Target Price Accuracy: Evidence from the Warsaw Stock Exchange

Abstract

Purpose: This paper aims to identify the determinants of the target price accuracy for stocks of companies listed on the Warsaw Stock Exchange and to assess the effectiveness of analysts in forecasting target prices on the Polish market**.**

Design/methodology/approach: The study was conducted using the POLS method and a probit model. The research sample comprises 1,121 valuation reports of companies listed on the Warsaw Stock Exchange, published between 2018 and 2024, on brokerage websites. The study utilised financial data from the companies in the Orbis database, as well as data on stock exchange listings and the P/BV ratio, which were downloaded from the Stooq platform.

Findings: Only 30.9% of the target prices are shown to have been achieved at the end of the forecast horizon and 52.3% during the forecast horizon. In particular, valuations of state-owned enterprises (SOEs) and those issued during the COVID-19 pandemic are less accurate. In contrast, the inclusion of the comparative method in addition to the DCF method increases the accuracy of valuations. It has been shown that there are time-persistent differences between brokerages in their ability to forecast target prices. A positive relationship was observed between the accuracy of valuations and the market momentum of the valued company, as well as the market return over the forecast horizon. In contrast, a negative relationship was identified for the absolute value of the implied share price change in the report, the P/BV ratio of the valued company and the volatility of its share price prior to the publication of the valuation report.

Originality: The uniqueness of the study lies in its analysis of whether the accuracy of a company's valuation depends on state ownership and the uncertainty surrounding the COVID-19 pandemic. This is the first analysis of the stability of brokerage houses' forecasting skills in the Polish market.

Research limitations/implications: A limitation of the study is that it only uses publicly available valuation reports.

Practical implications: Investors (users of valuation reports) should exercise greater caution when the DCF method is included and the comparative method is not; when the issuing brokerage has a history of relatively poor accuracy; and in the case of valuations of state-owned enterprises (SOEs).

Introduction

This paper aims to determine the determinants of the target price accuracy for stocks of companies listed on the Warsaw Stock Exchange and to assess the effectiveness of analysts in forecasting target prices. The analysis of valuation reports, together with the results of an econometric study, will contribute to the broadening of knowledge about the practice of valuation of companies listed on the Polish stock exchange, the quality (accuracy) of valuations made, and will indicate the elements of valuation to which both their authors (brokerage house analysts) and users should devote more attention.

The target price represents the analyst's estimate of the value that the company's shares should reach at the end of the forecast horizon, which is typically 12 months (Bilinski et al., 2013, p. 825). By comparing it with the current price of the stock, the investor obtains easy-to-interpret investment advice, often further expressed by the analyst in a direct recommendation, e.g., *buy*, *hold*, or *sell*. Valuation reports, and in particular their target prices, which are in a way the culmination of all the work done by the analyst, thus play a crucial role in the capital market, both for the investor who is the recipient of the report and for the brokerage houses issuing them. This is because the high quality of the valuations produced increases the prestige of the brokerage house and gives it the chance to win more clients (Gregoire and Marcet, 2014, p. 154).

Taking this into account, the study of valuation accuracy and its determinants may be valuable and useful from the perspective of many market participants, especially in cases such as Poland, where a research gap exists on this topic. To date, research on companies listed on the Polish stock exchange has primarily focused on the description of valuation practices (Głębocki et al., 2011) and the market reaction to the publication of a valuation report (Buzała, 2012, 2015; Czapiewski, 2015). An analysis of the accuracy of the recommendations issued has been carried out in professional services (Adamczyk, 2010; Torchała, 2017), but in a very simplified manner. Zaremba and Konieczka (2014) assessed the effectiveness of stock recommendations by examining the investment results that a portfolio created on their basis can provide.

The research sample comprises 1,121 valuation reports of companies listed on the Warsaw Stock Exchange, published between January 2018 and March 2024 by 16 brokerage houses. The reports were downloaded from the websites of the brokerage houses, and the data used in the analysis and econometric models were collected manually. Stock quotes and P/BV ratio data downloaded from the Stooq platform and financial data of companies from the Orbis database were also used. The econometric study was conducted using the STATA package, employing the POLS model and the probit model. In the course of the analysis, the following research hypotheses were verified:

H1a: Valuations of state-owned enterprises (SOEs) exhibit lower forecast accuracy.

H1b: Valuations of state-owned enterprises (SOEs) are characterized by higher forecast errors.

H2a: Company valuations issued during the COVID-19 pandemic exhibit lower forecast accuracy.

H2b: Company valuations issued during the COVID-19 pandemic are characterised by higher forecast errors.

H3a: The inclusion of the comparative method alongside the DCF approach significantly improves valuation accuracy.

H3b: The inclusion of the comparative method alongside the DCF approach significantly reduces valuation error.

H4: There are time-persistent differences between brokerages in their ability to forecast target prices.

The first two have not been previously examined in either Polish or foreign literature - thus constituting the originality of the work - and the next two make the work part of a discussion conducted in foreign literature, verifying the relevance of the relationships examined in it to the Polish market.

The structure of the article has been adapted to meet the aim of the article. The first section synthesises the literature. Then, the research hypotheses were formulated, the research sample was described, and the research methodology was discussed. This was followed by a presentation of the results obtained and verification of the research hypotheses. Finally, a summary and discussion of the literature was made.

1. Literature Review

Business valuation finds many applications in the market economy. Among other things, it is useful when making buy-sell transactions, making an initial public offering (IPO), in mergers and acquisitions or during the liquidation of a company. As Bancel and Mittoo (2014, p. 106) point out, the valuation of companies or their assets underpins most financial and investment decisions. In principle, it can serve four functions: advisory, argumentative, mediating and informational (Zarzecki, 1999, pp. 46-51). The advisory function, also known as the decision-making function, involves providing the entity considering an equity transaction with the necessary information on the value of the business involved in the potential transaction, enabling it to make a more informed decision. The advisory function of a valuation can be observed in the valuation reports issued by brokerage houses (Głębocki et al., 2011, p. 575), which typically include a recommendation and a target price. The purpose of the report is to facilitate the recipient of the report in making an investment decision regarding a given company. The argumentation function involves providing the entity with arguments in negotiations with the other party to the transaction, thereby increasing its bargaining power. The mediation function, on the other hand, highlights the role of valuation in situations where the parties to the transaction significantly differ in their opinions. The valuation can then help to reach a consensus by providing an objective point of reference. The mediation function thus acts somewhat in opposition to the argumentation function. The information function, on the other hand, involves communicating to the company's environment, which is represented, among others, by potential investors, competitors, or banks, information about the company's current situation and its development prospects.

Several strands can be distinguished in the domestic and foreign literature dealing with the topic of business valuation. The first is a description of the practice of business valuation, which was dealt with in the Polish market by Głębocki et al. (2011) and in the European market by Bancel and Mittoo (2014). Both found that the most commonly used valuation methods by analysts were the discounted cash flow method and the comparative method. In Poland, however, valuation was almost always (97.8%) based exactly on these two methods, and the situation was more diverse across Europe. The work by Głębocki et al. (2011) found that reports often lacked relevant information, thus preventing the recipient from seeing the details of the valuation. Bancel and Mitto (2014) pointed out, on the other hand, that analysts often differ in the assumptions they make, resulting in different final valuations. Moreover, analysts happen to act differently from what business valuation theory would dictate. On the other hand, Imam et al. (2013) and Frensidy et al. (2020) investigated which valuation methods analysts use. Their work shows that accrual-based models, such as the comparative model, are used more frequently than cash flow-based models, such as the DCF model.

Another important strand in the literature is the market reaction to the publication of a valuation report, often accompanied by testing of efficient-marktet hypothesis. For Poland, this has been studied by Buzała (2012) and Buzała (2015), among others, using the event study method. Both studies revealed the occurrence of abnormal returns on shares of highly valued companies on the day of publication, particularly in cases involving positive and negative recommendations. At the same time, it was found that the Polish market is not efficient in the sense of a semi-strong form of efficiency. Czapiewski's (2015) study also showed that the publication of a stock market recommendation is associated with a strong reaction from investors, which is positive for positive recommendations and negative for negative recommendations. Furthermore, the strength of the reaction is higher for the first recommendation of a given type than when it is upgraded or downgraded. It also varies by industry. Asquith et al. (2005) also noted the occurrence of abnormal returns around the date of the report, more specifically, when the recommendation changes to a more positive or more negative recommendation. They also found that the different elements of the report provide separate information value for investors, who react most strongly to a change in the target price and less strongly to changes in the earnings forecast and the type of recommendation. The analyst's reasoning also appeared to be important to investors. However, investors did not pay attention to the details of the report when the recommendation change was positive. The occurrence of abnormal returns in response to the publication of a valuation report was also found in the work of Bradshaw et al. (2013) and Gregoire and Marcet (2014). Both of the cited works suggest that the past quality of the forecasts issued by analysts or brokerage houses does not influence the market reaction. Cheng et al. (2019) showed that the higher the level of corporate governance, the stronger the positive and the weaker the negative investor reaction to the publication of a valuation report.

From the point of view of this paper, however, the most important studies are those on the accuracy of the forecasts made. Brycz et al. (2021) conducted a study of the accuracy of forecasts of revenue, EBIT, net profit and free cash flow (FCF) for companies listed on the WSE. It turned out that as the complexity of the forecast category increased, the accuracy decreased. Thus, revenue forecasts were characterised by the highest accuracy, while free cash flow (FCF) was characterised by the lowest. The analysts' optimistic attitude towards the valued companies was observed, as evidenced, among other things, by the consistently overestimated FCF forecasts. Determinants of earnings forecast accuracy were investigated by Schiemann and Tietmeyer (2022). Their findings indicated that such determinants may include, among others, the size of the forecasted company, which was found to be negatively associated with forecast error, as well as financial leverage, ROA volatility, and reporting a loss — all of which were positively associated with forecast error. A key conclusion of their study was the confirmation of a positive effect of ESG-related controversies on forecast error, which could be partially mitigated by ESG disclosure.

The subject of the target price accuracy in the Polish literature has been addressed by, among others, Kowalke (2012) and Brycz and Włodarczyk (2017), but no comprehensive analysis of its determinants has been conducted. The research sample in Kowalke's (2012) work was extremely modest, comprising only 21 observations, and the conclusions were limited to the overall target price accuracy. On the other hand, the work of Brycz and Wlodarczyk (2017) focused solely on the level of detail in the report and the quality of forecasts for its other components as factors related to the target price accuracy. Additionally, no econometric model was constructed, and the analysis relied on comparing accuracy across groups.

The impact of the valuation model on the target price accuracy formulated by analysts in valuation reports was studied by Asquith et al. (2005), among others. They found that a method using price-to-book multiples had the lowest accuracy, and one using revenue multiples had the highest accuracy. However, their study did not prove a relationship between the valuation model and accuracy. Imam et al. (2013) noted that the most commonly used methods, such as the DCF approach or the relative valuation based on the P/E ratio, lead to the worst results, while models based on accrual categories produce better results than models based on cash flows. Frensidy et al. (2020) reached a different conclusion, finding that cash flow-based models lead to more accurate valuations. This finding is corroborated by Sayed (2015), who found that forecasts created with a DCF approach were the most accurate, while those based on asset book values were the least accurate. Demirakos et al. (2010) concluded, on the other hand, that a model using the P/E ratio produces more accurate target price forecasts than the DCF approach. However, the difference was not statistically significant when controlling for the determinants of model choice. Erkilet et al. (2021), on the other hand, noted that while there was no statistically significant difference in the target price accuracy between the income model and the market model, valuations produced with the hybrid approach are clearly less accurate. The accuracy was also higher when the company was valued as a whole rather than as the sum of its parts. A more detailed analysis of the comparative method was conducted by Cheng and McNamara (2000), comparing the effectiveness of using P/BV and P/E ratios. They found that more accurate valuations are created using the P/E ratio. However, the best results can be achieved by using both ratios simultaneously. For the Polish market, the most effective ratios in the comparative method were identified by Wnuczak (2018). He found that at least in the food industry, the best results can be obtained using EV/EBITDA and P/BV ratios. The details of the DCF approach, on the other hand, were examined by Wróblewski (2016). He pointed out that free cash flow forecasts were subject to high error and mostly strongly overestimated. Analysing the accuracy of the individual components of FCF, Wróblewski (2016) noted that forecasts of depreciation and capital expenditures (CAPEX) were characterised by high accuracy, while forecasts of EBIT and changes in working capital were characterised by low accuracy. It was the latter two categories, therefore, that were primarily responsible for the inaccuracy of FCF forecasts.

