor Thesis

**Schedule for the bachelor exam:** 2015  
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## **Theme:**

Analysis of stock return valuation method and its dependence on industry affiliation.  
Best trading strategy.

## **Goals of the thesis:**

The main goal of this thesis is to investigate 10 Dow Jones U.S. industrial indices and to find the best valuation method of future returns to the index for concrete industry. Then I focus on appropriate trading strategy and its profitability. This thesis is unique in its way to test valuation methods efficiency depending on index industry affiliation.

## **Synopsis:**

1. Literature Review
2. Data Description
3. Methodology and Results
4. Results Interpretation and Hypotheses

## **References:**

Yue Fang, Daming Xu (2003): The predictability of asset returns: an approach combining technical analysis and time series forecasts, *International Journal of Forecasting* **19**, 369-385.

Andrei Shynkevich (2012): Short-term predictability of equity returns along two style dimensions, *Journal of Empirical Finance* **19**, 675-685.  
Tian, G. G., Wan, G. H. & Guo, M. (2002): Market efficiency and the returns to simple technical trading rules: new evidence from U.S. equity market and Chinese equity markets, *Research online* **9**, 241-258.

In Prague on July 31, 2015

Signature of the supervisor

Signature of the author

# Contents

<b>Introduction</b>	<b>2</b>
<b>1 Literature review</b>	<b>4</b>
1.1 Market Efficiency . . . . .	4
1.2 Methods of Analysis . . . . .	9
1.2.1 Fundamental Method of Analysis . . . . .	9
1.2.2 Technical Method of Analysis . . . . .	11
1.2.3 Other Types of Methods of Analysis . . . . .	14
<b>2 Data</b>	<b>18</b>
<b>3 Methodology and Preliminary Results</b>	<b>24</b>
3.1 Double-or-out Strategy . . . . .	25
3.2 Technical Method Trading rules . . . . .	26
3.3 Time-Series Forecast Method rules . . . . .	29
3.4 Combined Trading Rules Method . . . . .	36
<b>4 Methods' Results Interpretation and Hypotheses</b>	<b>38</b>
4.1 In general . . . . .	38
4.2 In particular . . . . .	43
<b>5 Conclusion</b>	<b>50</b>
<b>References</b>	<b>53</b>
<b>List of tables and figures</b>	<b>57</b>



# Introduction

The topic of stock market trade has recently become very popular even among people without financial education as they realize that there is a possibility to earn money from trade on stocks.

Fama (1970) defines the market to be efficient saying that there is no chance to profit from trade on the market, since price changes can not be predicted. He came to this conclusion assuming that prices fully reflect market information and that each investor behaves rationally and identically. Yet, already from nowadays situation, it is evident that individuals have neither the full access to the market information, nor they have same preferences and nor make same decisions.

As efficiency of markets was disproved by many researchers ( Brock, Lakonishok and LeBaron, 1992, Bessembinder and Chan, 1995, Kwon and Kish, 2002, and other) and the profitability of trading rules was confirmed, there appeared a question: what are the other methods of price changes predictions and what are the strategies? This question was approached by Yeyu Fang and Zhidong Xu's (2003), who tried to create and investigate hybrid of technical analysis and time series forecast method rules, Jenni L. Bettman, Stephen J. Sault, Emma L. Schultz (2009), who combined technical and fundamental analyses, Neely, Christopher J et al. (2001) used economical fundamentals with technical trading rules, and others.

However, no one has questioned the dependence of those methods on stocks nature, or its company/index industry affiliation. Thus, I found it interesting to try to answer this question, assuming that there are some patterns of applicability of concrete method of stock valuation to particular industrial index. Due to the wish to make investigation on the whole industries and to make the results representative, I chose Dow Jones U.S. industrial indices. The other reason to take exactly these indices was the fact that they are relatively new and only few, if any, researches have been done on them. So, I also tested for general statistical differences in indices and influences of crises on choices of methods.

From the broad spectrum of existing methods, I decided to choose technical analysis method, time series forecast method of valuation and the combination of rules from

the two. The reason for that was impossibility to collect component companies' specific information to perform, for example fundamental analysis, while the chosen three methods, being totally distinct, require only financial time-series data.

As for profitability of each of methods in industries I use double-or-out strategy, since it seems to be more realistic and essential to be willing to bet on higher number of stocks and to borrow money at some interest rate (lower than the expected return, though), when one has optimistic forecasts about market stock prices, or to put money under risk-free interest rate to the bank, when one is pessimistic about the next day's stock price changes, than simply buying and selling the stock. So, with this strategy the profitability of trade in the indices will be investigated, showing if it is profitable to trade in particular index at all, or is it better to choose buy-and-hold strategy.

This bachelor thesis is organised in the following manner: in the first part I review previous empirical researches and their findings. I explain why there is a possibility to profit from trade, and I present existing methods of analysis and their applications. In the following, second, part statistical description of data, as well as general distinctions in returns to indices of 10 industries are presented. Then, I proceed with models explanation and present the results of their estimations. In the fourth part of thesis I interpret the results and test hypotheses. In the last part I conclude the paper and make suggestion about improvement of investigation.

# 1 Literature review

These days, when there is such a competition on the market and the markets themselves are very integrated, there is a possibility for one to benefit not only from simple investment into a perspective or stable company or growing index, but also from frequent trade on them, trying to buy stocks today, such that to sell them for bigger price tomorrow. For this, there should be done two assumptions: market is not fully efficient, so that there is a possibility to make predictions, and there is a method for forecasts and a strategy for trade in the short-run that allow, with the presence of transaction costs, to make positive profits.

## 1.1 Market Efficiency

The first thoughts of efficiency of markets can be referenced back to 1900, when Bachelier presented the random walk theory, lately confirmed empirically by Cootner (1966). The Market Efficiency Theory states that no investment strategy can beat the market. The theory hypothesizes that the price of a stock perfectly reflects knowledge and expectations of investors. The intuition behind is that, as soon market information becomes publicly available, all market participants receive it and act accordingly. Because everybody has the same amount of information, stocks cannot be over- or underpriced.

The Efficient Market Theory is usually linked to the random walk theory, which, in turn, explains that stock price changes can not be predicted by the past price movements or trend due to their independency and identical distribution.

Since the introduction of term “Efficient Market” (Fama, 1965), there were many researches testing efficient-market hypothesis in order to support (Beechey et al., 2000; Kendall, M. G. & A. B. Hill, 1953) or to reject the Efficient Market Theory (Burton G. Malkiel, 2003; Mandelbrot, B., 1963).

E. Fama (1965) conducted several tests for verification of the random walk theory, those include: test on independence of the price changes and the test on price changes to follow some probability distribution. The results relied on the data,

which dates from around 1957 until 1962 and the tests were run on 30 stocks of Dow Jones Industrial Average. He found no evidence to reject the theory and stated that there cannot exist a profit-making trading strategy for the stock market, which is based on analysis of past information.

However, the author also did not fully exclude that there might be some exceptions, which are nevertheless negligible against the number of evidential and systematic tests.

Despite the fact that he observed some slight departures from the independence of data during the tests, he pointed out that for traders this almost negligible dependence is of no value. This means that it is of insignificant importance for trader just to know, that the large changes in the stock price are also followed by large changes, because one usually bet on the scale of those changes rather than on the general notion of the direction of them.

In the next topic-related paper, Eugene Fama (1970) develops his theory <sup>1</sup>. The paper is based on theoretical analysis of broad pool of empirical works of other researchers, including the paper written by Fama in 1965. In “Efficient Capital Markets: A Review of Theory and Empirical Work” (1970) he formulates the following forms of market efficiency:

1. Weak Form Efficiency: the current price of the security (bonds, stocks etc.) is the reflection of the historical publicly available information, meaning that whatever happens in the market, in the past of the traded financial asset, affects the current price of it.
2. Semi-strong Form Efficiency: the current price captures the past as well as the present publically available market information.
3. Strong Form Efficiency: current price reflects not only the past and present

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<sup>1</sup>Theoretically speaking, he differentiates between the “fair game”, submartingale and the random walk models. In the former case return does not depend on the whole past available information matrix, while in the later, we need to account for the fact that future/expected return is unconditional on the past information too. The latest of three considered models stipulates the strongest conditions to hold: not only the full reflection of the available information, which implies in independency of successive price changes, is assumed, but also that those successive one-period returns are identically distributed. This then allows considering the random walk model with the density function  $f$ , which is, of course, the same for all times  $t$ .

publically available information on the traded asset, but also the “insider” information.

Campbell et al. (1997) tried to disprove validity of the Efficient market theory even after these three specifications were formed. He presented the notion of the *relative* efficiency of the market, allowing to judge about the particular market’s efficiency in comparison to the other markets, rather than just looking at them in overall. He said, that if a market is said to be *relatively* efficient, there is some degree of predictability of future returns, thus a chance to make some profit from trade. The basing idea of this paper is that the theory of efficient market is rather a utopian view, in which every decision is totally rational and the information is fully available.

Campbell’s approach to look at the efficiency in relative terms questions efficient market hypothesis and, as it was thought, unpredictable character of the stock returns.

R Giglio, R Matsushita, S Da Silva (Economics Bulletin, 2008) conducted a survey looking for the relative efficiency of the stock exchange and individual company stocks. They confirmed the theory that stock markets incorporate different amounts of nonredundant information. This invalidated the Efficiency Market Hypotheses. They run a test for efficacy, interpreted by algorithmic complexity theory, using Lempel and Ziv’s (1976) measure- LZ index- for estimation of the extend to which the behaviour of indices or stocks is random and found that some companies and markets even only half-efficient.

Another flaw of Efficient Market Hypothesis is seen to be in assumption of normal distribution. In order to improve the plausibility, Gaussian distribution for log price changes, often referred to Brownian motion model<sup>2</sup> was replaced by Jonathan Blackledge (2010) by Levy distribution. The reason lies in fact that Brownian motion model, even after modifications with further addition of the size of price

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<sup>2</sup>The primary model for random walk process. This modification was needed due to discovery of price movements volume to be dependent on the size of price itself. So, then with Gaussian distribution model was revised to Brownian model for randomness estimations.

and the size of its changes into consideration, by the definition, applies only to such outcomes, which does not include any memory on the past, meaning that the outcomes are totally independent, though, this may be not the case. Indeed, the results of such analyses, run on 5932 daily price movements, made by Jonathan Blackledge (2010), have invalidated the independence assumption of the EMH.

Hurst process is recognised as the first connection to the Fractal Market Hypothesis. J Blackledge (2010) states, followed by Hurst's theory, that to have an evidence of persistent time series, characterised by positive correlation, Hurst exponent has to lie within 0.5 and 1, excluded from the left. The main point of this process is that the range of calibrations within some period of time is established and rescaled by the standard deviations from the mean (see also Mandelbrot, B. B. & J. R. Wallis, 1968). The estimate of Hurst exponent,  $H$ , is the slope of equation of LSR<sup>3</sup> on  $\log(n)$  as independent and  $\log(\frac{R}{S})$  as dependent variable. The test conducted on NYA (1960-1998) <sup>4</sup> observations yielded  $H$  to fall between 0.54 and 0.59, leading to the conclusion:

The market reacts to information, and the way it reacts is not very different from the way it reacts previously, even though the information is different.

They performed this process on in order to describe a stochastic time series. But there were no assumptions made about the distribution and where the fractional Brownian motion was described.

