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Forecasting the Profitability of the Textile Sector in Emerging European Countries Using Artificial Neural Networks

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Abstract
This study analyzes a set of key performance indicators for listed companies in the textile industry in emerging European countries: EBITDA margin, operating margin, pretax ROA, pretax ROE. Several statistical-econometric methods (dynamics analysis, structural analysis and regression) were used to provide an overview of the evolution of the public companies studied for the period 2012-2022, as well as a number of forecasts for the period 2023-2025. GMDH Shell software was used for public companies' pretax ROA forecast analysis in the textile industry in emerging European countries. The factor regression models that were constructed are valid for eight of the nine countries studied.

Keywords
emerging European countries, listed companies, performance indicators, textile industry.

1. Introduction

The textile and apparel industry is a genuine driving force of the global economy, representing "a highly globalized industry" [1], with a value amounting to USD 1,695.13 billion in 2022, and it is anticipated to grow in the coming years [2].

Despite the fierce competition that low-cost products manufactured in developing countries exert on the global market, the European textile and apparel industry is competitive, thanks to the high purchasing power of Europeans in Western countries, and the openness of companies in the sector to innovation. Emerging European countries play a very important role in the textile and apparel industry because their geographical proximity to Europe's major "fashion consumers" makes them very attractive to investors.

The textile industry is considered one of the oldest and largest industries in the world [3]. According to a report of the Business Research Company, [4] the global textile market was $573.22 billion in 2022, and is expected to grow to $755.38 billion in 2027 at a compound annual growth rate of 5.5%. The same study states that Asia-Pacific was the largest region in the textile market in 2022, followed by Western Europe. From the Asia-Pacific region, China has mass productivity that provides its textile industry with economies of scale unmatched by its rivals [3]. A recent report [5] shows that China, the European Union, India and Turkey comprise 75% of the world's exports. China is the world's biggest textiles exporter with a value of 148 billion U.S. dollars. Some countries such as Italy, France, Germany and the USA produce high-end or technologically advanced fabric.

The European Apparel and Textile Confederation, EURATEX, reports that in 2022 European textile activity fully recovered from the strong contraction caused by the Covid-19 pandemic, while clothing companies almost returned to their pre-pandemic level.

The research was based on the assumption that there is a direct link between the financial performance of companies and the change or variation in economic growth (as measured by the GDP/capita growth rate). The research objectives are as follows:

- generating estimates concerning the evolution of some representative indicators over the period 2023-2025 for the financial performance of public textile companies in the emerging European countries under analysis;
- modelling the link between the financial performance of public textile companies and the change in economic growth in the emerging European countries under analysis.

To achieve these objectives, the research tool available in GMDH Sheel Forecasting Software 3.5.8, [6] based on the artificial neural networks, was used. This application allows time series forecasting and regression analysis. We opted to use this application because the accuracy of neural networks and other artificial intelligence methods is superior that of traditional statistical methods. GMDH Shell software was used for forecasting analysis of public companies' pre-tax ROA (Return on Assets) in the textile industry in emerging European countries for the years 2023, 2024 and 2025.

2. Methodology

The GMDH Sheel Forecasting Software 3.5.8 [7] research toolkit is based on learning algorithms of the Group Method of Data Handling developed in the 1960's. Over time, the method has been improved and perfected, in consequence of which GMDH Sheel Forecasting Software is a powerful tool for predictive analytics and forecasting of multi-parametric datasets. Detailed information about this algorithm is available at https://gmdhsoftware.

com/docs/learning_algorithms [7]. In brief, the algorithm applies a "generator of gradually complicating models and selects a set of models that show the highest forecasting accuracy for previously unseen data. GMDH-type neural networks employ a combinatorial algorithm for optimization of neuron connection. The algorithm iteratively creates layers of neurons with two or more inputs. Every new layer is created using two or more neurons taken from any of the previous layers. Every neuron in the network applies a transfer function that allows the exhaustive combinatorial search to choose a transfer function that predicts testing data most accurately. Since every new layer can connect to previous layers, the layer width grows constantly. The generation of new layers is usually stopped when a new layer cannot show better testing accuracy than the previous one.

