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A Time Series Approach to Forecasting Financial Indicators in the Wholesale and Retail Trade

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Abstract: Forecasting using historical time series data has become increasingly important in today's world. This paper aims to assess the potential for stable positive development within the wholesale and retail trade sector (SK NACE Section G) and the operations of HORTI, Ltd.(Košice, Slovakia), a company within this industry (SK NACE 46.31—wholesale of fruit and vegetables) by predicting three financial indicators: costs, revenues, and earnings before taxes (EBT) (or earnings after taxes (EAT)). We analyze quarterly data from Q1 2009 to Q4 2023 taken from the sector and monthly data from January 2013 to December 2022 for HORTI, Ltd. Through time series analysis, we aim to identify the most suitable model for forecasting the trends in these financial indicators. The study demonstrates that simple legacy forecasting methods, such as exponential smoothing and Box–Jenkins methodology, are sufficient for accurately predicting financial indicators. These models were selected for their simplicity, interpretability, and efficiency in capturing stable trends, and seasonality, especially in sectors with relatively stable financial behavior. The results confirm that traditional Holt–Winters' and Autoregressive Integrated Moving Average (ARIMA) models can provide reliable forecasts without the need for more complex approaches. While advanced methods, such as GARCH or machine learning, could improve predictions in volatile conditions, the traditional models offer robust, interpretable results that support managerial decision-making. The findings can help managers estimate the financial health of the company and assess risks such as bankruptcy or insolvency, while also acknowledging the limitations of these models in predicting large shifts due to external factors or market disruptions.

Keywords: business development; financial indicators; forecasting; models; time series; Holt–Winters; Box–Jenkins; ARIMA; economic development

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1. Introduction

Knowledge of the corporate diagnosis is becoming a growing trend and significantly influences managers' decision-making. Methods derived from model approaches, based on mathematical frameworks, are increasingly applied in the analysis of the production process. Accurate economic forecasting plays a crucial role in shaping government policy and financial planning, helping policymakers make informed decisions for the future [1]. Forecasting has become vital across various economic sectors for making decisions related to local and regional policies [2]. Forecasting financial indicators is a key tool for decision-making in the business sector, particularly in the wholesale and retail trade sector, where forecasts are used to optimize production, sales, and inventory planning. This sector faces specific forecasting challenges, as it frequently experiences significant changes in consumer behavior, sales seasonality, and external influences, e.g., economic and political factors [3]. However, forecasting financial indicators such as revenues, costs, and profitability is critical for setting the right corporate strategies, achieving long-term stability, and ensuring the competitiveness of businesses. Profit forecasting is essential for managing cash flow, ensuring liquidity, and evaluating business strategy. For this reason, in the wholesale and retail trade sector, forecasting is both a challenge and an invaluable tool for optimizing financial planning and supporting decision-making by managers.

When forecasting the evolution of the observed financial indicators ex ante, it is essential to document their values over time. In engineering disciplines, the evolution of the indicators under study is often described, for example, by a system of partial differential equations [4]. If the set of economic or financial data contains sufficient records, it is possible to forecast its future development using existing technical tools for time series analysis. Forecasting based on historical time series data has become increasingly crucial in today's context [5]. Time series data can serve as a foundation for predicting future events and trends [6]. Predicting future revenues, costs, and profit is a critical factor that underpins all strategic and planning decisions that are essential for the successful operation of retail businesses [7]. Sales (revenues) forecasting is particularly important for any retail business at the organizational level, as its results support decision-making across various departments. The finance and accounting team can estimate costs, profits, and capital requirements; the sales team gains insight into product sales volumes; the purchasing department can plan both short- and long-term purchases; the marketing team can strategize and evaluate the effects of different marketing approaches on sales; and the logistics department can determine specific logistical requirements [7,8]. Additionally, precise retail sales and cost forecasts can enhance portfolio investors' ability to anticipate changes in the stock prices of retail chains [9]. The difference between a company's total revenue and direct costs is referred to as its accounting profit, also known as financial or net profit. The profit metric is used to evaluate a company's profitability and compare its financial position with that of its competitors [10]. Forecasting profit helps guide decision-making and long-term financial stability.

The paper aims to assess the potential for stable positive development within the wholesale and retail trade sector (SK NACE section G) and of the operations of HORTI, Ltd., a company within this industry (SK NACE 46.31—wholesale of fruit and vegetables) by predicting three financial indicators: costs, revenues, and Earnings Before Taxes (EBT) (or Earnings After Taxes (EAT)). For this purpose, we analyze the time series of these indicators in both the wholesale and retail trade sector and HORTI, Ltd. Through time series analysis, we aim to identify the most suitable model for forecasting the trends in costs, revenues, and EBT (EAT) for the wholesale and retail sector, as well as for HORTI, Ltd. In the context of V4 countries, there is a notable lack of studies on forecasting financial absolute or ratio indicators specific to the wholesale and retail trade sectors. This study seeks to fill this gap.

Distributive trade (retail and wholesale) is a service sector that has become a significant economic segment in recent years. It encompasses all forms of distributive trade, from purchasing goods from manufacturers to delivering them to consumers [11]. Most studies examine the relationship between distributive trade and economic growth or competitiveness in specific regions or economic systems, e.g., in South Africa [12], Malaysia [13], Greece [14], Spain [15], and Italy [16]. This paper contributes to existing research by addressing a gap in the literature, as it forecasts revenues, costs, and profits in the wholesale and retail trade sector, an area not covered by previous studies.

Over the past three decades, exponential smoothing and Autoregressive Integrated Moving Average (ARIMA) models have been among the most popular and widely used approaches for time series forecasting [17]. These models are particularly effective when the data are relatively stable, without sudden changes in trends or seasonality. They offer the advantages of ease of implementation, robustness, and interpretability. Exponential smoothing is especially useful when stable seasonal influences or trends are present, as it can respond quickly to these changes and provide accurate short-term forecasts [3]. In contrast, ARIMA models are suitable for analyzing data with trends or seasonal components and are highly flexible in modeling and removing these effects. This flexibility allows ARIMA models to provide stable and accurate forecasts even for moderately volatile time series [18].

Although more advanced and accurate techniques, such as generalized autoregressive conditional heteroscedasticity (GARCH) models for volatility modeling or machine learning methods, exist, their implementation requires large amounts of data and complex settings that are not always necessary for forecasting financial indicators with relatively stable behavior. In our analysis, we chose exponential smoothing and ARIMA models because of their ease of application and ability to provide interpretable results, making them ideal for strategic decision-making at the managerial level [3,18]. These models are sufficient for our purposes; in the future, we plan to extend our analysis using more advanced methods if the need arises to work with data exhibiting higher volatility or non-standard patterns of behavior.

In discussing the limitations of the traditional methods used in this paper, we note that while exponential smoothing and ARIMA models provide satisfactory results, they may struggle to predict significant changes in consumer behavior that they cannot easily capture. These methods also do not account for external factors, such as unexpected political or economic shocks, which could impact financial indicators. Therefore, it is important to emphasize that these traditional models are highly effective for stable and short-term forecasts. However, more advanced methods would be better suited for predicting long-term trends or highly volatile data [18,19].

In this paper, we aim to develop a statistical model that provides high prediction accuracy for financial indicators in the wholesale and retail trade sector, as well as for HORTI, Ltd., to support strategic decision-making at the managerial level. Based on the literature, we hypothesize that traditional methods (ARIMA and exponential smoothing) offer sufficiently accurate forecasts and are suitable for modeling stable time series. As part of the research, we pose two research questions: Can ARIMA and exponential smoothing be used to predict the financial indicators of the wholesale and retail trade sector and HORTI, Ltd.? What are the limitations of traditional models when time series are affected by external shocks or volatile changes? Based on these questions, the following research hypothesis is formulated:

Hypothesis 1. *ARIMA and exponential smoothing can provide accurate predictions for stable time series, which will be verified by MAPE, BIC and* R^2.

The remainder of this paper is organized as follows. Section 2 provides the literature review. Section 3 presents the data and methods. Section 4 provides the results, including visualization of time series models. Section 5 discusses the findings, and Section 6 concludes the paper.

2. Literature Review

The relevant literature on statistical forecasting has evolved from simple exponential smoothing [20] to various extensions [21,22]. Exponential smoothing methods emerged in the 1950s and 1960s through the contributions of Brown [20,23], Holt [21], and Winters [22]. Pegels [24] provided a practical classification of trend and seasonal patterns, distinguishing between additive (linear) and multiplicative (nonlinear) types. Advances in integrating exponential smoothing within a statistical framework were made by Winters [22], Roberts [25], and Abraham and Ledolter [26,27], who demonstrated that certain linear exponential smoothing forecasts are special cases of ARIMA models. ARIMA models, introduced in 1970, have since been extensively studied by many researchers. Their theoretical underpinnings were described by Box and Jenkins [28] and later by Box et al. [29]. Gardner [30] provided a comprehensive review of the field and expanded Pegels' classification to include damped trends. In the same year, Snyder [31] showed that Simple Exponential Smoothing (SES) could be understood as arising from an innovation state-space model characterized by a single source of error.