Determinants of the target price accuracy have been addressed by Bonini et al. (2010), Demirakos et al. (2010), Kerl (2011), Bilinski et al. (2013), Bradshaw et al. (2013), Gregoire and Marcet (2014), Erkilet et al. (2021), Bonini et al. (2022) and Umar et al. (2022), among others. Among the most frequently examined determinants—typically found to be negatively related to the valuation accuracy—are analysts' boldness, measured by the implied stock price increase in the report, the P/BV ratio of the valued company, and the volatility of its stock price prior to the issuance of the report. The most frequently indicated determinants characterised by a positive relationship with the accuracy of target price forecasts, in turn, are the size of the valued company, its market momentum measured by the return on its stocks from a given time before the report was issued, its profitability and the return on the market over the forecast horizon. The type of recommendation was also often analysed, but in this case, the research results are less clear. For example, Kerl (2011) found that the most accurate target price forecasts occur for *buy* recommendations and the least for *sell* recommendations. Similarly, according to the work of Demirakos et al. (2010), *positive* recommendations are characterised by higher accuracy than others. The exact opposite conclusion, on the other hand, was reached by Brycz and Włodarczyk (2017). In contrast, in the work of Gregoire and Marcet (2014), *hold* forecasts were the most accurate, while *buy* forecasts were the least accurate.

In addition to these frequently studied determinants, most of the authors mentioned above also considered other determinants specific to their study. Bilinski et al. (2013) investigated the impact of cultural factors, institutional and regulatory environment in different countries on the target price accuracy. Among other things, they showed that accuracy is positively influenced by accounting policy disclosures or the level of *uncertainty avoidance* as defined by Geert Hofstede. In addition, the negative impact of the 2008 financial crisis was highlighted, as valuation reports published at that time proved to be less accurate. A similar conclusion regarding the crisis was reached by Gregoire and Marcet (2014).

On the other hand, Cheng et al. (2019) and Bouteska and Mili (2022) demonstrated that a higher level of corporate governance significantly enhances accuracy, primarily due to greater transparency and improved monitoring, which facilitate valuation. The ESG rating of the valued company enhances the accuracy of the target price forecast due to its association with the company's stability, which facilitates forecasting (Umar et al., 2022). Analysts have differential and time-sustained forecasting ability, and past valuation accuracy influences the ongoing accuracy of target price forecasts (Bradshaw et al., 2013; Bilinski et al., 2013; Bouteska and Mili, 2022). On the other hand, Gregoire and Marcet (2014) found a similar relationship, but at the level of research departments issuing company valuation reports.

2. Research Hypotheses

The first research hypothesis concerns state-owned enterprises (SOEs) of considerable importance on the Polish stock exchange, which can be distinguished into companies under the direct and indirect control of the Treasury. In this work, we consider a company in which the main shareholder is the Treasury or an entity controlled by the Treasury to be a SOE. The aforementioned importance of SOEs on the WSE is evidenced by their share in market indices. The WIG20 consists of 7 SOEs, with approximately 53% share in the index. In turn, according to the report prepared by Baker Tilly (2024), although the share of these companies in the number of all companies listed on the WSE is very low, as it amounts to less than 5%, their share in capitalisation is already significant and at the end of 2023 amounted to approximately 40%.

Listed SOEs arouse numerous controversies among institutional and individual investors related to, inter alia, the pursuit of political objectives instead of maximising shareholder value, the lack of a consistent dividend policy or frequent changes in the governing bodies of these companies linked to the election of persons without the required competence to the highest positions. Similar issues are highlighted by Postula (2014, p. 140), who argues that the influence of political factors on SOEs is inherent because the owning state is itself a political organisation and its bodies, through which it operates, are also political and directly or indirectly derived from elections. The political affiliations of members of management or supervisory boards may alter the time horizon of their decisions, tying them to the electoral cycle (Postula, 2015, p. 215). Additionally, the criteria for making decisions themselves may sometimes be more political than business-oriented (Postula, 2013, p. 237). It is also noted that such companies tend to have less autonomy at the operational level and less transparency in their operations (Postuła, 2014, p. 141).

The influence of state ownership on a listed company and its presence as a major shareholder can also be linked to the strand of corporate governance influence on the accuracy of valuations, as mentioned in the literature review. According to corporate governance theory, the accuracy of valuations should be positively influenced by board independence, which improves monitoring and transparency (Cheng et al., 2019, p. 96). However, this may be questionable in the case of SOEs, given the political connections previously mentioned. SOEs are also characterised by rather concentrated shareholding, but there is no consensus in the literature as to whether this increases or decreases valuation accuracy. Indeed, on the one hand, increased concentration of ownership may benefit the company's decision-making and increase the shareholder's incentive to implement effective monitoring (Cheng et al. 2019: 99), while on the other hand, it may enable the shareholder to manipulate or even conceal information (Bouteska and Mili, 2022, p. 2146), thus hindering a reliable valuation.

Previous studies available in the literature have not examined the relationship between SOEs and the accuracy of valuations. However, given the arguments presented, it can be expected that SOE ownership may hinder an analyst's ability to produce an accurate valuation due to the accompanying uncertainty arising from political factors and concerning the composition of its management, supervisory board and business decisions made by the company, as well as lower transparency of operations. Accordingly, the following research hypotheses were formulated:

H1a: Valuations of state-owned enterprises (SOEs) exhibit lower forecast accuracy.

H1b: Valuations of state-owned enterprises (SOEs) are characterized by higher forecast errors.

The second research hypothesis relates to valuations issued during the COVID-19 pandemic. A research sample covering periods before, during and after the COVID-19 pandemic allows us to investigate whether there is a relationship between the pandemic and the accuracy of valuations. In the study, the period of the COVID-19 pandemic is narrowed down to the period of the epidemic state in Poland, i.e. from 20.03.2020 to 15.05.2022 (Regulations of the Minister of Health of 20.03.2020 and 12.05.2022) as characterised by the highest intensity of the pandemic's effects. The literature published to date has not examined how the COVID-19 pandemic affected the accuracy of the published target prices. Instead, the issue of the 2008 financial crisis has been studied, as mentioned in the literature review, and target price forecasts, as well as profit forecasts, issued during this crisis proved to be less accurate (Bilinski et al., 2013; Schiemann and Tietmeyer, 2022; Gregoire and Marcet, 2014). Most likely, this was due to the high degree of uncertainty and the unexpectedly low returns on companies' shares (Bilinski et al., 2013). Although during the COVID-19 pandemic (the duration of the epidemic state in Poland), there were both periods of strong declines and increases, as during the 2008 financial crisis, the level of uncertainty, and therefore the degree of difficulty in making accurate forecasts, was much higher. Hence, the following research hypotheses were put forward:

H2a: Company valuations issued during the COVID-19 pandemic exhibit lower forecast accuracy.

H2b: Company valuations issued during the COVID-19 pandemic are characterised by higher forecast errors.

The third research hypothesis pertains to the valuation model employed by the analyst. As shown by the results of previous research (e.g. Głębocki et al., 2011; Bancel and Mittoo, 2014), the most popular approaches in business valuation are the income and comparative approaches. Analysts also often employ a mixed approach, combining the two approaches or one of them with another, assigning weights to each. For example, in the sample used in the Erkilet et al. (2021) study, 28% of the reports employed a hybrid approach that combined income and comparative approaches. In contrast, in the sample from the Bonini et al. (2022) study, nearly 32% of the reports used another model in addition to the relative valuation. As indicated by the National Specialist Valuation Standard - General Principles of Business Valuation adopted on 19 August 2015 by the Association of Chartered Business Valuers in Poland, "*all approaches considered appropriate by the valuator are taken into account in the valuation*". The choice of approach, as noted by Demirakos et al. (2010), reflects the analyst's willingness to focus on the key elements of the valuation that are appropriate for capturing the characteristic attributes of the valuation object. For example, a valuation based on the P/E multiple means that, in the analyst's view, it is the earnings measure that best reflects the value of the company. The use of the DCF method, on the other hand, implies a lesser emphasis on the current situation in favor of the company’s projected cash flows over a longer time horizon (including the residual value). As Demirakos et al. (2010) note, the choice of approach can also be related to its suitability for the company's specific situation.

Due to the small number of reports (259) in which the target price was set solely or mainly based on only one approach, the research sample used in this paper does not make it possible to compare the accuracy of the valuations depending on the method used. The exception is the analysts relied exclusively or predominantly on the DCF approach. Thus, it is not possible to compare the DCF method with other approaches. At the same time, the most common valuation approach used in more than half of the reports was a mixed approach consisting of the DCF and comparative methods. Therefore, this study investigated whether combining the comparative method with the DCF method in company valuation improves the accuracy of projected target prices. The results of Erkilet et al. (2021) suggest that the hybrid approach reduces valuation accuracy. Bonini et al. (2022), on the other hand, showed that including an additional model in addition to the relative valuation does not affect the target price accuracy. There is, therefore, no consensus in the literature on this issue. On the one hand, the inclusion of another model in the valuation may have a positive effect on it by taking more factors into account. On the other hand, the effect can be just the opposite, and instead of benefiting from the strengths of both methods, they are offset by using them together. There are also doubts about the subjective choice of weights assigned to the valuation results from the individual models in determining the final target price, which even allows for manipulation of the valuation process. Given the inconclusive conclusions of the analyses carried out so far, the following research hypotheses will be verified in this thesis:

H3a: The inclusion of the comparative method alongside the DCF approach significantly improves valuation accuracy.

H3b: The inclusion of the comparative method alongside the DCF approach significantly reduces valuation error.

The fourth and final research hypothesis relates to the sustainability of the forecasting capabilities of brokerages issuing valuation reports, the differences in forecast quality between them and the persistence of these differences. As indicated in the literature review, analysts' ability to make (in)accurate forecasts is constant over time so that accuracy in the previous period influences accuracy in the current period (Bradshaw et al., 2013; Bilinski et al., 2013; Bouteska and Mili, 2022). This also implies that analysts differ in their forecasting abilities, and these differences persist over time. In other words, there is no evidence of a learning process whereby “weaker” analysts catch up with their “stronger” peers.

The research sample used in this paper does not allow for a study of analysts' predictive capabilities, as multiple analysts often carry out single valuations. Therefore, this paper will investigate the persistence of predictive capabilities at the level of brokerage houses, similar to the work of Gregoire and Marcet (2014). Assuming that, just as there can be persistent differences in the production of accurate forecasts over time between analysts for a variety of reasons, there can also be differences between brokerages as a result of different valuation practices, methods of analysis or different access to specific tools, experience, datasets or the organisation's tacit knowledge. Hence, the following research hypothesis will be tested:

H4: There are time-persistent differences between brokerages in their ability to forecast target prices.

3. Research Sample

The research sample comprises 1,121 valuation reports of companies listed on the Warsaw Stock Exchange, sourced from the websites of the issuing brokerages, with the majority originating from consecutive editions of the Stock Exchange Analyst Coverage Support Programme between January 2018 and March 2024, inclusive. The analyst report data used in this paper was collected manually. In addition to this, the paper utilises stock market data, including stock quotes and P/BV ratios, downloaded from the Stooq platform, as well as financial data of companies from the Orbis database. The structure of the sample by time is shown in Table 1. Except for 2024, the distribution of observations over time is fairly even, with the share of reports from any year in the sample not exceeding 20%. The largest number of reports is from 2023 (19.8%) and the smallest from 2024 (2.9%), which is due to the inclusion, for the most recent year, of only the first quarter for which data on the realisation of target price forecasts in the first quarter of 2025 were available. The sample does not include reports published thereafter due to the typical 12-month forecast horizon and, consequently, the inability to verify the accuracy of the published valuation at the time of the survey.

The sample includes reports published by the 16 brokerages listed in Table 2. The shares of reports from individual brokerages in the sample are relatively diverse, with only two brokerages having a single report. For three brokerages, the number of reports exceeded 100, and the combined sample share of these three brokerages is approximately 46%. By far, the largest number of reports included in the research sample was published by Dom Maklerski BDM, namely 279, representing nearly 25% of the total sample.

Table 1. Structure of the sample by time section

No.	Year of Publication	No. of Reports	Share
1.	2018	147	13,1%
2.	2019	197	17,6%
3.	2020	150	13,4%
4.	2021	186	16,6%
5.	2022	187	16,7%
6.	2023	222	19,8%
	Total	1121	100%

Source: own elaboration.