The forecast of financial performance indicators for textile companies in emerging European countries was based on average values of the EBITDA (Earnings Before Interest, Taxes, Depreciation and Amortization) margin, operating margin, pretax ROA and pretax ROE (Return on Equity), recorded over the period 2011-2022 for all countries included in the analysis. In accordance with the GMDH Shell Forecasting Software guidelines, the following steps were followed [6]:

- establishing the forecast range: the period 2023-2025;
- setting the data window used for model creation to the 30 most recent observations;
- using 2-fold validation to select the best models;
- using RMSE as the error measure during validation;
- using a Neural-type generator of candidate models;
- using linear GMDH neurons with 2 inputs, limiting the network depth to 2 layers;
- maintaining 300 top-ranked models (200 single-layer, 100 double-layer).

The accuracy of the prediction models was evaluated using the mean absolute error and root mean square error. For the financial performance indicator (taking into account the average value across all countries included in the analysis) with the best performing forecasting model, the research was deepened for each state. Thus, one-factor linear regression was used, the dependent variable being the financial performance indicator, and the independent variable, GDP per capita growth (annual %).

The Eikon Refinitiv platform [8] (named LSEG Data & Analytics from August 2023**)** was accessed to collect the data required for the study in September 2023, as a search was done for textile companies in emerging European countries over the period 2003-2022. The results of the search indicated the existence of 127 companies in the textile industry in 12 emerging European countries (including Turkey and Russia). According to the statements of the provider for the financial market (LSEG Data & Analytics), the company database covers 99% of the world's market cap. Data concerning the performance indicators covered by the study are not available for 58 companies. After testing the data series for homogeneity and normality, by using the ANOVA test, 22 companies were eliminated, for which the statistical data volume was small, having been listed on the stock exchange for short periods of time. Thus, we considered relevant companies listed at least in the period 2011-2022, which were as many as 47 (Appendix 1), as the research aimed at the performance indicators of those companies, from the following countries: Turkey, Serbia, Russia, Romania, Poland, Lithuania, Estonia, Croatia and Bulgaria. It should be mentioned that the Eikon Refinitiv platform offers the possibility to access information about public companies (companies whose shares are traded on the stock market).

Our research involves a financial analysis of profitability (cost-benefit analysis). Financial analysis is the selection, evaluation, and interpretation of financial data, along with other pertinent information, to assist in assessing the risk and return associated with an investment [9].

The financial indicators considered in our analysis are profitability ratios:

1. *EBITDA Margin* represents annual earnings before interest, taxes and depreciation, expressed as a percentage of the annual total revenue.

$$EBITDA\ Margin = \frac{EBITDA}{Total\ revenue} \times 100$$

2. *Operating Margin* measures the percentage of revenues remaining after paying all operating expenses. It is calculated as the annual operating income divided by the annual total revenue, multiplied by 100.

$$Operating\ Margin = \frac{Operating\ income}{Total\ revenue} \times 100$$

3. *Pretax ROA* represents the return on assets before taxes. It is calculated as the income before tax for the fiscal year divided by the average total assets for the same period, and is expressed as a percentage.

$$Pretax\ ROA = \frac{Income\ before\ tax}{Total\ assets} \times 100$$

4. *Pretax ROE* represents the return on equity before taxes. It is calculated as income before tax for the fiscal year divided by the total equity, and is expressed as a percentage.

$$Pretax\ ROE = \frac{Income\ before\ tax}{Total\ equity} \times 100$$

3. Literature Review

3.1. The textile sector and financial ratios

Our research approach starts from the premise that investigating the performance of the textile sector for a forecast of profitability rates can be useful to potential investors.

Berk and De Marzo [10] describe the most commonly used ratios related to profitability: operating margin and net profit margin. They underline that the income statement provides information on the profitability of a company and how it relates to the value of its shares. Financial ratios were used by Kristóf and Virág [11] to measure the financial competitiveness of companies with a turnover of at least 1 million euro from Poland, Czechia, Slovakia, and Hungary based on available data for the period

2016-2020. The following profitability ratios were selected to analyze financial competitiveness: ROA, ROE, profit margin, EBITDA margin, EBIT (Earnings Before Interest and Taxes) margin, and cash flow/operating revenue. The researchers developed various predictive models to explain financial competitiveness, including neural networks (NN). A research of Lyroudi [12] investigated the relations of liquidity, indebtedness and profitability for some companies listed on the Warsaw Stock Exchange. In this study, profitability was measured by financial ratios such as the NPM ratio (Net Profit Margin), ROI (Return on Investments), ROA, ROE and GP ratio (gross profit). Green and Zhao [13] stated that "even with recent advancements, returns and earnings appear to be largely unpredictable". In their empirical design, they used a large cross-section of stocks and monthly returns from 2000 to 2020 with a large set of return predictors for ROE and change in earnings.

