PRACE NAUKOWE
Uniwersytetu Ekonomicznego we Wrocławiu

RESEARCH PAPERS
of Wrocław University of Economics

Nr 381

Financial Investments and Insurance – Global Trends and the Polish Market

edited by
Krzysztof Jajuga
Wanda Ronka-Chmielowiec

Publishing House of Wrocław University of Economics
Wrocław 2015

Copy-editing: Agnieszka Flasińska
Layout: Barbara Łopusiewicz
Proof-reading: Barbara Cibis
Typesetting: Małgorzata Czupryńska
Cover design: Beata Dębska

Information on submitting and reviewing papers is available on
the Publishing House's website
www.pracenaukowe.ue.wroc.pl
www.wydawnictwo.ue.wroc.pl

ISSN 1899-3192
e-ISSN 2392-0041

ISBN 978-83-7695-463-9

The original version: printed

Publication may be ordered in Publishing House
tel./fax 71 36-80-602; e-mail: econbook@ue.wroc.pl
www.ksiegarnia.ue.wroc.pl

Printing: TOTEM

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Streszczenia

PRACE NAUKOWE UNIWERSYTETU EKONOMICZNEGO WE WROCŁAWIU
RESEARCH PAPERS OF WROCŁAW UNIVERSITY OF ECONOMICS **nr 381 • 2015**

Financial Investment and Insurance –
Global Trends and the Polish Market

ISSN 1899-3192
e-ISSN 2392-0041

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DECISION-MAKING PROCESS: TECHNICAL ANALYSIS VERSUS FINANCIAL MODELLING

Summary: Every decision-making process is a consequence of the selected investment strategy. The choice of the strategy depends on the expected rate of return, risk aversion of the investor, investment horizon, etc. If the long-term investment on the capital market is concerned, there are two options, among others, that can be taken into account. One of them is the application of the technical analysis that is based only on the past data. According to the Charles Henry Dow approach the prices move in trends, market action discounts everything and history repeats itself. On the other hand there is the modelling approach that takes into account macroeconomic environment of price volatilities and assumes that prices change randomly. The purpose of this paper is to evaluate the performance of both technical analysis and financial modelling in the context of the forecasting accuracy. The empirical part is based on the stock prices of financial companies traded on the Warsaw Stock Exchange. This is an attempt to compare the idea of turning points in technical analysis with structural changes in asset pricing models.

Keywords: Technical analysis, investment strategy, financial modelling.

DOI: 10.15611/pn.2015.381.15

1. Introduction

The investment strategy can be understood as the long-run growth criterion to investment policy, which assumes maximisation of the capital growth and at the same time gains a given probability of maintaining an accumulated risk-free return over expected investment horizon [Li 1993]. The long-run investment horizon can involve a considerable risk of losing a substantial part of wealth in the short-run. So the starting point of the analysis is to select clearly such a horizon.

Expectations of future price movements could be based on many approaches. One of the possibilities is to analyse prices applying the technical analysis for modelling and for forecasting future behaviour of prices. In this sense behaviour of prices follow trends and from past trends we can predict the future. Neely [1997] presents the profitable use of technical analysis to trade in foreign exchange markets. However, Hoffmann and Shefrin [2014] found that investors who use technical analysis and trade options frequently make wronging in dramatically lower returns than other investors. Menkhoff [2010] pointed out that technicians apply trend-following behaviour and their view is mainly determined by psychological influences. Tian, Wan and Guo [2002] tried to explore whether some forms of technical analysis can predict stock price movements and make excess profits based on selected trading rules.

From all tools proposed by the technicians mainly in use are moving average, applied for example by Schulmeister [2009] or Borowski [2006], Fibonacci projection [Banasiak 2010] or just candlestick charting ([Marshall, Young, Cahan 2008] or [Fock, Klein, Zwergel 2005]). It is worth mentioning that any of the methods seems to be the perfect one. For example Zielonka [2004] proves that the technical analysis is the representation of typical cognitive biases.

The modelling, standard approach in decision-making process is based on the Markowitz [1952] mean-variance portfolio selection models. Such attempt assumes linear dependency of the rate of return of the portfolio or an asset on selected factors, mainly the market return. Portfolio analysis is based on the efficient market hypothesis that claims that price changes are serially independent and can be treated as a random walk. According to that the price movement is random and unpredictable in its nature. Forecasts based on modelled returns are widely presented in the literature, for example by Fama [1996], Wang [2003], O'Doherty, Savin, Tiwari [2012].