The taxonomy developed by Hyndman et al. [32], later extended by Taylor [33], provides a useful framework for categorizing various forecasting methods. Each method is characterized by one of five trend types (none, additive, damped additive, multiplicative, and damped multiplicative) and one of three types of seasonality (none, additive, and multiplicative), resulting in 15 distinct methods. Some of the most well-known methods include SES, which has no trend and no seasonality; Holt's linear method, which involves an additive trend and no seasonality; Holt–Winters' additive method, which combines an additive trend with additive seasonality; and Holt–Winters' multiplicative method, which features an additive trend and multiplicative seasonality.

Following this, Engle [34] introduced autoregressive conditional heteroscedasticity (ARCH) models for financial time series. A later modification of the ARCH model is the GARCH model, developed by Bollerslev [35] and Taylor [36]. For more information on the development of forecasting methods, see [37]. More advanced models and associated statistical tests are now being employed as well (see [38–40]).

We then focused on reviewing the current literature addressing forecasting methods. To illustrate recent developments in the field, we conducted a bibliometric analysis, which includes publications exported from the scientific database Web of Science. A search query command was entered into the search bar for the Topic option using the Boolean operator 'OR' in the following format: 'ARIMA' OR 'SARIMA' OR 'ARCH' OR 'GARCH' OR 'Box–Jenkins'. Only recent publications from 2022 to 2024 within the categories of Economics, Management, Business, and Business Finance were included. After applying these filters, 1,483 publications were selected for the bibliometric analysis. Bibliometric maps were then generated using VOSviewer.

Initially, the analysis aimed to identify the countries that have contributed to the topic. A country was included only if it had at least 10 related publications. Figure 1 shows the bibliometric map, which divides the 37 collaborating countries into seven color-coded clusters. Countries positioned higher on the map have made more significant contributions to the issue. China, India, and the USA are among the most influential countries. Thicker connections between countries indicate more frequent collaboration. The grouping of countries into clusters is presented in Table 1.

In the first part of the bibliometric analysis, we focused on the countries that have addressed the issue within the category of Economics and Management that we studied. This analysis reveals which countries are collaborating on the topic and identifies those that have made the greatest contributions over the past three years.

The second part of the bibliometric analysis involves examining the occurrence of keywords within the relevant field. A keyword was included if it appeared at least 30 times in the relevant publications. Figure 2 presents a generated bibliometric map that categorizes the four color-coded clusters (as also shown in Table 2). A higher position on the map indicates a more frequent occurrence of a keyword, while a thicker link between keywords signifies their more frequent co-occurrence in publications.

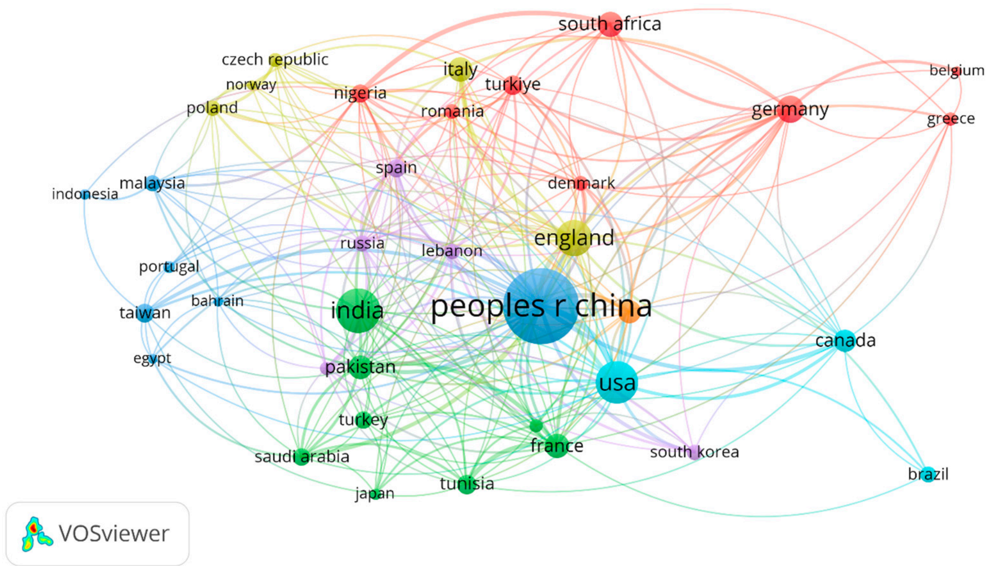

Figure 1. Bibliometric map of country occurrence. Source: own processing in VOSviewer.

Table 1. Classification of countries into clusters.

Cluster	Color	Countries
1	Red	Belgium, Denmark, Germany, Greece, Nigeria, Romania, South Africa, Türkiye
2	Green	France, India, Japan, Pakistan, Saudi Arabia, Tunisia, Turkey, Vietnam
3	Dark blue	Bahrain, Egypt, Indonesia, Malaysia, China, Portugal, Taiwan
4	Yellow	Czech Republic, England, Italy, Norway, Poland
5	Violet	Lebanon, Russia, South Korea, Spain, United Arab Emirates
6	Light blue	Brazil, Canada, USA
7	Orange	Australia

Source: own processing according to VOSviewer.

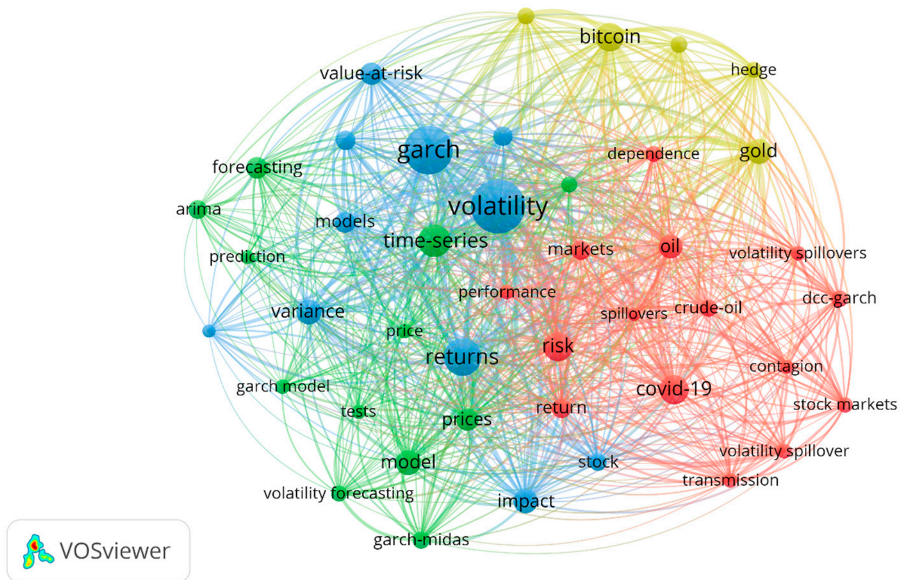

Figure 2. Bibliometric map of keywords occurrence. Source: own processing in VOSviewer.

Table 2. Classification of keywords into clusters.

Cluster	Color	Keywords
1	Red	contagion, COVID-19, crude-oil, DCC-GARCH, dependence, markets, oil, performance, return, risk, spillovers, stock markets, transmission, volatility spillover(s)
2	Green	ARIMA, forecasting, GARCH model, GARCH-MIDAS, market, model, prediction, price(s), tests, time-series, volatility forecasting
3	Blue	GARCH, GARCH models, impact, models, returns, stochastic volatility, stock, uncertainty, value-at-risk, variance, volatility
4	Yellow	bitcoin, cryptocurrencies, cryptocurrency, gold, hedge

Source: own processing according to VOSviewer.

Finally, Figure 3 displays the keywords that were most frequently mentioned in the analyzed publications, using density visualization. The larger the area surrounding a keyword, the more extensive its reach. GARCH, volatility, and returns are among the most discussed keywords.

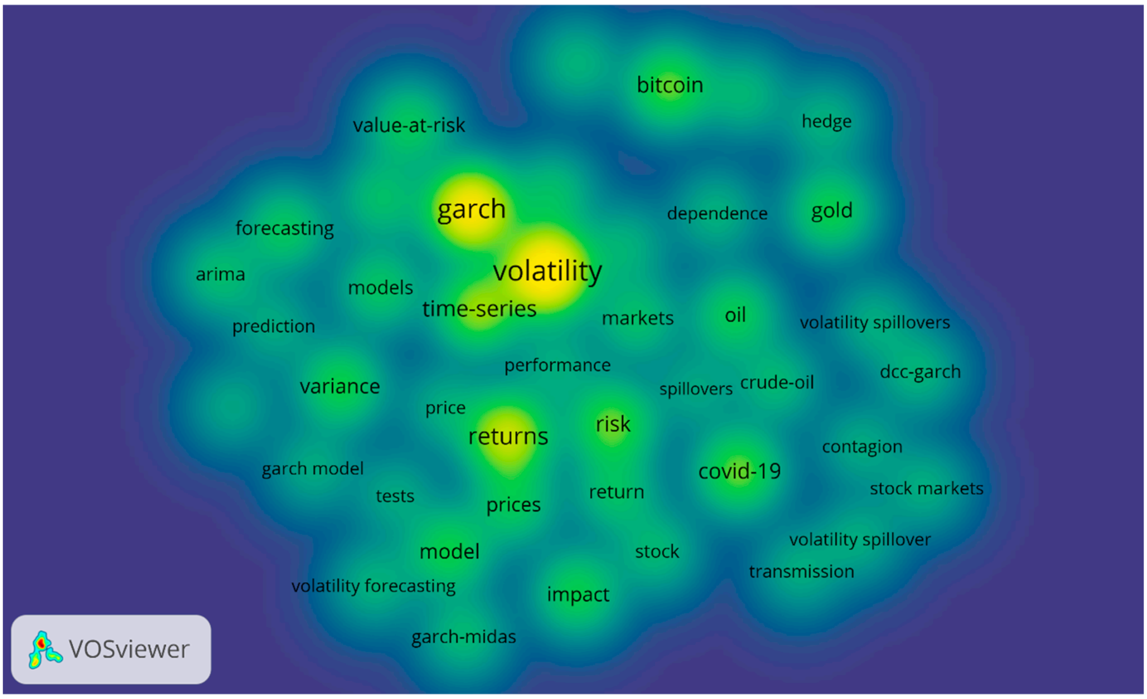

Figure 3. Bibliometric map of the most discussed keywords. Source: own processing in VOSviewer.