Only a few recent studies investigating the profitability or financial performance have focused on the textile sector, particularly on Asian economies [14, 15, 16, 17, 18, 19]. The economic potential of textile industry companies was investigated by Burkhanov and Bakhodirovna [20], and they included ROA among the key indicators for assessing the short-term economic potential of textile enterprises. Arslan [21] carried out a study on predicting some profitability ratios, such as ROE, ROA, and ROS (Return on Sales) of textile industry companies trading in Borsa İstanbul. The relation between real and estimated values revealed that profitability ratios could be very successfully estimated.

A research of Suh [22] on U.S. textile industry profitability during the period 1961-1988 observed that the profit margins of the U.S. textile industry, as a whole, followed a random-walk process with a stable average very close to zero in spite of the tumultuous business conditions present during the period analyzed.

3.2. Neural networks and financial analysis

Artificial Neural Networks (ANN) have been used in some financial forecasting studies. Artificial neural systems can be used to create models of segments of the corporate financial environment [23]. Hoptroff [24] discussed the potential for neural network approaches to forecasting and modelling in business. He defined forecasting as the rational prediction of future events on the basis of information about past and current events. Martín-del-Brío and Serrano-Cinca [25] investigated self-organizing feature maps for the analysis and representation of some financial data, and their conclusion is that this neural model is a very interesting tool for financial decision-making. Neural networks as a forecasting tool were used by Maciel and Ballini [26] to predict future trends of stock market indexes and the research concluded that neural networks do have a powerful capacity to forecast those indexes. Adhikari and Agrawal [27] proposed a novel weighted ensemble scheme which intelligently combines multiple training algorithms, and the results suggest that ANN forecasting accuracy is significantly improved through this ensemble method. Mihai and Pica [28] state that neural networks and other technologies in business fields induce humanity to look for new opportunities to increase income through efficiency and productivity.

Serrano-Cinca [29] carried out an exploratory analysis of nine financial ratios (of which four profitability ratios) for Spanish companies. He used one feedforward neural network, known as the multilayer perceptron, which managed to learn the entire sample with zero error. Aliahmadi et al. [30] conducted a comparative analysis between linear regression and ANN to forecast total productivity growth in Iran. According to their study, the performance of an artificial neural network model is better than a linear regression model, but the difference is not very significant. Neural networks are tested to be more accurate in predicting bankruptcy, in which macroeconomic and financial company data are used [31, 32].

Mostafa et al. [33] present a detailed literature review of neural network research in financial forecasting, including Time Series Forecasting. They stated that selecting the correct artificial neural network architecture (the correct number of hidden layers, the correct number of nodes in each of the input, hidden and output layers) is essential in order to obtain optimal performance. A research of Marak et al. [34] used an artificial neural network model to predict the profitability of Indian banks, in which they found the models based on an artificial neural network to offer very accurate results in prediction, working with large panel data.

To our knowledge, no previous study has investigated financial performance in the textile sector through the agency of those profitability ratios for European companies using artificial neural networks.

4. Data analysis

The analysis of the evolution of representative indicators for the financial performance of public companies in the textile industry in emerging European countries, in the period 2012-2022 (Table 1), highlights the considerable decrease in the activity of companies in the sector and, therefore, in profits and profitability rates, in the period 2019-2020, under the impact of the COVID 19 pandemic.

The year 2021 marked the beginning of the recovery of economic indicators, but not to the values before the outbreak of the pandemic. In the year 2022, the indicators analyzed are found to have registered significant increases, falling in line with the global trend. A McKinsey and Company report [35] on the global fashion industry showed that 2022 saw the highest profit margins compared to those in all years between 2011 and 2020, except for one.