Lukas Vacha and Miloslav Vosvrda (2005) also made a research on topic of fractionness of markets<sup>5</sup>. They concluded:

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<sup>3</sup>Least squares regression

<sup>4</sup>New York Stock Exchange Composite Index

<sup>5</sup>In their paper they considered different types of traders, *where past excess return data is used*: strong /pure trade chaser, contrarian, purely biased trader or fundamentalist( the one, who believes that prices return to their *fundamental* value).They used twenty belief types. This helps to construct formation of expectations.Then each particular type of function is multiplied be by its fractions in market. This reveals the realized excess return on the trade.

The FMH<sup>6</sup> is a more general notation than the EMH. [...] Therefore financial markets are nonlinear systems with a fractal structure of agent's investment horizons. These markets are unpredictable in the long-term period, but predictable in the short-term period.

Apart of numerous price changes empirical studies on the topic of market efficiency, another source of critique takes significant place in the discussion-behavioral finance. Degree of agents' behavior rationality <sup>7</sup> is emphasized to be an important element, which is often not counted for, when talking about markets. Barberis, N. & R. Thaler (2003) argued that, under the presence of aggressive, riskier behaviour of some traders, noticable noises in fair prices of stocks might be caused. This violated conditional assumption of EMH even further.

Traders' overconfidence or overreaction, information or representative bias, transaction costs and other market frictions also question the Theory of market efficiency.

From this, we can conclude that the theory of a fair price is not solid, moreover, prices may be predicted.

One shall notice, that nothing was said about any kind of certainty of benefits in (or out of) presense of dependence between past, present and future prices of the stocks. This is the matter of ability of market player to correctly extract information from available sources and then employ it in a right way. Simply speaking, one need to behave strategically to make use of the conclusion made above.

So, from showing the market predictability I am now turning to investigation of profit possibilities. I will now consider a couple of main methods of estimation of price (returns) movements.

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<sup>6</sup>more detailed researches on this topic can be found in works of Peters EE (1994) Fractal Market Analysis, Applying Chaos Theory to Investment and Economics; Brock WA (2001) Growth Theory, Nonlinear Dynamics and Economic Modelling Edward Elgar and other.

<sup>7</sup>Rational behavior is refered to the process based on optimal in terms of benefits decisions

## 1.2 Methods of Analysis

Analysis is an essential process of human brain. So, in order to begin trading one usually analyses entity/industry/economy. This gives a broad spectrum of information, which can then be applied in valuation (not only of the stocks and indices, but also of the prospective benefits of trade).

### 1.2.1 Fundamental Method of Analysis

It comes with an absolute sense to look at the very basics of anything to give it a value. The same principle is used by fundamental analysis. The fundamental analysis is a mean of valuation of stocks of company/index looking at company's/industry's economic well-being. Meaning, what is the current performance and what are the prospects. This technique can be also applied to economy as a whole. Fundamental analysis can be subdivided into two parts: qualitative and quantitative. For the short-run trades or for the trade itself, as opposed to investment, it makes more sense to pay more attention to the quantitative section of the analysis.

By “quantitative method of fundamental analysis” it is usually meant comparison across financial entities/industries with the help of relative values such as ratios. Yet, one also should not disregard importance of qualitative component of analytical process. This may include corporate governance, business model and competitive advantages of the entity inspection (in case one want to value a stock; for industry and economy this does not apply).

Fundamental analysis, as a mean of share valuation, was granted with attention by Graham and Dodd (1934). Then significant word came after Gordon and Shapiro's (1956) with the Dividend Discount Model, which then gave the ground for further researches. Those researches resulted in various extended models of the fundamental analysis as methods for investment strategies and addition to models of trading strategies. Up until now, the fundamental analysis of the stock presents itself as a detailed inspection of the firm-specific data along with non-financial market information in order evaluate price of company's stocks.



The most comprehended enumeration of relevant values for price explanation was introduced in papers by Amir and Lev (1996); Amir et al. (1997) and summarized by Holthausen and Watts (2001). The paper of 1996 underlines the significance of accounting information only in combination with the nonfinancial one. Earnings, book values and cash flows are said to be better representatives in each sector once taken together with the nonfinancial variables such as POPS<sup>8</sup>, explaining the company's potential to grow, subscribers per cite and per employee, also churn rate and other. They established those particular complementary to the basic financial indicators variables to explain better the valuation model for cellular industry. This means, that one shall apply relevant variables for the examined industry, to which the firm of valuation belongs. As, for example, Jeffrey J. Quirin et. Al (2000) have released from their study's research the explanatory variables for the oil and gas industry, which differ significantly from the cellular industry.

These findings show that fundamental analysis is sometimes difficult to perform due to the lack of value-relevant information available. Moreover, fundamental analysis gives an investor or trader understanding of the current value of the company/market, but has very little sensitivity and feel towards the future short-term movements of its stock prices. It is explained by the fact that this method of analysis is usually performed on the yearly data, and does not account for *stock market prices* of its shares themselves . Lastly, it is nearly impossible to perform the analysis on the whole industry by collecting this type of firm-specific information.

After once again concluding that, indeed, the future prices of the stocks might be predicted, thus, one is able to make the profit relying on the correct, in a sense of forecast, analysis and establishing the right strategy for investment, it is better to take a closer look at the analyses which have some shorter than one-year-period predictive power, since the fundamental analysis is usually made relying on the, at most, quarterly basis. So that we could then establish best, by excess returns, starategy.

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<sup>8</sup>population size

### 1.2.2 Technical Method of Analysis

The most common analysis for short-term investment, or trade in principle, is known as technical analysis. This analysis is based on, just as missed in fundamental, use of historical stock market prices. The earliest notes about the use of some aspects of this analysis date to the 17<sup>th</sup> century, applied by Joseph de la Vega to the Dutch markets. The rise of its popularity was with development of computer assistance. The most usual referee of this analysis is Charles Dow who was the inventor of point and figure chart analysis and, with the help of editorials of Wall Street Journal, the developer of the Dow theory.

This particular analysis is used for generation of positive returns from trade. Such returns are possible because of several reasons such as non-synchronous trading, sluggish adjustment<sup>9</sup> of stock prices, and self-fulfilling expectations<sup>10</sup> of traders, who use technical analysis. About popularity of technical analysis and its computer-guided trading systems it is written in studies of Smidt (1965) and Billingsley and Chance (1996).

Despite of countless variety of existing methods of technical analysis, it has never been as accepted and as academically scrutinized as fundamental analysis. One of considerable reasons can be that price of an asset can vary dramatically among different methods of valuation, and also the danger of setting the methods based on the properties of data to perform the test statistics, in particular, data-snooping biases<sup>11</sup> danger (Jensen and Bennington, 1970).

This danger was controlled for in the work of Sullivan et al. (1999). After testing data for data-snooping using White's Reality Check bootstrap methodology, they found that increased efficiency of equity markets, after improvements of the liquidity, transaction costs and computing power, leaves no place for profitability

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<sup>9</sup>As opposed to assumptions of EMT

<sup>10</sup>By self-fulfilling expectations of traders one understands the degree of rationality and similarity of each trader's reaction to market signals, which are yet generated automatically by various trading platforms and services or can be produced using publicly available databases.

<sup>11</sup>"Data-snooping arises when the properties of a data series influence the researcher's choice of model specification" - DIMSON, E. and P. MARSH (1990): Volatility forecasting without data-snooping, Journal of Banking and Finance, Volume 14, Issues 2-3, August 1990, Pages 399-421.

of technical analysis. Specifically, these results were concluded regarding the trading rules and dataset of Brock et al. (1992).

Nevertheless, technical method of analysis was shown by Ivona Hrusova (2011) to be a profitable analysis while being applied to stock markets, also using bootstrap methodology. Many other researches have examined rewards from usage of this analysis for the different underlying: Chew, Manzur and Wong (2003) showed that the member firms of Singapore Stock Exchange receive substantial profits, Taylor (2000) finds superior returns from trade of stocks on US and UK stock indices, controlling for the level of the transaction costs, and others. Park and Irwin (2007) shown in their study that 56 out of 95 studies, since 1988, had found that technical analysis in trading does provide better returns than the buy-and-hold strategy, plus 19 of mixed-results studies.

A primary difference between fundamental and technical analysis performance procedure is that for the later there are no internal firm-specific variables used. And the process itself is not based on estimation of variables' coefficients of their weight, attributed to the stock value of a share. To analyse technically a stock price of a firm one need to choose particular approach. The approaches can be different: each market player uniquely decides about the way of trend determination, support and resistance values establishment, and choice of price extremes to generate specific signals.

Secondary but very crucial difference lies in assumptions.

Fundamental analysis is based on the assumption of possibility of intrinsic value of an asset to differ from its market price. It also supposes that, having unsystematic market price deviations, price of an asset will converge to its true value. So that the principal strategy for fundamental analyst is to trade in periods of those deviations.

While in technical analysis the assumptions are:

1. price is determined through supply and demand

Prices are driven by stock demand- the more investors want to buy, the higher the price is.

2. price discounts everything

Men makes judgements based on price, bafaving sometimes irrationally<sup>12</sup> causing excess or depression.

3. prices are normal/nonrandom

Price can be predicted.

4. history repeats itself leading to patterns

5. patterns are fractal

6. emotioonal feedback influences investor sentiment causing “bubbles” and “booms”

Similar to 2 but in 2 we talk about price changes depending on run on asset and its “scarsity”, which causes price o rise or to fall, while in 6 prices we are talking about the reason of human behaviour in case of outcomes from expectations: if they are approved, then more investors are attracted, thus, the prices rise, and vice versa.

These assumptions lead to no concrete strategically established common time frames for excessive return of an asset. Because not only at the time of trade a stock can be under-/overpriced, but also in the future, depending on the above stated.

Though it was stated above, that technical analysis is not as academically scrutinized as fundamental, C. Kirkpatrick II and J. Dahlquist released in 2010 a book called “Technical Analysis: The Complete Resource for Financial Market Technicians (2nd Edition)”. In this book they give precise explanations of many techniques and rules of trade along with terms and definition such as sentiment, market strength, trends, breakouts, stops, retracements, moving avarages and other. And it is not the only book, which was recently written, showing the growing academical attention towards this method.

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<sup>12</sup>Here: about ‘irriational exuberance’

Moving average<sup>13</sup>, or MA, was approved early in 1992 by Brock, Lakonishok, and LeBaron(1992) to be an effective tool for development of profitable trading strategy. The results were based on study made on Dow Jones Industrials using statistical bias-reducing methods, showed that moving average crossover systems give intristically signifacan signals<sup>14</sup>. This findings became one of the most crucial controvercials of EHM. Their study results were later summarised by Gregoire (2001).

Nevertheless, C. Kirkpatrick II explained about efficiency of MA usage and the trade-of between trend reversal recognition and its reliability (certanty of a trend):

Because the moving averages are based on historical prices, by nature, they will be a lagging indicator of trends. The shorter the period covered by the moving average, the less of a lag there will be. However, using a shorter period also leads to more false signals.

Thus, the MA is also to be modified depending on particular specifications of subject of analysis.

These modifications are needed in order to improve efficiency of analysis.

### **1.2.3 Other Types of Methods of Analysis**

The more and more attention is being devoted to possibility to increase efficiency, or accuracy, of potential analysis to receive higher returns from trading strategies. Yet, both of the analyses, technical and fundamental, are very powerful and have different properties and thus can be used as complements.