In the second part of the bibliometric analysis, we focused on the frequency of keywords within the Economics and Management category we studied over the past three years. Figure 2 and Table 2 show that ARIMA and GARCH methods have been commonly used in this category during the studied period. These methods have been applied to predict volatility, performance, price (returns), risk, or dependence while examining various commodities such as gold, crude oil, bitcoin, cryptocurrencies, stocks, and more.

Rostami-Tabar and Hyndman [41] utilized the hierarchical and grouped structure of demand time series and applied these methods to daily incident data from an ambulance service in Great Britain spanning from October 2015 to July 2019. The data were broken down by incident type, priority, health board management, and control area. Scher et al. [42] employed the autoregressive–moving–average (ARMA) model to predict levels of stored hydroelectric energy and the helpful volume of a water reservoir in the South of Brazil. Berger and Koubova [43] evaluated advanced machine learning techniques, comparing them to econometric time series models. Their analysis demonstrated that machine learning methods outperformed econometric models in forecasting accuracy. Research by Paeng et al. [44] investigated the spillover effects among the S&P 500 Index, stable coins, and selected cryptocurrencies, analyzing the lead and lag interrelationships among these time series.

Khan and Gunwant [45] used time series data on remittance inflows to Yemen from 2000 to 2019, obtained from the World Bank database, to predict remittance inflows for the period from 2020 to 2026. They applied the Box–Jenkins ARIMA method. In a study by Oikonomou and Damigos [46], they forecasted the logarithmic returns of base metals using an autoregressive Light Gradient Boosting Machine (LightGBM) and also developed an ensemble model that combined this algorithm with a traditional time series forecasting ARIMA model.

A study by Agrawal et al. [47] provided an empirical study of the Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMA-X) method, using root mean square error (RMSE) and mean absolute percentage error (MAPE) metrics to forecast crude oil prices during the highly volatile periods from 2020 to 2023, including the COVID-19 pandemic and the Russia–Ukraine conflict.

The purpose of the study by Safi et al. [48] was to examine the behavior and characteristics of the Indian stock index (SENSEX) using the GARCH model and data from 2011 to 2020. Demirel [49] focused on analyzing the variables affecting the most popular cryptocurrency, Bitcoin. They employed ARCH models, linear ARC, GARCH, exponential GARCH, and threshold GARCH. The analysis covered the period from 2020 to 2023 using daily data.

Al-Rjoub and Azzam [50] examined the response of the Jordanian stock market to the 2008 global economic crisis using the GARCH modeling approach, analyzing time-series data from 1992 to 2009. Abbas et al. [51] employed GARCH and Vector Autoregressive (VAR) modeling techniques to assess the impact of macroeconomic volatility on stock returns in G7 countries, analyzing time-series data from 1985 to 2015. Neveen [52] explored the interplay between exchange rates and stock indices in the Middle East and North Africa region, using symmetric models such as Vector Error Correction Model (VECM) and VECH-GARCH to analyze the volatility characteristics of exchange rate fluctuations and stock indices. Hung [53] investigated the dynamics between currency value fluctuations and stock indices in Europe, employing both constant conditional correlation and dynamic conditional correlation GARCH models for the period from 2000 to 2017. Similarly, Sheikh et al. [54] segmented the time-series data into three distinct periods—before the economic downturn, after the downturn, and across the entire period—to assess the asymmetrical effects of oil price volatility, gold prices, and currency fluctuations on the Karachi Stock Exchange in Pakistan.

Tajmouati et al. [55] analyzed real data examples on retail and food services sales in the United States and milk production in the United Kingdom using methods such as Classical Parameters Tuning in Weighted Nearest Neighbors and Fast Parameters Tuning in Weighted Nearest Neighbors. Zupan [56] used data from four journal accounts over a 14-year period to forecast the debit and credit sides of the wholesale warehouse for 150 working days. A study by Trofimov [57] analyzed the dynamic patterns of corporate profits in chosen developed economies using quarterly data. The ARIMA and seasonal ARIMA (SARIMA) models were applied to forecast of tuna landings based on data from the Malaysian Department of Fisheries. A study was conducted to forecast the monthly number of tuna landings from 2023 to 2030 and determine whether the estimated number meets the government's target [58].

Sokolov Mladenovic et al. [59] aimed to examine the relationship between economic activity in the distributive trade sector and economic growth across 28 European Union countries. The study used data from 2008 to 2015 and applied a multiple regression model, with the robustness of the results tested using the Hausman test. The study by Javed et al. [60] examined the relationship between various dimensions of mall relevance and shoppers' well-being, and how this, in turn, impacts mall loyalty. The research also sought to explore the moderating role of social media influencers in the relationship between shoppers' well-being and their loyalty to malls.

3. Materials and Methods

The study first analyses the time series for the SK NACE Section G sector, encompassing –wholesale and retail trade, and the repair of motor vehicles and motorcycles. We conduct a time series analysis using three financial indicators from the sector: costs, revenues, and EBT. Sixty quarterly data points given in EUR million were available, spanning from the first quarter of 2009 to the fourth quarter of 2023. Both ARIMA and exponential smoothing models were utilized.

Second, the study analyses the time series for HORTI, Ltd., which operates within the SK NACE sector section G. We employ the same indicators (but EAT instead of EBT) in a monthly time series spanning ten years, from January 2013 to December 2022.

We chose these indicators because they are particularly relevant for forecasting in the wholesale and retail trade sector, capturing essential financial and operational characteristics that align with the objectives of this sector-specific analysis.

Before creating the prediction models, we computed descriptive statistics of the underlying data, including mean, median, standard deviation, minimum, maximum, first and third quartiles, skewness, and kurtosis (see Table 3). The descriptive characteristics provide important initial insights into the dataset, including its central tendencies, variability, and distribution, which are crucial for selecting an appropriate model and correctly interpreting the results.

Table 3. Descriptive statistics. Source: own processing in SPSS.

	Monthly Data for HORTI, Ltd.			Quarterly Data for SK NACE Section G Sector		
	Costs	**Revenues**	**EAT**	**Costs (EUR mil.)**	**Revenues (EUR mil.)**	**EBT (EUR mil.)**
Valid N	120	120	120	60	60	60
Mean	950,571.491	960,945.046	10,373.555	9396.122	9746.241	350.120
Median	792,810.910	834,424.125	12,033.045	8685.895	9013.695	313.640
Min	65,329.500	63,588.060	−300,741.050	5617.000	5698.070	81.080
Max	5,169,164.010	5,184,975.480	419,968.260	18,029.910	18,637.160	803.810
Q1	538,392.595	501,538.830	−21,906.810	7552.650	7822.100	238.750
Q3	1,307,049.380	1,327,452.475	40,292.020	10,075.115	10,498.870	431.780
Std. Dev.	653,551.9161	662,930.2913	72,649.7915	2708.0953	2858.1942	166.1401
Skewness	2.4537	2.3563	0.7995	1.3704	1.3390	0.8967
Kurtosis	13.5480	12.8257	11.2157	1.5255	1.3926	0.5081

Note: N denotes number, Min and Max represent minimum and maximum, Q1 and Q3 are the first and third quartiles, Std. Dev. denotes standard deviation, EUR mil. represent EUR thousand.

Skewness indicates the degree of asymmetry in the data distribution—positive values suggest a rightward skew, where data points are more concentrated at lower levels, while negative values indicate a leftward skew. Kurtosis measures the presence of extreme values compared to a normal distribution—values greater than three may indicate a higher frequency of outliers, which can influence the choice of predictive models. A comparison of the monthly data for the company and the quarterly data for the sector highlights differences in the variability ranges of individual indicators, as well as distinct dynamics in the time series. Notable disparities, such as in the variability of EAT and EBT, reflect differences in structure and cyclical influences between the business entity and the sector. The time series data span from the first quarter of 2009 to the fourth quarter of 2023 for the sector, and from January 2013 to December 2022 for the company, providing a sufficiently broad foundation for identifying long-term trends, seasonal effects, and potential anomalies.

We verified stationarity using the KPSS test, which accounts for both trend and seasonality. The KPSS test is particularly sensitive to detecting stationarity when trends or seasonality are present, making it well-suited for the characteristics of the time series under study, which may include these components. This approach enabled us to accurately assess the stationarity of each time series.

