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Marek Straszak*

Accuracy as one of the dimensions of the quality of stock market recommendations published by Polish brokerage houses

1. Introduction

Thanks to the analyses of various aspects (internal and external) of the functioning of listed companies, investment recommendations increase the amount of available and professionally processed information, thereby improving the efficiency of capital markets.

In addition to their undoubtedly important function in improving the efficiency of capital markets, recommendations are primarily a source of knowledge for investors (Jegadeesh, Kim 2006; Hashim, Strong 2016). Equity investment requires market participants to devote more and more attention and time, and to have the appropriate analytical skills (Lusardi, Mitchell 2014). This is not only due to the growing number of listed financial instruments but also because of the increasing amount of information available to market participants. This information covers both the general macroeconomic situation and individual segments of the economy, as well as data from companies.

Due to their function, recommendations are an important tool for investors seeking support in the investment process and for the capital market in its development. It is crucial that they are prepared with due care and objectivity by persons with the appropriate knowledge and qualifications. Brokerage houses employ stock market analysts who provide their clients with professional assistance in decisions regarding capital allocation. In addition to daily commentary and minor ad hoc analyses, the essence of analysts' work is to publish recommendations that

* Krakow University of Economics, Krakow, Poland, e-mail: straszak.marek.pawel@gmail.com, ORCID: 0009-0001-0366-2128

indicate the expected direction of changes in the prices of financial instruments. The qualifications of equity analysts, combined with the standards for making recommendations set by brokerage houses, should ensure the high quality of the published materials.

This is also particularly important in the context of technological changes taking place in the financial sector. An increasingly common service offered by some financial institutions is **robo-advisory**. Currently, there is no legal definition of this type of service, but in market practice it is assumed that robo-advisory is a process in which recommendations are made and communicated using algorithms and automatic or semi-automatic systems (UKNF, 2024). Research shows that recommendations generated using artificial intelligence are less optimistic and are more evenly distributed between positive, negative, and neutral. In addition, they are published or updated more frequently and are more effective in the long term than those developed by stock market analysts (Coleman et al. 2022). As a result, they may become serious competition for traditionally produced analytical reports, especially if the latter are not sufficiently useful for investors.

Stock market analysts are usually qualified professionals whose skills in financial modeling and company valuation are confirmed by reputable certificates (e.g. Chartered Financial Analyst or Investment Advisor license). They are also subject to market standards and guidelines imposed by the institutions that employ them, as well as customer expectations, which may influence their work and the valuations of listed companies consequently (Brown et al. 2015). The impact of psychological (behavioral) factors, which may affect the content of the recommendations issued, is also significant (Mokoaleli-Mokoteli et al. 2009; Machado 2021). The influence of these factors means that the reports they produce may not always contain information processed in a way that ensures the highest value for investors. Therefore, there is a need to examine the quality of recommendations, which determines their macroeconomic (impact on financial market efficiency) and microeconomic (impact on the financial performance of investors using them) functions.

This research makes three distinct contributions to the literature. Firstly, the study extends the literature on investment recommendation by defining the concept of investment recommendation quality and classifying the dimensions through which it can be assessed. While prior studies have often described the results on different kinds of recommendation parameters, this article provides a systematic review of the dimensions of their quality and contributes to the theoretical understanding of the difference between the effectiveness and accuracy of investment recommendations.

Secondly, previous publications on the accuracy of recommendations have mostly focused on individual aspects. This study is intended to be a comprehensive analysis of the recommendations published for companies listed on the Warsaw Stock Exchange and proposes four indicators to examine the accuracy of target prices in recommendations in order to show the full picture of their quality in this dimension. Moreover, this article unveils a novel approach to examining accuracy by positive and negative recommendations and by sector.

Thirdly, what makes this research stand out among other works on the Polish stock exchange is the number of examined recommendations and the long range of data. The inclusion of 10,469 recommendations issued between 2005 and 2019 in the scope of the study made it possible to cover more than four economic and stock market cycles, and therefore should well illustrate the changing conditions on the capital market.

This article aims to answer the following research questions:

- What percentage of recommendations accurately indicate the direction of investment?
- What percentage of recommendations are implemented at the end of their validity period?
- What percentage of recommendations are implemented during their validity period?
- Are stock market analysts wrong when determining the investment potential of companies, and if so, to what extent?

Chapter 2 is devoted to defining the concept of recommendation quality and describing the dimensions by which it can be assessed. Chapter 3 reviews the existing literature on the accuracy of recommendations. Chapter 4 presents the scope of the data used and the research methodology applied. Chapters 5 and 6 are devoted to presenting the empirical results and conclusions of the study.

2. Quality, relevance, and effectiveness of recommendations

There are many definitions of quality in the literature that attempt to capture its meaning from different angles (Rura-Polley, Clegg 1999; Seawright, Young 1996). Garvin (Garvin 1984) divided definitions of quality into seven categories: general (transcendent), production-related, product-related, user-related, value-related, multidimensional, and strategic. Another division of definitions was proposed by Reeves and Bednar (Reeves, Bednar 1994), who believe that quality can be

perceived as: excellence, value, compliance with specifications, meeting or exceeding customer requirements, and as a dynamic process. Quality can be defined as the degree to which an object (e.g. a product, service, process, organization, or phenomenon) meets the requirements of a specific entity (Badura 2022). It can also be considered from the point of view of meeting the manufacturer's expectations (profitability and competitiveness of the product) and from the point of view of satisfying the user's needs (Frąś 2000). According to ISO 8402-1986, quality can be defined as the totality of features and characteristics of a product or service that determine its ability to satisfy stated or implied needs (Szutkowska, 2016). Although this definition could well fit the description of recommendation quality, it seems too general.

Since there is no single consistent definition of recommendation quality in the literature, it is reasonable to fill this gap based on a framework drawn from management and quality science. With regard to the shares of listed companies, the quality of a recommendation encompasses all the features and characteristics that determine its ability to systematically provide reliable and professional-standard information on the company's financial situation and the expected value of its securities, thereby effectively supporting investors' decision-making, improving efficiency and promoting the capital market.

There is no consensus among researchers as to whether the quality of recommendations (manifested primarily in their accuracy) has a significant impact on their effectiveness. There are studies indicating the existence of such a relationship (Loh, Mian 2006; Ertimur et al. 2007), but there are also those that deny it (Mikhail et al. 1999; Hall, Tacon 2010). However, the quality of a recommendation should somehow translate into its effectiveness. However, the relationship between the quality and effectiveness of a recommendation is sometimes ambiguous. For example, it may turn out that even though a recommendation was made carefully, in accordance with regulations and applicable standards, and even proved to be accurate, the investment made on its basis generates a lower rate of return than the market benchmark. The opposite situation may also occur, where a poor-quality recommendation leads to a successful investment. It follows that the effectiveness of recommendations may largely depend on their skillful use in the investment process applied by the market participant. Based on recommendations, appropriate investment strategies can be developed that exploit their certain properties while mitigating any shortcomings. The relationship between effectiveness, quality and its dimensions, as well as the factors that shape it, is shown in Figure 1.