Jenni L. Bettman, Stephen J. Sault, Emma L. Schultz (2009) looked at the case when the two are used together. They emphasized strength of such a model due to the complementary nature of technical and fundamental analyses. In the paper they examined explanatory power of each type of analysis as it stands alone and then took them together. In fact, they compared several models for significance of

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<sup>13</sup>A sum of values of historical prices for some stated period of time, divided by number of taken prices. It is called “moving” because it is recalculated contineously, so that “trend” is obtained. Trend is a general indication of price changes direction

<sup>14</sup>Here: trade signal for the trader to sell or to buy a stock

forecast, of predicted price. The first and the second models were based fully on fundamental variables, namely: book value of the firm's equity and the diluted earning per share- in the first; and in the second model they included consensus forecast earning per share to the first. Then they established a model, representing technical part of the analysis: they took the firm's end-of-month share price 6 months prior to the time of prediction, and two dummies, standing for lowest and highest performance docile placement of the stock holding period return in the six month period starting one year prior to the forecasting time, as the explanatory variables. In the following two models they put each of the fundamental models together with the technical. The authors of paper run test on the US listed companies from January 1983 through December 2002 dataset. As the results of fitting models, and they concluded, that

contall technical factors are highly significant in explaining contemporaneous price and are significant in the predicted directionsent...

moreover,

contesting reveals the importance of technical analysis even in the presence of fundamental factors, with lagged price and both momentum dummies remaining significant in explaining contemporaneous pricent.

What is also noteworthy is that the latest combination of the explanatory variables gave the highest significance in explaining the equity prices, with adjusted  $R^2$  to be equal to 76.86 per cent and the lowest Akaike Information Criterion of 6.5955. Though, the authors in their tests neither distinguish for the business cycles, nor they do break the firms into industrial affiliation groups, rather than just looking at the general picture.

Showing empirically the positive results on price prediction using the combination of technical and fundamental values of the firms, Jenni L. Bettman, Stephen J. Sault, Emma L. Schultz (2009) did not tell, how exactly to work with those values in order to make profit from trade of stocks of firms/indices, for which we could have the price movement directions predicted. In other words, authors of the

paper showed dependence of price on the mentioned variables and concluded, that one should better work with both technical and fundamental analyses for price forecasting, but left the question of trading strategy for the investors untouched.

This is treated in the next analyzed work made by Neely, Christopher J et al. (2001). They incorporated in their study economical fundamentals with the technical trading rules such as popular moving-averages, momentum and volume-based variables to discover forecasting ability. The key reason for doing that is the fact that “technical rules detect the typical decline in the equity premium near cyclical peaks; economic fundamentals more readily pick up the typical rise in the equity premium near cyclical troughs”. The authors examine efficacy of analyses using out-of-sample<sup>15</sup> returns data. The choice of technical repressors is also not randomly chosen: MA is a good tool in detection of the stock price trend changes; momentum rule serves for generation of buy signals based on the positive difference in the current and past stock price,  $m$  periods ago, meaning relatively high expected excess returns for the next period; lastly, on-balance volume indicates strength of market trend, thereafter gives signals.

It is significant that the time span of data is larger than in the previously mentioned work- from January 1927 until December 2008, adding representativeness due to the bigger number of economical fluctuations. The time until 1960 was used as a fallback for the estimations.

Yet, another research paper is writted on the topic of combination of methods of market valuation in order to predict profitable trading strategy. And this is the paper, on which I will consentrare the most in my further analysis.

In 2003 Yeyu Fang and Zhidong Xu published their study. In this work they introduces the alliance between technical trading rules and time series forecasts. They found that:

Technical trading rules and time series forecasts capture different aspects of market predictability: the former tends to identify periods to

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<sup>15</sup>The data, which is not for investigation, but which serves as a background for sample.

be in the market when returns are positive and the latter is capable of identifying periods to be out when returns are negative.

They concluded, that the combination of the technical and time-series methods's rules yield greater, than technical and time-series-forecast analyses separately, returns due to this method's higher accuracy of predictability of future stock price changes.

In the coming sections I will try to verify validity of the above conclusion applied to the 10 different by industrial affiliation indices and to investigate, if there is a difference between the results depending on nature of index (its industry). I will also approach the question about profitability of different trading strategies.



## 2 Data

Different industries incorporate distinct companies, performance of which is dependent on different by nature and market scarcity inputs. Therefore, it is reasonable to assume that the return on particular industry's index will differ from one another in same time frames. As an example, a tendency in healthy lifestyle, leading to strength of health, could stimulate Consumer Services Index returns and weaken Health Care Index returns, while bringing no changes to the Oil & Gas Index returns. Or another examples could be seen in the Mohamed El Hedi Aroui & Duc Khuong Nguyen's (2010) findings, which illustrate the fact that a sign of stock prices sensitivity (to oil price changes) varies across industries. They found that from 1998 to 2008 there was a negative correlation of oil prices to Food and Beverages and Health care industries. As we assume variations in index returns depending on industries, we may also ask a question whether there exists only one valuation method, which is to the same extend efficient, applied to all of the industries, or shall we differentiate by industries while choosing a method of valuation.

To try to answer this question I investigate the topic on 10 Dow Jones industry indices: Dow Jones U.S. Basic Materials Index (DJUSBM), Dow Jones U.S. Consumer Goods Index (DJUSNC), Dow Jones U.S. Consumer Services Index (DJUSCY), Dow Jones U.S. Financials Index (DJUSFN), Dow Jones U.S. Health Care Index (DJUSHC), Dow Jones U.S. Industrials Index (DJUSIN), Dow Jones U.S. Oil & Gas Index (DJUSEN), Dow Jones U.S. Technology Index (DJUSTC), Dow Jones U.S. Telecommunications Index (DJUSTL), and Dow Jones U.S. Utilities Index (DJUSUT).

These indices are relatively new- they were first calculated on 14<sup>th</sup> of February, 2000. Each include on average 130 components (lowest for Telecommunications index- 10, highest for Financials index- 281)<sup>16</sup> totalling in 1250 companies.

Combined, U.S. Index represent close to 95% market capitalization coverage of U.S.-traded stocks. The annual price return to DJUS since inception is 9,49%.

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<sup>16</sup>As of end of May, 2015

Daily closing prices from 2<sup>d</sup> of January, 2001 until 31<sup>st</sup> of December, 2014 are taken and converted into *log*-returns<sup>17</sup>. The number of observations during 3573 trading days<sup>18</sup> for indices is different, because some were not traded during the days, when the other indices were (e.g. DJUSUT was reported on 3539 days, while DJUSNC – 3573).

For computation of excess from Double-or-out strategy over Buy-and-hold strategy return (both of the strategies will be explained later in methodology) I used LIBOR<sup>19</sup> and Treasury Bill 3-month maturity rates, reported monthly. To obtain the returns for each day of the month I applied the formula

$$r^{1D3M} = \frac{i^{1M3M} / 100}{NDY} \quad (1)$$

Where  $r^{1D3M}$  stands for daily interest rate from 3-month return,  $i^{1M3M}$  is 3-month percentage rate quoted each month and NDY is the number of days in corresponding to 3-month rate year (365 for common and 366 days for leap years). This formula is chosen because in case of no signal in Double-or-out strategy is issued, which is to hold the long position for one more period on the 3-month interest of LIBOR/T-Bill rate (following buy or sell signal, respectively)<sup>20</sup>. The data source for prices is S&P Dow Jones Indices, the London interbank offered rates are collected from ICE Benchmark Administration Limited (IBA) and Treasury Bill rates- from the Board of Governors of the Federal Reserve System (US).

The summary statistics for daily returns are presented in Table 1.

From this table we can see that the greater average return during the inspected period is on the Dow Jones U.S. Consumer Services Index, Dow Jones U.S. Oil & Gas Index, and Dow Jones U.S. Consumer Goods Index with 0,011% (2,8157% annual<sup>21</sup>), 0,0109% (2,7523% annual), and 0,0106% (2,6775% annual) monthly return respectively. The annualized average returns can be found on Table 3.

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<sup>17</sup> $r_t = \log\left(\frac{P_t}{P_{t-1}}\right)$

<sup>18</sup>Each day of the week except of US National Holidays

<sup>19</sup>London Interbank Offered Rate

<sup>20</sup>Rather than compared to continuous compounding in case of stripping and reinvesting/paying back and taking out a new loan

<sup>21</sup>The daily rates are continuously compounded with the formula  $i^y = ((1 + r^d)^{250} - 1) * 100$ ,

Table 2 shows that the number of negative returns is greater, meaning that price of stock decreased more often, than rose. But the mean return for all, except of Telecommunications Index, is positive, meaning that, on average, price rises were larger, than drops. The majority of observations ranged within 0 and 0,001, though for DJUSTL index the difference in number of returns lying within (0;-0,001) interval and (0;0,001) is almost negligible, and negative average return can be explained by overweight of number of outcomes lying within (-0,001;-0,01) rather than within (0,001;0,01).

It is worth to notice, that, compared to Y. Fang and D. Xu's paper, the mean returns for the two investigated averages (Industrial and Utilities) were greater for 100 years period, than for the U.S. corresponding (Industrials and Utilities) indices in the 10 recent years. This difference may come from the difference between DJIA & DJUSIN and DJUA & DJUSUT: number of components and weighting.

Nevertheless, since the components are very close by production companies, I believe, that the difference between means in Fang and Xu's and this paper is due to different length of period of description. This will be seen from the results after breaking the data into two parts: period from 2001 until December 2007 and the second period will be examined from June 2009. This choice is made in desire to eliminate the effect of both The Great Recession and The Quantitative Easing influences. We will then compare the results obtained from the two smaller periods to the initial results.

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where  $i^y$  is an annual rate in percents,  $r^d$  is a daily return on index and 250 stands for the number of days, when the indices were traded.

Table 2.1: Discriptive Statistics of *log*-returns

	$N$	Mean	Std.	Maximum	Minimum	Skewness	Kurtosis
DJUSBM	3552	9,38848E-05	0,007745696	0,060474935	-0,0622284	-0,4905846	7,48027035
DJUSNC	3573	0,000105666	0,004182731	0.0384829	-0,031739447	-0,195063885	8,584942556
DJUSCY	3573	0,00011108	0,005670605	0,04771894	-0,041088045	-0,055453643	6,641733095
DJUSFN	3553	2,10262E-06	0,008347895	0,066847409	-0,078178591	-0,161466934	14,32160834
DJUSHC	3553	8,55576E-05	0,004814174	0,049700996	-0,031585068	-0,16852253	7,458703064
DJUSIN	3553	7,64688E-05	0,006188203	0,039982654	-0,042432149	-0,317336989	5,505726122
DJUSEN	3554	0,000109265	0,007543758	0,074812547	-0,074404278	-0,432321275	10,97353723
DJUSTC	3553	4,4085E-05	0,007603949	0,070534074	-0,042120469	0,280910575	6,422582428
DJUSTL	3553	-3,27595E-05	0,006299143	0,057311199	-0,045286506	0,139111314	8,212014216
DJUSUT	3539	3,80655E-05	0,00526314	0,057520451	-0,037562814	0,030813894	11,53642072