For HORTI, Ltd., the KPSS tests for each monthly time series (revenues: test statistics = 0.0656, p-value > 0.10; costs: test statistics = 0.0606, p-value > 0.10; and EAT: test statistics = 0.1253, p-value = 0.091) revealed no significant irregularities. Since the p-values for all time series were greater than 0.09, the null hypothesis of stationarity was not rejected. Therefore, no adjustments to the data were needed to achieve stationarity.

For the sector SK NACE, section G, the KPSS tests for quarterly time series (revenues, costs, and EBT) showed that the p-value for the time series examined is less than 0.01, indicating that the null hypothesis of stationarity was rejected. This suggests that the time series are not stationary. It was, therefore, necessary to adjust the data to achieve stationarity before applying SARIMA models. This adjustment involved differencing the time series to remove long-term trends and seasonal influences. The KPSS test results after the first differencing are as follows:

- d_EBT: test statistics = 0.0517, p-value > 0.10.
- d_revenues: test statistics = 0.1521, interpolated p-value > 0.048.
- d_costs: test statistics = 0.1581, interpolated p-value > 0.044.

The methods employed are fundamental linear models designed for modeling univariate time series. We then generated forecasts for the next 24 months. IBM SPSS Statistics software (IBM SPSS Statistics 26) was used for the analysis due to its accessibility and capability to implement traditional time series models, such as ARIMA and exponential smoothing. IBM SPSS Statistics offers an intuitive user interface and automated procedures to identify the most suitable models, ensuring replicability and consistent data processing. No specific modules or custom scripts were utilized in this study; all calculations and model implementations were performed using the software's basic functionalities.

3.1. Holt–Winters' Method

Holt–Winters' method is based on three smoothing equations: one for the level, one for trend, and one for seasonality. There are two variations of Holt–Winters' method, depending on how seasonality is modeled—either additively or multiplicatively [61].

The basic equations for Holt–Winters' multiplicative method are as follows:

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (1)$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (2)$$

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s} \quad (3)$$

$$F_{t+m} = (L_t + b_t m) S_{t-s+m}, \tag{4}$$

where Y_t denotes observed values, L_t represents the level of series, b_t denotes the trend, S_t is the seasonal component, F_{t+m} is the forecast for m periods ahead, and s is the length of seasonality (e.g., number of months or quarters in a year). α, β, and γ are smoothing constants with values between 0 and 1. Appropriate smoothing constants are often determined subjectively based on the researcher's analytical experience. Alternatively, automatic searches can be performed using subjectively specified criteria to identify potential combinations of values in statistical software [61].

The seasonal component in Holt–Winters' method may also be treated additively. The basic equations for Holt–Winters' additive method are as follows [61]:

$$L_t = \alpha(Y_t + S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{5}$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta) b_{t-1} \tag{6}$$

$$S_t = \gamma(Y_t - L_t) + (1-\gamma) S_{t-s} \tag{7}$$

$$F_{t+m} = L_t + b_t m + S_{t-s+m}. \tag{8}$$

3.2. Box–Jenkins ARIMA Model

The Box–Jenkins ARIMA model is another commonly used approach for predicting future trends. The autoregressive moving average (ARMA) (p, q) model for a stationary time series is defined by a simple equation [62]:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots \theta_q \varepsilon_{t-q}. \tag{9}$$

The initial term in the ARIMA model corresponds to the autoregressive (AR) component of the order p, represented as follows [62]:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t. \tag{10}$$

The (AR) term represents to the current time series values Y_t as a function of its previous values Y_{t-1}, Y_{t-2}, …, Y_{t-p}. The coefficients ϕ_1, ϕ_2, …, ϕ_p are autoregressive coefficients that relate Y_t to its past values Y_{t-1}, Y_{t-2}, …, Y_{t-p} [62].

The moving average MA (q) term can be expressed as follows:

$$Y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots \theta_q \varepsilon_{t-q}, \tag{11}$$

where ε_{t-1}, ε_{t-2}, …, ε_{t-p} represent past random shocks or an independent white noise sequence with mean of 0 and variance of σ^2. The coefficients θ_1, θ_2, …, θ_q are the moving average coefficients that connect Y_t to ε_{t-1}, ε_{t-2}, …, ε_{t-p} [62].

When the (AR) and (MA) components are combined with an integration (differencing) term, they form an ARIMA (p, d, q) model, where p, d, and q denote the orders of autoregression, differencing, and moving average, respectively. The model can be expressed mathematically as follows:

$$(1-B)^d Y_t = \frac{\theta(B)}{\phi(B)} \varepsilon_t, \tag{12}$$

where t represents the time indices, and B is the backshift operator, meaning that $BY_t = Y_{t-1}$. The terms $\phi(B)$ and $\theta(B)$ represent the autoregressive and moving average operators, respectively, and are defined as follows [62]:

$$\phi(B) = 1 - \phi_1 B^1 - \phi_2 B^2 - \ldots - \phi_p B^p \tag{13}$$

$$\theta(B) = 1 - \theta_1 B^1 - \theta_2 B^2 - \ldots - \theta_q B^q. \tag{14}$$

3.3. Seasonal ARIMA (SARIMA) Model

Seasonality refers to a pattern that repeats over a fixed time interval. To achieve a stationary seasonal time series, seasonal differencing is carried out by calculating the difference between the current observation and the related observation from the prior year. Considering the seasonality of the available time series, a multiplicative ARIMA, represented as ARIMA (p, d, q) × (P, D, Q)s, is employed. Here, P, D, and Q indicate seasonal autoregressive, differencing, and moving average components, respectively, and s represents the number of seasons. The SARIMA (p, d, q) × (P, D, Q)s model developed for the time series is formulated as follows:

$$\phi_p(B)\Phi_P(B^s)(1-B)^d Y_t = \theta_q(B)\Theta_Q\left(B^S\right)\varepsilon_t, \tag{15}$$

where B denotes the backshift or lag operator; s represents the seasonal lag; ε_t indicates the error terms; d and D correspond to the non-seasonal and seasonal differences, respectively; ϕ and Φ are the non-seasonal and seasonal autoregressive parameters; and θ and Θ represent the non-seasonal and seasonal moving average parameters, respectively [62].

3.4. Forecast Accuracy

To assess forecasting accuracy, commonly used measures include mean absolute percentage error (MAPE). According to Lewis [63], the MAPE statistic can be interpreted as follows: forecasts are considered highly accurate if the MAPE is less than or equal to 10%; good if the MAPE is between 10% and 20%; reasonable if the MAPE is between 20% and 50%; and inaccurate if the MAPE exceeds 50%. The MAPE is calculated using the following equation:

$$\text{MAPE} = \sum_{i=1}^{n}\left|\frac{(X_i - F_i)/X_i}{n}\right| \times 100, \tag{16}$$

where X_i denotes the actual data for period i; F_i is the forecast for period i; $|\ |$ indicates the absolute value; and n represents the number of observations [64].

To assess the forecast accuracy, we use Theil's inequality coefficient U, defined as follows:

$$U = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - F_i)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}X_i^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n}F_i^2}}, \tag{17}$$

where X_i represents the actual observation for period i; and F_i is the forecast for period i [65]. The coefficient ranges from 0 to 1, where U = 0 indicates equality and U = 1 signifies maximum inequality [66].

A stationary R-squared is the other goodness-of-fit statistics. It is given by [67]

$$R_S^2 = 1 - \frac{\sum_t \left(Z(t) - \hat{Z}(t)\right)^2}{\sum_t \left(\Delta Z(t) - \overline{\Delta Z}\right)^2}, \tag{18}$$

where the sum is over the terms in which neither $Z(t) - \hat{Z}(t)$ nor $\Delta Z(t) - \overline{\Delta Z}$ are missing. $\overline{\Delta Z}$ represents the simple mean model for the differenced transformed series, which corresponds to the univariate baseline model ARIMA (0, d, 0)(0, D, 0). It can be negative with range $(-\infty, 1\rangle$. A negative stationary R-squared value indicates that the model being evaluated performs worse than the baseline model. Zero stationary R-squared indicates that the model being evaluated performs as good or bad as the baseline model. A positive stationary R-squared value suggests that the model being evaluated outperforms the baseline model [68].

We also present the R-squared (R^2) value, which provides an estimate of the proportion of total variation in the time series explained by the model.

To compare different models for the same data, we use the Bayesian Information Criterion (BIC). The BIC facilitates the comparison of models with varying numbers of parameters, helping to identify the one that best balances data fit and model complexity. A lower BIC value indicates a better model, reflecting an optimal trade-off between accuracy and complexity [69]. This approach is particularly useful for comparing models with different structures, such as ARIMA and Holt–Winters', as it enables an objective evaluation of which model best fits the data while minimizing the risk of overfitting. In this paper, the BIC is used as a criterion for model comparison because it provides an efficient method for selecting between models with different numbers of parameters, effectively accounting for model complexity.

We also use the Ljung–Box statistic (L-B Q') to test the randomness of the residual errors in the model. Greater randomness in the residuals indicates a better-fitting model. A significance value (p-value, Sig.) less than 0.05 suggests that the residual errors are not random, implying the presence of a structure in the observed series that the model has not accounted for [70]. In this paper, based on the results of this test, the residuals of all models were found to be independent, and no modifications to the models were necessary. If autocorrelation had been detected, further steps would have been taken to improve the model, such as adjusting the model parameters or selecting alternative methods.