Table 2. Structure of the sample by a brokerage house

No.	Brokerage House	No. of Reports	Share
1.	Dom Maklerski BDM	279	24,9%
2.	Dom Maklerski BOŚ	125	11,2%
3.	Biuro Maklerskie mBank	113	10,1%
4.	Dom Maklerski Noble Securities	93	8,3%
5.	Dom Maklerski Trigon	87	7,8%
6.	Ipopema Securities	79	7,0%
7.	Dom Maklerski Banku BPS	66	5,9%
8.	Dom Maklerski Vestor	51	4,5%
9.	East Value Research	48	4,3%
10.	Biuro Maklerskie Bank Pekao	46	4,1%
11.	Dom Maklerski Millenium	41	3,7%
12.	Biuro Maklerskie PKO BP	37	3,3%
13.	Biuro Maklerskie Santander	29	2,6%
14.	Erste Securities Polska	22	2,0%
15.	Dom Analiz SII	4	0,4%
16.	Biuro Maklerskie BGŻ BNP Paribas	1	0,1%
	Total	1121	100%

Source: own elaboration.

The structure of the sample by business sector of the valued companies is presented in Table 3. The classification was made based on information from the Biznes Radar website and the WSE. The largest share of the sample consists of valuation reports for companies from the Industrial Production and Construction sector (23.6%), while the smallest share comes from the Fuel and Energy sector (5.2%). The shares of each sector in the sample are similar to their shares in the broad WIG index. It therefore appears that, in terms of representing individual sectors, the sample reflects this broadest index on the Polish stock market well.

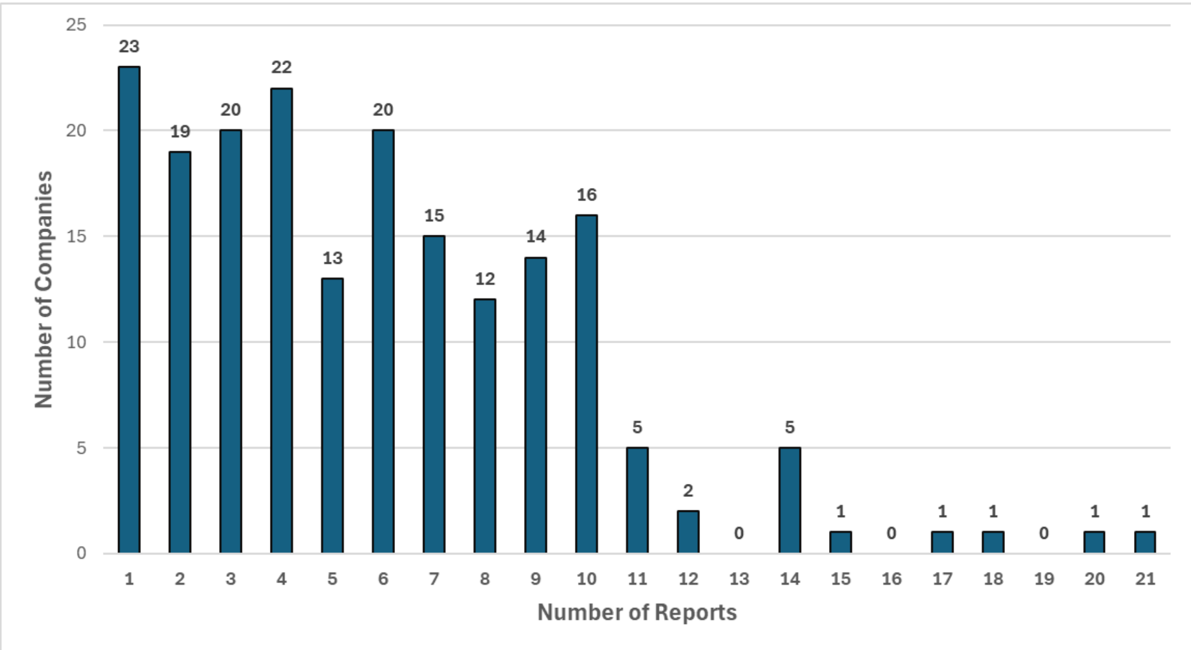
The collected reports forming the research sample valued 191 companies, of which nearly 88% were valued more than once. Figure 1 illustrates the structure of the sample based on the frequency of companies valued during the study period. The vast majority of companies, 174, were valued no more than 10 times. Voxel S.A. and Agora S.A. were valued most frequently, 20 and 21 times, respectively.

Table 3. Structure of the sample by sector of activity of the valued companies together with the share of the sectors in the WIG index (as of 15.12.2023-14.03.2024)

No.	Sector of Activity	No. of Reports	Share	Share in WIG Index
1.	Industrial and Construction Production	265	23,6%	22,4%
2.	Trade and Services	217	19,4%	16,4%
3.	Finance	153	13,6%	17,6%
4.	Technology	126	11,2%	10,9%
5.	Consumer Goods	107	9,5%	12,1%
6.	Healthcare	103	9,2%	8,8%
7.	Chemicals and Raw Materials	92	8,2%	6,7%
8.	Fuels and Energy	58	5,2%	5,2%
	Total	1121	100%	100%

Source: own elaboration.

Figure 1 . Frequency distribution of company valuations in the survey sample



Source: own elaboration.

Analysts preparing the reports included in the sample were generally positive about the valued companies, as evidenced by the fact that for more than half (51%) a *buy* recommendation was issued (Table 4). The second most frequently issued recommendation type was *hold* (14%), and the least frequently issued recommendations were *neutral* (1.1%) and *sell* (2.8%). In almost 17% of the reports, analysts stopped at setting a target price without issuing a specific recommendation. The optimistic attitude of analysts does not, however, seem to be specific to the Polish market, as also in the works by Kerl (2011) and Bonini et al. (2010) concerning the German and Italian markets, respectively, the most frequent recommendation was to buy shares. The share of reports with such a recommendation in the sample was 47% and 74%, respectively. To obtain more numerous and better comparable classes, recommendations from reports were assigned to three classes: *positive*, *neutral*, and *negative.* Reports with *buy* and *accumulate* recommendations were classified into the first, *hold* and *neutral* into the second, and *reduce* and *sell* into the third. This classification also reflects the positive attitude of analysts, as nearly 60% of the reports carry a *positive* recommendation, while only 8.3% have *a negative* one.

Table 4 . Structure of the sample by type and class of recommendation

Type of recommendation	No. of Reports	Share	Class of recommendation	No. of Reports	Share
Buy	572	51,0%	Positive	670	59,8%
Accumulate	98	8,7%			
Hold	157	14,0%	Neutral	169	15,1%
Neutral	12	1,1%			
Reduce	62	5,5%	Negative	93	8,3%
Sell	31	2,8%			
Not Disclosed	189	16,9%	Not Disclosed	189	16,9%
Total	1121	100%	Total	1121	100%

Source: own elaboration.

As shown in Table 5, analysts most often used two valuation methods to calculate their target price. Taking into account reports that provided information on the methods used, this occurred in as many as 71% of cases. By far, the most common method, in 58% of the valuations, was a combination of the DCF method and the comparative method. By comparison, in the study by Erkilet et al. (2021), the income approach was combined with the comparative approach in 28% of the reports. In the study by Bonini et al. (2022), another model was used in conjunction with the multiples model in almost 32% of the reports. Hence, it appears that Polish analysts are relatively more likely to use this method of valuation than analysts in the German market, which was the subject of the two studies mentioned. In the Polish market, where one valuation method was used (26.6% of reports in the sample), the DCF method was most often employed (73%). Analysts rarely used more than two valuation methods, in only 2% of the reports where information on the number of valuation methods applied was disclosed.

Table 6 shows the number of years for which analysts made forecasts as part of the valuation developed[1] . The most common projection for the DCF method is made for a 10-year

[1] It should be noted that only cases in which a given method was actually incorporated into the target price calculation were considered. Methods shown for illustrative purposes only— as was often the case with the comparative approach — were not taken into account.

horizon (57.5%), and for the comparative method, it is for a 3-year horizon (84.4%). The second most common cases are a 5-year projection for the DCF method (16.7%) and a 2-year projection for the comparative method (11.8%).

Table 5. Structure of the sample by valuation method

No. of Valuation Methods	No. of Reports	Share	Share (of Non-Missing)	Valuation method	No. of Reports	Share (of Non-Missing)
1	259	23,1%	26,6%	DCF	185	19,0%
				Other	74	7,6%
2	692	61,7%	71,0%	DCF + MP	565	58,0%
				DCF + Other	65	6,7%
				MP + Other	27	2,8%
				Two Others	35	3,6%
3	17	1,5%	1,7%	DCF + MP + Other	15	1,5%
				MP + Two Others	2	0,2%
4	6	0,5%	0,6%	DCF + MP + Two Others	6	0,6%
N/A	147	13,1%	-	-	-	-
Total	1121	100%	100%	-	974	100%

Legend: DCF - discounted cash flow method, MP - comparative method. Other methods include: SOTP - sum-of-the-parts method, DDM - discounted dividend model, scenario analysis, RIV - residual income method, valuation based on the target enterprise value to earnings before interest, taxes, depreciation, and amortization (EV/EBITDA) multiple, NAV - net asset value method, rNPV - risk-weighted net present value method, ZZR - discounted residual income method, growth-adjusted comparative method, ROE-P/BV regression model.

Source: own elaboration.

In contrast, Figure 2 shows the number of comparable companies selected by analysts carrying out a comparative valuation. This information appeared in 575 reports where the comparative method was used to set the target price. Most often, the number of comparable companies was 6 or 10 - a total of about 20% of the cases. Analysts rarely selected more than 18 comparable companies, as this was done in only about 9% of the reports. At the same time, it is worth noting that about 85% of the valuations included at least one foreign company among the comparable companies.

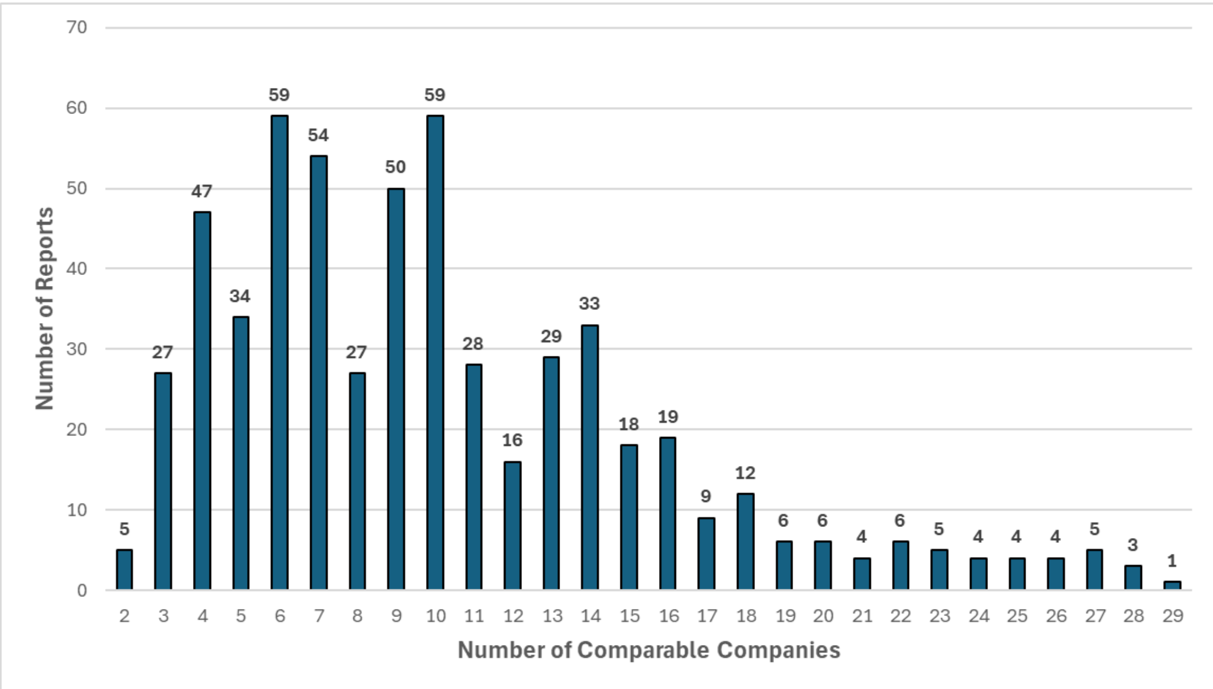
Table 7 shows the number of multiples used in the comparative valuations. The number ranges from 1 to 4, but most often (in 87% of valuations), analysts used 2 or 3 multiples.