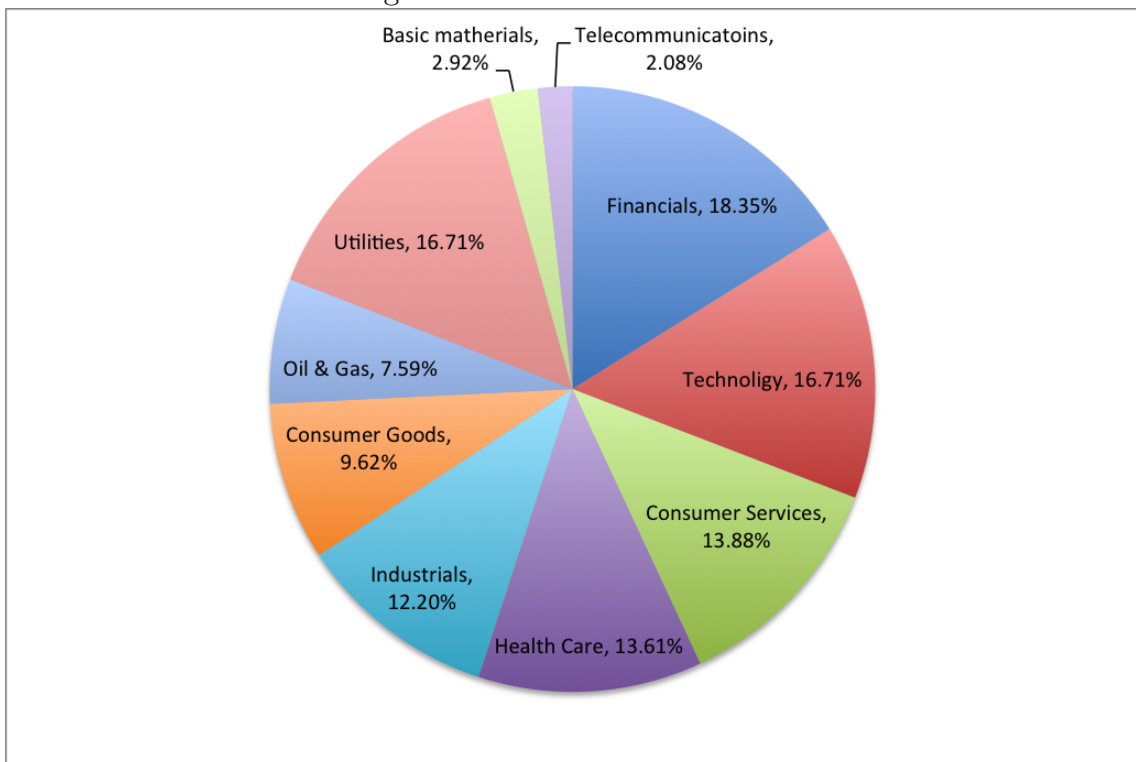
Table 2.2: General Statistics of Observations

Index	>0,0	<0,0	>0,001	>0,01	>0,1	<-0,001	<-0,01	<-0,1
DJUSBM	1863	1955	1597	227	0	1387	252	0
DJUSNC	1887	2167	1406	40	0	1193	64	0
DJUSCY	1866	2083	1490	119	0	1283	144	0
DJUSFN	1816	2064	1489	193	0	1383	220	0
DJUSHC	1869	2125	1428	78	0	1277	90	0
DJUSIN	1874	2040	1513	147	0	1320	162	0
DJUSEN	1849	1945	1609	200	0	1428	233	0
DJUSTC	1878	1981	1572	223	0	1381	274	0
DJUSTL	1798	2094	1459	153	0	1394	176	0
DJUSUT	1874	2025	1514	68	0	1277	116	0

Table 2.3: General Statistics of Indices

Index	Number of components	Annualized returns %
DJUSBM	56	2,3777
DJUSNC	114	2,6775
DJUSCY	179	2,8157
DJUSFN	281	0,0525
DJUSHC	105	2,1731
DJUSIN	213	1,9180
DJUSEN	93	2,7523
DJUSTC	193	1,1060
DJUSTL	10	-0,8284
DJUSUT	60	0,9545

Figure 1: Dow Jones U.S. index



### 3 Methodology and Preliminary Results

To investigate stock valuation methods for their validity in particular industries and to answer the question if there is any necessity to change the methods when changing from one industry of investment to another, I will consider returns from Double-or-out strategy. Through this strategy three methods of future stock returns prediction will be examined:

1. the technical analysis: when relying on signals from moving averages crossovers;
2. the time series analysis: when forecasting based on regression predictions from the time series;
3. and the combination of both.

In principle, I will be comparing the profitability of following the predictions, made at time  $t - 1$  for the time  $t$ , from three methods. The predictions are based on the historical at time  $t - 1$  prices/returns, which give signals to buy/sell or hold a stock for the next period. To see the real profitability, as if we following in the past those signals, I will compute the Double-or-out strategy using the time- $t - 1$  end-of-the-day returns.

Further, in order to evaluate suitability of the methods of evaluation, or their ability to predict the price changes of the stocks, I assume transaction costs of one share to be negligible and equal to zero<sup>22</sup>. An investor is assumed to be making predictions based on nearly closing prices and changing/holding the position on the same date, due to the lack of information available (such as opening prices), so, this could make a little bias, though, this bias is assumed to be insignificant.

The difference in applicability of the particular method, technical rules/time series forecasts/combination of the two, will be shown through breaking the final from Double-or-out strategy returns into early averages for each of the indices.

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<sup>22</sup>Nevertheless, the transaction costs are not negligible, and have to be considered later in the analysis of break-even costs.

Finally, the break-even costs<sup>23</sup> will be calculated in order to show the threshold, until which the strategies are profitable in case of transaction costs, or the necessary amount of shares need at minimum.

### 3.1 Double-or-out Strategy

To employ the forecasts obtained by the three methods and to compare them among each other, I will use the double-or-out strategy. These tactics were first used by Brock et al. (1992), originally, for the technical trading rules to investigate their predictive ability. Lately, in 1998, Bessembinder and Chan released their study, in which they generalized this strategy including in the test for negativity of risk premium the risk-free rate, which will be used in this work as well.

I apply this strategy in order to allow for borrowing and lending, as it is possible in the current market situation. This also gives me more sensitivity to the methods of analysis results for trade (putting more emphasis on buy and sell signals, compared to buy-and-hold strategy<sup>24</sup>, because in the former there is a borrowing step, which represents the willingness to risk and take out the loan, and security step, as a form of risk-free investments, in case of pessimistic forecasts), which is important for the further conclusion about applicability of a particular method to a particular index.

This strategical trading method is described as: An investor enters the market with one share at time  $t - 1$ . In case generated buy signal for time  $t$ , they double their equity position in Dow Jones index portfolio by borrowing the additional money at the LIBOR rate. They hold the position, having one share, when no sell or buy signal is generated. And they liquidate the portfolio in favor of T-Bill share, when there is sell signal given.

The reason for taking the different rates is to show that borrowing money in the

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<sup>23</sup>The costs, which make the profit from trade to be equal to zero. The larger the break-even costs are, the more transactions can be done before there is no excess return from trading but not holding the stock.

<sup>24</sup>A passive trading strategy, according to which investor buys a stock and holds it for some period of time regardless of stock price fluctuations.



market is always more expensive, than lending them.

So, the excess return from trading according to double-or-out strategy on day  $t$  using rule  $i$  can be expressed as:

$$\pi_{(i,t)} = \begin{cases} y_t - r_{(L,t)}, & \text{if trading rule } i \text{ yields buy signal at day } t - 1 \\ 0, & \text{if no trading signal at day } t - 1 \\ r_{(T,t)} - y_t, & \text{if trading rule } i \text{ yields sell signal at day } t - 1 \end{cases} \quad (2)$$

Though, as I will be comparing all of the three methods by the same double-or-out strategy, I will report the gross returns to the strategy:

$$\Pi_{(i,t)} = \begin{cases} 2 \cdot y_t - r_{(L,t)}, & \text{if trading rule } i \text{ yields buy signal at day } t - 1 \\ y_t, & \text{if no trading signal at day } t - 1 \\ r_{(T,t)}, & \text{if trading rule } i \text{ yields sell signal at day } t - 1 \end{cases} \quad (3)$$

Where  $r_{(L,t)}$  and  $r_{(T,t)}$  stand for LIBOR and Treasury Bill rate at time  $t$ , respectively.

### 3.2 Technical Method Trading rules

The technical trading rules are various and used by traders for identification of initiation of new trends. In this paper I use technical trading rules, which are based on moving averages. These moving averages are calculated depending on their lengths and then used in combination of two (some papers document that more than 2 moving averages can be used to process signals, but such multicombinations “may bias the statistical inference by reducing the power of the test”- Andrey Synkevich, 2012), so that buy and sell signals are issued at the crossovers. These moving averages are also combined with bands, as a filter to reduce (in case it is selected to be nonzero) number of signals.

The simple (unweighted) moving averages<sup>25</sup> are calculated according to the formula:

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<sup>25</sup>All past prices are given with the same weight. There exist many other moving averages, such as cumulative moving average, weighted moving average, exponential moving average, and other.

$$SMA_t(N) = \frac{1}{N} \sum_{i=1}^N P_{(t-i)+1} \quad N \leq t \quad (4)$$

Where  $SMA_t(N)$  is simple moving average at time  $t$  of  $N$ -days length, and  $P_{(t-i)+1}$  is a price at a corresponding past day.

Except of moving average crossovers, there are also rules, according to which buy and sell signals are given after change of price by certain proportion, since recent trough or peak, occurs- so called filter rules, or trading range beaks - after change of price rises/drops by a recently established trading range.

Brock et al. (1992) showed that technical analysis is efficient to predict stock price changes, for that he provided the results, which are based on the measure of mean excess return over the buy-and-hold benchmark. Following his findings, Bessembinder and Chan (1998) made crucial research on 26 technical trading rules<sup>26</sup>. These strategies and their findings were then used as a base for many further researches on numerous markets and indices (Sullivan, R., Timmermann, A., White, H., 1999, Massoud Metghalchi et al., 2007, P.N.D. Fernando, 2011, Andrei Shynkevich, 2012, and others), including the authors of one of the core papers for this work, Yue Fanga, Daming Xu (2003).

In my investigation I will use only five variable-length moving-average rules. According to these rules, an action (sell/buy/hold) is taken upon a signal, or, the position is hold exactly until the next cross of two moving averages. A buy(sell) signal is given once short MA crosses long MA from below(above). As a filter, I will use zero-percent band, in order to generalize the case and to see the costs of transactions (although I assume zero costs for simplicity of computation of excess return from double-or-out strategy, the number of transactions will be later accounted for, when calculating the break-even costs).

So, the results from 5 technical rules will be analysed: (1, 50, 0), (1, 150, 0), (5, 150, 0), (1, 200, 0), (2, 200, 0)<sup>27</sup>. These rules were taken from Brock et al. (1992).

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<sup>26</sup>Ten variable-length-moving-average (VMA), ten fixed-length moving-average (FMA), and six trading-range-break (TRB) rules were taken to be examined.

<sup>27</sup> $(m_1, m_2, d)$ , where  $m_1$  and  $m_2$  are short and long MA respectively, and  $d$  is a band. The band is the least percentage change that have to occur in order the signal to be generated.

They will be applied to the close prices of indices, and the price series is denoted as  $\{x_t\}$  with buy and sell signals enenerated in the following way:

$$\tau_i^B \equiv \inf\{t : t > \tau_{i-1}^B, M_1[x_t] - M_2[x_t] > dx_{t-1}\} \quad (5)$$

$$\tau_i^S \equiv \inf\{t : t > \tau_{i-1}^S, M_2[x_t] - M_1[x_t] > dx_{t-1}\} \quad (6)$$

Where  $\tau_i^B$  and  $\tau_i^S$  are buy and sell signals generated sequentially at the times  $\{\tau_i^B, i \geq 1\}$  and  $\{\tau_i^S, i \geq 1\}$ , respectively.  $M_1[x_t]$  and  $M_2[x_t]$  stand for moving averages of price sequence and their lengthes are  $m_2 > m_1 \geq 1$ .

The following tables, 3.1 3.2 & 3.3, show general statistics on signals obtained via technical trading rules. These results will lately used for testing hypotheses.

Table 3.1: DJUSBM-DJUSFN Results for technical trading rules.