The quality of recommendations can be assessed in many dimensions. Based on the literature, an attempt was made to classify them, as shown in Figure 2.

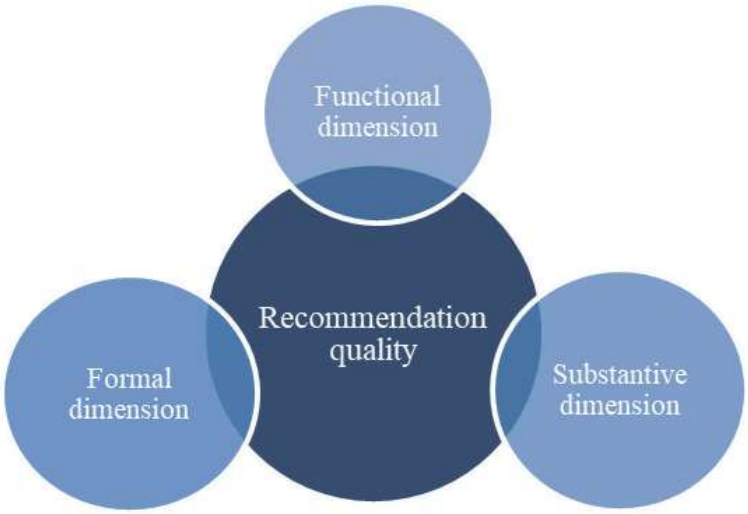

Figure 1. Effectiveness and quality of recommendations

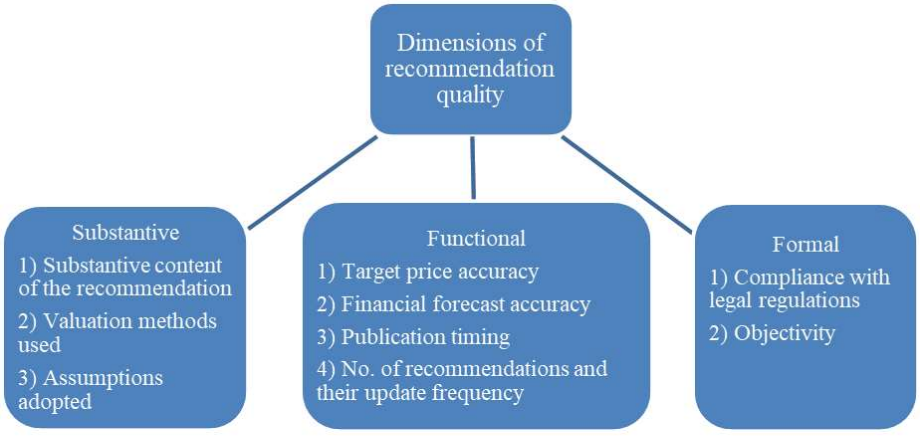

Figure 2. Dimensions of recommendation quality

Firstly, the substantive dimension of analytical reports can be assessed. To this end, it is necessary to check whether the recommendation contains an appropriate macroeconomic and sectoral analysis, whether historical data from financial statements are included and presented in an appropriate manner, and what macroeconomic assumptions have been made for the purpose of forecasting

results. Włodarczyk shows that while almost every recommendation includes historical financial data generated by the company, more than half of the reports do not contain a macroeconomic analysis and a description of the sector in which it operates (Włodarczyk 2020). The research also shows that the majority of recommendations do not include assumptions about the future macroeconomic environment. These were described in only one-third of the cases examined.

Secondly, quality can be determined based on the number and adequacy of the valuation models used. The choice of valuation methods may prove crucial for determining the value of a company, as different approaches usually indicate different investment potentials. A well-executed valuation requires the adoption of an appropriate approach to determining the intrinsic value of a company, so the use of inappropriate methods may result in an incorrectly calculated target price. However, there is no single market practice indicating how many and which methods should be used. Asquith and colleagues, after analyzing 1,126 analytical reports, revealed that almost all of them used a comparative valuation method based primarily on P/E and EV/EBITDA ratios, and only 12.8% of the reports contained a valuation based on discounted cash flow models (Asquith et al. 2005). Demirakos and colleagues, examining recommendations issued for companies in the United Kingdom, noted that multiplier analysis was used in 52.86% of cases, which is only slightly more often than the DCF method, which analysts used in 47.14% of recommendations (Demirakos et al. 2010). They also noted that analysts more often use the DCF method for smaller companies whose cash flows are characterized by greater uncertainty and for those for which the peer group in a given industry is limited. In addition, they pointed out that DCF methods are used more often in a declining market, while comparative methods are used more often in a growing market. Huang and colleagues noted that the DCF model is more readily used by analysts in relation to companies with poorer performance and higher risk (Huang et al. 2023). In addition, they observed that investors react more strongly to recommendations supported by the DCF model. A similar relationship is also confirmed by the research of Sayed, who points out that although analysts are least willing to use the DCF method, this approach provides the most accurate target price forecast (Sayed 2015). On the other hand, Prusak examined the accuracy of valuation models used in stock market recommendations on the Polish market (Prusak 2015). It turns out that the highest accuracy can be achieved by using a combined valuation, i.e. a weighted average of two other valuations, e.g. DCF and comparative valuation. Next in line in terms of effectiveness was comparative valuation, followed by DCF valuation.

It is not only the choice of the method itself that can affect the calculated value of a company. The assumptions made, and errors in their application, are also important. This is particularly important in the DCF method, which depends on

many parameters, which are decided on a discretionary basis by the analyst or imposed from above by the brokerage house's policy. Research indicates numerous shortcomings committed in this regard by analysts (Kowalski 2018; Zarzecki 2024). It has been shown that the recommendations lack information on how to calculate the cost of capital used for discounting, especially in relation to the risk-free rate and the risk premium. Another shortcoming of the valuations prepared is that when determining the beta coefficient, leverage is often not applied (i.e. adjusting its value depending on the changing level of debt in the company), but is arbitrarily assumed to be 1 throughout the forecast period. Analysts also often use the nominal rather than the effective tax rate. Furthermore, detailed calculations of residual value are very rarely included in analytical reports. Researchers also point to simple calculation errors made by analysts. Using various valuation methods, primarily comparative methods, analysts often apply various types of subjective adjustments to make their valuations more consistent with the characteristics of a given company. These adjustments relate, among other things, to the structure of the company, its relative market position, or past share price performance. Research shows that recommendations in which analysts apply subjective valuation adjustments are more accurate (Bonini et al. 2022).