The above set of indicators provides an overview of the evolution of public textile companies in the emerging European countries surveyed. The higher values of the average EBITDA margin compared to

Year	Average EBITDA Margin	Average Operating Margin	Average Pretax ROA	Average Pretax ROE
2012	5.29%	0.19%	0.78%	2.58%
2013	9.96%	5.45%	1.65%	6.66%
2014	10.79%	7.20%	4.28%	14.26%
2015	9.91%	6.14%	3.21%	14.44%
2016	8.30%	4.47%	3.56%	12.02%
2017	10.75%	6.42%	4.23%	18.25%
2018	17.16%	8.46%	3.93%	16.00%
2019	8.04%	4.03%	2.53%	3.57%
2020	14.37%	4.62%	1.15%	3.11%
2021	13.32%	2.75%	6.13%	15.70%
2022	17.69%	13.18%	9.62%	23.86%

Table 1. Evolution of representative indicators for the financial performance of public textile companies in emerging European countries, 2012-2022
Source: own compilation based on data from Refinitiv, accessed on the 9th of September 2023

Specialties	EBITDA Margin-Industry Median	Operating Margin-Industry Median	Pretax ROA-Industry Median	Pretax ROE-Industry Median
clothing manufacturers	16.4%	11.8%	24.6%	34.2%
production of coated fabrics, ecological leather, and other textiles	22.6%	16.9%	11.5%	20.6%
production of polyester staple fiber, filament yarn and polymer	23.6%	17%	11.5%	20.6%
production of apparel and accessories	12.4%	8.2%	9.3%	18.5%
production of individual protective equipment, combat clothing, camouflage and more	10.5%	7.6%	2.9%	7.6%
production of cotton fabrics and dyed yarn	6.0%	4.5%	2.9%	13.4%
production of cotton yarns, carpets and rugs	12.3%	10.9%	8.6%	24.5%

Table 2. Median values of representative economic performance indicators by textile industry specialties in emerging European countries in 2022
Source: own compilation based on data from Refinitiv, accessed on the 9th of September 2023

Year	2023	2024	2025
Average EBITDA Margin	16.85%	16.17%	18.77%
Average Operating Margin	6.78%	6.59%	6.62%
Average Pretax ROA	7.68%	8.82%	9.77%
Average Pretax ROE	15.80%	15.92%	14.51%

Table 3. Forecasts for the evolution of representative economic indicators for the textile industry in emerging European countries
Source: own compilation based on GMDH Shell Predictions

the average operating margin suggest that the share of operating costs in total costs is very high. The upward trend of the average pretax ROE was higher than that of the average pretax ROA, but it showed stronger fluctuations during the period under analysis, which suggests that equity performance is more volatile than asset performance in the textile industry. Median values are useful in financial analysis because they tend to reflect a more accurate view than averages; medians are typically less affected than averages by large deviations or outliers in the data. The analysis of the textile industry in emerging European countries in 2022, based on the median values of 4 economic performance indicators (Table 2), shows the following situation:

Clothing manufacturers and the production of coated fabrics, ecological leather, and other textiles are the specialties that have obtained the best economic results, in terms of the indicators analyzed. Increased consumer purchasing power in developing regions leads to profitability rates in the two specialties mentioned being higher than the general market profitability. For example, compared to the S&P Global ROE in 2022 (around 17%), the median pretax ROE in clothing manufacturers was double, and compared to the S&P Global ROA in 2022 (around 8.5%), the median pretax ROA in clothing manufacturers was triple.

The forecasts for the evolution of representative economic indicators for the textile industry in emerging European countries, for the period 2023-2025, indicate a slight decrease in the operating profits obtained by the companies that were the subject of the observations, with direct implications for their financial performance (Table 3).

The likelihood of this development is high if we take into account the estimates of rising production costs, so that even if the textile industry market grows in the future, the rates of return may be on a falling course.

Fig. 1. Trends in pretax ROA and GDP per capita growth (annual %) in emerging European countries
Source: own compilation based on data from Refinitiv and World Bank [36]

	Mean absolute error	Root mean square error
Average EBITDA Margin	0.0211	0.0266
Average Operating Margin	0.0402	0.0280
Average Pretax ROA	0.0169	0.0204
Average Pretax ROE	0.0517	0.0622

Table 4. Accuracy of forecasting models
Source: own compilation based on GMDH Shell Predictions

An assessment of the performance of the forecasting models was carried out using errors, and is presented in Table 4. The low error values indicate a good performance of the forecasting models, the best performance being observed for the average pretax ROA. All the forecasting models show small errors.

The general template used to forecast the time series pretax ROA is suitable for multivariate and univariate time series analysis and forecasting. We considered it appropriate to complement the performance profile of the analyzed public companies in emerging European countries by analyzing the sensitivity of ROA to changes in economic growth (GDP/capita growth rate). Pretax ROA developments of public companies in the textile industry and GDP per capita growth (annual %) for the emerging European countries researched are highlighted below (Figure 1).