Economists try to compare results of forecasting returns taking into account different approaches to data analysis. Lui and Mole [1998] showed forecasts of exchange rate based on technical analysis and fundamental analysis. They concluded that technical analysis seems to be slightly more useful in forecasting trends than the fundamental analysis, but significantly more useful in predicting turning points. Chou et al. [1997] compared the effectiveness of the application of the technical analysis and the artificial intelligence. Their results confirm that the synergy of both outperforms systems using any one particular technique alone. Dourra and Siy [2002] analysed investment using technical analysis and fuzzy logic. In their paper, Liu and Zheng [2011] introduced the Bollinger Bands into the stochastic volatility model.

If the efficient market hypothesis holds then it possible to forecast future prices of assets on the basis of their previous level. The purpose of the paper is to evaluate whether the forecasts of prices of assets, based on previous periods prices, calculated according to the technical analysis approach are more accurate than those based on financial models. The two approaches proposed take into account structural breaks, understood as turning points, in time series. Relying on price movements it is possible to identify moments or signals for buying or selling assets.

2. Modelling approach

Generally, a strategy is a set of ordered steps to enable the effective implementation of the priorities and objectives. In the case of an entity that is the financial sector, strategic planning is a process in which economists predict and control their development, not waiting passively for future events. They skilfully try to respond to changes in the environment and react in advance. The main objectives of the construction of the development strategy are: minimizing uncertainty in the functioning of the sector, the implementation of long-term development, the identification of promising directions of development, optimal use of resources and the efficient management of entities as a system of mutually reinforcing elements.

In the long-run investment the investment strategy can be used for recognizing signals for selling or buying assets. Such activity, known as market timing, helps to identify when assets in general are under- or overvalued relative to the fixed-income securities [Merton 1981]. On the basis of market timing it is possible to forecast when shocks will outperform bonds or when bonds will outperform stocks. So in practice it refers to predicting if market prices will rise or fall [Grant 1978]. The signals for selling or buying assets very often come from structural breaks, identified as turning points in the series.

The starting point for identifying turning points in proposed approach is modelling prices of assets as a simple linear time series function:

$$p_{it} = \beta_{i0} + \beta_{i1t} + \xi_{it}, \tag{1}$$

where: p_{it} – a price of asset i in time t; t – a time trend; β_{i0}, β_{i1} – the structural parameters; ξ_{it} – the error term.

Price modelling and forecasting based on the models make sense if the structural parameters of the model are stable in time, which means that they do not change over time. Applying the most popular test of the stability parameters, known as Chow test, the structural changes in the model can be identified [Kufel 2007]. The test ignores 15% of observations and then divides the sample into two parts. On the basis of these subsamples the F statistic is calculated under the null hypothesis that the parameters are stable in time. It can be shown that even when the number of observations does not exceed the number of predictor variables, the test remains uniformly most powerful [Wilson 1978].

In order to confirm structural changes some other stability tests can be applied, for example the Quandt likelihood ratio test (QLR) for structural break at an unknown point, with 15% trimming. The QLR is a general test, based on the likelihood function. It can be used if periods of the structural breaks are not known [Thursby 1982]. The null hypothesis assumes, as in the above test, the stability parameters, so no structural changes in series. The Brown, Durbin and Evans test, known as CUSUM test [Brown, Durbin, Evans 1975], allows for drawing two lines around the statistics of the test, calculated from the subsamples. Exceeding these lines is the instability of parameters and therefore the occurrence of the turning points. Extension of the CUSUM test, the CUSUMSQ test, operates similarly, is based on sum of squares of residuals [Coutts, Roberts, Mills 1997]. Another test was proposed by Harvey and Collier [Harvey, Collier 1997].

After identification of the turning point or points (structural breaks) that could exist in the series, it is reasonable to test whether the analysed series is a stationary or a non-stationary process. According to Hylleberg and Mizon the main forms of non-stationarity in series are trend and seasonal variation [Hylleberg, Mizon 1989]. Both of elements can be deterministic or stochastic, so the time series y_t can be factored into five components:

$$y_t = T_t + S_t + \mu_t + \xi_t + \varepsilon_t, \tag{2}$$

where: T_t – deterministic trends (for example a polynomial in t); S_t – deterministic seasonal effects (e.g. seasonal dummy variables); μ_t – stochastic trends (it could be a random walk or integrated process); ξ_t – stochastic seasonal effects (for example seasonally integrated process); ε_t – a stationary random vector with finite mean and variance.