Table 6. Number of forecast years in reports using the DCF method and the comparative method

Number of forecast years	No. of Reports - DCF Method	Share	Share (of Non-Missing)	No. of Reports - Comparative Method	Share	Share (of Non-Missing)
0	-	-	-	2	0,3%	0,3%
1	-	-	-	20	3,2%	3,4%
2	-	-	-	69	11,1%	11,8%
3	-	-	-	493	79,0%	84,4%
4	8	1,0%	1,0%	-	-	-
5	130	15,6%	16,7%	-	-	-
6	42	5,0%	5,4%	-	-	-
7	23	2,8%	3,0%	-	-	-
8	25	3,0%	3,2%	-	-	-
9	77	9,2%	9,9%	-	-	-
10	447	53,5%	57,5%	-	-	-
11	16	1,9%	2,1%	-	-	-
12	7	0,8%	0,9%	-	-	-
15	1	0,1%	0,1%	-	-	-
22	1	0,1%	0,1%	-	-	-
N/A	59	7,1%	-	40	6,4%	-
Total	836	100%	100%	624	100,0%	100,0%

Source: own elaboration.

Figure 2. Sample structure by number of comparable companies in reports using the comparative method



Source: own elaboration.

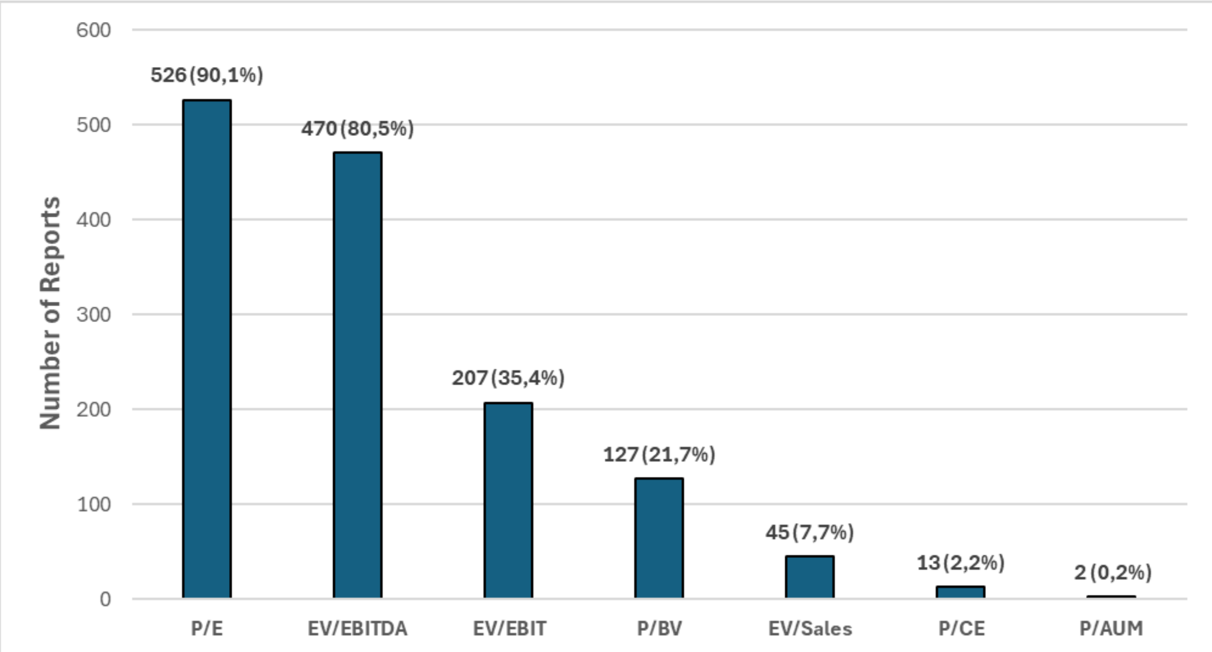
Table 7. Number of multiples in valuations using the comparative method

No. of Multiples	No. of Reports	Share	Share (of Non-Missing)
1	52	8,3%	8,9%
2	282	45,2%	48,3%
3	225	36,1%	38,5%
4	25	4,0%	4,3%
N/A	40	6,4%	-
Total	624	100%	100%

Source: own elaboration.

Figure 3 illustrates the multiples used by analysts. The most popular multiples were P/E and EV/EBITDA, which were used in 90.1% and 80.5% of the reports using the comparative method, respectively. The EV/EBIT, P/BV or EV/Sales multiples were used less frequently. The other multiples (P/CE and P/AUM) were used very rarely.

Figure 3. Multiples used in comparative valuations



Legend: P/E - price to earnings, EV/EBITDA - enterprise value to operating profit before deducting depreciation and amortisation, EV/EBIT - enterprise value to operating profit, P/BV - price to book value, EV/Sales - enterprise value to sales, P/CE - price to cash earnings, P/AUM - price to assets under management.

Source: own elaboration.

4. Survey methodology

The research hypotheses formulated at the outset will be tested based on the results of four groups of econometric models, drawing on the works of Kerl (2011), Bonini et al. (2010), Demirakos et al. (2010), and Bradshaw et al. (2012). Within each group, a model analogous (similar) to the one estimated in the cited literature is first replicated as faithfully as the collected data on the Polish market allow. Subsequently, additional variables are included in the models to test new relationships. The necessary modifications are discussed in more detail at the introduction of each group of models. Definitions of dependent variables are presented in Table 8, and independent variables - in Table 9. Variables with kurtosis exceeding 6 were winsorized above the 95th percentile (below the 5th percentile for *Acc* and *Acc_Adj*). Table 10 presents the correlation matrix of the variables, which includes only correlations significant at the 5% level to enhance readability. There is no problem of collinearity in the estimated models due to the low values of the VIF. The exception is the use of the square of the variable already included in the model.

Table 8. Definitions of dependent variables

Variable	Definition
Ach_End	1 if the TP was achieved at the end of the forecast horizon; 0 otherwise
Ach_In	1 if the TP was achieved within the forecast horizon; 0 otherwise
Acc	$1 - \lvert \frac{P_{end} - TP}{TP} \rvert$
Acc_Adj	$1 - \frac{\lvert \frac{P_{end} - TP}{TP} \rvert}{Volatility\_1}$
Error_1	$\lvert \frac{TP - P_{end}}{P_t} \rvert$
Error_1_NA	$\lvert \frac{TP - P_{end}}{P_t} \rvert$ if the TP was not achieved at the end of the forecast horizon; 0 otherwise
Error_2	$\lvert \frac{TP - P_{end-3}}{P_{end-3}} \rvert$
Error_3	$\lvert \frac{TP - P_{max}}{P_{max}} \rvert$ if $TP \geq P_t$ $\lvert \frac{TP - P_{min}}{P_{min}} \rvert$ if $TP < P_t$

Legend: TP - target price, P_{end}- stock price at the end of the forecast horizon, P_t- stock price on the day the report is published, P_{end-3}- stock price 3 days before the end of the forecast horizon, P_{max}- maximum stock price at the forecast horizon, P_{min}- minimum stock price at the forecast horizon, Volatility_1 is defined in Table 9. If the forecast horizon is not specified in a given report, a period of 12 months is taken as the default.

Source: own elaboration.

Table 9. Definitions of independent variables

Variable	Definition	Variable type / Hypothesis	Expected Sign (Accuracy)	Expected Sign (Error)
State_Treasury	1 if the main shareholder is the State Treasury or a state-controlled entity; 0 otherwise	Test / H1a and H1b	-	+
COVID	1 if the report was published during the official COVID-19 epidemic period in Poland (20/03/2020–15/05/2022); 0 otherwise	Test / H2a and H2b	-	+
Method_1	0 if the DCF method was used without the comparative method; 1 if both were used	Test / H3a and H3b	+	-
Method_2	0 if only the DCF method was used; 1 if both the DCF and comparative method were used	Test / H3a and H3b	+	-
LagAch_End	Average value of Ach_End for a given broker in the previous calendar year; calculated for min. 5 observations	Test / H4	+	n/a
LagAch_In	Average value of Ach_In for a given broker in the previous calendar year; calculated for min. 5 observations	Test / H4	+	n/a
LagAcc	Average value of Acc for a given broker in the previous calendar year; calculated for min. 5 observations	Test / H4	+	n/a
LagError_1	Average value of Error_1 for a given broker in the previous calendar year; calculated for min. 5 observations	Test / H4	n/a	+
Year	Report Publication Year	Control	No expectation	No expectation
Broker	Brokerage House	Control	No expectation	No expectation
Sector	Industry Sector (GPW Classification)	Control	No expectation	No expectation
Positive	1 if the recommendation is Buy or Accumulate; 0 otherwise	Control	?	?
Neutral	1 if the recommendation is Hold or Neutral; 0 otherwise	Control	?	?
Negative	1 if the recommendation is Reduce or Sell; 0 otherwise	Control	?	?

Foreign	1 if the peer group included at least one foreign company; 0 otherwise	Control	?	?
lLenght	Natural logarithm of report length (in pages)	Control	+	-
Boldness_1	$\lvert \frac{TP-P_t}{P_t} \rvert$	Control	-	+
Boldness_1Q	$(Boldness\_1)^2$	Control	?	?
Boldness_1_Adj	$\frac{Boldness\_1}{Volatility\_1}$	Control	-	+
Boldness_2	$\lvert \frac{TP - P_{t-3}}{P_{t-3}} \rvert$	Control	-	+
lSize	Natural logarithm of the company's market capitalization on the report date	Control	+	-
PBV	Price-to-Book Value (P/BV) ratio of the company on the report date	Control	-	+
Growth	Geometric average of sales growth between (t–1)/(t–2) and (t–2)/(t–3), where t is the report year; assigned 0 if sales growth negative in either period	Control	?	?
Profit	1 if the company was profitable in the year preceding the report; 0 otherwise	Control	+	-
ROA_Volatility	Standard deviation of ROA over the 5 years before report publication; calculated for min. 3 observations	Control	-	+
Volatility_1	Standard deviation of daily stock returns over the year preceding the report	Control	-	+
Volatility_2	Standard deviation of daily stock returns over the period from 90 days to 3 days prior to the report's publication	Control	-	+
Momentum	Stock return over the period from 6 months to 3 days prior to the report's publication	Control	+	-
Market_Return	WIG index return over the forecast horizon	Control	+	-

Legend: TP - target price, P_t- stock price on the day of report publication, P_{t-3}- stock price 3 days before report publication. If the forecast horizon is not specified, a period of 12 months is assumed as default.

Source: own elaboration.

Table 10. Matrix of Pearson (below diagonal) and Spearman (above diagonal) correlation coefficients of variables significant at the 5% level