The unifactorial regression problem was solved using the GMDH Shell application, which generated valid econometric models for 8 of the 9 countries studied. In the case of the available data for Croatia, no unifactorial regression model could be identified.

The regression models constructed using the GMDH Shell application, which can be used for forecasting analyses of public companies' pretax ROA in the textile industry in emerging European countries, are presented in graphical form in the following figures (Figure 2).

The analysis of the correlation between public companies' pretax ROA in the

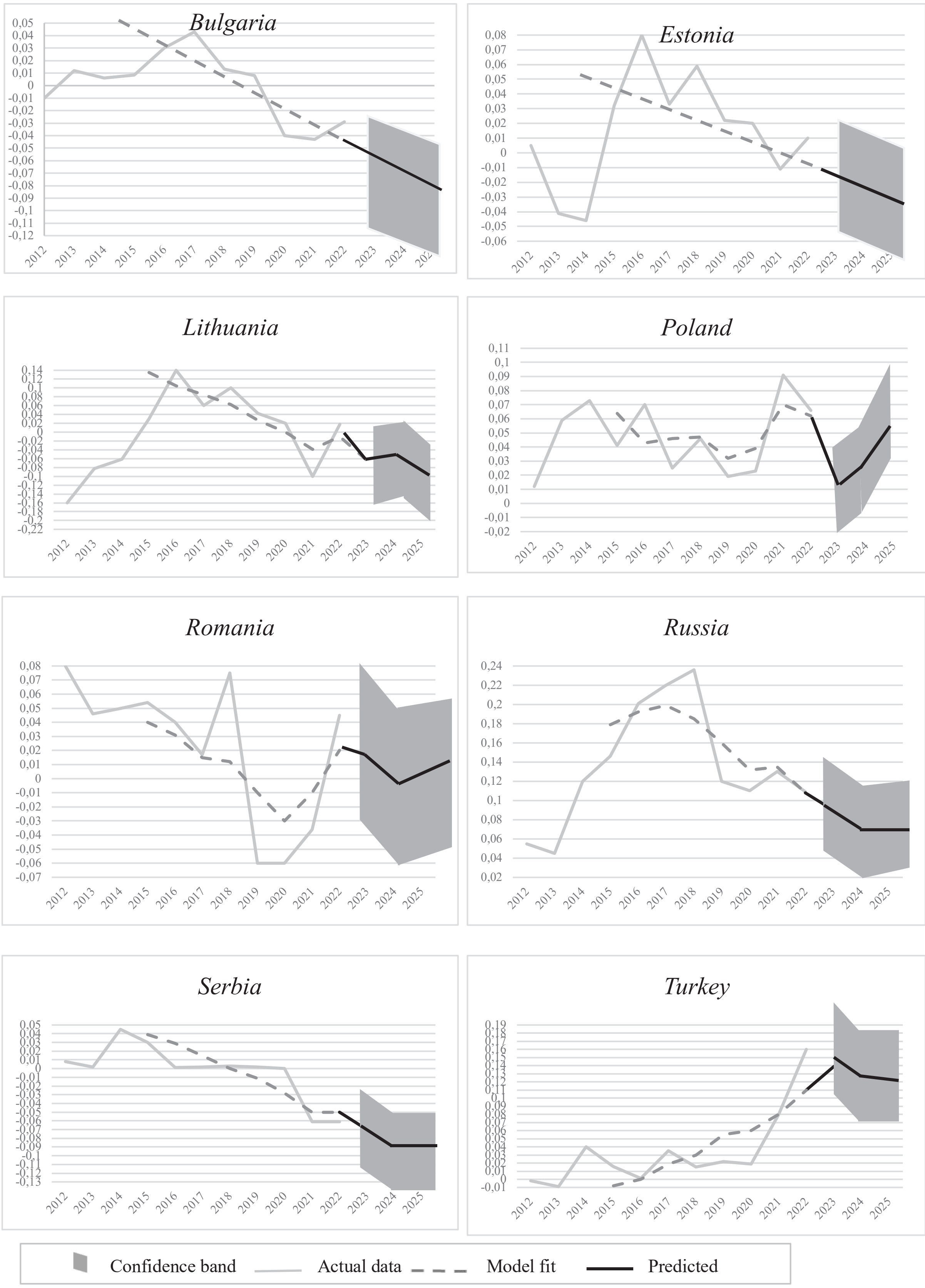

Fig. 2. Public companies' pretax ROA forecasting in the textile industry in emerging European countries