In analysed time series any or at least one of the mentioned elements can exist. Under the null hypothesis of the ADF test the series is integrated in order one in opposite of the alternative hypothesis that is $I(0)$.

The integration level determines if the variable can be used in the model straight or needs any transformation. The proposed model that includes turning points takes a form:

$$p_{it} = \beta_{i0} + \beta_{i1}t + \sum_{j=1}^{k}\gamma_{ij}D_{ijt} + \sum_{j=1}^{k}\delta_{ij}D_{ijt}\cdot t + \xi_{it}, \tag{3}$$

where: D_{ijt} – the zero-one variable for the asset i after the j-th turning point in time t, where $j = 1, \ldots, k$; γ_{ij} – the value of constant after the turning point; δ_{ij} – the parameter of the time trend after the turning point. The rest of symbols are as in (1).

3. Technical analysis approach

Technical analysis is the study of market action, mainly through the analysis of charts, for the purpose of forecasting future price trends. The main features of assets are: price, volume and open interest (the last one only for futures and options). The philosophy of the technical analysis is based on three statements. The first one is that the market action discounts everything, which means that changes in demand and supply are reflected by the prices. The analysts are not concerned with the reasons of price changes and they believe that knowing those reasons is not a necessity in the forecasting process. The second fundamental and essential element of the technical analysis is that the prices move in trends. So the key point is to identify trends and to recognize trend-following nature of the prices. Finally, it is assumed that history repeats itself. It is believed that if the particular patterns have worked well in the past, they should continue to work well in the future, in another words the future lies in a study of the past [Murphy 1999; Pring 2002].

As the first one Charles Dow[1] defined the basic principles of the technical analysis [Murphy 1999]:

- the averages discount everything,
- the market has three trends: the primary trend, the intermediate (secondary) trend, and the minor trend,
- major trends have three phases,
- the averages must confirm each other,
- volume must confirm the trend,
- a trend is assumed to be in effect until it gives definite signals that it has reversed.

Comparing modelling approach, based on the fundamental analysis, we can say that the fundamental studies concentrate on the cause of the market movement, while technical approach concentrates on effects. Both approaches allow for forecasting future price movements.

On the long term charts trends, major reversal patterns (for example the head and shoulders reversal pattern, double or triple tops and bottoms patterns) and continuation patterns (e.g. triangles) can be found.

4. Data and empirical results

The empirical analysis includes prices of assets (closing prices at the end of each month) representing the bank sector on the Warsaw Stock Exchange. From among all the assets those traded for longer than 200 months were selected. The data included the prices of assets from the first day of their appearance on the Warsaw Stock Exchange until May 2014, so the number of observations varies, depending on the asset.

At the beginning of the empirical work the turning points need to be identified. For the purpose of this paper two points for each series were identified. The first one was the highest price in growing trend, after that the trend changes direction, and the second was the lowest price in downward trend. For simplicity sake the points are called Max and Min. Then the stability tests were employed in order to recognise if there were any structural breaks in the time series. Table 1 presents values of applied stability test. The Chow test (1) includes values of the Chow statistic if the date of dividing the sample into two parts is proposed automatically. The second one, Chow test (2), is for the dates suggested by the application of the QLR test. Both versions (3) and (4) are for the subsamples selected for the highest and the lowest prices of

[1] Charles Dow (1851–1902) was an American journalist who developed the main principles for understanding and analyzing market behaviour that gave the groundwork for the technical analysis. He co-founded an American publishing and financial information firm Dow Jones & Company.

assets. From these points the time trends change directions and the levels of constant change. The last column presents calculated statistics of the Harvey-Collier test (based on *t*-statistic). By the asterisk (*) the cases for statistics greater than the critical values were denoted. It can be noticed that the structural breaks appeared in each series.

Table 1. Results of the stability tests

Asset	Chow test (1)	Chow test (2)	Chow test (3)	Chow test (4)	QLR test	H-C test
BHW	0.3990	60.2708*	0.3086	26.8918*	120.542*	–0.0673
BNP	0.2368	481.609*	481.609*	42.1711*	963.219*	–0.7775
BOS	0.7408	160.665*	105.450*	59.8102*	321.329*	–5.2730*
BPH	4.4567*	221.166*	131.474*	117.099*	442.332*	–4.7203*
BZW	25.6364*	76.7032*	60.8202*	21.6981*	153.406*	6.4594*
ING	26.4811*	66.8265*	53.6582*	14.5452*	133.653*	9.3316*
MBK	11.8776*	46.3001*	37.3073*	26.4037*	92.6003*	3.7233*
MIL	8.1122*	35.3174*	13.3668*	15.9454*	70.6349*	–2.8329*
UCG	273.743*	593.851*	474.820*	57.9797*	1187.7*	–5.7003*

* Significant at 0.05 significance level.