Investment recommendations issued by analysts may also be assessed from a formal perspective. Analytical reports should be prepared with due diligence, in accordance with the law and objectively when determining the target price for a given security. However, it should be borne in mind that achieving this goal is difficult in practice. Analysts' access to information, especially from companies, is not always equal. Furthermore, close cooperation between an investment firm and an issuer on many levels may lead to conflicts of interest, often resulting in overvaluation. On the other hand, thanks to its contacts with the issuer on various levels, a brokerage house may be able to develop more accurate financial forecasts (Mehran, Stulz 2007).

Unfortunately, there are many violations of the principle of fairness toward clients on the capital market in order to achieve benefits for a financial institution or stock market analyst. This problem is analysed by Buczek (Buczek 2005). He points to several examples of practices by brokerage houses and analysts themselves that may affect the objectivity of the analysis presented and the valuation of the company. These include the following relationships:

- securities issuers are clients of brokerage houses,
- analysts prefer to issue positive recommendations in order to maintain good relations with company management,
- positive recommendations increase interest in transactions involving financial instruments.

The first two groups of recommendation quality dimensions mentioned above (substantive and formal) relate more to the way reports are produced. The last group, in turn, refers to their usefulness (functionality) for the final recipients, i.e. investors. An important parameter for assessing the quality of investment recommendations is the timing of their publication and the number and frequency of their updates. In this context, the uniqueness of the information provided in published recommendations is also important. Yezegel (Yezegel 2015) points out that almost 25% of all recommendations are issued within three days of the publication of quarterly results. On the other hand, Ivković and Jegadeesh (Ivković, Jegadeesh 2004) noted that recommendations have the greatest informational value when they are issued just before the publication of financial results by public companies, which may be due to the leakage of confidential information. Jacob and colleagues (Jacob et al. 1999) indicate that analysts who respond more frequently to new information by issuing new recommendations increase their accuracy. In turn, research by Chen and Cheng suggests that more frequent updates of reports lead to a reduction in their informational value and, consequently, to a smaller market reaction after their publication (Chen, Cheng 2003). Hobbs and colleagues indicate that the recommendations of those analysts who update their reports most frequently provide investors with the most value in both the short and long term (Hobbs et al. 2012). They note that the most profitable recommendations are those issued as soon as possible after the publication of important information for the company, but this is not true in the case of quarterly results announcements. The authors also point out that this may be at least partly related to the ability of analysts to discover unique information that other market participants are not yet aware of. Shroff and colleagues also point out that the strongest market reaction occurs in the case of recommendations that were published earliest after the release of specific information, but such reports are characterized by less accurate forecasts (Shroff et al. 2004). Agapova and Filatova noted that analysts tend to issue more positive investment recommendations in the last month of the quarter and more negative recommendations in the first month of the quarter (Agapova, Filatova 2023). This phenomenon is particularly evident in companies with a large share of institutional investors and is explained by analysts working on behalf of large clients. The presented research indicates that the capital market needs both recommendations that disclose new information as quickly as possible and those that are issued later but contain much more accurate forecasts, so quality assessment based on this dimension may depend on the function they perform.

However, the most frequently studied qualitative feature of recommendations in the literature is their accuracy, both in terms of the accuracy of analysts' forecasts of listed companies' results (Das et al. 1998; Brown, Huang 2013; Wróblewski 2016), as well as the accuracy of the target price contained therein (Bonini et al. 2010 ;

Bradshaw et al. 2013). It would seem that the accuracy of company earnings forecasts should translate into the accuracy of the calculated target price. The validity of this hypothesis is supported by research by Gleason and colleagues, who revealed that analysts who were better at forecasting earnings per share were able to estimate the target price more accurately (Gleason et al. 2013). On the other hand, Eames and colleagues pointed to the absence of such a relationship, indicating that analysts who are positive/negative about a given company forecast excessively high/low earnings, respectively (Eames et al. 2006). Similarly, Hwang and Lou point to the absence of this relationship (Hwang, Lou 2011). However, they showed that analysts with positive or negative recommendations forecast excessively low or high profits, respectively, so that on the day of their announcement, the market reaction will be stronger and allow them to reach their target price.

All the above-mentioned features may affect the predictive value of the recommendations issued, but one of the most important pieces of information resulting from an analytical report is the calculated target price, as it ultimately influences the message conveyed by the report. For this reason, the assessment of the quality of recommendations in this paper will be conducted from the perspective of the accuracy of the forecast prices contained therein. This aspect is particularly important from the point of view of the process of constructing an investment portfolio based on the recommendations of stock market analysts.

3. Literature review

Academics address the issue of recommendation accuracy in two aspects, i.e. the accuracy of target prices and the accuracy of forecasts of companies' financial results. The results of research on the accuracy of target prices will be discussed in more detail, as from the point of view of the empirical research conducted in this study, it seems to be the most important dimension of the quality of recommendations. The methodology used by various authors to study this issue is extensive. Asquith and colleagues examined accuracy using a dynamic accuracy coefficient for reports issued between 1997 and 1999 (Asquith et al. 2005).[1] Their tests showed that for 54.28% of recommendations, the price exceeded their target price and was on average 37.27% higher than it, while for the remaining positive (negative) recommendations that did not reach their target price, the market price approached on average 84.38% of the projected potential at its maximum (minimum) point. Bradshaw and Brown measured the accuracy of recommendations using a static

[1] Dynamic/static accuracy coefficients refer to the percentage of recommendations that exceeded their target price during their validity period/on the last day of their validity period.