$(m_1, m_2, d)$	N(sell)	N(buy)	L(sell)	L(buy)	N(trading)
DJUSBM					
(1, 50, 0,00)	126	125	10,6031746	17,488	65
(1, 150, 0,00)	13	12	248,538462	16,0833333	5
(5, 150, 0,00)	6	5	540,166667	36,6	0
(1, 200, 0,00)	63	62	16,9365079	37,2096774	31
(2, 200, 0,00)	47	46	22,5957447	50,2608696	12
DJUSNC					
(1, 50, 0,00)	137	137	8,94890511	16,7737226	88
(1, 150, 0,00)	75	75	13,0533333	32,6	46
(5, 150, 0,00)	37	37	26,4594595	66,0810811	7
(1, 200, 0,00)	61	61	14,4590164	40,852459	37
(2, 200, 0,00)	42	42	20,8333333	59,5	9
DJUSCY					
(1, 50, 0,00)	128	128	10,25	17,28125	77
(1, 150, 0,00)	34	34	14,5588235	78,7647059	15
(5, 150, 0,00)	16	16	31,125	167,125	4
(1, 200, 0,00)	47	47	22,9787234	48,80851064	25
(2, 200, 0,00)	35	35	31,02857143	65,37142857	10
DJUSFN					
(1, 50, 0,00)	123	123	11,56097561	17,08943089	56
(1, 150, 0,00)	15	14	92,9333333	17,1428571	14
(5, 150, 0,00)	7	6	200,714286	336,5	2
(1, 200, 0,00)	52	52	23,4423077	41,4423077	28
(2, 200, 0,00)	36	36	34,1388889	59,5833333	9

Table 3.2: DJUSHC-DJUSTC Results for technical trading rules.

$(m_1, m_2, d)$	N(sell)	N(buy)	L(sell)	L(buy)	N(trading)
DJUSHC					
(1, 50, 0,00)	134	134	9,58955224	16,7089552	65
(1, 150, 0,00)	18	18	7,2222222	183	12
(5, 150, 0,00)	11	11	11,5454545	299,727273	3
(1, 200, 0,00)	41	41	26,097561	56,195122	25
(2, 200, 0,00)	26	26	41,4615385	88,3076923	6
DJUSIN					
(1, 50, 0,00)	110	110	12	20,0363636	41
(1, 150, 0,00)	79	79	17,0379747	26,3037975	38
(5, 150, 0,00)	42	42	32,0714286	49,452381	4
(1, 200, 0,00)	47	47	21,7234043	50,0638298	23
(2, 200, 0,00)	34	34	30,2058824	69,0294118	3
DJUSEN					
(1, 50, 0,00)	129	128	10,751938	16,6640625	73
(1, 150, 0,00)	6	6	30,8333333	539,8333333	2
(5, 150, 0,00)	3	3	61,66666667	1079,66667	1
(1, 200, 0,00)	42	41	23,2619048	58,4634146	30
(2, 200, 0,00)	28	27	34,8928571	88,7777778	6
DJUSTC					
(1, 50, 0,00)	127	127	11,3464567	16,4015748	72
(1, 150, 0,00)	1	1	1	3423	1
(5, 150, 0,00)	1	1	1	3423	1
(1, 200, 0,00)	63	63	18,7142857	34,8412698	31
(2, 200, 0,00)	51	51	23,1960784	42,9607843	12

Table 3.3: DJUSTL-DJUSUT Results for technical trading rules.

$(m_1, m_2, d)$	N(sell)	N(buy)	L(sell)	L(buy)	N(trading)
DJUSTL					
(1, 50, 0,00)	125	124	13,336	14,9758065	76
(1, 150, 0,00)	2	1	1711,5	1	1
(5, 150, 0,00)	1	0	3424	-	1
(1, 200, 0,00)	74	73	18,2162162	27,7534247	52
(2, 200, 0,00)	52	51	25,9615385	39,6862745	14
DJUSUT					
(1, 50, 0,00)	128	128	10,515625	17,0078125	79
(1, 150, 0,00)	0	0	0	0	0
(5, 150, 0,00)	1	0	3424	-	0
(1, 200, 0,00)	54	54	18,0740741	44,4074074	34
(2, 200, 0,00)	45	45	21,7777778	53,2	19

### 3.3 Time-Series Forecast Method rules

To make forecasts for the next period prices, based on time series, we will use autoregressive models. These models describe time-varying processes, which are assumed to have each next variable dependent on the result of the previous plus an imperfectly predictable, also called stochastic<sup>28</sup>, term.

<sup>28</sup>The stochastic process means that the collection of consequential random variables (here time series of prices) within the time form some system, which can then be estimated and the further outcomes predicted.

$AR(p)$  , where  $p$  is an order of the model<sup>29</sup>, is defined as follows:

$$r_t = \beta_0 + \sum_{i=1}^p \beta_i \cdot r_{t-i} + \varepsilon_t \quad (7)$$

Where  $\beta_i$  are model parameters,  $\beta_0$  is a constant, and  $\varepsilon_t$  is an error term, white noise<sup>30</sup>, and has Student's  $t$ -distribution,  $\varepsilon_t \sim t(0, \sigma_t^2, \nu)$ , with 0 mean, variance at time  $t$ , and  $\nu = n - 1$  degrees of freedom,  $n$  is a number of observations.

According to ARCH model, conditional variance,  $h_t$ , depends on the past squared residuals from AR(p) model:

$$\varepsilon_t = e_t \cdot h_{t-i} \quad (8)$$

$$h_t^2 = \beta_0 + \sum_{i=1}^p \beta_i \cdot \varepsilon_{t-i}^2 \quad (9)$$

The specified forms of AR process- models including GARCH (Bollerslev, 1986) components- allow to predict the residuals from AR and account for the fat tails of distribution and volatility clustering<sup>31</sup>. This could enable my model to make more accurate forecasts, since the volatility in years around and during crises could be controlled for. GARCH stands for generalized autoregressive conditional heteroskedasticity. This model includes not only the squared residuals, but also the lagged values of conditional volatility, so that GARCH(q,p) model's conditional heteroscedasticity, where  $q$  is the order of lagged values and  $p$  is the order of squared residual values, can be written as:

$$h_t^2 = \alpha_0 + \sum_{i=1}^p \beta_i \cdot \varepsilon_{t-i}^2 + \sum_{j=1}^q \alpha_j \cdot h_{t-j}^2 \quad (10)$$

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<sup>29</sup>\*how many "lags"/past values are considered.

<sup>30</sup>"Random shock"

<sup>31</sup>Mandelbrot (1963) defined the volatility clustering as a fact of positive and statistically significant correlation between the absolute or square values of consequential returns, while returns themselves to be uncorrelated. Or, according to Engle(2001), it is an amplitude of the returns that varies over time.

Volatility clustering itself means that the periods of high (low) volatility are followed by periods of high (low) volatility.

Next, the extended version, that could be estimated is GARCH-M model.

GARCH-in-mean model inserts the conditional variance into the mean equation.

So, the mean becomes conditional on heteroskedasticity term:

$$r_t = \beta_0 + \sum_{i=1}^p \beta_i \cdot r_{t-i} + \sum_{j=1}^q \lambda_j \cdot h_{t-j} + \varepsilon_t \quad (11)$$

Where  $h_t$  is defined as a square root of conditional variance from GARCH.

Another model with GARCH in mean, that can be tested, is EGARCH (exponential), Nelson (1991). This model allows to put greater emphasis on negative returns, than on positive, and predicts higher volatility with the use of those.

$$\log(h_t^2) = \alpha_0 + \sum_{i=1}^p \beta_i \cdot g(e_{t-i}) + \sum_{j=1}^q \alpha_j \cdot \log(h_{t-j}) \quad (12)$$

Where  $e_t$  come from equation (8) and  $g$  is a function of  $z_t$  (from the same equation (8)):

$$g(z_t) = \theta \cdot z_t + \gamma \cdot [|z_t| - E|z_t|] \quad (13)$$

Although, the last two mentioned models could be helpful to explain the time-series better, I will leave them for my further diploma thesis investigation and consider the former two models.

The signals are generated at time  $t - 1$  as follows:

$$E(r_t | I_{t-1}) > \delta \quad (14)$$

For buy signal, and

$$E(r_t | I_{t-1}) < -\delta \quad (15)$$

For sell signal,

where  $r_t$  comes from the sequence of returns  $\{r_t\}$ ,  $I_{t-1}$  is a set containing the past information about the returns and is known at time  $t - 1$ ,  $\delta$  is nonnegative constant. Hereafter, I set  $\delta$  to be equal to the same threshold as for technical rules, 0.

An investor is assumed to take a decision to sell/buy/hold at the last moment of trade, according to the price at close, so that he reformates his portfolio before the

new trading day comes, but after the return of the current day and the estimations about the returns of the next day are made.

To obtain the continuous output of historical signals from models, rolling windows<sup>32</sup> are implemented.

I estimate the models with one-period lags: AR(1), AR(1)-GARCH(1,1). In sake of convenience, I will take the coefficient notation from Y. Fang & D. Xu.

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<sup>32</sup>Rolling window technique allows the parameters of estimated regression to change over time, due to change of period of estimation: the model takes the most recent observations (of stated time frame) and uses them instead of the those observations from the whole historical period.

Table 3.4: AR(1) & AR(1)-GARCH(1,1) Models Parameter Estimates.

Panel A: AR(1)					
$y_t = \mu + \phi y_{t-1} + \varepsilon_t$					
	$\mu$	$\phi$			
DJUSBM	0.0002297 (0.744226)	-0.0368018 (-3.95355)**			
DJUSNC	0.000263628 ( 1.60618)	-0.0579184 (-5.7158)**			
DJUSCY	0.000270526 (1.22047)	-0.0306007 (-2.79746)**			
DJUSFN	1.72277e-06 (0.00539368)	-0.123747 (-17.1371)**			
DJUSHC	0.000216961 (1.13846)	-0.028199 (-2.84169)**			
DJUSIN	0.000196729 (0.813323)	-0.0306916 (-2.79626)**			
DJUSEN	0.000277073 (0.89765)	-0.0710791 (-8.05644)**			
DJUSTC	0.000126562 (0.429588)	-0.0244816 (-2.2034)*			
DJUSTL	-8.41468e-05 (-0.345699)	-0.0312629 (-3.01413)**			
DJUSUT	0.00010665 (0.502091)	-0.0619576 (-7.09026)**			

Panel B: AR(1)-GARCH(1,1)					
$y_t = \mu + \phi y_{t-1} + \varepsilon_t,$	$\varepsilon_t = h_t e_t,$		$h_t^2 = w + \alpha \varepsilon_{t-1}^2 + \gamma h_{t-1},$		$e_t \sim IN(0, 1)$
	$\mu$	$\phi$	w	$\alpha$	$\gamma$
DJUSBM	0.000643415 (3.06357)**	-0.0118197 (-0.684423)	2.76313e-06 (3.86287)**	0.91203 (122.136)**	0.0779397 (12.1959)**
DJUSNC	0.000552758 (4.38455)**	-0.0345873 (-1.80077)*	2.50007e-06 (4.62529)**	0.868594 (82.5051)**	0.0967877 (12.9166)**
DJUSCY	0.000575038 (3.72545)**	-0.0101408 (-0.548477)	1.64422e-06 (3.27093)**	0.902405 (110.803)**	0.0859887 (12.1737)**
DJUSFN	0.000533395 (3.23151)**	-0.0522499 (-2.84696)**	1.54139e-06 (3.5813)**	0.900814 (155.761)**	0.0937497 (15.497)**
DJUSHC	0.000498341 (3.54779)**	-0.0290833 (-1.61775)	2.47173e-06 (4.09573)**	0.878653 (93.8533)**	0.0972956 (13.1765)**
DJUSIN	0.000628301 (3.76902)**	-0.00734998 (-0.397952)	1.97565e-06 (3.44992)**	0.903174 (117.672)**	0.0862997 (12.1654)**
DJUSEN	0.000642245 (2.96503)**	-0.0209956 (1.16284)	2.50737e-06 (3.13553)**	0.917076 (135.061)**	0.0736411 (12.3493)**
DJUSTC	0.00068814 (3.61759)**	-0.016316 (-0.882924)	1.53452e-06 (2.90596)**	0.926446 (150.036)**	0.0667192 (11.8597)**
DJUSTL	0.000276256 (1.64552)	-0.0152118 (-0.822371)	2.37114e-06 (4.11829)**	0.901126 (120.547)**	0.0845271 (13.0083)**
DJUSUT	0.000494761 (3.52504)**	0.00535978 (-0.305251)	2.34819e-06 (3.82503)**	0.866007 (92.3231)**	0.114012 (14.7133)**

Results are based upon the sample period from January 2, 2001 to December 31, 2014. The AR(1) is estimated by OLS. The AR(1)-GARCH model is estimated using maximum likelihood. The numbers in parantheses are  $t$ -ratios. The  $t$ -ratios marked with asterisks (double asterisks) indicate that the corresponding coefficients are statistically different from zero at the 5% (1%) level of significance.