To test for heteroskedasticity, or variability in the variance of residuals over time, we applied White's test, which did not reveal any signs of heteroskedasticity in our models. Additionally, we assessed the normality of the residuals using the Shapiro–Wilk test, which confirmed that the residuals followed a normal distribution. These diagnostic tests provided further evidence of the models' fit and helped ensure that the basic assumptions for their validity were met.

3.5. Procedures

IBM SPSS Statistics software automatically selected model parameters, including smoothing levels for Holt–Winters' method and the parameters (p, d, q) for ARIMA. These values were subsequently manually verified and fine-tuned by analyzing the outputs and evaluating the models' fit to the data. For this purpose, additional analytical techniques, such as residual visualization and model quality tests, were applied to ensure the reliability and accuracy of the predictions.

The seasonality for the SARIMA model was automatically determined by the software, incorporating domain knowledge of the SK NACE Section G sector, which exhibits characteristic seasonal patterns (e.g., higher business activity during specific times of the year). This procedure ensured that the selected seasonality was relevant and accurately reflected the trade dynamics in the sector.

In verifying the presence of outliers in ARIMA models, the following concepts, derived from SPSS software, will be used:

- Transient Magnitude refers to the absolute size of a temporary or short-term deviation from the expected pattern in the data. It measures the magnitude of an outlier or anomaly, which is typically of a short duration and may not represent a sustained trend.

- Transient Decay Factor represents how quickly the influence of a transient anomaly decays or diminishes over time. This factor assesses how fast the impact of an outlier fades as the data returns to its normal pattern.
- Additive refers to a seasonal or trend component in time series data where the effect is constant over time.
- Level refers to the baseline or central value of the time series around which data points fluctuate.
- Level shift refers to a sudden and sustained change in the baseline or central value of the time series. It represents a step-like change in the data where the series shifts to a new level, which persists over time.
- Innovational effect represents a new and unexpected change or innovation that alters the course of the series, usually by introducing a structural break or unexpected fluctuation. It is considered a more short-term effect compared to a level shift.
- Seasonal Additive refers to a type of seasonal effect in a time series model where the seasonal fluctuations are constant in magnitude over time. In an additive model, the seasonal variations are added to the baseline level, meaning the size of the seasonal effect remains unchanged, regardless of the level of the data.

Forecasts were generated for the next 24 months, along with 95% confidence intervals. These forecasts do not utilize rolling methods but provide monthly or quarterly predictions based on long-term trends and seasonal influences.

4. Results

A set of criteria, including MAPE, BIC, Theil's inequality coefficient U, and R-squared, was used to select the most appropriate prediction models. These metrics are widely recognized in the field of time series and predictive modeling, offering a comprehensive assessment of the accuracy and robustness of the models. Their characteristics and expected values are described in Section 3.4 of the paper. The model selection process also involved diagnostics such as autocorrelation of residuals, normality of residuals, and analysis of residual variations between predicted and actual values.

4.1. Forecasting Revenues in the SK NACE Section G Sector

In this section, we provide time series analyses of revenues for the SK NACE section G sector—wholesale and retail trade, repair of motor vehicles and motorcycles. Both ARIMA and exponential smoothing models were applied.

Figure 4 shows the development of revenues in the sector from the first quarter of 2009 to the fourth quarter of 2023. The time series is non-stationary (as verified by the KPSS test) and exhibits a trend. The seasonal fluctuations show a significant dependence on the trend, with a maximum in the fourth quarter and a minimum in the first quarter. Revenues initially show a slightly increasing trend, followed by stagnation between 2017 and 2020, and then a marked increase starting in 2021.

Among the exponential smoothing models, considering all criteria, the most suitable model for revenue forecasting is Holt–Winters' additive model (see Figure 5), with its parameters listed in Table 4. Autocorrelations and partial autocorrelations are not significant. The normality assumption for the residuals is satisfied, as the residuals follow a normal distribution with a mean value that is not significantly different from zero. The model explains 96.6% of the variability in the time series. Holt–Winters' additive model achieves the lowest BIC value (12.764), indicating that it is the most appropriate for forecasting revenues, as it satisfies all criteria while providing an optimal balance between model accuracy and complexity. The MAPE is less than 10%, indicating a highly accurate forecast.

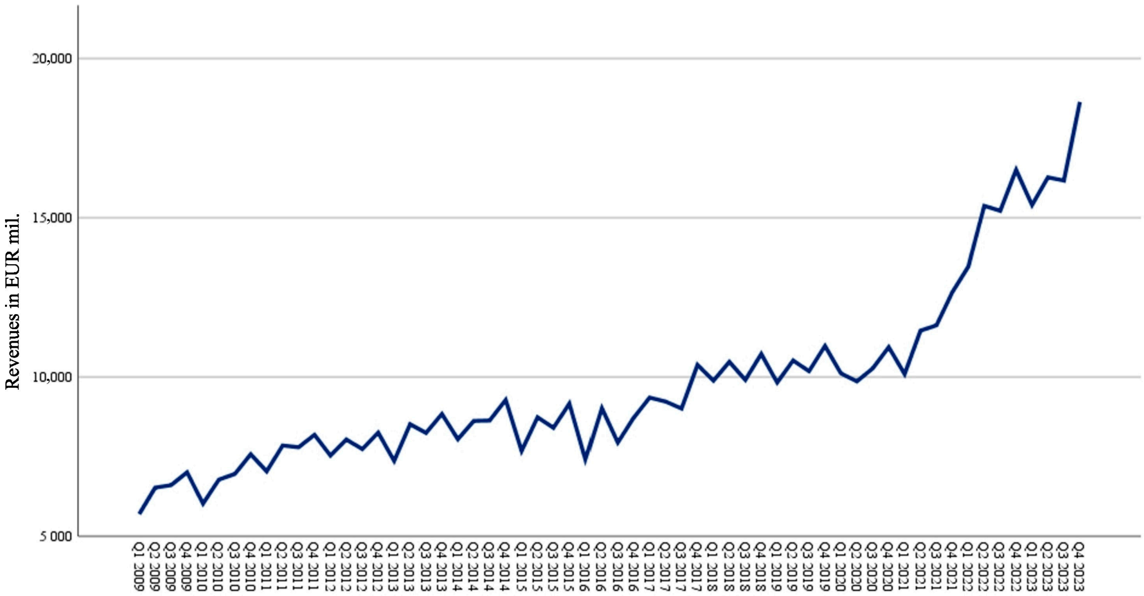

Figure 4. Development of revenues (in EUR mil.) in the SK NACE Section G sector. Source: own processing in SPSS.

Table 4. Parameters of time series models of revenues (in EUR mil.) in the SK NACE Section G sector. Source: own processing in SPSS.

	Holt–Winters' Additive Model	ARIMA (0,1,0)(0,1,1)	ARIMA (0,1,0)(0,1,1) (Outliers)	ARIMA (1,1,1)
L (Level)	0.791			
b (Trend)	0.136			
S (Season)	0.090			
$\Theta(1)$		0.813	0.738	
$\theta(0)$				208.587
$\theta(1)$				–1.000
$\theta(2)$				–0.984
Forecast accuracy				
MAPE	3.497	3.892	2.579	4.499
BIC	12.764	12.820	12.204	12.991
L-B Q′ (Sign.)	12.183 (0.665)	15.338 (0.571)	20.268 (0.261)	10.763 (0.824)
R_S^2	0.449	0.360	0.802	0.536
R^2	0.966	0.956	0.986	0.957
U	0.5765	0.6244	0.3705	0.6790

Considering Box–Jenkins methodology, among several tested autoregressive models with moving averages, the ARIMA(0,1,0)(0,1,1) model without a constant was selected (see Figure 5). The parameters are listed in Table 4. This model explains 95.6% of the variability in the time series. Subsequently, outliers were detected (see Table 5), and additional models accounting for these outliers were also tested. After evaluating all criteria, the ARIMA(0,1,0)(0,1,1) model without a constant was selected as the most appropriate. The parameters of the model are provided in Table 4, and its visualization is shown in Figure 5.

The model explains 98.6% of the variability in the time series. For these models, the normality of the residuals is satisfied, and no autocorrelation in the residuals was detected. The MAPE is less than 10%, indicating a highly accurate forecast. The ARIMA model with outliers achieves the lowest BIC value, suggesting that accounting for outliers in the model results in better optimization.