and dynamic accuracy coefficient for recommendations issued between 1997 and 2002 (Bradshaw, Brown 2005). The results of their tests showed that only in 24% and 45% of cases, respectively, did the stock market price exceed the target price. Using the same methodology, similar results for recommendations issued between 2000 and 2006 on the Italian market were obtained by Bonini and colleagues, who calculated that the above-mentioned coefficients were 20% and 33%, respectively (Bonini et al. 2010). Extensive analyses of this problem were carried out in a similar manner by Bradshaw and colleagues (Bradshaw et al. 2012). They showed that 64% of recommendations issued between 2000 and 2009 reached their target prices within 12 months of publication, while at the end of this period only 38% exceeded the prices assumed by analysts. The study also showed that target prices were on average 15% higher than the actual prices achieved, and the absolute forecast error averaged 45%. The authors noted that investors follow changes in target prices regardless of the analyst's reputation and ability. The hypothesis that analysts have the ability to predict future stock prices was positively confirmed as statistically significant, but its economic value was described by the authors as weak. Kerl calculated the dynamic accuracy coefficient for analytical reports issued in 2002–2004 on the German market (Kerl 2011). His results showed that this accuracy averages 73.64%, but varies for positive recommendations (75.69%) and negative recommendations (59.43%). The accuracy of analysts' forecasts was also tested by Bilinski and colleagues (Bilinski et al. 2013). They examined recommendations for 16 countries between 2002 and 2009. The analysis shows that the target prices in the published recommendations were exceeded in 59.1% of cases, with an absolute forecast error of 44.7%. According to the authors, these results allowed them to conclude that analysts demonstrate a consistent ability to forecast target prices. Tiberius and Lisiecki conducted accuracy studies for the German market (Tiberius, Lisiecki 2019). Their analysis shows that the average forecast error, measured by the average ex post error indicator, was +0.0095, which may indicate the very good accuracy of the recommendations issued. However, the standard deviation of this error was 0.3287, which led to the conclusion that the forecast for a single recommendation was poor. It also turned out that the distribution of the forecast error is very similar to the normal distribution. Kadam and Sethi conducted a study on the accuracy of target prices of recommendations issued on the Indian market in 2016–2020 in dynamic terms (Kadam, Sethi 2024). The recommendation accuracy coefficient was 63%.

Compared to developed markets, the topic of recommendation accuracy on the Polish capital market is much less frequently discussed in the literature. Extensive research on this topic was conducted by Prusak, who tested not only the accuracy but also the effectiveness of analytical reports issued by Polish brokerage houses (Prusak 2015). The study covered 470 recommendations issued between

2009 and 2012, using several approaches to assess the accuracy of analytical reports. Static accuracy tests showed that the actual price 6, 9 and 12 months after the recommendation was issued and at the end of its validity period differed from the target price by less than 10% in only 30.00%, 24.68%, 21.91% and 27.45% of cases, respectively. These results led to the conclusion that accuracy is very low and decreases over time. In the dynamic approach, the results showed that the analytical reports were at least good (defined by the author as a deviation from the target price of no more than 10%) in the corresponding periods in 63.37%, 67.82%, 71.78% and 67.82% of the analyzed reports. The second method proposed was to verify whether future prices fall within the range assumed by the brokerage house. It turned out that in all the above-mentioned time periods, analysts correctly predicted prices for only about one-third of all recommendations in static terms. In the dynamic approach, the accuracy rates increased to about 50%.

The assessment of the accuracy of recommendations on the Polish capital market was also a subject investigated by Biedrzycki, who examined the deviations of the actual price from the target price after 9 months for 516 recommendations (Biedrzycki 2008). The range of these deviations was from −77.66% to 922.86%, while the mean and median were 44.77% and 29.46%, respectively. In addition, it turned out that the number of underestimated companies was 271, while the number of overestimated companies was 120. The author noted that only in 57% of recommendations did the price follow the same direction as the investment recommendation. Significant deviations from target prices indicate that the recommendations are not very accurate. However, it is worth noting that the research was conducted in 2006–2007, which naturally resulted in unnatural valuations related to the bull market that was ongoing at the time. The second stage of the study was to assess the recommendations as accurate or inaccurate, depending on whether they fell within the ranges proposed by the author. The results revealed that only 43.2% of the recommendations were accurate. Czyżycki and Kłóska also conducted a study on the accuracy of analytical reports (Czyżycki, Kłóska 2010). They calculated Pearson's correlation coefficient between the investment potential resulting from the recommendation and the actual change in the share price after a period of three months. This coefficient was 0.73 and was statistically significant. The authors demonstrated a fairly high degree of convergence between analysts' forecasts and actual price changes. A study covering only the five largest companies in the WIG20 index was conducted by Dąbrowski (Dąbrowski 2013). The results indicate that only 44.63% of the recommendations issued in 2007–2011 reached their target price during their validity period. The author also ranked brokerage houses, which showed that the best houses in terms of recommendation accuracy at that time were Millennium Brokerage House, Goldman Sachs and DI BRE (now mBanku Brokerage House). A study of the competitiveness of

brokerage houses for recommendations issued between 2006 and 2012 was also conducted by Czyżycki (Czyżycki 2013). In this study, he analyzed the accuracy of the proposed target prices for periods from 1 to 100 days. It turned out that in the short term, Wood&Company was the best institution, while over time, Dom Maklerski BDM achieved better results. Brycz and Włodarczyk examined the accuracy of recommendations for Polish companies issued in 2012 using an accuracy coefficient in a dynamic approach (Brycz, Włodarczyk 2017). The index they calculated was 66.7%. Another assessment of the accuracy of recommendations as the deviation of the market price from the target price was carried out by Włodarczyk (Włodarczyk 2020). Her research covered the years 2005–2012 and proved that recommendations have predictive value only in the short term, as the accuracy of target price forecasts is highest for short periods (6–8 days from the publication of the report). However, over time, this accuracy deteriorates and is lowest for long-term periods (one and two years). The accuracy of recommendations issued in 2004–2016 was also assessed by Wnuczak (Wnuczak 2021). Using a static accuracy coefficient, he showed that in the case of buy recommendations, the target price was exceeded in only 30% of cases after one year. The results of the target price accuracy study are summarized in Table 1.

Table 1

Accepted ranges for assessing the accuracy of recommendations for individual indicators

Author(s)	Year of publication	Accuracy measures	Result of a given measure	Conclusion adopted by author
P. Asquith	2005	Dynamic accuracy coefficient	54.2%	No conclusion
		MAX/MIN average deviation of the target price from the actual price for realized recommendations	37.3	No conclusion
		MAX/MIN average deviation of the target price from the actual price for unrealized recommendations	−15.6	No conclusion
M. Bradshaw, L. Brown	2006	Static accuracy coefficient	24.0	Analysts' inability to predict prices
		Dynamic accuracy rate	45.0	Analysts' inability to predict exchange rates

Table 1 cont.