The results from regression show, that, however, coefficients for conditional heteroskedasticity from GARCH part are highly significant, coefficients from AR(1) - are not, in case of AR(1)-GARCH(1,1) model. This means that there is little value added to accuracy of forecasts, when using this model.



At the same time  $\phi$ -values from simple AR(1)-model are significant at 1%-level for all of the indices, except of DJUSTC, which is significant at 5%-level.

After having considered these results, I will make forecasts for next-day returns for indices based on simple AR(1)-model.

As the result I obtain the one-day return forecasts,  $r_t$  for each day  $t - 1$ , when the decision is to be made. These returns are then compared to the current day's return,  $r_{t-1}$ , and based on difference (between current and predicted, if positive,  $r_{t-1} - r_t > 0$ , then sell signal, buy- otherwise), the buy or sell signals are generated. In order to be able to use double-or-out strategy, in case of same following signal in the row, the second is assumed to be generalized to hold position, this hold position, which means stock in the index, is kept until the next different to the last signal comes.

The following table 3.6 shows the general statistics for signals obtained via time-series rules.

It is evident that, compared to technical trading rules, the ones of time series analysis generate buy/sell signals more frequently. As a result, looking at also higher number of days of trading,  $N(\text{trading})$ , this lowers the maximum possible transaction costs threshold in order for investor to break-even, when following the signals.

Table 3.5: Results for time series forecasts.

Index/Rule	N(sell)	N(buy )	L(sell)	L(buy)	N(trading)
DJUSBM					
AR50	447	448	3,00447427	4,86160714	414
AR150	453	453	2,55629139	4,99779249	450
AR200	449	448	2,42538976	5,09598214	441
DJUSNC					
AR50	517	517	2,48355899	4,32882012	513
AR150	469	470	2,21748401	5,06808511	470
AR200	419	419	2,3221957	5,7253699	413
DJUSCY					
AR50	475	476	2,81894737	4,58613445	445
AR150	407	408	2,79115479	5,60294118	400
AR200	388	388	2,7242268	5,96649485	376
DJUSFN					
AR50	495	496	2,94141414	4,16532258	494
AR150	513	513	2,417154	4,25341131	535
AR200	474	474	2,45780591	4,65611814	489
DJUSHC					
AR50	473	473	2,906976744	4,53911205	436
AR150	437	438	2,76887872	5,05022831	426
AR200	459	459	2,51633987	4,83006536	450
DJUSIN					
AR50	478	478	2,79288703	5,57531381	452
AR150	446	446	2,53139013	5,14125561	433
AR200	408	408	2,61764706	5,64705882	388
DJUSEN					
AR50	516	515	2,71124031	4,223301	506
AR150	466	465	2,4806867	4,87311828	469
AR200	451	451	2,47450111	5,00221729	447
DJUSTC					
AR50	408	409	3,71078431	4,90953545	395
AR150	402	402	3,15174129	5,36069652	391
AR200	362	362	3,32044199	5,99447514	336
DJUSTL					
AR50	464	464	3,59913793	3,99137931	444
AR150	463	463	3,33477322	4,05615551	469
AR200	410	409	3,53658537	4,6992665	403
DJUSUT					
AR50	465	465	3,16989247	4,40430108	448
AR150	427	427	2,77751756	5,23653396	427
AR200	367	367	2,9972752	6,19073569	361

Where AR50, AR150 & AR200 stand for time-series rules, estimated via AR(1)-model with information set of 50, 150 & 200 days respectively. N(.) stands for “number”.

### 3.4 Combined Trading Rules Method

The combined trading strategy is, as follows from the name, a combination of the technical trading and time series forecast rules. In this strategy the signal is issued only once the signals issued by the both methods (technical rules and time series forecasts) for the next day coincide.

Such rules incorporate the different strengths of the both technical and time series rules, allowing to make less transactions, at the same time, with more reliable signal estimations (note: this is not equal to saying "more profitable decision for all of the for trading strategies").

These signal-predictions are said to be more accurate, than those from the two separate methods, because Y. Fang and D. Xu concluded, that "when the market rises the technical rules perform typically better [...] the time series forecasts are in general superior to the technical rules when the market falls". In other words, the two capture better different economic states, combining which makes, then, absolute sense to obtain more productive results.

Table 3.6: Results for strategies combining technical trading rules and time series forecasts.

$(m_1, m_2, d, M)$	N(sell)	N(buy)	L(sell)	L(buy)	N(trading)
DJUSBM					
(1, 50, 0,00, 50)	51	60	1	1	14
(1, 150, 0,00, 150)	0	7	0	452,75	0
(5, 150, 0,00, 150)	1	5	147,75	227,4	0
(1, 200, 0,00, 200)	30	39	39,9642857	76,7931034	10
(2, 200, 0,00, 200)	24	28	47,1428571	107,045455	3
DJUSNC					
(1, 50, 0,00, 50)	60	66	21,3076923	45,7692308	31
(1, 150, 0,00, 150)	18	22	66,0625	145,6875	1
(5, 150, 0,00, 150)	19	22	35	133,65	8
(1, 200, 0,00, 200)	11	17	154,3	180,2	1
(2, 200, 0,00, 200)	0	0	-	-	0
DJUSCY					
(1, 50, 0,00, 50)	61	65	32,6595745	40,8541667	21
(1, 150, 0,00, 150)	8	5	236,166667	350,8	0
(5, 150, 0,00, 150)	17	24	128,888889	58,5	5
(1, 200, 0,00, 200)	14	14	159,083333	129	2
(2, 200, 0,00, 200)	0	0	-	-	00
DJUSFN					
(1, 50, 0,00, 50)	41	47	52,027027	41,3513514	11
(1, 150, 0,00, 150)	2	4	1,2	233,166667	0
(5, 150, 0,00, 150)	22	23	24,7391304	121,913043	11
(1, 200, 0,00, 200)	8	20	59,1	247,545455	1
(2, 200, 0,00, 200)	0	0	-	-	0

Table 3.7: Results for strategies combining technical trading rules and time series

forecasts.					
$(m_1, m_2, d, M)$	N(sell)	N(buy )	L(sell)	L(buy)	N(trading)
DJUSHC					
(1, 50, 0,00, 50)	60	58	35,2040816	36,1428571	18
(1, 150, 0,00, 150)	6	2	345,4	339	0
(5, 150, 0,00, 150)	19	17	118,809524	43,9	11
(1, 200, 0,00, 200)	10	15	31,9166667	229,615385	0
(2, 200, 0,00, 200)	0	0	-	-	0
DJUSIN					
(1, 50, 0,00, 50)	45	49	39,3783784	50,0789474	7
(1, 150, 0,00, 150)	14	34	140,083333	142	1
(5, 150, 0,00, 150)	17	23	54,5263158	123	8
(1, 200, 0,00, 200)	14	17	123,833333	141,153846	2
(2, 200, 0,00, 200)	0	0	-	-	0
DJUSEN					
(1, 50, 0,00, 50)	52	56	31,8863636	49,2093023	17
(1, 150, 0,00, 150)	1	0	845,25	0	0
(5, 150, 0,00, 150)	14	18	94,3571429	129,866667	6
(1, 200, 0,00, 200)	15	11	197,909091	99,2727273	1
(2, 200, 0,00, 200)	0	0	-	-	0
DJUSTC					
(1, 50, 0,00, 50)	52	50	43,952381	38,5714286	18
(1, 150, 0,00, 150)	0	0	-	-	0
(5, 150, 0,00, 150)	23	22	86,0952381	74,5238095	8
(1, 200, 0,00, 200)	19	18	145,214286	86,533333	0
(2, 200, 0,00, 200)	0	0	-	-	0
DJUSTL					
(1, 50, 0,00, 50)	66	53	40,5625	31,4893617	26
(1, 150, 0,00, 150)	0	0	-	-	0
(5, 150, 0,00, 150)	29	25	75,1904762	89,7	10
(1, 200, 0,00, 200)	19	23	103,533333	108,357143	1
(2, 200, 0,00, 200)	0	0	-	-	0
DJUSUT					
(1, 50, 0,00, 50)	64	59	24,1960784	45,76	25
(1, 150, 0,00, 150)	0	0	-	-	0
(5, 150, 0,00, 150)	22	30	54,0454545	99,2727273	11
(1, 200, 0,00, 200)	18	28	105,235294	84,7058824	2
(2, 200, 0,00, 200)	0	0	-	-	0

As it can be seen from the results, the number of buy and sell signals is considerably less than the number of buy and sell signals from either technical rules or time series forecasts. This could lead, in case of accurate estimations, to increase in nett proffit, as less transaction costs occur.

## 4 Methods' Results Interpretation and Hypotheses

### 4.1 In general

In total, I have employed to the data 13 different methods for one-day forecast of returns-to-index movements and the profitability of these methods, using Double-or-out strategy, for 10 indices and subdivided those results into 14 periods, each representing one calendar year.

The outcomes are shown in the Table 4.1.

It is evident, that for every analyzed index years 2002 and 2008, in general, brought negative returns no matter, which method was used.

From the Table 1 it can also be seen that, on average, throughout the whole analysed period of the time, the Time-series forecast strategy of analysis, as it stands alone, gives negative returns from trade for each of the indices.

Based on this fact, I compare the two different early average outcomes for each index: "AVERAGE.1" and "AVERAGE.2", where the former shows average returns to the all of the methods for each year from 2001 to 2014, and the later- the averages excluding the three time series methods, (AR50, AR150 and AR200).

Table 2 depicts the outcomes. This is done to show, how much the performance of the whole year depended on those three method's outcomes (could the average outcome from the all of the methods be improved, if computed with the time-series forecast models, which would mean, that these models were significantly positive at that year).





Table 4.2: Yearly AR rules performance

	AV.1	Included							
BM		2002				2008			2011
NC					2007	2008			2011
CY				2005	2007	2008		2010	2011
FN					2007	2008	2009		
HC		2002			2007	2008			
IN		2002				2008			
EN						2008	2009		2011
TC		2002		2005		2008			2012
TL	2001	2002	2003		2007	2008	2009		2011
UT	2001	2002				2008			
	AV.2	Excluded							
BM		2002				2008			2011
NC		2002				2008			
CY		2002			2007	2008			
FN		2002			2007	2008		2011	
HC		2002				2008			
IN		2002				2008			
EN		2002				2008			
TC		2002				2008			2014
TL	2001	2002		2005		2008			
UT	2001	2002				2008			

information set of length 200. However, still, application of these AR methods was rational only in 33% of cases.