	Mean absolute error	Root mean square error	Coefficient of determination (R^2)	Correlation	Function of regression
Bulgaria	0.01641	0.0196	0.6030	0.7982	Pretax ROA = 0.0458 +GDP per capita growth × 0.0013
Estonia	0.0154	0.0186	0.5144	0,7172	Pretax ROA = 0.0603 - GDP per capita growth × 0.0084
Lithuania	0.0420	0.0498	0.4777	0.7135	Pretax ROA = 0.1331- GDP per capita growth × 0.0259
Poland	0.0155	0.0178	0.4542	0.7204	Pretax ROA = 0.0114 + GDP per capita growth × 1.0351
Romania	0.0266	0.0331	0.5635	0.8617	Pretax ROA = -0.3828+ GDP per capita growth × 1.9529
Russia	0.0222	0.0277	0.6796	0.8476	Pretax ROA = -0.092 + GDP per capita growth × 1.6186
Serbia	0.0146	0.0166	0.7168	0.8638	Pretax ROA = 0.0265 + GDP per capita growth × 0.7795
Turkey	0.0230	0.0279	0.6759	0.8208	Pretax ROA = -0.0129+ GDP per capita growth × 0.0161

Table 5. Results of the analysis of the correlation between public companies' pretax ROA in the textile industry and GDP per capita growth
Source: own compilation based on GMDH Shell Predictions

textile industry and GDP per capita growth is shown in Table 5.

For most of the countries analyzed, there is a direct correlation between public companies' pretax ROA in the textile industry and GDP per capita growth, which is in line with the results of other previous research. In most cases the strength of the link between the two indicators is strong.

The regression functions show that the change in GDP per capita growth generates a change in public companies' pretax ROA in the textile industry.

5. Conclusions

The analysis of performance indicators EBITDA margin, operating margin, pretax ROA, and pretax ROE, is imperative in order to ensure an optimal business framework needed to achieve the desired results by companies in the textile industry, within the context of volatile international markets. At the same time, the investigation of key performance indicators allows to highlight the situation of the textile industry in a specific country or region, namely Turkey, Serbia, Russia, Romania, Poland, Lithuania, Estonia, Croatia and Bulgaria.

The dynamic analysis of the average values of the above-mentioned key performance indicators revealed the continuous improvement of the financial performance of public textile companies in emerging European countries in the period 2012-2018, followed by a steep decline in the years 2019-2020, caused by the decrease in economic activity during the pandemic period, and some recovery after 2021.

By 2022, the textile industry in emerging European countries is found to have outperformed as compared to the results recorded before the onset of the Covid 19 pandemic. In the context of the difficult situation in which the European textile industry has been placed, due to globalization and competition from developing countries, the good dynamics of the key performance indicators researched demonstrate that the textile industry in emerging European countries has a high competitive potential on the international market. Therefore, despite the difficult international political context (the Russian-Ukrainian conflict), which has led to rising energy and transport prices and therefore higher production costs, the textile industry is able to successfully face the economic challenges.

In 2022, the best performing specialties were clothing manufacturers, production of coated fabrics, ecological leather, and other textiles, as well as production of polyester staple fiber, filament yarn and polymer.

The use of GDMH Sheel techniques allowed us to obtain valid econometric models to forecast public companies' pretax ROA in the textile industry in emerging European countries and to highlight the sensitivity of ROA to changes in economic growth (GDP/ capita growth rate). For most of the cases investigated, it was observed that economic growth (measured by GDP/ capita growth rate) has a positive effect on financial performance (measured by ROA). The percentage of variability in the dependent variable explained by an independent variable is between 45% - 68%. In terms of estimates of ROA evolution over a three-year forecast period, the results of the GMDH Shell Forecast application suggest a slight downward trend in the financial performance of public companies in the countries, surveyed, with the exception of Turkey, compared to 2022. One of the reasons for the recovery of the Turkish textile industry immediately after the Covid-19 pandemic (the country showing pretax ROA on a major increasing trend in 2021 and 2022) is the technical textile sector (including masks and personal protective clothing). In addition to this, the geographical location of Turkey between Europe and Asia is a favorable issue in the recovery and financial performance of its textile sector. After the Covid-19 pandemic, many European companies adopted a nearshoring strategy to optimize their operations, thus, Turkish textile suppliers were preferred over Chinese ones.