ZMIENNA	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)
(1) Ach_End	1	0,64	0,12	0,09	-0,18	-0,81	-0,38	0,39									-0,11	0,11				-0,26	-0,26	-0,24	-0,25								0,12	0,22
(2) Ach_In	0,64	1	0,30	0,27	-0,39	-0,72	-0,54								0,08	-0,11	-0,27	0,23	0,11			-0,46	-0,46	-0,44	-0,44	0,08			0,06				0,08	0,19
(3) Acc	0,08	0,24	1	0,89	-0,97	-0,54	-0,85	-0,41	-0,07	-0,13	0,12	0,12			0,09			0,08				-0,18	-0,18	-0,11	-0,17		-0,07		0,09	-0,12	-0,21	-0,16		0,10
(4) Acc_Adj		0,22	0,88	1	-0,85	-0,44	-0,74	-0,34	-0,15													-0,08	-0,08	-0,16	-0,07	-0,10					0,18	0,12	0,08	0,15
(5) Error_1	-0,13	-0,33	-0,94	-0,81	1	0,61	0,86	0,44		0,14	-0,10	-0,10	-0,07		-0,13	0,12	0,19	-0,16	-0,09			0,37	0,37	0,29	0,36	-0,13			-0,08	0,15	0,24	0,16	-0,07	-0,08
(6) Error_1_NA	-0,67	-0,67	-0,58	-0,47	0,67	1	0,74	-0,07		0,09					-0,09	0,08	0,18	-0,19			0,06	0,43	0,43	0,37	0,41	-0,09			-0,08	0,11	0,15		-0,12	-0,26
(7) Error_2	-0,35	-0,48	-0,70	-0,57	0,73	0,79	1	0,30	0,11	0,11	-0,11	-0,10			-0,09	0,08	0,15	-0,12	-0,07			0,30	0,30	0,23	0,29	-0,10	0,07		-0,12	0,16	0,19	0,10	-0,10	-0,24
(8) Error_3	0,36	0,06	-0,45	-0,38	0,51	0,07	0,32	1		0,10			-0,13	-0,12	-0,13	0,14				-0,09		0,22	0,22	0,16	0,21	-0,17	-0,06			0,10	0,17	0,17		0,07
(9) State_Treasury				-0,15			0,09		1	-0,12			-0,07		0,14	-0,17				-0,14		-0,14	-0,14	-0,08	-0,13	0,38	-0,36	-0,17	0,07	-0,14	-0,18	-0,09	-0,14	-0,17
(10) COVID			-0,13		0,14	0,10	0,08	0,11	-0,12	1	-0,15	-0,14	0,20	0,32	-0,25	0,20	0,08	-0,08				0,10	0,10		0,10	-0,10		-0,07	-0,06		0,33	0,24	0,06	-0,13
(11) Method_1			0,11		-0,10		-0,11			-0,15	1	1,00	-0,10	-0,09	0,21	-0,21		-0,12			0,25			0,12		0,13	-0,13		0,12	-0,11	-0,16	-0,16	0,08	
(12) Method_2			0,11		-0,09		-0,10			-0,14	1,00	1	-0,09		0,19	-0,20		-0,14			0,23			0,13		0,14	-0,12		0,13	-0,14	-0,17	-0,17	0,08	
(13) LagAch_End					-0,08			-0,14	-0,07	0,21	-0,14	-0,11	1	0,78	0,16	-0,22					0,08	-0,09	-0,09	-0,09	-0,10		0,08					-0,12	0,32	-0,13
(14) LagAch_In								-0,13		0,28	-0,08		0,80	1	0,17	-0,31		-0,08	0,08	-0,13	0,19	-0,17	-0,17	-0,18	-0,17	0,19				-0,08			0,24	-0,25
(15) LagAcc		0,10	0,11		-0,16	-0,14	-0,13	-0,15	0,12	-0,23	0,18	0,18	0,21	0,27	1	-0,93	-0,10					-0,18	-0,18	-0,12	-0,20	0,15	-0,18	0,07	0,09	-0,19	-0,23	-0,15	0,11	
(16) LagError_1		-0,14	-0,10		0,17	0,17	0,16	0,17	-0,14	0,17	-0,13	-0,13	-0,29	-0,41	-0,92	1	0,12		-0,11	0,13		0,22	0,22	0,17	0,23	-0,23	0,16		-0,09	0,21	0,21	0,14	-0,09	0,11
(17) Positive	-0,11	-0,27			0,17	0,19	0,15			0,08					-0,10	0,13	1	-0,75	-0,53			0,63	0,63	0,63	0,61	-0,15			0,09				0,10	
(18) Neutral	0,11	0,23	0,06		-0,15	-0,20	-0,10			-0,08	-0,12	-0,14			0,08	-0,08	-0,75	1	-0,16		-0,13	-0,58	-0,58	-0,57	-0,56				-0,11				-0,09	
(19) Negative		0,11					-0,10									-0,09	-0,53	-0,16	1		0,08	-0,21	-0,21	-0,21	-0,20	0,22				-0,09				
(20) Foreign								-0,08	-0,14					-0,12	-0,09	0,15				1	0,08	0,08	0,08	0,09	0,08		0,21			0,16	-0,08			-0,08
(21) lLenght						0,06		0,06			0,25	0,23	0,08	0,16				-0,11	0,08	0,09	1	0,08	0,08	0,08	0,08					0,07		-0,11	0,12	-0,09
(22) Boldness_1	-0,26	-0,44	-0,17	-0,07	0,42	0,50	0,35	0,26	-0,12	0,10			-0,13	-0,23	-0,21	0,27	0,51	-0,44	-0,20	0,09	0,09	1	1,00	0,93	0,98	-0,32				0,19	0,21	0,10		
(23) Boldness_1Q	-0,24	-0,39	-0,18	-0,08	0,43	0,49	0,36	0,31	-0,09	0,09			-0,17	-0,25	-0,20	0,27	0,36	-0,29	-0,17	0,09	0,08	0,96	1	0,93	0,98	-0,32				0,19	0,21	0,10		
(24) Boldness_1_Adj	-0,25	-0,43	-0,10	-0,15	0,33	0,41	0,27	0,21			0,11	0,12	-0,12	-0,22	-0,14	0,22	0,52	-0,44	-0,21	0,10	0,08	0,91	0,86	1	0,91	-0,20	-0,13		0,08	0,07	-0,10	-0,12		
(25) Boldness_2	-0,25	-0,42	-0,17	-0,06	0,41	0,48	0,33	0,26	-0,12	0,10			-0,14	-0,23	-0,21	0,28	0,50	-0,44	-0,19	0,10	0,09	0,98	0,94	0,89	1	-0,32				0,19	0,22	0,11		
(26) lSize		0,09		-0,13	-0,13	-0,10	-0,08	-0,14	0,42	-0,12	0,15	0,15		0,17	0,17	-0,25	-0,16		0,24			-0,33	-0,30	-0,21	-0,33	1			0,08	-0,34	-0,38	-0,23		-0,21
(27) PBV			-0,15		0,13	0,12	0,18		-0,23		-0,13	-0,15			-0,19	0,16			0,08	0,16				-0,15		0,07	1	0,23	-0,11	0,29	0,20	0,12	0,12	
(28) Growth					0,08	0,10	0,15		-0,17		-0,10	-0,08				0,07	0,08		-0,08	0,07		0,08	0,06		0,07	-0,10	0,24	1	0,15					0,09
(29) Profit		0,06	0,09		-0,06	-0,08	-0,11		0,07	-0,06	0,12	0,13			0,07		0,09	-0,11								0,11	-0,21	0,08	1	-0,27	-0,24	-0,17		
(30) ROA_Volatility		-0,09	-0,15		0,17	0,20	0,23	0,08	-0,10		-0,10	-0,12			-0,15	0,15				0,08		0,16	0,14		0,15	-0,26	0,40	0,18	-0,28	1	0,37	0,24		0,11
(31) Volatility_1			-0,20	0,21	0,22	0,19	0,19	0,13	-0,17	0,30	-0,17	-0,19			-0,21	0,18						0,18	0,17	-0,15	0,20	-0,36	0,29	0,06	-0,27	0,34	1	0,71	0,07	0,20
(32) Volatility_2			-0,19	0,12	0,19	0,10	0,10	0,16	-0,09	0,26	-0,16	-0,17	-0,16	-0,10	-0,16	0,14			0,07		-0,07	0,13	0,14	-0,14	0,14	-0,24	0,22		-0,20	0,21	0,71	1		0,26
(33) Momentum	0,12	0,09		0,09		-0,11	-0,10		-0,13	0,09			0,29	0,25	0,07	-0,07	0,09	-0,09			0,10			-0,07			0,12				0,11		1	0,06
(34) Market_Return	0,23	0,19	0,08	0,14	-0,07	-0,25	-0,28		-0,17	-0,13			-0,18	-0,23						-0,07						-0,22		0,07		0,10	0,16	0,25	0,08	1

Only correlations significant at the 5% level have been included in the matrix for readability reasons. Blank spaces therefore, denote non-significant correlations.

Source: own elaboration.

The basic descriptive statistics of the variables used in the study are presented in Table 11. The different number of observations included in the individual models is mainly due to incomplete information in the analytical reports (missing data). In 13 cases, it was not possible to verify the accuracy of the target price forecast, i.e., to determine the values of the dependent variables, because the forecast horizon had not yet elapsed. The incomplete number of observations for the variable *lLenght* is, on the other hand, caused by the lack of information in sector reports concerning more than one company and reports available to the public only in an abridged version. In the case of the stock market listing variables, the shortcomings are due to the short period the company has been listed on the stock market, which limits the ability to calculate some variables or to missing data.

Table 11. Descriptive statistics of the variables

VARIABLE	N	Mean	Standard Deviation	Min	Max
Ach_End	1108	0,309	0,462	0	1
Ach_In	1108	0,523	0,5	0	1
Acc	1108	0,65	0,231	0,138	1
Acc_Adj	1104	-12,653	9,307	-33,235	1
Error_1	1108	0,463	0,339	0	1,292
Error_1_NA	1108	0,329	0,327	0	1,027
Error_2	1108	0,522	0,49	0,001	1,904
Error_3	1108	0,228	0,177	0	0,63
State_Treasury	1121	0,108	0,31	0	1
COVID	1121	0,326	0,469	0	1
Method_1	836	0,701	0,458	0	1
Method_2	772	0,732	0,443	0	1
LagAch_End	890	0,318	0,194	0	0,727
LagAch_In	890	0,522	0,217	0	1
LagAcc	890	0,646	0,082	0,421	0,815
LagError_1	890	0,467	0,137	0,245	0,966
Positive	932	0,719	0,45	0	1
Neutral	932	0,181	0,385	0	1
Negative	932	0,1	0,3	0	1
Foreign	828	0,832	0,374	0	1
lLenght	1029	2,636	0,537	0,693	4,466
Boldness_1	1121	0,296	0,235	0	0,842
Boldness_1Q	1121	0,143	0,196	0	0,709
Boldness_1_Adj	1104	11,256	8,917	0	32,606
Boldness_2	1121	0,303	0,24	0	0,87
lSize	1104	6,363	1,686	1,93	10,952
PBV	1098	2,719	2,879	0,15	11,322
Growth	1090	0,141	0,186	0	0,658
Profit	1121	0,881	0,324	0	1
ROA_Volatility	1086	0,051	0,055	0	0,199
Volatility_1	1104	0,027	0,009	0,009	0,049
Volatility_2	1107	0,025	0,009	0,006	0,049
Momentum	1100	0,07	0,348	-0,919	1,892
Market_Return	1115	0,09	0,229	-0,386	0,748

Source: own elaboration.

At the end of the forecast horizon, 30.9% of target prices were achieved, which is slightly weaker than in the sample of the Bradshaw et al. (2012) study, where it was 38%. In contrast, 52.3% of valuations reached the target price during the entire forecast horizon, which is lower than in the Brycz and Włodarczyk (2017) study, also concerning the Polish market, where 66.7% of valuations met this criterion or in the Bradshaw et al. (2012) work, where it was 64%. In contrast, in the sample studied by Kerl (2011), 56.5% of target prices were achieved during the valuation horizon, and in the study by Asquith et al. (2005), 54% achieved their target prices. The average accuracy measured by the *Acc* variable was 65%, a result similar to Kerl (2011), where 67.4% was achieved, and Bouteska and Mili (2022), for whom it was 66.6%. Considering the mean forecast error measured by the *Error_1* variable, the result obtained (46.3%) is similar to the work of Bilinski et al. (2013) (44.7%) or Bradshaw et al. (2012) (45%). In contrast, the mean value of *Error_2* (52.2%) is significantly higher than that obtained by Erkilet et al. (2021) (22%). A much closer value was obtained by Cheng et al. (2019) (49%). Also, the mean *Error_3* (22.8%) is very similar to that obtained by these authors (21%) (Cheng et al., 2019). The analysts' average projected price change for the Polish market was 29.6%, i.e. similar to the Bonini et al. (2022) study (23.8%) and well above the sample average of 15.9% from the Bilinski et al. (2013) paper.

As shown in Table 12, among the types of recommendations, *neutral* recommendations are associated with the highest (lowest) accuracy (error), except the *Error_2* measure, according to which *negative* recommendations record the smallest error. In terms of reaching the target price at the end (*Ach_End)* or during (*Ach_In)* of the forecast horizon, *positive* recommendations are the worst, which is in line with the results of Bonini et al. (2010). For these measures of accuracy, it is not surprising that the best performance is achieved by *neutral* recommendations, which generally predict the smallest change in share price. Similarly, for all error measures except *Error_3*, *positive* recommendations are the weakest, i.e. with the largest forecast error. The situation is different for the *Acc* and *Acc_Adj* accuracy measures, according to which the lowest accuracy is characteristic of reports with *negative* recommendations, which confirms Kerl's (2011) observations using the same measure. On the other hand, in his sample, the highest accuracy was achieved by reports with *positive recommendations,* which is not reflected in the sample used in this study for the Polish market. Thus, it can be seen that the results obtained depend on the measure of accuracy (error) used.

Comparing the mean values of the dependent variables presented in Table 13, it can also be seen that for almost every measure, the mean accuracy (error) is lower (larger) for SOEs than for other companies and reports published during the COVID-19 pandemic than during the rest of the period, which is consistent with H1a(b) and H2a(b). However, the t-test applied shows that these differences, especially for SOEs, are not necessarily statistically significant. This conclusion is confirmed by the results obtained by applying the non-parametric Mann-Whitney test, which is not included for readability. In turn, as shown in Table 14, the accuracy (error) is higher (smaller) in valuations where the comparative method, in addition to the DCF method, was included in the target price calculation for all measures except *Ach_End* and the variable *Method_2*. This result is consistent with H3a(b), but as before, the t-test shows that the differences are not always statistically significant. This is confirmed by the unstated results obtained by applying the non-parametric Mann-Whitney test.