Table 4.3: Choise of best rule by the years and industries

	BM	NC	CY	FN	HC	IN	EN	TC	TL	UT
2001	AR200	AR200	AR200	AR200	AR150	AR200	AR200	AR200	(1,50,00)	AR200
2002	AR200	AR200	AR200	AR200	AR200	AR200	AR200	AR200	(1,50,00)	(1,50,00)
2003	(1,50,00)	(1,50,00)	(1,150,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,200,00)	(1,50,00)
2004	AR150	(1,50,00)	AR200	AR150	(1,50,00)	AR50	AR50	(1,50,00)	(1,50,00)	AR150
2005	AR200	(1,50,00)	(2,200,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	AR200	AR50
2006	AR200	(1,50,00)	(2,200,00)	(1,50,00)	AR150	(1,50,00)	AR150	AR200	AR50	AR200
2007	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)
2008	(1,50,00)	(1,150,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)
2009	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,150,00)	(1,150,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)
2010	(1,200,00)	(1,200,00)	(1,50,00)	(1,50,00)	(1,50,00)	AR200	AR50	(1,200,00)	AR200	AR150
2011	AR50	(1,200,00)	(1,150,00)	(1,50,00)	(1,150,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)
2012	AR200	AR50	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	AR150	(1,50,00)	AR50	(1,50,00)
2013	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,50,00)	(1,150,00)	(1,50,00)	(1,50,00)	(1,50,00)	AR150
2014	AR200	(1,50,00)	AR150	(1,50,00)	(1,50,00)	AR150	(1,50,00)	(1,50,00)	AR50	(1,50,00)
AVERAGE	4,2655E-05	0,00040879	0,00054694	0,000706836	0,00042782	0,00024022	0,00012186	0,0006284	0,00046807	0,00026017
TS		46	32,86%							
TA		94	67,14%							
(1,50,00)/TA			85,11%							

After concluding that, I want to consider another statistical data from Table 4.4, which shows if technical method of analysis's outcomes beat those from corresponding combination of technical and time-series forecasts for each index in particular year. In this table "1" stands for positive result from test:

$$\Omega_{i,j} > \Omega_{i,j} \tag{16}$$

Where  $\Omega_{i,j}$  is return from year  $j$ ,  $j = 2001, \dots, 2014$ , for index  $i$  for one of the technical methods, and  $\Omega_{i,j}$  - for the combination method.



And “0” is for:

$$\Omega_{i,j} < \Omega_{i,j} \tag{17}$$

Putting in other words, “1” (“0”) indicates outperformance (underperformance) of technical over its combination with time-series forecast method.

According to this table, one can see that, on average, (1,150,00) and (5,150,00) rules of technical analysis were less predictive, than the referig (1,150,00,150) and (5,150,00,150) rules from the combination of technical analysis and time series forecast. Moreover, the most commonly outperforming rule is the crossover of MAs with the smaller length<sup>33</sup>. And from the Table 6 it is, moreover, proved to be the most accurate also among the other technical rules with 85% of all technical-rule-usage cases during the analyzed time. However, according to Table 4.1 and Table 4.3, at the years, when combination-of-methods rules were better, than corresponding technical rules, they were not better than the other possible, since neither of them apper in the Table 4.3.

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<sup>33\*</sup>looking at the average number of 0,98.

Table 4.4: Yearly performance comparison of technical to combination of technical and time-series forecasting rules

	(1,50,00)	(1,150,00)	(5,150,00)	(1,200,00)	(2,200,00)	(1,50,00)	(1,150,00)	(5,150,00)	(1,200,00)	(2,200,00)	(1,50,00)	(1,150,00)	(5,150,00)	(1,200,00)	(2,200,00)		
<b>BM</b>						<b>FN</b>						<b>EN</b>					
2001	1	1	1	1	1	1	0	0	1	1	1	1	0	1	1	1	
2002	1	0	0	0	0	1	0	0	1	1	1	1	0	1	1	1	
2003	1	0	0	0	1	1	0	0	1	1	1	1	0	1	0	0	
2004	1	0	0	0	1	1	0	0	1	1	1	1	0	0	0	0	
2005	1	0	0	0	0	1	0	0	1	1	1	1	0	0	0	0	
2006	1	0	0	1	1	1	0	0	1	1	1	1	0	0	1	1	
2007	1	1	0	1	1	1	0	1	1	1	1	1	0	0	1	1	
2008	1	1	0	1	1	1	1	1	0	1	1	1	0	0	1	1	
2009	1	0	0	1	1	1	1	0	1	1	1	1	0	0	1	1	
2010	1	0	0	1	1	1	1	0	1	1	1	1	0	0	1	1	
2011	1	1	1	1	1	1	1	0	1	1	1	1	0	0	1	1	
2012	1	0	0	1	0	1	0	0	1	1	1	1	0	0	1	1	
2013	1	0	0	1	1	1	0	0	0	1	1	1	0	0	1	0	
2014	1	0	0	1	1	1	0	0	1	1	1	1	0	0	1	1	
<b>NC</b>						<b>HC</b>						<b>TC</b>					
2001	1	1	0	1	1	0	1	0	1	1	1	1	0	1	1	1	
2002	1	1	1	1	1	1	1	0	1	1	1	1	0	0	1	1	
2003	1	1	1	1	1	1	0	0	1	1	1	1	0	0	1	1	
2004	1	1	0	1	1	1	0	0	1	1	1	1	0	0	1	1	
2005	1	1	1	1	1	1	0	0	1	1	1	1	0	0	1	1	
2006	1	1	0	1	1	1	0	0	1	1	1	1	0	0	1	1	
2007	1	1	0	1	1	1	0	0	1	1	1	1	0	0	1	1	
2008	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	
2009	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	
2010	1	1	0	1	1	1	0	0	1	1	1	1	0	0	1	1	
2011	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	
2012	1	1	0	1	1	1	0	0	0	1	1	1	0	0	1	1	
2013	1	1	0	0	0	1	0	0	0	0	1	1	0	0	1	1	
2014	1	1	0	1	1	1	0	0	0	0	1	1	0	0	1	0	
<b>EN</b>						<b>TC</b>						<b>TL</b>					
2001	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	
2002	1	1	0	1	1	1	0	0	1	1	1	1	0	0	1	1	
2003	1	1	0	1	0	1	0	0	1	1	1	1	0	0	1	1	
2004	1	0	0	0	0	1	0	0	1	1	1	1	0	1	1	1	
2005	1	0	0	0	0	1	0	0	1	1	1	1	0	0	1	1	
2006	1	0	0	1	1	1	0	0	1	1	1	1	0	0	1	1	
2007	1	0	0	1	1	1	0	0	0	1	1	1	0	0	1	1	
2008	1	0	0	1	1	1	0	0	1	1	1	1	0	0	0	0	
2009	1	0	0	1	1	1	0	0	1	1	1	1	0	0	1	1	
2010	1	0	0	1	1	1	0	0	1	1	1	1	0	0	1	1	
2011	1	0	0	1	1	1	0	0	1	1	1	1	0	0	1	1	
2012	1	0	0	1	1	1	0	0	1	1	1	1	0	0	1	1	
2013	1	0	0	0	0	1	0	0	1	1	1	1	0	0	1	1	
2014	1	0	0	1	1	1	0	0	0	0	1	1	0	0	1	1	
<b>UT</b>																	
2001	1	1	1	1	1												
2002	1	0	0	0	0												
2003	1	0	0	0	1												
2004	0	0	0	0	0												
2005	1	0	0	1	1												
2006	1	0	1	1	1												
2007	1	0	0	1	1												
2008	1	0	0	1	1												
2009	1	0	0	1	1												
2010	1	0	0	1	1												
2011	1	0	0	1	1												
2012	1	0	0	1	0												
2013	1	0	0	1	1												
2014	1	0	0	1	1												
Average	0,97857143	0,37142857	0,2	0,84285714	0,82857143												

At this point I would like to move to more industry-specific results explanation and to discuss the main hypothesis of this work.

## 4.2 In particular

The main aim of this thesis is to investigate the ten different indices and to find out if the choice of method of valuation, the method of forecasting the future prices or returns movements, should differ according to the industry, meaning-index. So, the first hypothesis is:

**Hypothesis 1.** *Choice of method of forecast of future price changes of the stock depends on index's industry affiliation.*

Table 4.3 depicts the most accurate in terms of predictions rules of either of the methods by the years for all of indices. It is evident, that hypothesis 1 should be **rejected**, because there can be been no significant difference in choice of the best method depending of index.

In this case, the other question is if:

**Hypothesis 2.** *There exists unique most-accurate method, which can be universally used for any index.*

Once again, referring to the Table 4.3, I can conclude, that technical rules tend to consistently outperform the rules of other methods, having success in 67,14% of cases. Moreover, I can define 1-50-moving-average-crossover rule to be the most efficient rule of the method, totalling in 85,11% of times, when technical analysis is was appropriate to use. Thus, I **do not reject** hypothesis 2.

Further in detailes, I want to know, if:

**Hypothesis 3.** *Choise of **method** of future stock prices changes depends on presence of global market crashes and is different for all of the indices. The unique **rule** can be determined.*

I found that there is a strong general relation between applicability of particular method and financial crises.

The attacks of September 11 in 2001 caused sharp drop of stock markets. It was followed by the world stock market downturn in 2002. In those two years *for 9 out of 10 in 2001 and for 8 out of 10 indices in 2002* forecasts from time series autoregressive analyzes were the most profitable.

In years 2007, 2008, and 2009 there was a series of market crishes: “Chinise stock bubble of 2007”, “ United States bear market of 2007-2009”, “Financial Crisis of 2007-2008”, and also “2009 Dubai debt standstill”. During these years, it is evident from the Table 4.3 that the best-working method for *all* indices was technical method of valuation of future returns.

However, this does not enable investor to make decision about the choise of method during the next time of crisis, since the the results in Tabе 4.3 are not

only different by the rules of methods, during the crashes of examined period of time, but also opposite to each other in terms of methods in general. Also, I believe, that, in case there existed more data on these indices, it could be possible to try to find some consistency in crisis-profitable method. Until then, I conclude that neither difference in unique rules for indices nor their consistency is proven, with that I **reject** Hypothesis 3.

Although, I have found out that an investor should not consider index's industrial affiliation when deciding about the method of valuation of future returns, I want to know, how much the return is different for indices from different industries:

**Hypothesis 4.** *Profits from investment in the long-run are different among indices.*

Table 4.5: Total Average Index Returns

	AVERAGE.1	annualized	AVERAGE.2	annualized
BM	0,00018486	0,04729409	0,0002655	0,06861825
NC	9,0859E-05	0,02297371	0,00021553	0,05535345
CY	0,00016085	0,04102962	0,00025376	0,06548809
FN	-0,0001708	-0,0418139	0,00013277	0,03374638
HC	9,7886E-05	0,02477211	0,00020428	0,05239202
IN	9,4914E-05	0,02401108	0,00017642	0,045087
EN	8,1006E-05	0,02045706	0,00023075	0,05937576
TC	0,00011748	0,02980306	0,00024593	0,06340282
TL	-7,505E-05	-0,0185876	4,6214E-05	0,01162022
UT	3,3491E-05	0,00840782	0,00011812	0,02996768

The outputs of the table are computed as follows: the average year returns for each index were taken from Table 4.1 and were averaged for the whole period of time. "annualized" are the outputs of averaged results converted to the annualized percentages.

The above table shows the annualized percentage returns to the investor for particular industries. As followed by the table 4.3, I take two possibilities for investment: employing time-series method, or using only technical and combined rules. "AVERAGE.1" represents returns from the former and "AVERAGE.2"- for

the later. In any of the case, averaged from all of the rules of the year and then averaged through the whole period return for an index varies according to the industry of the index. So, that it is evident that DJUSBM, DJUSCY and DJUSTC indices were among the best performing during 2001-20014 period. Having this stated, I **do not reject** null hypothesis.