S. Bonini et al.	2010	Static accuracy coefficient	20.0	No accuracy
		Dynamic accuracy coefficient	33.1	No accuracy
A.G. Kerl	2011	Dynamic accuracy coefficient	56.5	No conclusion
		MAX/MIN average deviation of the target price from the actual price for realized recommendations	42.0	No conclusion
		MAX/MIN average deviation of the target price from the actual price for unrealized recommendations	−13.8	No conclusion
M.T. Bradshaw et al.	2012	Deviation of the target price from the actual price	15.0	Economically weak
		Absolute forecast error	45.0	Economically weak
		Static accuracy coefficient	38.0	Economically weak
		Dynamic accuracy coefficient	64.0	Economically weak
P. Bilinski et al.	2013	Dynamic accuracy coefficient	59.1	Sustainable ability to forecast target prices
		Absolute forecast error	44.7%	Sustainable ability to forecast target prices
V. Tiberius, L. Lisiecki	2019	Average forecast error	0.0095	Very high accuracy
		Deviation of the mean forecast error	0.3287	Poor accuracy for a single company
S. Kadam, M. Sethi	2024	Dynamic accuracy coefficient	63	Good accuracy
R. Biedrzyński	2008	Percentage of recommendations for which the price followed the investment recommendation	57	Poor accuracy
		Average absolute deviation between the market price and the target price	44.8	Poor accuracy
		Proprietary accuracy coefficient	43.2	Poor accuracy
R. Czyżycki, R. Kłóska	2010	Pearson correlation coefficient	73.0	High accuracy

Table 1 cont.

Author(s)	Year of publication	Accuracy measures	Result of a given measure	Conclusion adopted by author
P. Dąbrowski	2013	Dynamic accuracy coefficient	44.63	Low quality
B. Prusak	2015	Static accuracy coefficient	21.9	Very low accuracy
		Dynamic accuracy coefficient	71.8	Not very high added value
		Static accuracy coefficient for brokerage house intervals	~33	Very low accuracy level
		Dynamic accuracy coefficient for brokerage house ranges	~50%	Low accuracy level
B. Brycz, K. Włodarczyk	2017	Dynamic accuracy coefficient	66.7	No conclusion
K. Włodarczyk	2020	Average absolute deviation between market price and target price	From a few to several dozen per cent	Good accuracy only in the short term
P. Wnuczak	2021	Static accuracy coefficient	30% for buy recommendations	Recommendations should not be the only guide for investors

Based on the literature cited, the accuracy of recommendations should be assessed as average. Studies conducted to date do not provide clear confirmation of whether analysts accurately forecast the target prices of listed companies. Often, the authors of these studies do not provide a clear assessment of the results obtained. Table 2 was created based on the results of previous tests (summarized in Table 1) and the author's subjective assessment. It will be used to evaluate the results of research on the accuracy of recommendations.

Table 2

Adopted ranges for assessing the accuracy of recommendations for individual indicators

Indicators used to assess the accuracy of recommendations	Low accuracy	Average relevance	High accuracy
Percentage of cases where the price of a given asset followed the direction indicated by the recommendation	<67%	≥67%; ≤80%	>80%
Static accuracy coefficient	<33%	≥33%; ≤50%	>50%
Dynamic accuracy coefficient	<60%	≥60%; ≤75%	>75%
Average absolute deviation between market price and target price	>20%	≥10%; ≤20%	<10%

4. Data and methodology

The study used recommendations for companies listed on the Warsaw Stock Exchange published on www.bankier.pl and historical share prices downloaded from Bloomberg. The number of analytical reports was an important factor in determining the correctness of the proposed research. Therefore, it was assumed that only companies for which at least 99 recommendations were issued in 2005–2019 by all 69 investment firms operating on the Polish capital market at that time would qualify for the research sample. This limited the sample to companies that are most frequently analyzed by analysts and investors and have an adequate history of recommendations. It also excludes from the study companies that are valued sporadically, which may distort the impact of reports on their share prices and raise doubts about their quality.

Finally, 45 companies were selected for the study, for which a total of 10,469 recommendations were issued during this period. During the period under review, these companies were mainly included in the WIG20 and mWIG40 indices, although it should be added that the classification of some of them in a given index changed during this time. Although the names of individual companies and investment firms also changed during the period under review, the most current versions were used in this study. To avoid the "survivorship bias" effect (Liu et al. 2022), which consists in excluding from consideration entities that have ceased operations or been delisted from the stock exchange, neither companies nor brokerage houses that went bankrupt, were taken over or ceased operations during that time were eliminated from the research sample.

In order to ensure a uniform approach to all calculations, the closing prices for a given day were used. These prices are most commonly used in market practice and form the basis for the valuation of, among other things, investment funds.

Table 3 presents the companies selected for the study by sector, together with the total number of recommendations issued for all securities in a given sector.

Table 3

Companies participating in the research sample by sector, with the number of recommendations published for them

Sector	Companies	No. of companies	No. of recommendations
Financial	PKO BP, PEKAO SA, PZU, Alior, Millennium, Getin Holding, mBank, Santander, Bank Handlowy, ING	10	3135
Fuel and energy Energy	PKN, Lotos, MOL, PGNIG, PGE, ENEA, Tauron, CEZ	8	1820
Technology, Media, and Telecommunications	Cyfrowy Polsat, Orange, Netia, Agora, Asseco Poland, Comarch, Sygnity	7	1734
Construction and Real estate	Budimex,Trakcja,Polimex-Mostostal, PBG, Elektrobudowa, GTC, ECHO, Dom Development	8	1205
Retail	LPP, CCC, Amrest, Eurocash	4	874
Mining	KGHM, JSW, Bogdanka	3	857
Industrial	Kęty, Grupa Azoty, Police, Puławy, Ciech	5	844
Total		**45**	**10,469**

The accuracy of the investment recommendations was assessed using the following measures:

- percentage of cases where the price of a given asset followed the direction indicated by the recommendation,
- static accuracy coefficients in different periods,
- dynamic accuracy coefficient,
- deviation of the actual price at the end of the recommendation's validity period from the target price forecast by the analyst.

First, in how many cases the rate of return at the end of their validity period had the same sign (positive or negative) corresponding to the investment recommendation (positive or negative) was checked for positive and negative recommendations.

Second, the static accuracy coefficients of the recommendation were calculated for different periods using the following formula:

$$\text{Static accuracy coefficient}_t = \frac{\text{No. of recommendations for which the target prices were reached in the period } t}{\text{No. of issued recommendations}} \quad (1)$$

Various periods were assumed, where t (subscript) = 5, 30, 90, 182, 273 days and the end of the recommendation validity period (273 or 365 days, depending on the brokerage house). Third, the dynamic accuracy coefficient of the recommendation was calculated using the following formula:

$$\text{Dynamic accuracy coefficient} = \frac{\text{No. of recommendations for which the target prices were reached at the end of their validity period}}{\text{No. of issued recommendations}} \quad (2)$$

The dynamic accuracy coefficient differs from static accuracy in that it includes all cases where a company's share price exceeded the target price on any day during the entire validity period of the recommendation (273 or 365 days). Naturally, it must be higher than or equal to the static coefficient. Both studies also took into account only analytical reports with positive or negative recommendations. Those with neutral recommendations were omitted, as they usually include a forecast of price changes within a narrow range of ±10% set by the brokerage house. Including neutral reports in the study would distort the correct conclusions about their accuracy, as a large proportion of them would not result from trends affecting the price, but could be realized through natural market volatility, which would lead to an overestimation of the accuracy coefficient.