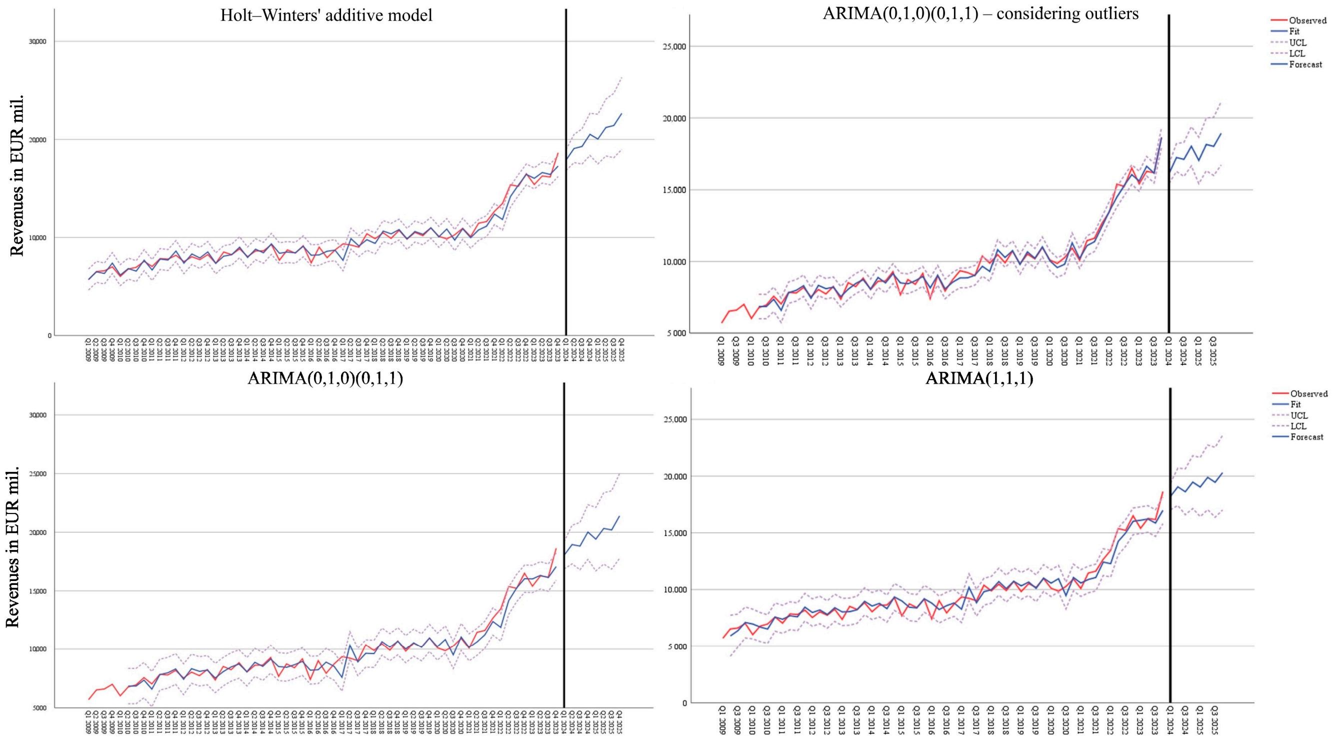

Figure 5. Time series models of revenues (in EUR mil.) in the SK NACE Section G sector. Source: own processing in SPSS.

Table 5 presents the observed outliers for the ARIMA(0,1,0)(0,1,1) model. Outliers were observed in 2016, 2017, 2020, 2022, and 2023, which may be attributed to specific economic events or political factors (e.g., economic crises, government interventions, or pandemics). These values were corrected using additive and transient methods to maintain the overall stability of the model while avoiding unnecessary biases. This approach was selected based on the literature and best practices, which show that additive adjustments are effective in accounting for sudden and significant fluctuations in time series.

Table 5. Outliers of the model ARIMA (0,1,0)(0,1,1) of revenues. Source: own processing in SPSS.

Outliers—Revenues ARIMA(0,1,0)(0,1,1)		Estimate	SE	t	Sig.
Q2 2016	Additive	779.939	226.235	3.447	0.001
Q1 2017	Additive	1334.209	234.719	5.684	0.000
Q2 2020	Transient Magnitude	–1347.652	315.610	–4.270	0.000
	Transient Decay factor	0.811	0.186	4.367	0.000
Q1 2022	Level	1704.500	332.416	5.128	0.000
Q4 2023	Additive	1543.915	351.730	4.389	0.000

Note: Q1, Q2, and Q4 represent quarters, SE denotes standard error, t is test statistics, and Sig. represents significance.

Finally, non-seasonal exponential smoothing models and non-seasonal ARIMA models were also tested to address ambiguous evidence of seasonality based on the obtained results of the time series of revenues. From the perspective of all criteria, the ARIMA(1,1,1) model was selected as the most suitable model for revenue forecasting (see Figure 5). The model parameters are listed in Table 4. This model explains 95.7% of the variability in the time series. The normality of the residuals was satisfied, and no autocorrelation in the residuals was detected. The MAPE is less than 10%, indicating a highly accurate forecast.

The models presented were chosen from several validated options as the most comparable and satisfactory in terms of forecast accuracy, while also meeting all required assumptions. In Figure 5, we see both the observed (red line) and expected (blue line) values of revenues, along with 95% confidence intervals (upper confidence limit–UCL, lower confidence limit–LCL). The figure shows that the models effectively capture the dynamics and seasonality, with predictions closely matching the actual values.

Table 6 compares the revenue forecasts for these models. Revenue growth is expected in the future. Based on the models selected for forecasting revenue for the SK NACE Section G sector, growth is expected in the coming years. Among all the forecasting models proposed, Holt–Winters' additive model (when outliers are not considered) is the most accurate in estimating revenues for the SK NACE Section G sector. Based on Theil's inequality coefficient *U* (see Table 4), MAPE (3.497%), and the BIC (12.864), which is the lowest for this model, it was selected as the best fit for forecasting the years 2024–2025. The model assumes that revenue growth will continue in 2024, reaching approximately EUR 12.588 million, and will further increase to EUR 14.173 million in 2025. Given that the Theil's inequality coefficient *U* (see in Table 4) is less than 1 for all proposed models, all the presented models can be considered satisfactory. Furthermore, all forecasts fall within the 95% confidence interval.

Table 6. Comparison of the revenues forecasts using different models (in EUR mil.) in the SK NACE Section G sector. Source: own processing in SPSS.

	Holt–Winters' Additive Model			**ARIMA(0,1,0)(0,1,1)**		
Period	**Forecast**	**LCL**	**UCL**	**Forecast**	**LCL**	**UCL**
2024 Q1	17,897.96	16,829.65	18,966.28	18,032.63	16,868.15	19,197.12
2024 Q2	19,075.39	17,638.99	20,511.80	18,947.39	17,300.70	20,594.07
2024 Q3	19,280.48	17,486.20	21,074.77	18,815.38	16,798.67	20,832.09
2024 Q4	20,516.83	18,363.60	22,670.06	20,014.13	17,685.47	22,342.79
2025 Q1	20,035.44	17,506.97	22,563.92	19,409.60	16,701.08	22,118.13
2025 Q2	21,212.87	18,312.69	24,113.06	20,324.36	17,283.43	23,365.29
2025 Q3	21,417.96	18,136.33	24,699.60	20,192.35	16,851.80	23,532.90
2025 Q4	22,654.31	18,980.90	26,327.71	21,391.10	17,775.67	25,006.53
	ARIMA(0,1,0)(0,1,1): outliers			**ARIMA(1,1,1)**		
Period	**Forecast**	**LCL**	**UCL**	**Forecast**	**LCL**	**UCL**
2024 Q1	16,111.80	15,425.86	16,797.74	18,201.37	17,025.55	19,377.20
2024 Q2	17,232.75	16,262.70	18,202.81	19,054.28	17,409.00	20,699.55
2024 Q3	17,103.65	15,915.59	18,291.72	18,618.60	16,596.36	20,640.85
2024 Q4	18,020.24	16,648.38	19,392.10	19,471.39	17,144.40	21,798.39
2025 Q1	17,031.11	15,408.87	18,653.34	19,035.83	16,428.65	21,643.02

Table 6. *Cont.*

	Holt–Winters' Additive Model			ARIMA(0,1,0)(0,1,1)		
Period	**Forecast**	**LCL**	**UCL**	**Forecast**	**LCL**	**UCL**
2025 Q2	18,145.83	16,307.03	19,984.63	19,888.51	17,038.29	22,738.73
2025 Q3	18,011.67	15,979.25	20,044.10	19,453.06	16,369.86	22,536.27
2025 Q4	18,924.16	16,715.01	21,133.31	20,305.63	17,014.23	23,597.03

Note: Q1–Q4 represent quarters, LCL denotes lower confidence limit, UCL denotes upper confidence limit.

4.2. Forecasting Costs in the SK NACE Section G Sector

In this section, we provide time series cost analyses for the SK NACE Section G sector (wholesale and retail trade, repair of motor vehicles and motorcycles) using ARIMA and exponential smoothing models.

Figure 6 shows the development of costs in the sector from the first quarter of 2009 to the fourth quarter of 2023. The time series is non-stationary (as verified by the KPSS test) and exhibits a trend. Seasonal fluctuations are strongly influenced by the trend, reaching a maximum in the fourth quarter and a minimum in the first quarter. Costs in the sector follow a similar trend to revenues. When interpreting these seasonal fluctuations, it is important to consider potential factors that may influence cost evolution, such as economic conditions, industry events, or changes in consumer behavior. These factors can significantly impact costs from quarter to quarter, and their inclusion would provide better context for the observed seasonal variations. From the beginning of the monitored period, costs show a slightly increasing trend, stagnate between 2017 and 2020, and then begin to rise significantly from 2021 onward.

We address the nonlinearity of the cost time series development and the present seasonality by using local linear trends with time-varying parameters, applying Holt–Winters' exponential smoothing multiplicative model with linear local trends. The most suitable model for cost forecasting is Holt–Winters' multiplicative model (see Figure 7). This model explains 96.5% of the variability in the time series. The choice of Holt–Winters' model was motivated by its ability to effectively capture seasonal fluctuations and time series trends. This model strikes a good balance between accuracy and complexity, which is essential for reliable predictions. Its success is further supported by a very low BIC value, indicating its efficiency relative to other models.