Table 12. Mean values of the dependent variables in the cross-section by class of recommendation, together with the results of the ANOVA analysis

VARIABLE	Negative	Neutral	Positive	F-Statistic (ANOVA)
Ach_End	0,34	0,43	0,29	6,32***
Ach_In	0,71	0,78	0,46	36,41***
Acc	0,61	0,68	0,65	3,14**
Acc_Adj	-14,50	-11,84	-12,96	2,43*
Error_1	0,40	0,35	0,49	13,96***
Error_1_NA	0,29	0,18	0,36	20,09***
Error_2	0,37	0,41	0,56	10,73***
Error_3	0,26	0,21	0,23	2,09
N	93	169	670	-

*, **, *** denote statistical significance at the 10%, 5%, 1% level respectively.

Source: own elaboration.

Table 13. Mean values of the dependent variables by Treasury ownership of the company being valued and the valuation period together with the results of t-test

VARIABLE	*State_Treasury=0*	*State_Treasury=1*	t-Statistic	COVID=0	COVID=1	t-Statistic
Ach_End	0,31	0,27	0,91	0,32	0,30	0,66
Ach_In	0,53	0,47	1,22	0,54	0,49	1,73*
Acc	0,65	0,62	1,73*	0,67	0,61	4,28***
Acc_Adj	-12,17	-16,59	4,98***	-12,65	-12,66	0,01
Error_1	0,46	0,47	-0,39	0,43	0,53	-4,73***
Error_1_NA	0,33	0,36	-1,14	0,31	0,38	-3,43***
Error_2	0,51	0,65	-3,07***	0,49	0,58	-2,70***
Error_3	0,23	0,24	-0,53	0,22	0,26	-3,53***
N	1000	121	-	755	366	-

*, **, *** denote statistical significance at the 10%, 5%, 1% level respectively.

Source: own elaboration.

Table 14. Mean values of dependent variables by valuation method together with results of t-test

VARIABLE	Method_1=0	Method_1=1	t-Statistic	Method_2=0	Method_2=1	t-Statistic
Ach_End	0,32	0,34	-0,34	0,34	0,32	0,50
Ach_In	0,53	0,56	-0,74	0,54	0,54	-0,08
Acc	0,62	0,68	-3,17***	0,62	0,67	-2,96***
Acc_Adj	-12,47	-11,78	-0,99	-12,45	-11,90	-0,73
Error_1	0,50	0,43	2,84***	0,51	0,43	2,55**
Error_1_NA	0,34	0,30	1,92*	0,34	0,30	1,31
Error_2	0,58	0,47	3,17***	0,59	0,48	2,79***
Error_3	0,24	0,23	0,81	0,24	0,23	0,96
N	250	586	-	207	565	-

*, **, *** denote statistical significance at the 10%, 5%, 1% level respectively.

Source: own elaboration.

Table 15 shows the mean values of the four dependent variables used in the verification of hypothesis H4, cross-sectioned by quartiles of the mean accuracy (error) of brokerage house valuations in the previous year. Mean valuation accuracy (error) was calculated for a minimum of 5 observations. The mean value of a given dependent variable for brokerages in the respective quartile is presented in column (*t-1*). The quartiles were arranged in order of valuation accuracy, from worst to best. Column (*t*), on the other hand, shows the average value of a given variable for these brokerages in the current year. It can be seen that for all the valuation accuracy (error) measures used, there is some persistence in the quality (accuracy) of the brokerage houses' forecasts, but it is not very strong. For example, the top quartile of brokerages in the previous year for the *Ach_End* variable averaged the second-weakest performance in the current year. Thus, under this analysis, there is no strong evidence to support or reject H4.

Table 15. Average values of dependent variables by quartiles of average accuracy (error) of brokerage valuation in the previous year

Quartile	Ach_End (t-1)	Ach_End (t)	Ach_In (t-1)	Ach_In (t)	Acc (t-1)	Acc (t)	Error_1 (t-1)	Error_1 (t)
1	0,14	0,27	0,28	0,50	0,54	0,62	0,65	0,54
2	0,31	0,37	0,41	0,48	0,63	0,65	0,51	0,47
3	0,36	0,38	0,62	0,55	0,69	0,65	0,43	0,43
4	0,50	0,29	0,72	0,63	0,74	0,66	0,34	0,46

Source: own elaboration.

The first group of models, based on the work of Kerl (2011), is presented in equation (A). The original model has been modified by adding new variables – *State_Treasury, COVID, and Foreign* – to capture additional dependencies not previously discussed in the literature. According to equation (A), models (1), (2), and (3) are estimated, and hypotheses H1a, H1b, H2a and H2b are verified.

$$Measure\_A_i = \beta_0 + \beta_1 State\_Treasury_i + \beta_2 COVID_i + \beta_3 Boldness_i + \beta_4 PBV_i + \beta_5 Volatility\_1_i + \beta_6 Positive_i + \beta_7 Negative_i + \beta_8 Foreign_i + \beta_9 lSize_i + \beta_{10} lLenght_i + \varepsilon_i \qquad (A)$$

where: *Measure_A* is *Acc* or *Acc_Adj*, *Boldness* means *Boldness_1* or *Boldness_1*_Ad. In the model where *Acc_Adj* is the dependent variable, *Volatility_1* was omitted due to its use in the variables *Acc_Adj* and *Boldness_1_Adj*.

The second group of models, based on the work of Demirakos et al. (2010), is presented in equation (B). Due to the use of a different research sample, this study verifies hypotheses H3a and H3b rather than comparing the effectiveness of the DCF method and the comparison method, as done by the mentioned authors. Based on equation (B), models (4), (5), (11) and (12) are estimated. The inclusion of the categorical variable *Broker* in the model identifies brokerages that produced at least 20 reports (observations) in the analysed sample.

$$Measure\_B_i = \beta_0 + \beta_1 Method_i + \beta_2 Boldness\_2_i + \beta_3 Volatility\_2_i + \beta_4 Market\_Return_i + \beta_5 Positive_i + \beta_6 Growth_i + \sum_{k=2}^{14} \beta_{5+k} Broker\_k_i + \varepsilon_i \qquad (B)$$

where: *Measure_B* is *Ach_End* or *Ach_In* or *Error_1* or *Error_1_NA* and *Method* is *Method_1* or *Method_2*.

The third group of models, illustrated by equation (C), is based on the work of Bradshaw et al. (2012). Regarding the model estimated by the cited authors, the test variable was modified like that of Bilinski et al. (2013). According to Equation (C), models (6), (7), (8), and (13) are estimated, and Hypothesis H4 is verified.

$$Measure\_C_i = \beta_0 + \beta_1 LagMeasure\_C_i + \beta_2 Momentum_i + \beta_3 Volatility\_1_i + \beta_4 Market\_Return_i + \sum_{k=2}^{8} \beta_{3+k} Sector\_k_i + \sum_{k=2}^{7} \beta_{10+k} Year\_k_i + \varepsilon_i \qquad (C)$$

where: *Measure_C* is *Ach_End* or *Ach_In* or *Acc* or *Error_1*. Similarly, *LagMeasure_C* is *LagAch_End* or *LagAch_In* or *LagAcc* or *LagError_1*.

The fourth and final group of models is based on the work of Bonini et al. (2010). Compared to the model cited by the authors, the dependent variables take a different form, similar to those in the studies by Cheng et al. (2019) and Erkilet et al. (2021). In addition, to obtain the correct functional form of the model, the variable *Error_2* was subjected to a logarithmic transformation (*lError_2*) and the variable *Boldness_1Q* was included. Its inclusion results in a higher VIF for these variables but it is necessary to explain the non-linear relationship. The results do not change when the dependent variable is the natural logarithm of (1+*Error_2*). The inclusion of the variables *ROA_Volatility*, *State_Treasury* and *COVID* allows the hypotheses H1a, H1b, H2a and H2b to be verified on a different group of models than the first. Based on equation (D), models (9) and (10) are estimated.

$$\begin{aligned} Measure\_D_i = {} & \beta_0 + \beta_1 State\_Treasury_i + \beta_2 COVID_i + \beta_3 Boldness\_1_i + \beta_4 Boldness\_1Q_i \\ & + \beta_5 lSize_i + \beta_6 Profit_i + \beta_7 PBV_i + \beta_8 Market\_Return_i + \beta_9 ROA\_Volatility_i \\ & + \sum_{k=2}^{8} \beta_{8+k} Sector\_k_i + \varepsilon_i \qquad (D) \end{aligned}$$

where: *Measure_D* is *Error_3* or *lError_2*.

In the absence of an identical variable to that in the publication on which the model group is based, it was omitted or replaced by a variable with the closest possible definition. The RESET test for the correctness of the functional form of the model determined the choice of the final variable definition from among the available possibilities. For the sake of clarity, equations (A), (B), (C), and (D) do not display the control variables included in the original models proposed by other authors, if the coefficients estimated for the Polish market were statistically insignificant across all models in the given group.

All models with a continuous dependent variable are estimated using POLS, and those with a binary dependent variable are estimated using a probit model. In all models, clustering is performed at the level of the company to which the valuation report pertains. Differences in the number of observations across models result from data gaps discussed earlier, but they do not affect the overall conclusions. To facilitate interpretation of the results, the tables present the final model specifications obtained through a general-to-specific procedure, retaining all variables necessary to ensure the correct functional form. First, we report the estimation results for models where the dependent variable is the accuracy of target price forecasts, followed by those where the dependent variable is the forecast error.

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5. Results

5.1. SOEs and the COVID-19 Pandemic vs Target Price Accuracy

The estimation results of models (1) and (2) are shown in Table 16. The coefficients for all included variables are jointly statistically significant at the 1% level in these models. In the first model, the dependent variable is *Acc*, while the second model, which serves as a robustness check, uses *Acc_Adj*. The negative and statistically significant coefficients on the variables S*tate_Treasury* and *COVID* indicate lower forecast accuracy for target prices issued for SOEs and during the Covid-19 pandemic. These findings are consistent with **hypotheses H1a and H2a**, although the coefficient for *COVID* is not statistically significant in model (2). The results suggest that increased uncertainty stemming from the political ties of SOEs or from the turbulence in financial markets during the pandemic made it more difficult for analysts to issue accurate target price forecasts.

In the case of control variables, the results obtained are in line with expectations, except for the variable *lSize*, for which statistically significant and negative coefficients were obtained in models (2a) and (2b). This demonstrates the greater accuracy of smaller company valuations despite the widely held belief that valuations of larger companies are more accurate due to the higher reliability of their reported data and greater stability. It is also worth noting that the significance, as well as the magnitude (in terms of absolute value) of the coefficient on the *lSize* variable, decreased markedly after including the S*tate_Treasury* variable in the model (2b). This may be related to the fact that SOEs are relatively larger, as although they account for about 11% of the entire sample, their share in the group of reports of the 25% largest companies is as high as 31.5%. Thus, when we omit the S*tate_Treasury* variable from the model, the *lSize* variable can take on some of the negative effects of the *State_Treasury* variable.

Negative and statistically significant coefficients on the variables *Boldness_1* and *Boldness_1_Adj* show that the greater the price change the analyst forecasts, the lower the accuracy of such a valuation. More bold forecasts may suggest that the analyst has some information or interprets the data at hand in a way that allows them to claim that the company's future situation will be significantly different from its current one. However, as the results show, such predictions are unlikely to materialise in reality, and the projected target prices themselves turn out to be less accurate.

The P/BV ratio of the company being valued also appears to be negatively related to the accuracy of valuations. Firstly, this may be related to the fact that a high value of this ratio suggests a large role of intangible assets in the company, which may be more difficult to value. Secondly, a high P/BV may mean that the company is already overvalued or close to its maximum value, and analysts recognise this too late, having previously forecast a further increase in its share price (Bonini et al., 2010).

Another variable that has a negative relationship with the target price accuracy is *Volatility_1*, which confirms the intuitive assumption that the more volatile a company's share prices are, the more difficult it is to predict its future value. Most of the results from the models estimated in this paper indicate that *positive* recommendations are more accurate than *neutral* and *negative* recommendations when treated as a single baseline. According to the estimation results of model (1b), it is the *negative* recommendations that are less accurate than the others. The coefficient on *Foreign* is positive, indicating that including at least one foreign company in the comparative valuation enhances the accuracy of the valuation.

The estimation results, split by recommendation type, are presented in Table 17. For the two models, the coefficients for all included variables are jointly significant at the 1% level, and for the third model at the 5% level. Relative to the models estimated on the whole sample, the signs of the statistically significant coefficients remain the same. The only difference lies in obtaining statistically non-significant coefficients for some variables, particularly for *State_Treasury* in the subsample of *neutral* and *negative* recommendations and for *COVID* in the subsample of *negative* recommendations. In its case, a significant and positive relationship with accuracy turns out to be *lLength*, and thus, at least in the *negative* recommendation group, the more details analysts provide, the better their predictions. Negative recommendations are issued reluctantly (less frequently). They may involve more pressure on analysts due to the different relationships that exist or may occur in the future between the brokerages where they work and the companies being valued. Perhaps, therefore, this motivates at least some analysts to be more cautious, reflected in the provision of greater detail in their reports, which in turn results in greater accuracy.