The fourth method of verifying the accuracy of the recommendations was to analyze the relative and absolute deviations of the actual share price at the end of the recommendation period from the target price. Firstly, the relative deviations were taken into the account, which were calculated using the following formula:

$$\text{Deviation of market price from target price} = \frac{\text{Market price at the end of the recommendation validity period} - \text{Target price}}{\text{Target price}} \cdot 100\% \quad (3)$$

This formula was applied to positive and neutral recommendations, while for negative recommendations, it was multiplied by a factor of −1 in order to

determine whether the deviation was positive or negative in relation to the target price. Based on the calculated deviations, a histogram showing their distribution was created. The intervals of this histogram, as well as all subsequent ones, were designed according to Scott's rule (Grzegorzewski et al. 2014). The basic parameters of this distribution, such as the mean, median, 1st and 3rd quartiles, as well as the standard deviation, skewness, and kurtosis, were also calculated and presented. Three statistical tests were used to test the conformity of the distribution of deviations with the normal distribution:

- Kolmogorov–Smirnov,
- Lilliefors,
- Anderson–Darling.

The calculated relative deviations are highly informative in the context of examining whether analysts are too conservative or optimistic about target prices. However, they do not show how far the actual price deviated from the target price on average, as positive and negative deviations cancel each other out. For this reason, absolute deviations of actual prices at the end of the recommendation period from target prices were also calculated using Formula 3 (absolute deviations).

Next, histograms were developed for relative deviations, broken down into positive and negative recommendations. Basic descriptive parameters were also calculated for them. As these distributions did not show the characteristics of a normal distribution, the non-parametric Mann–Whitney U test was used to test the equality of their medians. The distributions of the deviations and their parameters were also shown, broken down by sector. All recommendation accuracy tests were calculated using the closing prices on a given day.

5. Empirical results

The study of the accuracy of recommendations began by checking in how many cases for positive and negative reports the rate of return at the end of their validity period had the same sign (positive or negative) as the investment recommendation (positive or negative). The results show that analysts' investment recommendations were directionally accurate in only 47.0% of cases. This means that they were more often wrong about the future direction of price changes than they were right. This test was a prelude to the study of the static accuracy coefficient, and the calculated value was the upper limit that this coefficient could reach.

Next, how often analysts are able to accurately determine the appropriate target price was checked. To this end, we calculated the static accuracy coefficient,

i.e. the percentage of recommendations that reached a specific target price at the end of the assumed period. Only positive or negative reports were included in the study. The values of the static accuracy indicators for individual periods are presented in Table 4.

Table 4

Static recommendation accuracy coefficients in different periods

Number of days	5	30	90	182	273	End of recommendation validity period
Average accuracy [%]	9.1	14.9	22.1	28.4	30.8	29.0

The above data shows that in almost every eleventh recommendation, the target price was reached on average after just one week. In turn, in approximately 22.1% of analytical reports, the price exceeded the target price after one quarter. The accuracy coefficient increases over time, but reaches its highest value (30.8%) nine months after the recommendation is issued. At the end of the validity period, the accuracy rate is lower, at 29.0%. In turn, the calculated dynamic accuracy rate was higher, reaching 55.0%.

Accuracy coefficients for individual companies were also estimated to verify whether there are any specific correlations in this area, e.g. related to membership of a given sector. Deviations from the average static accuracy coefficient for individual securities range from −16.8 p. p. to +19.1 p. p. (Appendix 1). Analysts were least successful in predicting the correct price in the case of companies from the energy sector, i.e. ENEA (where the accuracy coefficient was 12.1%), PGE (16.2%), CEZ (17.3%) and Tauron (22.1%). On the other hand, some of the highest coefficients were achieved for companies in the retail sector: CCC (43.4%), Eurocash (43.0%) and Amrest (41.3%). In the case of the dynamic indicator, these deviations are very similar and range from −16.2 p. p. to +19.3 p. p.

The fourth method used to analyze the accuracy of the analytical reports was the deviation of the actual price at the end of the recommendation period from the forecast target price. The histogram of relative deviations is presented in Figure 3.

The deviations of the actual price at the end of the recommendation period from the target price forecast by analysts have a distribution similar to the normal distribution, but are not consistent with it, mainly due to the high kurtosis. This observation is also confirmed by the results of three independent statistical tests, i.e. Kolmogorov–Smirnov, Lilliefors, and Anderson–Darling, at a significance level of 0.05 (Tab. 5).

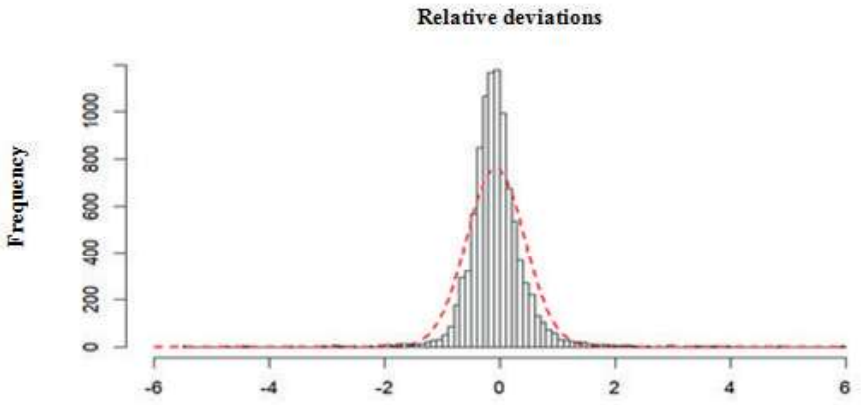

Figure 3. Histogram of relative deviations of the actual price at the end of the recommendation period from the target price forecast by analysts, with a normal distribution superimposed (red dashed line)

Table 5

Tests verifying the normal distribution of relative deviations obtained

Test	p-value	Compliance with a normal distribution at the 0.05 level
Kolmogorov–Smirnov	<0.01	None
Lilliefors	<0.01	None
Anderson–Darling	<0.01	None

The mean of this distribution is below zero and amounts to −7.08%, while the median is equal to −9.77%. This means that the distribution is right-skewed with a longer tail on the right side of the chart (skewness >0) (Tab. 6). Its analysis shows that as many as 62% of recommendations have target prices that are too high or too low (in the case of positive and negative analytical reports, respectively) compared to the actual prices of financial instruments. It can therefore be concluded that, on average, analysts forecast too-high positive investment potential for positive recommendations and too-high negative potential for negative recommendations (upside/downside). There may be at least two mutually non-exclusive reasons for this. Firstly, analysts, wanting to increase the attractiveness of buying or selling a company (and thus also their report), tend to overestimate the investment potential. Investors approach a recommendation that assumes a 10% increase differently than one that predicts, for example, a 40% increase. The latter is more

interesting to them because the range of potential price movement is much greater. On the other hand, when the price of an asset approaches its target price, market participants usually close their positions. This is often because as the price approaches the target price, the ratio of further potential profit to risk becomes less favorable, which encourages investors to close their positions on a given asset.