The Chow test: (1) samples divided in two equal parts, (2) samples divided in the month suggested by the QLR statistic, (3) and (4) samples divided in the month with highest (smallest) values in the series.

Source: own calculations.

To confirm above results, another test was applied. Figure 1 illustrates values of statistics calculated according to the CUSUM test. Statistics for each company are presented on separate graphs. It can be noticed that in almost all cases results confirm above conclusion, so the parameters cannot be treated as being stable over time, so the turning points exist in analysed series.

Then the turning points, representing structural breaks, were recognized. As it was mentioned above, only two points for each asset were selected. One of them represents the highest price (max), so the turning point from growth to fall and another one from fall to growth (min). Including these points the ADF test was applied. First, stationarity around the constant and the time trend was tested. Then around the constant and the time trend with changed level according to one of the selected points separately and then including two of them. For changes in constant and the time trend dummy variables were created. Table 2 includes results of testing the stationarity for two breaks jointly. Variables *D* and *Dt* denote changes in constant and in time trends in two turning points (as in the model 3).

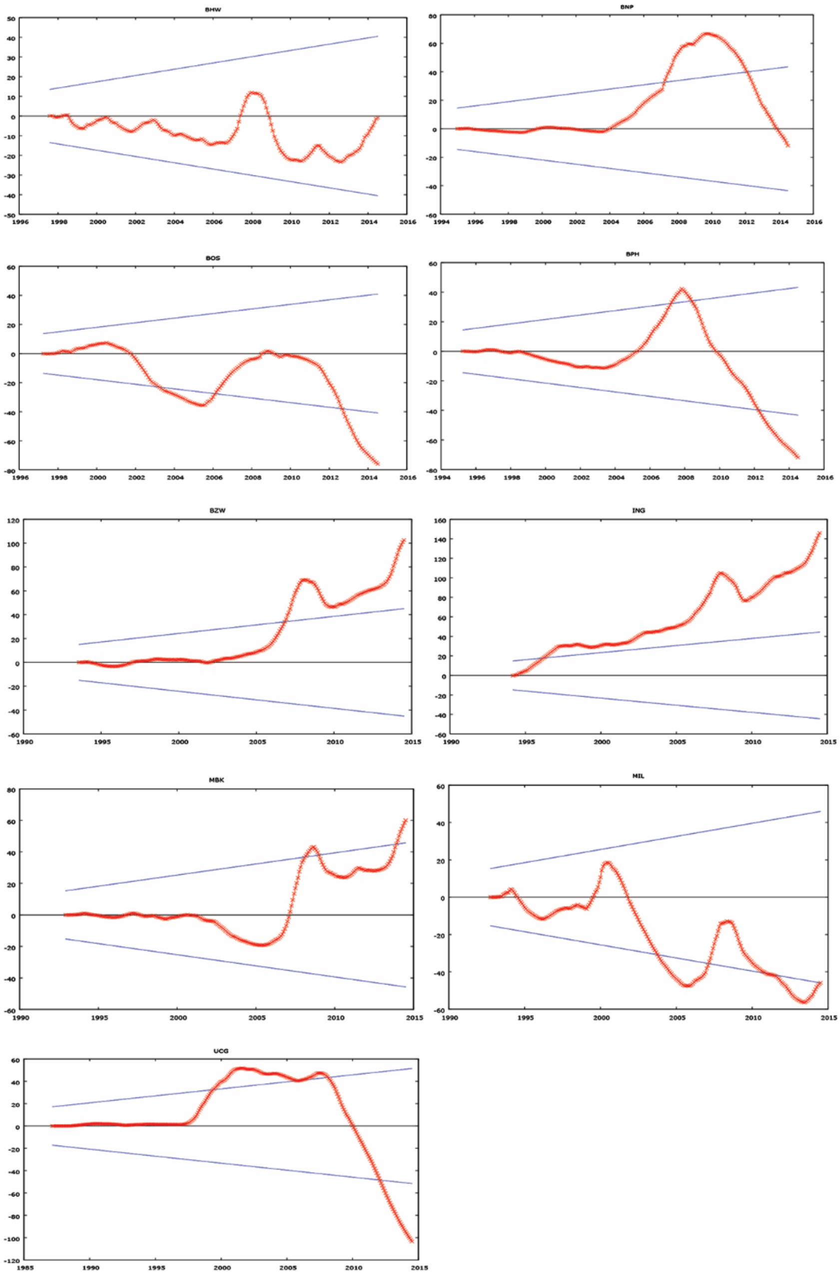

Figure 1. Results of the CUSUM test, 95% confidence interval

Source: own calculations.