Considering Box–Jenkins methodology, among several tested autoregressive models with moving averages, the ARIMA(0,1,0)(0,1,1) model without a constant was selected (see Figure 7). This model explains 95.4% of the variability in the time series. The ARIMA(0,1,0)(0,1,1) model provided an excellent prediction of the time series structure, as it exhibited very low autocorrelation of the residuals and met the normality of residuals, making it suitable for forecasting in this case. Moreover, non-seasonal exponential smoothing models and non-seasonal ARIMA models were also tested due to ambiguous evidence of seasonality based on the time series results.

In testing these non-seasonal models, the focus was on determining whether seasonal models would provide better predictions by evaluating the ambiguous evidence of seasonality in the time series. This step allowed for a more effective comparison of model performance and the selection of the most appropriate model for the time series. Based on all criteria, the ARIMA(1,1,1) model was chosen as the most suitable model for cost forecasting (see Figure 7). This model explains 95.5% of the variability in the time series.

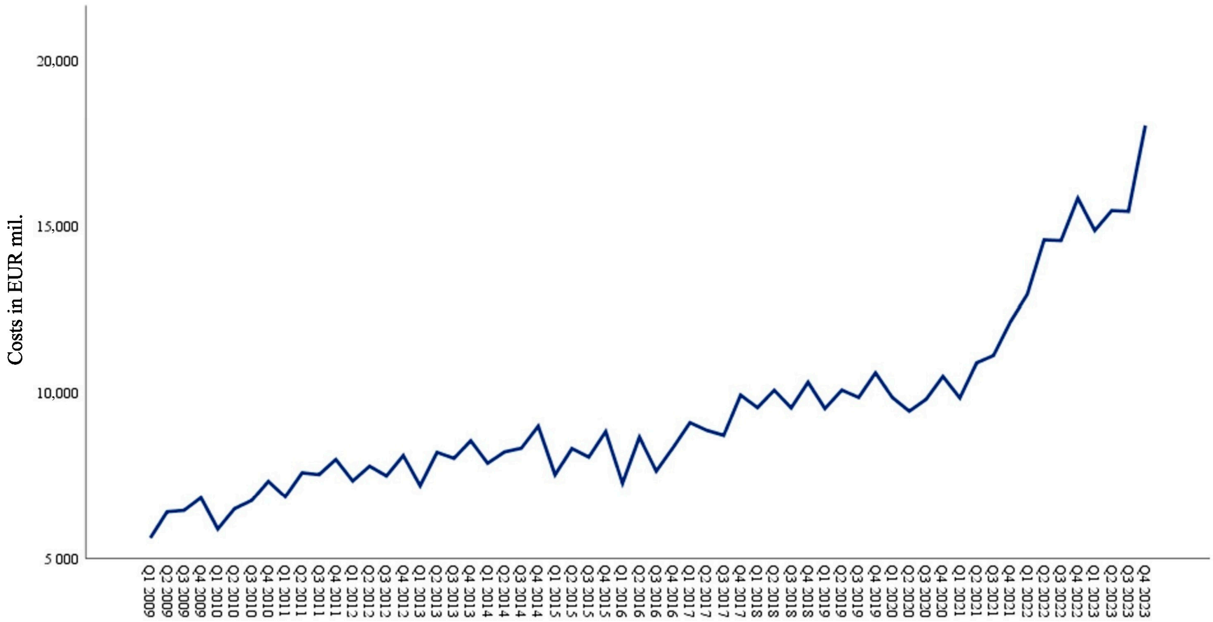

Figure 6. Development of costs (in EUR mil.) in the SK NACE Section G sector. Source: own processing in SPSS.

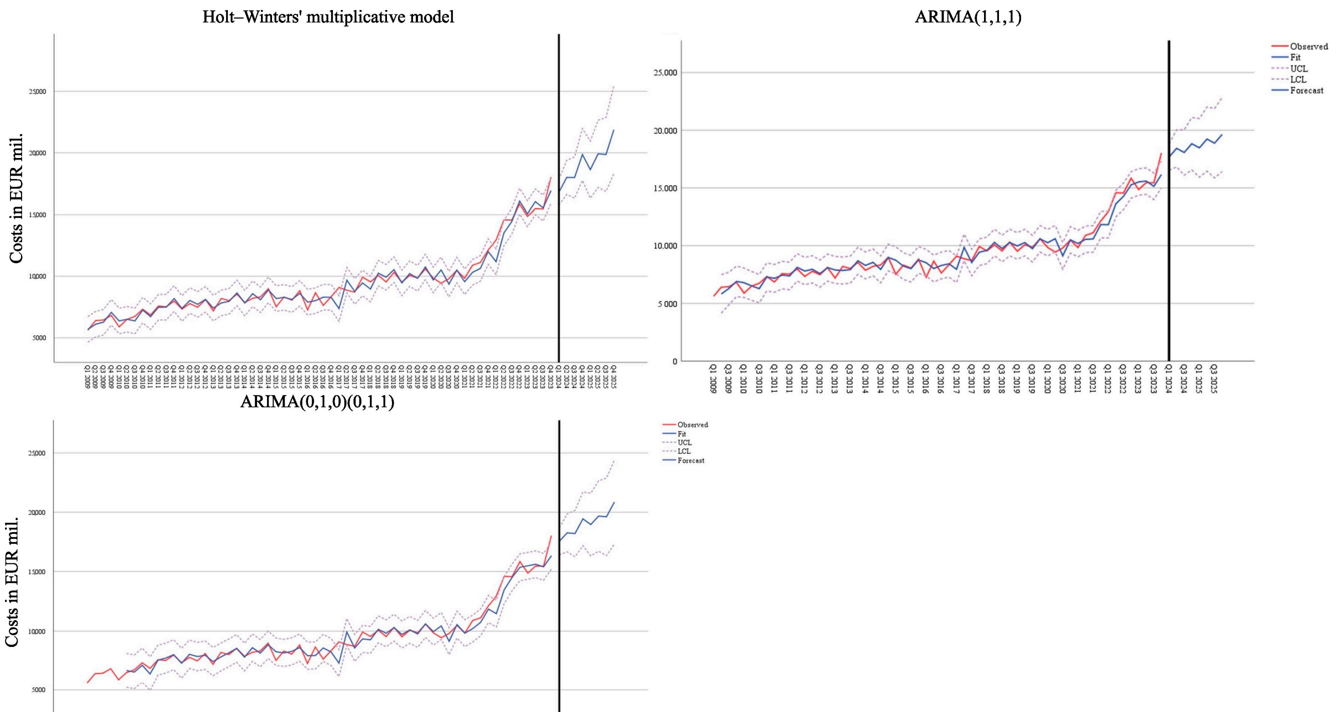

Figure 7. Time series models of costs (in EUR mil.) in the SK NACE Section G sector. Source: own processing in SPSS.

Table 7 lists the parameters of all models, including the level, trend, and seasonality values for Holt–Winters' model, as well as the theta coefficients for the ARIMA models. These parameters provide important insights into how each model captures the evolution of costs, and their interpretation helps us better understand why certain models are more accurate. Holt–Winters' multiplicative model achieves the lowest BIC value (12.704), making it the most suitable model for cost prediction, as it satisfies all criteria and provides an optimal balance between model accuracy and complexity. A MAPE of less than 10% indicates that the model provides highly accurate predictions, while the BIC and Theil's U value demonstrate its strong ability to capture the structure of the time series.

Table 7. Parameters of time series models of costs (in EUR mil.) in the SK NACE Section G sector. Source: own processing in SPSS.

	Holt–Winters' Multiplicative Model	**ARIMA (0,1,0)(0,1,1)**	**ARIMA (1,1,1)**
L (Level)	0.752		
b (Trend)	0.129		
S (Season)	0.351		
$\Theta(1)$		0.795	
$\theta(0)$			201.017
$\theta(1)$			–1.000
$\theta(2)$			–0.987
Forecast accuracy			
MAPE	3.565	3.894	4.382
BIC	12.704	12.763	12.936
L-B Q' (Sign.)	12.730 (0.623)	14.272 (0.648)	12.160 (0.733)
R_S^2	0.451	0.354	0.480
R^2	0.965	0.954	0.955
U	0.6168	0.6674	0.6619

In all models, the autocorrelations and partial autocorrelations of the residuals are not significant, and the normality of the residuals is fulfilled. The finding that the autocorrelations and partial autocorrelations of the residuals are not significant supports the stability and reliability of the models. Additionally, the normality of the residuals confirms that the models are suitable for prediction and that their forecasts are reliable. The MAPE of less than 10% indicates highly accurate forecasts.

In Figure 7, we see both the observed (red line) and expected (blue line) values of costs, along with 95% confidence intervals (upper confidence limit–UCL, lower confidence limit–LCL).

Table 8 compares the cost forecasts for these models. These models were selected from a range of reviewed options as the most comparable and satisfactory, both in terms of forecast accuracy and adherence to all assumptions (e.g., MAPE, BIC, Theil's U), making them suitable for predicting costs in this sector.