Table 6

Descriptive statistics of the distribution of relative deviations of the actual price at the end of the recommendation period from the target price forecast by analysts

Parameter	Value
Average	−7.08%
1st quartile	−31.30%
2nd quartile (median)	−9.77%
3rd quartile	13.30%
Standard deviation	49.75%
Kurtosis	15.12
Skewness	0.56

In order to examine the average difference between the actual price at the end of the recommendation period and the target price, the median and mean values of the absolute deviations of the actual price from the target price were also calculated. The average absolute deviation was 33.56%, with a median and standard deviation of 24.36% and 37.41%, respectively. Figure 4 shows a histogram of the absolute deviations of the actual price from the target price.

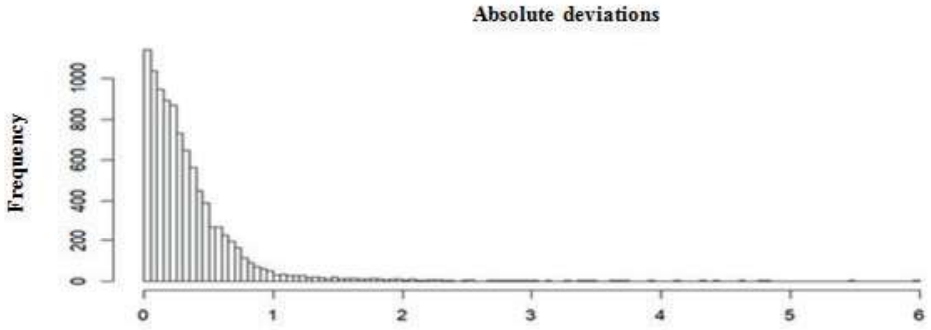

Figure 4. Histogram of absolute deviations of the actual price at the end of the recommendation period from the target price

The study of the accuracy of recommendations was supplemented by a comparison of the distributions of deviations for positive and negative recommendations. Histograms and statistics of these deviations are presented in Figure 5 and Table 7, respectively.

a) b)

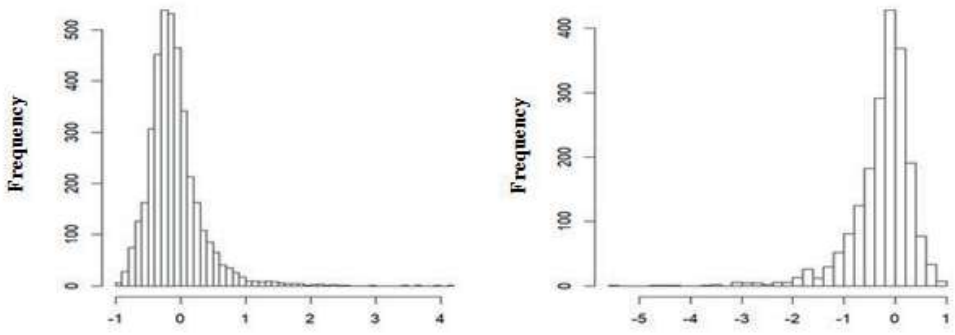

Figure 5. Histogram of relative deviations of the actual price at the end of the recommendation period from the target price forecast by analysts for positive (a) and negative (b) recommendations

Table 7

Descriptive statistics of the distribution of deviations of the actual price at the end of the recommendation period from the target price forecast by analysts for positive and negative recommendations

Parameter	Positive	Negative
Average	−9.50%	−25.47%
1st quartile	−34.19%	−45.93%
2nd quartile (median)	−15.53%	−13.16%
3rd quartile	5.75%	9.16%
Standard deviation	41.82%	59.71%
Kurtosis	12.51	10.43
Skewness	2.31	−2.31

Deviations for positive recommendations are characterized by a right-skewed distribution with a long tail on the right. Observations to the left of the mean take

values not lower than −1. This is a natural consequence of the fact that share prices cannot fall below 0. Both the mean and the median are negative, which indicates that analysts are too optimistic in their estimates of target prices for shares when they recommend buying them. The situation is similar for negative recommendations. The distribution of these deviations is similar to the distribution of positive recommendations. It is characterized by negative skewness and a long tail on the left. In this case, the mean and median take negative values, confirming that analysts also overestimate the negative potential for negative recommendations. However, it is worth noting that the mean in this case is almost twice as small as the median. This indicates that the authors of reports recommending the sale of shares make significantly larger errors (compared to recommendations suggesting a purchase), which means that these deviations more often take on extreme values, e.g. below −100% or −200%. This is also confirmed by the relatively high standard deviation for this group of recommendations, which is 59.71%. Actual prices deviate from the target price by ±10% in only 19.8% of cases for positive recommendations and 21.3% of cases for negative recommendations. The non-parametric Mann–Whitney U test (also known as the Wilcoxon rank test) returned a statistic value of W = 3,952,510 and a p-value <0.01, which allows us to conclude that there is a statistically significant difference between the medians of both distributions.[2]

In the next step, an analysis of the distributions of deviations for individual sectors was performed and their descriptive statistics are presented in Table 8.

Analysis of these results allows us to draw important conclusions that can be used to make more effective use of analytical reports. It is worth noting that only in the case of recommendations for the retail sector are both the mean and the median positive, which indicates that analysts are too conservative in their target price forecasts for companies in this industry. In the case of the other sectors, they are too optimistic, most notably in the case of the mining sector. The standard deviation for this sector (84.39%) is significantly higher than for the other industries. Also noteworthy are the relative deviations of the industrial segment, which is the only one with a platykurtic distribution. This shows that in this case, there are relatively fewer extreme values, which indicates a smaller number of extreme errors by analysts. In statistical terms, the Wilcoxon signed-rank test clearly showed that for all sectors, the medians of relative deviations differ significantly from zero. The results of the test are presented in Table 9.