Table 2. Results of the test of the existence of the unit root

	Date on ADF		ADF statistics		
	Max	Min	*D*	*Dt*	*D & Dt*
BHW	2007m5	2009m2	–4.4589*	–4.3765*	–4.6048*
BNP	2007m3	2012m10	–2.4001	–2.4318	–2.6595
BOS	2008m7	2012m8	–2.6553	–2.6641	–2.9407
BPH	2007m1	2009m2	–3.9810	–3.9895	–2.4728
BZW	2014m2	2009m3	–3.8216	–3.8285	–4.1115
ING	2014m4	2009m2	–3.4374	–3.4938	–3.3991
MBK	2013m11	2009m2	–3.4038	–3.4418	–3.2710
MIL	2000m2	2009m2	–4.1376*	–4.2000*	–4,1528
UCG	2007m4	2012m5	–3.2415	–3.3537	–3.3705

* Significant at 0.05 significance level.

Source: own calculation

As it was expected, according to above results, in almost all cases the null hypothesis cannot be rejected. It means that the prices were not stationary. It confirms reasonability of including changing elements in the series. The results for BHW and MIL are not surprising. Because of the monthly data up two twelve lags were tested. Statistics for BHW were not significant up to the five lags and for MIL up to 9 lags. Then for each asset the model was estimated:

$$p_{it} = \beta_{i0} + \beta_{i1}t + \gamma_{i1}D_{i1t} + \gamma_{i2}D_{ij2} + \delta_{i1}D_{i1t} \cdot t + \delta_{i2}D_{i2t} \cdot t + \xi_{it}. \qquad (4)$$

As it was mentioned, the model included six elements: constant, time trend, constant after the first turning point, constant after the second turning point, time trend after the first turning point and time trend and after the second turning point. The results are given in Table 3.

Table 3. Estimated models

	Const	Time	Const1	Const2	Time1	Time2	R^2
BHW	30.5315*	0.2287*	961.7476*	–1112.2*	–4.6713*	5.2692*	0.78812
BNP	–37.268*	0.67798*	780.3424*	–1017.6*	–3.2687*	3.9044*	0.90172
BOS	28.0784*	0.24197*	257.9759*	–521.93*	–1.1647*	1.9464*	0.56245
BPH	–31.361*	0.72893*	1571.7*	–1451.0*	–7.7862*	6.9112*	0.78823
BZW	–48.705*	1.0440*	6672.8	–613.16*	–23.9447	2.5813*	0.85327
ING	0.65431	0.28389*	1559.7	–177.98*	–5.5544	0.77099*	0.81264
MBK	–48.547*	1.4210*	28881.0	–701.32*	–10.1020	2.8234*	0.76792
MIL	–0.42684	0.05982*	1.2463	–11.353*	–0.0343*	0.03701*	0.30802
UCG	–1.3378	0.75362*	464.9785*	–616.83*	–2.5660*	2.4577*	0.80140

* Significant at 0.05 significance level.

Source: own calculation.

Generally, estimated models were well fitted. Mostly they have significant explanatory variables. Diagnostic tests, based on regressions residuals, showed that almost in all cases normally distributed with constant variance. The problem that appeared is the serial correlation of residuals. The question that arises is if the time trend in the analysed series is deterministic, as it was assumed in the model and confirmed by the significance test, or the stochastic trend should be included. In all cases predictive failure test shows no reason to reject the null hypothesis so the models can be used for forecasting. On the basis of estimated models, consequently, the forecasts for the next month, June 2014, were calculated.

According to the purpose of the paper, in the next step the forecasts based on the technical analysis were calculated. Murphy suggests application of long term trends and four period moving averages for monthly data [Murphy 1999].

Table 4 includes forecasts calculated on both strategies of decision-making. Then, comparing to the realisations, the *ex post* type of errors of forecast were calculated. It can be seen that in six cases the technical analysis gave results closer to the real values, in three cases the model better predicted future prices.