Table 16. Estimation results of models (1) and (2)

VARIABLE	(1a) POLS Acc	(1b) POLS Acc	(1c) POLS Acc	(2a) POLS Acc_Adj	(2b) POLS Acc_Adj
State_Treasury	-	-0,0978***	-0,1114***	-	-3,5827***
		(0,028)	(0,040)		(1,287)
COVID	-	-	-0,0559**	-	-
			(0,024)		
Boldness_1	-0,1971***	-0,1850***	-0,2486***	-	-
	(0,053)	(0,046)	(0,056)		
Boldness_1_Adj	-	-	-	-0,2379***	-0,2331***
				(0,053)	(0,054)
PBV	-0,0083**	-0,0104**	-0,0161***	-	-
	(0,004)	(0,004)	(0,005)		
Volatility_1	-4,6333***	-5,0538***	-2,8758*	-	-
	(1,427)	(1,410)	(1,571)		
Positive	0,0435*	-	0,0483*	1,8755**	1,8407**
	(0,025)		(0,028)	(0,908)	(0,903)
Negative	-	-0,0636*	-	-	-
		(0,038)			
Foreign	-	-	0,0643*	-	-
			(0,035)		
lSize	-	-	-	-0,8191***	-0,5218*
				(0,267)	(0,308)
Constant	0,8177***	0,8807***	0,7766***	-6,2289***	-7,7628***
	(0,037)	(0,037)	(0,050)	(1,967)	(2,111)
N	916	916	653	916	916
F-Statistic	12,70***	13,00***	12,38***	7,76***	8,77***
RESET Test (p-value)	0,7070	0,7618	0,3582	0,7502	0,5534
R^2	0,0829	0,1018	0,1218	0,0465	0,0598

Standard errors were clustered at the company level. Robust standard errors are shown in brackets. *, **, *** denote the statistical significance of the estimates at the 10%, 5%, and 1% levels, respectively.

Source: own elaboration.

Table 17. Estimation results of model (3)

VARIABLE	(3a - positive) POLS Acc	(3b - neutral) POLS Acc	(3c - negative) POLS Acc
State_Treasury	-0,1023*** (0,030)	-	-
COVID	-0,0417* (0,022)	-0,1048* (0,059)	-
Boldness_1	-0,2183*** (0,050)	-	-
PBV	-0,0183*** (0,004)	-	-0,0117 (0,009)
Volatility_1	-	-4,9326* (2,626)	-16,0519*** (3,392)
Foreign	-	0,1260** (0,062)	-
lLenght	-	-	0,1041* (0,061)
Constant	0,7970*** (0,028)	0,7375*** (0,09)	0,7831*** (0,196)
N	662	110	76
F-Statistic	10,54***	3,96**	9,39***
RESET Test (p-value)	0,6481	0,9942	0,0718
R^2	0,1046	0,1271	0,3633

Standard errors were clustered at the company level. Robust standard errors are shown in brackets. *, **, *** denote the statistical significance of the estimates at the 10%, 5% and 1% levels, respectively.
Source: own elaboration.

5.2. Valuation Method and Target Price Accuracy

The estimation results of models (4) and (5) are presented in Table 18. In all models, the coefficients for all included variables included are jointly significant at the 1% level. The positive and statistiaclly significant coefficient on *Method_1* indicates that the inclusion of the comparative method in the target price calculation in addition to the DCF method improves the accuracy of the valuation and, more precisely, increases the probability of the stock price of the valued company reaching the target price both at the end (*Ach_End*) and during (*Ach_In*) the forecast horizon. The coefficient on *Method_2*, on the other hand, is only significant when the measure of accuracy is *Ach_In*. Then, the coefficient is positive, which means that calculating the target price using a combination of the comparative and DCF methods increases the probability of achieving this price during the forecast horizon compared to a valuation carried out with the DCF method alone. The results **support hypothesis H3a**, which posits a positive relationship between the inclusion of the comparative method alongside the DCF approach and the accuracy of target price forecasts. This suggests that the two valuation methods are, to some extent, complementary, and that their combined application allows analysts to capture a broader set of relevant factors affecting firm value.

Table 18. Estimation results of models (4) and (5)

VARIABLE	(4a) Probit Ach_End	(4b) Probit Ach_End	(5a) Probit Ach_In	(5b) Probit Ach_In
Method_1	0,2694* (0,139)	-	0,3592*** (0,133)	-
Method_2	-	0,2278 (0,170)	-	0,2886** (0,141)
Boldness_2	-1,4479*** (0,273)	-1,5700*** (0,271)	-2,6845*** (0,272)	-2,7408*** (0,284)
Volatility_2	-	-	17,3770*** (6,670)	21,1757*** (7,135)
Market_Return	1,8746*** (0,345)	1,9372*** (0,351)	1,3912*** (0,342)	1,4456*** (0,362)
Broker_3	-	-	-0,4858** (0,238)	-0,4125* (0,239)
Broker_6	-0,4022* (0,233)	-	-0,4203* (0,242)	-
Broker_10	0,6360*** (0,206)	0,6661*** (0,227)	-	-
Broker_15	-0,7095* (0,425)	-	-0,5776** (0,290)	-0,7086** (0,291)
Broker_16	-	0,4994** (0,249)	-	0,4556* (0,256)
Constant	-0,4039*** (0,138)	-0,4247** (0,166)	0,2244 (0,204)	0,1359 (0,222)
N	727	670	727	670
Wald chi2-Statistic	97,63***	83,41***	172,91***	145,74***
Linktest (_hat p-value)	0,000	0,000	0,000	0,000
Linktest (_hatsq p-value)	0,512	0,692	0,604	0,390
Pseudo R^2	0,1395	0,1370	0,2078	0,2135

Standard errors were clustered at the company level. Robust standard errors are shown in brackets. *, **, *** denote the statistical significance of the estimates at the 10%, 5% and 1% levels, respectively.

Source: own elaboration.

Analysts' boldness in forecasting target prices, despite the change in the measure of accuracy compared to the models presented earlier, has a negative relationship with it. The coefficient on *Volatility_2* is statistically insignificant in models where the measure of accuracy is *Ach_End*, and significant and positive where it is *Ach_In*. These differences are related to the dependent variable used in the model. When this is the relative deviation of the target price from the actual price, subtracted from unity, share price volatility reduces the accuracy of target price forecasts, as was the case in the models presented in the previous section. When, on the other hand, the dependent variable is a binary variable reporting only whether the stock price of the valued company has reached the target price, the effect of volatility on the accuracy of the target price forecast can be quite the opposite, as happened in models (5a) and (5b). Stocks with more volatile quotations will reach the target price more easily, especially when considering the entire forecast horizon (*Ach_In*). However, they can also deviate significantly from the set target price forecast in either direction, reducing the relative accuracy of the forecast (*Acc*).

In all models, the coefficient estimate on *Market_Return* is positive and statistically significant, as expected, given that most stocks have positive beta coefficients (Bonini et al., 2010). Significant and different coefficients were also obtained for some variables identifying individual brokers, suggesting that some brokerages issue more or less accurate forecasts than others.

5.3. Stability of Target Price Accuracy in Brokerage Valuations

Table 19 shows the estimation results of models (6), (7) and (8). From the point of view of this paper, the most important are the coefficients on the variables *LagAch_End*, *LagAch_In* and *LagAcc*. For the first one, the result is statistically insignificant, while for the other two, the coefficients are statistically significant and positive. This implies that brokerages have persistent forecasting capabilities and that some of them regularly forecast target prices more accurately than others, as measured by the achievement of the target price over the forecast horizon and the relative accuracy of the forecast. The higher average accuracy of a brokerage in the previous year is associated with a higher probability of reaching target prices in the valuation reports issued in the current year. Also, it has a positive relationship with the accuracy of valuations in the current year. This finding is **consistent with H4**. Such time-permanent differences in the accuracy of brokerage valuations may be the result of variations in the tools and ways of working (valuation procedures) used or the use of relatively time-constant methodologies yielding different results (providing systematically different accuracy). It also means that the flow of information between different brokerages on the valuation methodologies used is not so strong that, over time, the "worse" brokerages (issuing less accurate target pricec) catch up with the "better" brokerages in terms of forecast quality (with higher target price accuracy).

Table 19. Estimation results of models (6), (7) and (8)

VARIABLE	(6) Probit Ach_End	(7) Probit Ach_In	(8) POLS Acc
LagAch_End	0,2617 (0,342)	-	-
LagAch_In	-	0,6187* (0,332)	-
LagAcc	-	-	0,2605** (0,127)
Momentum	0,3521** (0,161)	0,2938* (0,159)	0,0752** (0,032)
Volatility_1	-16,4119** (7,570)	-	-6,0194*** (1,316)
Market_Return	1,4497*** (0,315)	1,2181*** (0,320)	0,0732* (0,040)
Consumer_Goods	-0,4916* (0,283)	-	0,0885*** (0,031)
Finance	-0,3328 (0,233)	-	-
Trade_and_Services	-0,2977* (0,165)	-	-
Healthcare	-0,3205 (0,291)	-	-
Technology	-0,3872* (0,209)	-	0,0835** (0,035)
Constant	0,0234 (0,220)	0,0340 (0,211)	0,5899*** (0,096)
N	832	832	832
Wald chi2/F-Statistic	58,29***	58,15***	8,72***
Linktest (_hat p-value)	0,000	0,000	-
Linktest (_hatsq p-value)	0,922	0,193	-
RESET Test (p-value)	-	-	0,0511
Year fixed effects	YES	YES	YES
Pseudo R^2/R^2	0,0897	0,0721	0,1065

Standard errors were clustered at the company level. Robust standard errors are shown in brackets. *, **, *** denote the statistical significance of the estimates at the 10%, 5% and 1% levels, respectively.

Source: own elaboration.

The variable with a significant positive coefficient in all models is also *Momentum*. This suggests that the upward trend of the stock enables analysts to make more accurate forecasts. This is as expected, and it may be because forecasting future share prices with a clear trend is easier. However, this conclusion is only true for an upward trend, which, firstly, may be related to the general tendency of analysts to make positive recommendations and, secondly, to the fact that forecasting downturns is more difficult, perhaps due to the stronger emotions among stock market participants during stock price declines.

Statistically significant and positive coefficient on the variables *Volatility_2* and *Market_Return* confirm the results obtained in earlier models. Furthermore, a statistically significant industry variation in the relationship with accuracy was also found, with the results for the *Consumer_Goods* and *Technology* sectors depending on the dependent variable. The valuations of companies in these sectors exhibit higher relative valuation accuracy (*Acc*), but are less likely to achieve the target price by the end of the forecast horizon (*Ach_End*).

5.4. Valuation Error in SOEs' Reports and Issued During the COVID-19 Pandemic

In this, as in the following sections, the measure of accuracy is the forecast error, so the opposite relationship to accuracy is expected. As shown in Table 20, the parameter estimates for the variables *State_Treasury* and *COVID* are statistically significant and positive. Consequently, the forecast error is larger for reports on SOEs and for reports published during the COVID-19 pandemic, which is **consistent with H1b and H2b**. This also confirms the results presented in subsection 5.1., where these reports were shown to have lower accuracy. Also consistent with the results obtained in the earlier models are the coeffient on the variables *PBV* (positive relationship with forecast error) and *Market_Return* (negative relationship).

The coefficient on *lSize* is consistent with the expectation that valuations of larger companies are subject to lower forecast error. At the same time, this is a different result from that obtained in subsection 5.1. for model (2). A smaller error is also found for companies in the *Consumer_Goods* and *Technology* sectors. In addition, as can be seen from the coefficients on variables *Profit* and *Volatility_ROA*, the target prices of profit-making companies are characterised by a smaller error. In contrast, the volatility of the company's performance increases the error. This result seems intuitive and corresponds to the prediction that valuing loss-making companies is more challenging, while the stability of performance facilitates the issuance of more accurate forecasts.