The most important limitation of the research stems from the limited content of the database, which is limited to public companies, since the Refinitiv platform collects information on companies listed on stock exchanges. As the impact of the activity of unlisted companies on the textile industry in emerging European countries has not been taken into account, it is possible that the overall picture of the field studied is to some extent biased. Another limitation is related to the short observation period, but we consider that this shortcoming has been largely overcome by using neural networks for prediction.

Conflicts of Interest

The Authors declare there is no conflict of interest.

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Appendix 1

	Company Name	Country of domicile	RIC codes
1	SASA Polyester Sanayi AS	Turkey	SASA.IS
2	Aksa Akrilik Kimya Sanayii AS	Turkey	AKSA.IS
3	Vakko Tekstil ve Hazir Giyim Sanayi Isletmeleri AS	Turkey	VAKKO.IS
4	Bossa Ticaret ve Sanayi Isletmeleri TAS	Turkey	BOSSA.IS
5	Ral Yatirim Holding AS	Turkey	RALYH.IS
6	Yunsa Yunlu Sanayi ve Ticaret AS	Turkey	YUNSA.IS
7	Desa Deri Sanayi ve Ticaret AS	Turkey	DESA.IS
8	Sanko Pazarlama Ithalat Ihracat AS	Turkey	SANKO.IS
9	Menderes Tekstil Sanayi ve Ticaret AS	Turkey	MNDRS.IS
10	Akin Tekstil AS	Turkey	ATEKS.IS
11	Sonmez Pamuklu Sanayii AS	Turkey	SNPAM.IS
12	Arsan Tekstil Ticaret ve Sanayi AS	Turkey	ARSAN.IS
13	Bilici Yatirim Sanayi ve Ticaret AS	Turkey	BLCYT.IS
14	Luks Kadife Ticaret ve Sanayi AS	Turkey	LUKSK.IS
15	Dagi Giyim Sanayi ve Ticaret AS	Turkey	DAGI.IS
16	Soktas Tekstil Sanayi ve Ticaret AS	Turkey	SKTAS.IS
17	Karsu Tekstil Sanayi ve Ticaret AS	Turkey	KRTEK.IS
18	Birko Birlesik Koyunlulular Mensucat Ticaret ve Sanayi AS	Turkey	BRKO.IS
19	Hateks Hatay Tekstil Isletmeleri AS	Turkey	HATEK.IS
20	Rodrigo Tekstil Sanayi ve Ticaret AS	Turkey	RODRG.IS
21	Pergamon Status Dis Ticaret AS	Turkey	PSDTC.IS
22	Birlik Mensucat Ticaret ve Sanayi Isletmesi AS	Turkey	BRMEN.IS
23	Diriteks Dirilis Tekstil Sanayi ve Ticaret AS	Turkey	DIRIT.IS
24	Dunav ad Grocka	Serbia	DNVG.BEL
25	Komiteks AO	Russia	KMTXI.RTS
26	Polet Ivanovskiy Parashyutnyi Zavod AO	Russia	PIPZI.RTS
27	Braiconf SA	Romania	BRCR.BX
28	Confectii Vaslui SA	Romania	COVB.BX
29	VRG SA	Poland	VRGP.WA
30	Wittchen SA	Poland	WTN.WA
31	Lubawa SA	Poland	LBW.WA
32	Novita SA	Poland	NVT.WA
33	CDRL SA	Poland	CDLP.WA
34	Wojas SA	Poland	WOJ.WA
35	Protektor SA	Poland	PRTE.WA
36	Sanwil Holding SA	Poland	SNW.WA
37	Solar Company SA	Poland	SOLP.WA
38	Redan SA	Poland	RDNP.WA
39	Utenos Trikotazas AB	Lithuania	UTR1L.VL
40	Linas AB	Lithuania	LNS1L.VL
41	Silvano Fashion Group AS	Estonia	SFG1T.TL
42	Tekstilpromet dd	Croatia	TKPR.ZA
43	Varteks dd	Croatia	VART.ZA
44	Mak AD	Bulgaria	MAK.BB
45	Katex AD	Bulgaria	KTEX.BB
46	Mizia 96 AD	Bulgaria	MIZA.BB
47	Velbazhd AD	Bulgaria	VELB.BB