Table 4. Forecasts on June 2014 based on two strategies

	Forecasts based on models		Forecasts based on technical analysis	
Asset	Forecasted price	*Ex post* error (%)	Forecasted price	*Ex post* error (%)
BHW	110.7351	7.5248	115.1843	3.8092
BNP	91.9952	58.7493	87.3375	50.7118
BOS	49.7545	5.0560	46.9400	0.8868
BPH	48.6235	4.9504	52.7175	13.7870
BZW	341.8008	7.3711	392.599	6.3955
ING	127.0005	4.2285	133.0375	0.3300
MBK	496.8541	1.6130	518.748	2.7223
MIL	6.9142	11.0138	8.7950	13.1917
UCG	26.8679	5.8625	26.4025	4.0288

Source: own calculations.

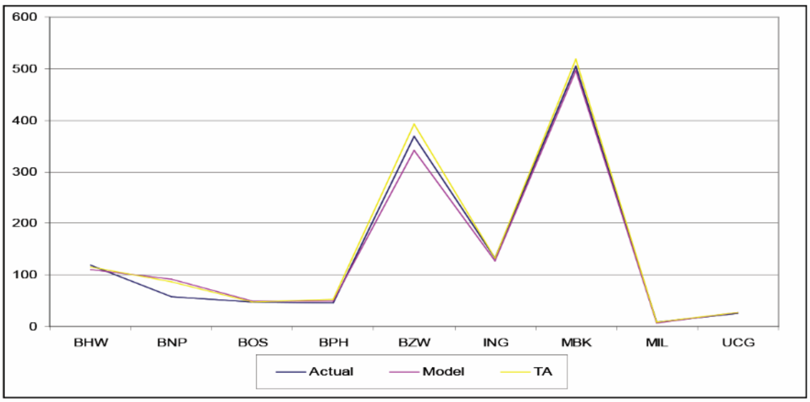

Figure 2. Comparison of forecasts and real prices of assets

Source: own calculations.

Figure 2 shows the comparison of assets price realisations (Actual) and forecasts obtained by the estimated models (Model) and by the technical analysis (TA) for one period ahead. It can be said that in some cases forecasts undervalued in some overvalued. It does not depend on the choice of method.

5. Conclusions

It is known that the decision-making process is based on the particularapproach. Proposed in the paper, two alternative approaches, one of them based on modelling the structural breaks and the second, based on the technical analysis, allowed us to identify the turning points that are useful determinants for predicting future prices and selecting the right moments for buying and selling assets.

As it was showed, it is not possible clearly to decide which strategy gives better fitted forecast. Comparison showed that forecasts with smaller *ex post* errors were obtained if the technical analysis was in use. Such results can slightly confirm the hypothesis given in the introduction. However, we should have in mind that only one of the techniques of the technical analysis was employed and only forecasts for one period ahead were calculated. It could be interesting to compare results among forecasts calculated with range of techniques and from more periods.

On the other hand, good model specification is required for forecast calculation. As it was mentioned, maybe an introduction of the stochastic trends in the models would provide better forecasts.

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PODEJMOWANIE DECYZJI INWESTYCYJNYCH: ANALIZA TECHNICZNA A MODELOWANIE PROCESÓW FINANSOWYCH

Streszczenie: Każdy proces podejmowania decyzji jest oparty na wybranej strategii inwestowania. Wybór strategii zależy m.in. od oczekiwanej stopy zwrotu, awersji inwestora wobec ryzyka oraz od horyzontu inwestowania. W przypadku długoterminowych inwestycji na rynku kapitałowym decyzje podejmować można na podstawie dwóch alternatywnych podejść. Jedno z nich wykorzystuje analizę techniczną, opartą na danych z przeszłości. Według teorii Charlesa Dowa ceny podlegają trendom, rynek dyskontuje wszystko, a historia się powtarza. Drugie podejście, jakim jest modelowanie, bierze pod uwagę otoczenie makroekonomiczne wpływające na zmienność cen oraz zakłada, że ceny zmieniają się w sposób losowy. Celem artykułu jest ocena skuteczności wykorzystania analizy technicznej oraz modelowania finansowego w kontekście efektywności prognoz. Część empiryczna oparta jest na cenach akcji spółek sektora bankowego notowanych na GPW w Warszawie. Artykuł stanowi próbę porównania idei punktów zwrotnych, identyfikowanych w analizie technicznej, ze zmianami strukturalnymi, identyfikowanymi w modelach wyceny kapitałowej.

Słowa kluczowe: analiza techniczna, strategie inwestycyjne, modelowanie procesów finansowych.