Since I evaluate credibility of signals from methods, technical rules , time-series forecast rules or the combination of them, on double-or-out strategy, I find it essential to take transaction costs into consideration, when evaluating applicability of those rules. For this I investigate, the return from how many stocks in the index would cover the transaction costs associated with trade, rather than just holding the stock for the whole period of time. So that investor could understand, if it makes sense to trade in the particular industry's index, or not.

**Hypothesis 5.** *Break-even number of stocks in index is same for all industries.*

To investigate the break-even<sup>34</sup> number of stocks in index I use results from Tables 4.1, 3.1, 3.2, 3.3, 3.7, 3.6 & 4.3.

The number of trading days, change of position from “in” to “out” of market is taken from all of the rules for index and then divided by 13, number of rules, and by 14, the number of years. Doing so I obtain an average number of transaction days per year for the index. I multiply this number by 5 (\$), which is around regular cost per transaction and this is the average value of transaction per year. To “break-even” the return from index per year should be equal to this value.

To compare, I find an average price for stock in index during the whole period. I convert the average return for corresponding index from Table 4.3 to annualized values, and multiply price and annualized return.

For the number of stocks, I divide the costs per year by profit stock profit and receive the number of stocks.

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<sup>34</sup>The minimal number of units that has to be bought or sold in order to make zero profits.

Table 4.6: Break-even number of stocks

Only Trading Days						Total Number of B/S Days					
	AVN	C/Y	AP	ER	Number		AVN	C/Y	AP	ER	Number
BM	7,93956044	39,6978022	229,119824	10,8360128	<b>3,66350639</b>	BM	18,9450549	94,7252747	229,119824	10,8360128	8,74170937
NC	8,92307692	44,6153846	297,863524	6,84303059	6,51982832	NC	20,6043956	103,021978	297,863524	6,84303059	15,0550223
CY	7,58241758	37,9120879	337,102536	13,8311901	2,74105755	CY	17,967033	89,8351648	337,102536	13,8311901	6,49511463
FN	9,06593407	45,3296703	384,309384	-16,069471	-2,8208563	FN	19,7582418	98,7912088	384,309384	-16,069471	-6,1477572
HC	7,97802198	39,8901099	350,09672	8,67263602	4,59953696	HC	18,6043956	93,021978	350,09672	8,67263602	10,7259175
IN	7,69230769	38,4615385	295,738844	7,10100785	5,41634924	IN	19,2362637	96,1813187	295,738844	7,10100785	13,5447419
EN	8,56043956	42,8021978	470,246709	9,61986642	4,4493547	EN	18,9230769	94,6153846	470,246709	9,61986642	9,83541564
TC	6,95054945	34,7527473	588,375721	17,5353944	1,98186288	TC	16,5659341	82,8296703	588,375721	17,5353944	4,72357043
TL	8,21978022	41,0989011	141,981055	-2,639082	-15,573181	TL	18,6318681	93,1593407	141,981055	-2,639082	-35,299904
UT	7,72527473	38,6263736	154,993109	1,30315432	29,6406749	UT	17,5494505	87,7472527	154,993109	1,30315432	67,3345061

Horizontal bold-faced column lists Dow Jones U.S. Indices. AVN is “average number of change of position” (in the left table only the number of days in which the position was changed from “in” to “out” or vice versa, in the right- the average sum of buy and sell days). C/Y is “costs per year”, AP stands for Average price of corresponding stock in the index, ER is excess return in dollars and Number is the break-even number of shares.

From table 4.6 it is evident, that the number of stocks in the index needed to eliminate transaction costs and to make zero excess from buy-and-hold strategy profit by using double-or-out strategy is significantly different among indices. So, for example, as DJUSUT index has the lowest excess return with relatively high number of transaction per year ( as compared to other indices’ with higher returns), thus the number of stocks, which would cover these transaction costs is the highest, 30 when considering only days with consequential buy/sell- sell/buy signals from strategies, and 67, when also changes of signal from/to hold signal are counted.

The negative values mean that trading stocks with the double-or-out strategy in this index would cause investor losses after extracting from profit the transaction costs.

Thus, I **reject** the hypothesis 5.

Lastly, I would like to present the reason for choice of strategy for methods’ outcomes verification. Putting in other words, why to use double-or-out strategy, as opposed to buy-and-hold strategy.

**Hypothesis 6.**

*Difference in returns between those from double-or-out and those from buy-and-hold strategy is not equal to zero.*

The bottom line, “AVERAGE”, in Table 4.3 represents the average daily excess (from duple-or-out over buy-and-hold strategy) return to the index through the whole period of time if the most profitable rules were known to investor beforehand and he followed them, for example,for trade in DJUSBM index in year 2001 and 2002 he relied on signals generated from AR200 and in 2003 he changed his rules to technical (1,50,00) rule and so on. I decided to follow exactly the most accurate for particular indices in particullar years methods and rules to show the ideal excess return, which investor could obtain during period from 2001 to 2014.

Table 4.7: Excess Return from Double-or-Out Strategy, combined rules.

Index	Average annualized return %
DJUSFN	0,19320921
DJUSTC	0,17005344
DJUSCY	0,1464824
DJUSTL	0,12410763
DJUSHC	0,112857927
DJUSNC	0,10757927
DJUSUT	0,06719548
DJUSIN	0,06188659
DJUSEN	0,0309314
DJUSBM	0,01072061

This difference is significant, taking in account that the excess returns,  $\pi_{(i,average)}$ , they are nearly equal to the annualized average gross returns,  $\Pi_{(i,average)}$ , from double-or-out strategy, which can be computed from Table 4.1, meaning that buy-and-hold strategy itself in the long run brings almost zero returns. I find these results to be strong enough **not** to **reject** the hypothesis.

Interestingly enough, it can be seen from comparison of results from table 4.5 and 4.7, the Basic Matherials, DJUSBM, index seem to be the hardest to outperform the mean return value, choosing the best forecasting rules. At the same time, with the smallest excess return from double-ou-out strategy, followed by most accurate signals, the average total return to this index is the highest.



## 5 Conclusion

The focus of this bachelor thesis was made on investigation of methods of forecast and strategies of trade of stocks in different industries. In this work I aimed to contribute some knowledge about relation between the choice of method of analysis of estimations of returns to stocks and these stock's industry affiliation. This topic has not yet been touched by any researchers, thus my results can be used for the further studies.

The investigation was made on 10 U.S. relatively young traded indices, each taken as a representator of distinct industry. The time-span of data is from the 2<sup>d</sup> of January, 2001 until the 31<sup>st</sup> of December, 2014. The data consisted of closing stock prices.

Following Yeyu Fang and Zhidong Xu's (2003) paper, I tested on my financial time series three valuation methods of stock prices' movements: technical analysis method, time series forecast method, combined-rules analysis method. For calculations of profitability and applicability of each I used the double-or-out strategy. The technical analysis was represented by five rules, based on moving-average crossovers, time series forecasts were made based on three rules, which incorporated different information sets, and these eight rules were combined into five, in order to test for their compliance and to improve accuracy of predictions. Each rule was used to generate signals, according to which the decisions about market position were made. The rule was said to be efficient to use, if the final profit of trade followed by the signals generated by this rule, was positive, and those profits were later compared by the value and conclusion about applicability of the method, to which this rule belongs, was drawn. This process was performed for all indices and the differences of conclusions, depending on index for which they are made, allowed to judge about industry's affiliation influence on the choice of proper method of analysis. The results for each index were presented on base of calendar years.

The main finding was that the choice of method does not depend on index's industry affiliation, neither does the rule for the method chosen. I concluded that

based on the fact that there was no solid pattern for any method to consistently outperform the other in one particular index. However, the results show that, in overall, the best decision of investor could be to rely on technical analysis, specifically, on its rule with shortest moving-average crossover, (1,50,0.00). This finding was very interesting, because it is different from what Yeyu Fang and Zhidong Xu showed: in their case they concluded, that neither technical analysis, nor time-series forecast analysis gives such market explanatory power to make predictions for price changes and thus, does not generate accurate signals, leading to misleading trading strategy for investor. The difference in findings could be due to the age of indices examined and the number of observations with nature of indices: their data was based on first 100 trading years for Dow Jones Averages, while I tested the the first and the most recent trading year of Dow Jones U.S. industrial indices.

In the course of investigations, I found it to be interesting to look, if the conclusion about independence of method choice and index's industry affiliation changes in times of crises. My findings show that, indeed the choice of method of valuation of prospective price changes seems to differ in times of crashed from those, which would normally be better to apply in absence of crises. Nevertheless, the timespan does not allow to see, if there is any pattern in applicability of some concrete method. Until then, the results are not informative enough, to decide on the one method, moreover, they show that, not only the rules of methods in different times of crises differ, but also the methods themselves.

As an accompanying subject-matter, I looked at differences in returns to individual indices. I found that, however, there can not be seen much of the difference in price movements prediction methods, the returns to indices are significantly different, varying from positive to even negative in case of following the "average from all methods rule" (taking in account generally unprofitable time series forecast). These negative returns would mean that trading for the long time in particular index is, on average, unprofitable.

Yet, another significant difference in indices was found in a form of differing number of stocks needed to break-even when trading during the long period of

time, here I used average of one year from the first 14.

As for verification of reliability of my investigation, for which I chose double-or-out strategy, I showed that this strategy allows to generate excess over buy-and-hold strategy return while following the most appropriate for concrete year and index rule's signals.

I see several more possible modifications for testing the dependence of choice of stock prices methods of valuation on index's industry affiliation. In my diploma thesis I would like to concentrate more on improvement of time series forecasts, applying other GARCH-family models to produce more accurate predicted returns. Also, the other strategies of trade could be invented, as for example, I would like to make some corrections to double-or-out strategy in a form of considering returns from uninterrupted and not isolated strategy, meaning that for hold signals an investor would keep the previous position, rather, than one stock, in index. Under this condition, to make it practicable, if the previous signal was buy, then the investor would continue paying LIBOR at the rate of the previous day, and the same would hold in case of sell signal, but he would be receiving fixed in previous day T-Bill interest.

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## List of Figures

1	Dow Jones U.S. index . . . . .	23
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## List of Tables

2.1	Discriptive Statistics of <i>log</i> -returns . . . . .	21
2.2	General Statistics of Observations . . . . .	22
2.3	General Statistics of Indices . . . . .	23
3.1	DJUSBM-DJUSFN Results for technical trading rules. . . . .	28
3.2	DJUSHC-DJUSTC Results for technical trading rules. . . . .	29
3.3	DJUSTL-DJUSUT Results for technical trading rules. . . . .	29
3.4	AR(1) & AR(1)-GARCH(1,1) Models Parameter Estimates. . . . .	33
3.5	Results for time series forecasts. . . . .	35
3.6	Results for strategies combining technical trading rules and time series forecasts. . . . .	36
3.7	Results for strategies combining technical trading rules and time series forecasts. . . . .	37
4.1	Average daily indices returns from double-or-out strategy by the years (left) & Rules comparison(right) . . . . .	39
4.2	Yearly AR rules performance . . . . .	41
4.3	Choise of best rule by the years and industries . . . . .	41
4.4	Yearly performance comparison of technical to combination of tech- nical and time-series forecasting rules . . . . .	43
4.5	Total Average Index Returns . . . . .	45
4.6	Break-even number of stocks . . . . .	47
4.7	Excess Return from Double-or-Out Strategy, combined rules. . . . .	48