Table 20. Estimation results of models (9) and (10)

VARIABLE	(9a) POLS Error_3	(9b) POLS Error_3	(10a) POLS lError_2	(10b) POLS lError_2
State_Treasury	-	0,0369* (0,021)	-	0,4981*** (0,142)
COVID	-	0,0330*** (0,013)	-	0,1499* (0,076)
Boldness_1	-0,3103*** (0,089)	-0,3103*** (0,089)	1,4823*** (0,173)	1,4236*** (0,180)
Boldness_1Q	0,6100*** (0,107)	0,6040*** (0,106)	-	-
lSize	-0,0075** (0,004)	-0,0094** (0,004)	-	-
Profit	-	-	-0,3066** (0,128)	-
PBV	-	-	0,0454** (0,018)	0,0489** (0,022)
Market_Return	-	-	-1,0093*** (0,170)	-0,8674*** (0,171)
ROA_Volatility	-	-	-	2,4582***
Consumer_Goods	-0,0442** (0,018)	-0,0383** (0,019)	-	-
Technology	-	-	-0,3151** (0,157)	-0,2942* (0,173)
Constant	0,2848*** (0,034)	0,2822*** (0,037)	-1,3342*** (0,143)	-1,8429*** (0,106)
N	1091	1091	1090	1057
F-Statistic	16,63***	29,73***	20,65***	6,92***
RESET Test (p-value)	0,7458	0,1895	0,1983	0,3066
R^2	0,1123	0,1225	0,1451	0,1628

Standard errors were clustered at the company level. Robust standard errors are shown in brackets. *, **, *** denote the statistical significance of the estimates at the 10%, 5% and 1% levels, respectively.

Source: own elaboration.

An interesting relationship arises in the case of analysts' boldness when the error measure utilises the maximum (or minimum) price at the forecast horizon (*Error_3*). This is because the coefficient on the variable *Boldness_1* is, contrary to expectations, negative, but the coefficient on the variable *Boldness_1Q* is statistically significant and positive. This means that for a valuation error measure defined in this way, the relationship between the error and analysts' boldness is non-linear and, up to a certain point (*Boldness_1≈0.25),* reduces the forecast error and later increases it. This leads us to speculate that it is the inclusion of the maximum (minimum) price in the forecast error that may be related to this result. In positive (negative) recommendations, the price is forecast to increase (decrease), so assuming the analyst is not wrong about the direction of the change, moderate optimism may reduce the forecast error when it is calculated using the maximum (minimum) price of the stock over the forecast horizon. For example, in the typical situation where a strong increase in the stock price is forecast, and it turns out to be moderate at the end of the forecast horizon, the usual measure of error using the terminal price will take on a significant value and the analyst's boldness will act adversely. At the same time, it seems likely that the maximum stock price over the entire forecast horizon will be markedly higher than both the final price and the initial price; therefore, the analyst's moderate boldness may reduce the error by taking this into account. It is also worth noting that in models (10a) and (10b) using the final stock price, the relationship between analyst boldness and error returns to the expected positive form.

5.5. Valuation Method and Valuation Error

Table 21 shows the estimation results of models (11) and (12), where the key variables are *Method_1* and *Method_2*. When *Error_1* is the dependent variable, the coefficients on these variables are statistically significant and negative, which means that, respectively, the inclusion of the comparative method in the valuation in addition to the DCF method negatively affects the target price error and that valuations based exactly on the comparative and DCF methods have a lower error than those using only the DCF method. This conclusion is in **line with H3b** and the result obtained in subsection 5.2. In contrast, when the forecast error was calculated only if the target price was not reached at the end of the forecast horizon (*Error_1_NA*), the coefficients on both variables were found to be statistically insignificant.

The conclusions for the variables *Boldness_2*, *Volatility_2* and *Market_Return* are as expected and do not differ from those obtained in most previous models. Several coefficients associated with individual brokerage houses also turned out to be statistically significant, in line with the findings discussed previously. For model (12a), an additional significant and positive coefficient on the *Growth* variable was obtained, indicating that in cases involving valuations of companies with high sales growth, we have a higher forecast error. It is probably more difficult for analysts to value companies that are less stable and rapidly increasing their revenues, as preparing an accurate forecast of their future situation is more challenging, i.e., more difficult to predict.

Table 21. Estimation results of models (11) and (12)

VARIABLE	(11a) POLS Error_1	(11b) POLS Error_1	(12a) POLS Error_1_NA	(12b) POLS Error_1_NA
Method_1	-0,0883*** (0,032)	-	-0,0454 (0,030)	-
Method_2	-	-0,0737* (0,038)	-	-0,0170 (0,034)
Boldness_2	0,5871*** (0,077)	0,6037*** (0,080)	0,6739*** (0,077)	0,6434*** (0,083)
Volatility_2	2,9887* (1,534)	2,1193 (1,437)	-	-
Market_Return	-0,1135* (0,062)	-0,1246* (0,067)	-0,4140*** (0,071)	-0,4428*** (0,077)
Positive	-	-	-0,0438 (0,034)	-0,0407 (0,035)
Growth	-	-	0,1534** (0,076)	0,1301 (0,079)
Broker_8	-	-0,0573 (0,035)	-0,0783* (0,040)	-0,0781* (0,041)
Broker_11	-0,1091** (0,053)	-0,0808 (0,052)	-0,0815 (0,053)	-
Broker_15	0,1850** (0,071)	0,1661** (0,071)	0,1672** (0,067)	0,2192*** (0,061)
Broker_16	-	-	-	-0,0855** (0,039)
Constant	0,2749*** (0,050)	0,2922*** (0,048)	0,1941*** (0,035)	0,1816*** (0,036)
N	727	670	630	573
F-Statistic	17,98***	14,68***	36,45***	38,95***
RESET Test (p-value)	0,0803	0,0608	0,0893	0,2922
R^2	0,2435	0,2459	0,3560	0,3650

Standard errors were clustered at the company level. Robust standard errors are shown in brackets. *, **, *** denote the statistical significance of the estimates at the 10%, 5% and 1% levels, respectively.

Source: own elaboration.

5.6. Persistence of Brokerage Houses' Predictive Ability in Valuation Errors

The results of model (13) are presented in Table 22. The coefficient on the variable *LagError_1* is statistically significant and positive, thus indicating the existence of a positive relationship between the average error of a brokerage house in the previous year and the errors of valuations issued in the current year. This confirms the conclusion of the analysis carried out in subsection 5.3., **in line with the expectations formulated in hypothesis H4**, that brokerages have persistent forecasting capabilities and that the differences occurring between the quality of their forecasts are persistent over time. The coefficients on the other variables, are consistent with those obtained in the previously discussed models.

Table 22. Estimation results of models (13)

VARIABLE	(13) POLS Error_1
LagError_1	0,4629***
	(0,119)
*Mom*entum	-0,0997**
	(0,043)
*Volatility*_1	8,0060***
	(1,703)
Market_Return	-0,1454**
	(0,066)
Consumer_Goods	-0,0884**
	(0,044)
Technology	-0,1071**
	(0,049)
Constant	0,0945
	(0,069)
N	832
F-Statistic	7,75***
RESET Test (p-value)	0,0948
Year fixed effects	YES
R^2	0,1131

Standard errors were clustered at the company level. Robust standard errors are shown in brackets. *, **, *** denote the statistical significance of the estimates at the 10%, 5% and 1% levels, respectively.

Source: own elaboration.

6. Conclusions

The aim of the article was achieved by identifying the determinants of target price accuracy for stocks of companies listed on the Warsaw Stock Exchange and assessing the effectiveness of analysts in forecasting target prices. The study, based on data collected from

1121 valuation reports published from January 2018 to March 2024 inclusive, allowed for the verification of the research hypotheses set out at the outset using POLS and probit models.

Firstly, it has been shown that valuations of SOEs are characterised by lower accuracy (higher error) (according to H1a and H1b), which may be related to the political connections of their managers and their decision-making based on criteria other than purely business criteria. Another reason may be the lower transparency of SOEs. Both of these factors imply a higher level of difficulty in forecasting target prices and, ultimately, lower accuracy. From the analysts' point of view, this conclusion implies that they should exercise above-standard vigilance and diligence when valuing a SOE. Recipients of valuation reports should also exercise increased caution when the subject of the valuation is a SOE This finding constitutes an added value of the study, as this issue has not been addressed in the existing literature. At the same time, it aligns with the broader strand of research on the impact of corporate governance on valuation accuracy, which suggests that factors such as board independence or transparency of the valued company positively affect the accuracy of target price forecasts (Cheng et al., 2019; Bouteska and Mili, 2022; Umar et al., 2022).

Secondly, it was shown that valuations created during the COVID-19 pandemic were less accurate (subject to higher error) than valuations published during the rest of the period (according to H2a and H2b). The reason for this phenomenon is likely the high degree of uncertainty prevailing during the pandemic period and the associated difficulty in forecasting the company's future situation. This finding confirms the intuitive assumption that reports issued during crisis periods should be approached by their recipients with less confidence and increased caution. The relationship obtained has not been studied before and, therefore, constitutes the originality of the present study. At the same time, it confirms the results obtained in the existing literature on the impact of the 2008 financial crisis on the accuracy of valuations (Bilinski et al., 2012; Gregoire and Marcet, 2014) and complements the existing knowledge on the impact of the COVID-19 pandemic on the quality of economic forecasts with its impact on the target price accuracy.

Thirdly, it has been shown that valuations which include the comparative method in addition to the DCF method are characterised by higher accuracy (lower error) (according to H3a and H3b). Concerns about the lack of clear guidance on the use of hybrid approach proved unfounded for the Polish market. The DCF and comparative methods appear to be complementary, and using them together in a valuation makes it possible to increase the accuracy of the valuation, perhaps by taking into account more relevant factors. The additional work done by the analyst in considering the comparative method results in a more accurate valuation. The result obtained can, therefore, serve as a suggestion to analysts preparing company valuations regarding the methods used. It also provides an argument for the effectiveness of hybrid approach in the ongoing discussion on this topic in the literature. Results obtained to date have either indicated lower valuation efficiency using a hybrid approach (Erkilet et al., 2021) or a non-significant impact of including an additional model in the valuation in addition to the relative valuation (Bonini et al., 2022).

Finally, it has been shown that there are persistent differences between brokerages in their ability to forecast target prices over time (H4). This may be the result of the use of different tools and datasets, the use of different valuation practices or the presence of organisation *tacit knowledge.* In interpreting the results obtained, it can also be noted that there is probably not a strong flow of information between brokerages, as the differences between them remain persistent over time. From the point of view of the recipient of a valuation report, the conclusion presented means that it should be more useful for them to receive reports from those brokerages whose earlier forecasts were more accurate. The result obtained is in line with the existing literature, which has better studied time-permanent differences in forecasting abilities at the analyst level (Bradshaw et al., 2013; Bilinski et al., 2013; Bouteska and Mili, 2022) and extends this relationship to the level of brokerages on the Polish market. The conclusions of the study for the Polish market are similar to those obtained by Gregoire and Marcet (2014), who investigated an analogous relationship at the level of brokerage house departments. The stability of forecasting capabilities thus occurs not only at the analyst level, as shown in the cited literature, but also at a higher level, i.e. entire brokerage houses.

A positive relationship was found between the target price accuracy and the market momentum of the valued company, as well as the market return over the forecast horizon. In contrast, a negative relationship was found for the analyst's boldness as measured by the absolute value of the implied change in stock price, the P/BV ratio of the valued company and the volatility of its stock price prior to the publication of the valuation report. These results are in line with those obtained by Demirakos et al. (2010), Kerl (2011), Bradshaw et al. (2013), Bilinski et al. (2013) and Gregoire and Marcet (2014), among others. The added value of this work lies in examining these relationships for the first time in the Polish market.

The overall effectiveness of analysts in forecasting target prices in the Polish market should be described as rather low, as evidenced, inter alia, by the fact that only 30.9% of target prices were achieved at the end of the forecast horizon, which is lower than that obtained by

Bradshaw et al. (2012), where it was 38%. Also, considering the entire forecast horizon, the efficiency was low, as it amounted to only 52.3%, which is lower than both that obtained by Brycz and Włodarczyk (2017) for the Polish market (66.7%) and authors studying foreign markets such as Asquith et al. (2005) (54%), Kerl (2011) (56.5%) or Bradshaw et al. (2012) (64%). Comparing the obtained result with the one obtained by Brycz and Włodarczyk (2017), one can conclude that the quality (accuracy) of valuations in Poland is deteriorating. However, due to the use of data from only one year (2012) in the cited work, this conclusion would be rather far-fetched. In summary, the results obtained in this study indicate a relatively low quality of valuations in Poland, and this conclusion is confirmed by other measures of target price accuracy (error) used in this study.

The main limitation of the study conducted in this paper is the use of only publicly available valuation reports. Including in the sample also reports to which access is limited to clients of the brokerage house would allow the research sample to be increased. The presented study does not fully exhaust the subject matter undertaken in the paper. A potential further direction of research could be the relationship between corporate governance, or ESG more broadly, and the accuracy of valuations on the Polish market. Another research niche remains the determination of the determinants of market reaction to the publication of a valuation report on the Polish market, which could, in particular, be the past quality (accuracy) of the forecasts of a given analyst or brokerage house.

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