[2] The t-test was not used due to distributions that deviated significantly from the normal distribution.

Table 8

Descriptive statistics of the distribution of deviations between the actual price at the end of the recommendation period and the target price forecast by analysts for recommendations broken down by sector

Parameter	Financial	Fuel and Energy	TMT	Construction and real estate	Retail	Mining	Industrial
Average	−4.86%	−11.14%	−9.13%	−10.22%	5.83%	−11.24%	−6.40%
1st quartile	−30.20%	−30.15%	−25.44%	−39.78%	−23.62%	−42.06%	−35.13%
2nd quartile (median)	−8.07%	−12.92%	−9.24%	−11.97%	0.80%	−15.79%	−8.36%
3rd quartile	16.67%	6.48%	4.95%	13.96%	30.92%	15.00%	18.33%
Standard deviation	50.29%	32.72%	34.16%	52.07%	53.27%	84.39%	45.12%
Kurtosis	10.08	10.49	10.88	4.76	5.95	12.58	1.32
Skewness	0.81	−0.93	0.80	0.37	0.51	0.49	0.19

Table 9

Results of the Wilcoxon signed-rank test for different sectors

Sector	Test statistic V	p-value
Financial	1,537,843	<0.01
Fuel and Energy	384,353	<0.01
TMT	385,131	<0.01
Construction and real estate	214,176	<0.01
Retail	177,629	0.0274
Mining	111,974	<0.01
Industrial	124,728	<0.01

6. Conclusions

The percentage of recommendations for which the generated rate of return was consistent with the expectations resulting from the investment recommendation

was only 47.0%, which means that analysts were more often wrong than right about the direction in which the company's share price would move in the future. Next, the static and dynamic accuracy coefficients achieved only 29.0% and 55%, respectively. The results obtained are similar to those of previous studies. Static accuracy coefficients in previous papers ranged from 20% to 38%, and the accuracy of recommendations was generally assessed by the authors as low or very low. In turn, dynamic accuracy coefficients in other studies ranged from 33% to 71.5%, and the authors' conclusions were generally consistent with those concerning static accuracy coefficients, i.e. that the accuracy of recommendations is poor. Based on the ranges established in Table 2, the results obtained for both accuracy coefficients justify a negative assessment of analysts' ability to correctly forecast share prices and an assessment of the accuracy of recommendations as low.

The low accuracy may be partly due to the fact that neutral recommendations were not taken into account in this study, and their inclusion would certainly increase the levels of the indicators in question. However, including them could lead to incorrect conclusions about the accuracy of recommendations (especially in the case of dynamic accuracy) due to the low investment potential that could be realized by market volatility rather than by trends shaping the price of a given company.

In the case of the dynamic approach, accuracy improved by 26 percentage points compared to the static approach. This is a natural consequence of the fact that for this approach, all cases were taken into account where the share price exceeded the target price on any day during the recommendation's validity period. It follows that investments based on recommendations should be monitored by market participants, as statically waiting for the end of the recommendation's validity period is less likely to bring the desired results. A dynamic approach to investing, in line with recommendations, therefore provides greater benefits for the investor.

However, the distribution of deviations indicates that only 38% of recommendations exceeded their target price at the end of the recommendation period (the discrepancy with the static accuracy coefficient is due to the fact that neutral recommendations were not included in that study). Moreover, one year after the report was published, the actual price deviated from the target price by more than 10% or 20% in 77.3% and 58.0% of recommendations, respectively. To emphasize the scale of the discrepancy between the forecasts and actual prices, it can also be pointed out that almost one-third of all target price forecasts differed from the actual values by more than ± 40%. Such a wide range of deviations is also confirmed by the standard deviation, which is close to 50%. Such frequent and significant errors can seriously limit the use of recommendations as an effective

tool in the investment process, especially when target prices are the only criterion on which market participants base their decisions.

The average absolute deviation was 33.6%. The presented results of deviations of the actual price from the target price are lower than the deviations in previous studies, but their high levels still justify a negative assessment of the ability of domestic analysts to correctly forecast share prices on the Warsaw Stock Exchange and to determine the accuracy of recommendations to be low.

The results of all the methods used to verify the accuracy of investment recommendations justify a negative assessment. However, this does not mean that analytical reports are not useful for the investment process, as their effectiveness is key in this case.

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Appendix 1

Dynamic and static accuracy coefficients of recommendations for individual companies at the end of the recommendation validity period

Company	Static accuracy coefficient [%]	Dynamic accuracy coefficient [%]
Enea	12.1	40.7
Sygnity	15.2	48.1
PGE	16.2	44.8
CEZ	17.3	38.8
Alior Bank	17.7	46.8
ECHO	18.3	40.0
Bogdanka	20.5	39.8
PKO	20.9	40.3
Tauron	22.1	44.2
Millennium	22.5	53.5
DOMDEV	23.0	56.3
PGNIG	23.7	57.2
Orange	24.6	62.9
PZU	25.0	54.5
Trakcja	25.4	49.3
mBank	25.5	58.8
Cyfrowy Polsat	25.6	59.7
Asseco Poland	25.7	48.6
Elektrobudowa	26.2	41.0
Police	26.4	29.7
KGHM	26.7	54.7
Ciech	27.4	49.2
Agora	28.6	54.4
Netia	28.6	55.6
Handlowy Bank	28.7	53.2
Pekao	28.8	56.4
Lotos	30.0	56.7
PKN Orlen	31.3	59.7
GTC	31.3	51.1

Appendix 1 cont.

Company	Static accuracy coefficient [%]	Dynamic accuracy coefficient [%]
PBG	32.9	55.3
Comarch	33.0	58.3
LPP	33.9	64.4
Polimex Mostostal	34.0	63.3
Azoty Group	34.2	60.5
Getin Holding	34.3	74.3
Puławy	34.3	57.8
ING Bank	35.1	53.5
MOL	35.8	53.1
Budimex	39.1	60.1
Santander	39.2	66.0
Amrest	41.3	71.3
Kęty	42.1	69.0
Eurocash	43.0	63.9
CCC	43.4	69.8
JSW	48.0	59.1
Average	29.0	55.0

Summary

The aim of this article is to provide an empirical analysis of investment recommendation accuracy on Polish Stock Exchange. The study also intended to defining the concept of investment recommendation quality and classifying the dimensions through which it can be assessed. Based on data from 2005 to 2019 the accuracy of investment recommendation was calculated using four approaches. All four indicators indicate low level of accuracy of investment recommendation in Poland.

JEL codes: G11, G14, G24

Keywords: *investment recommendation, accuracy, quality, effectiveness*