Cost growth is expected in the future, consistent with historical developments and trends in the sector. This growth is likely to be influenced by factors such as inflation, changes in commodity prices, and potential increases in demand. Among all the forecasting models proposed, Holt–Winters' multiplicative model is the most accurate in estimating costs in the SK NACE Section G sector. Based on the Theil's inequality coefficient U (see Table 7), which is less than 1 for all proposed models, all presented models can be considered satisfactory. Furthermore, all forecasts fall within the 95% confidence interval.

Table 8. Comparison of the cost forecasts using different models (in EUR mil.) in the SK NACE Section G sector. Source: own processing in SPSS.

	Holt–Winters' Multiplicative Model			ARIMA(0,1,0)(0,1,1)			ARIMA(1,1,1)		
Period	**Forecast**	**LCL**	**UCL**	**Forecast**	**LCL**	**UCL**	**Forecast**	**LCL**	**UCL**
2024 Q1	17,897.96	16,829.65	18,966.28	18,032.63	16,868.15	19,197.12	17,672.18	16,526.00	18,818.36
2024 Q2	19,075.39	17,638.99	20,511.80	18,947.39	17,300.70	20,594.07	18,431.90	16,826.88	20,036.92
2024 Q3	19,280.48	17,486.20	21,074.77	18,815.38	16,798.67	20,832.09	18,074.26	16,101.99	20,046.52
2024 Q4	20,516.83	18,363.60	22,670.06	20,014.13	17,685.47	22,342.79	18,833.90	16,563.81	21,103.98
2025 Q1	20,035.44	17,506.97	22,563.92	19,409.60	16,701.08	22,118.13	18,476.33	15,933.31	21,019.35
2025 Q2	21,212.87	18,312.69	24,113.06	20,324.36	17,283.43	23,365.29	19,235.89	16,455.35	22,016.42
2025 Q3	21,417.96	18,136.33	24,699.60	20,192.35	16,851.80	23,532.90	18,878.41	15,870.92	21,885.90
2025 Q4	22,654.31	18,980.90	26,327.71	21,391.10	17,775.67	25,006.53	19,637.88	16,426.92	22,848.84

Note: Q1–Q4 represent quarters, LCL denotes lower confidence limit, UCL denotes upper confidence limit.

4.3. Forecasting EBT in the SK NACE Section G Sector

In this section, we provide time series analyses of EBT for the SK NACE Section G sector–wholesale and retail trade, repair of motor vehicles and motorcycles.

Figure 8 shows the development of EBT in the sector from the first quarter of 2009 to the fourth quarter of 2023. The time series is non-stationary (as verified by the KPSS test), with a slightly increasing trend. Based on White's test for heteroskedasticity, its presence was not demonstrated (p-value = 0.2105).

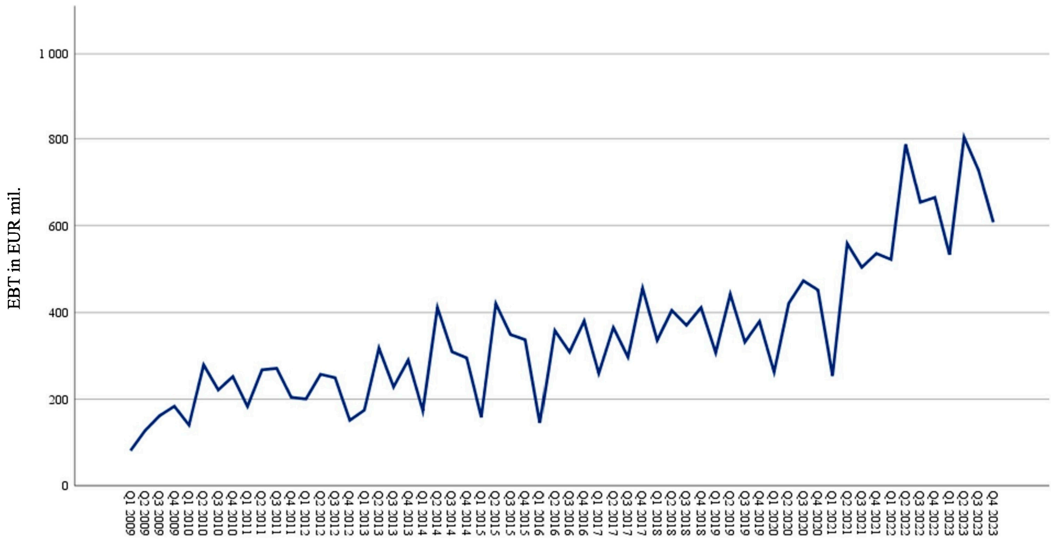

Figure 8. Development of EBT (in EUR mil.) in the SK NACE Section G sector. Source: own processing in SPSS.

For ambiguous visual evidence of seasonality in the EBT time series, both non-seasonal and seasonal exponential smoothing models were examined. Seasonality was not conclusively confirmed, leading to the testing of several alternative models, including exponential smoothing and ARIMA models, which were deemed appropriate based on the model diagnostics. Both seasonal ARIMA and exponential models tested failed to meet the basic assumptions for their acceptance (autocorrelation of residuals, statistically insignificant model parameters). Seasonal models were found to be inappropriate as they failed to meet the basic assumptions of model acceptability, including the lack of residual autocorrelation and the statistical significance of model parameters. Therefore, only non-seasonal models were considered, as they better satisfied the assumptions of residual randomness and the requirements for the statistical significance of parameters. Suitable models were searched for using SPSS. We experimented with exponential models and linear ARIMA models. Considering all criteria (e.g., MAPE, BIC, and Theil's U), the most suitable model for EBT forecasting is the ARIMA(4,1,0) model, whose parameters are in Table 9. This model was selected based on diagnostic results, which demonstrated a good balance between accuracy and simplicity. The MAPE of 16.782 indicates good predictive accuracy, as it is below 20%. The BIC value of 8.706 reflects the model's goodness of fit relative to the number of parameters. The L-B Q' test (19.376, p-value = 0.151) confirms that the residuals are not autocorrelated and satisfy the assumption of randomness. R-squared indicates that the model explains approximately 85% of the variability in the time series data. Theil's U (0.4445) indicates an acceptable level of predictive accuracy, as its value is below 1.

Table 9. Parameters of time series model of EBT (in EUR mil.) in the SK NACE Section G sector. Source: own processing in SPSS.

	ARIMA(4,1,0)
$\theta(0)$	9.309
$\theta(1)$	$\theta_1 = -0.609$ $\theta_2 = -0.510$ $\theta_3 = -0.479$ $\theta_4 = 0.311$
Forecast accuracy	
MAPE	16.782
BIC	8.706
L-B Q' (Sign.)	19.376 (0.151)
R_S^2	0.729
R^2	0.852
U	0.4445

In Figure 9, we see both the observed (red line) and expected (blue line) values of EBT, along with 95% confidence intervals (upper confidence limit—UCL, lower confidence limit—LCL). The model explains 85.2% of the variability in the time series, meaning that most of the EBT changes in this sector can be accurately predicted using this model. The requirement for normality of the residuals is satisfied, and the autocorrelation of the residuals was detected.

Table 10 presents the EBT forecasts for the models. These forecasts fall within the 95% confidence interval. The EBT forecast shows an increasing trend.

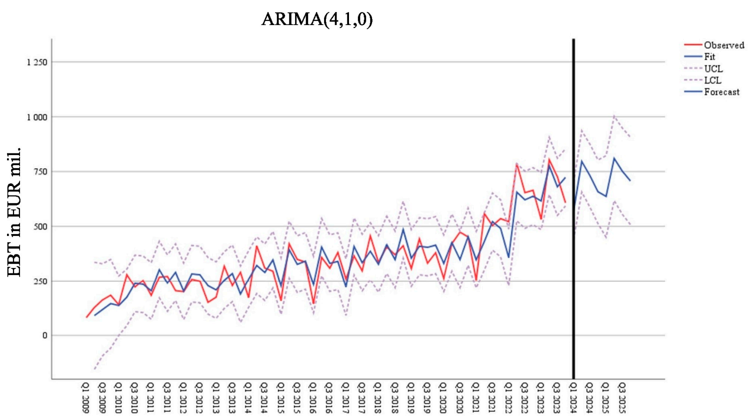

Figure 9. Time series model of EBT (in EUR mil.) in the SK NACE Section G sector. Source: own processing in SPSS.

Table 10. The EBT forecasts using ARIMA(4,1,0) model (in EUR mil.) in the SK NACE Section G sector. Source: own processing in SPSS.

	ARIMA(4,1,0)		
Period	**Forecast**	**LCL**	**UCL**
2024 Q1	569.46	439.24	699.69
2024 Q2	796.05	656.23	935.88
2024 Q3	731.57	587.94	875.19
2024 Q4	657.62	512.34	802.91
2025 Q1	636.55	450.44	822.65
2025 Q2	809.78	617.50	1002.06
2025 Q3	751.62	554.97	948.27
2025 Q4	707.10	507.93	906.28

Note: Q1–Q4 represent quarters, LCL denotes lower confidence limit, UCL denotes upper confidence limit.

4.4. Forecasting Revenues for HORTI, Ltd.

In this section, we provide a time series analysis of the revenues for the company HORTI, Ltd. Both ARIMA and exponential smoothing models were applied.

Figure 10 illustrates the revenue development of HORTI, Ltd. from January 2013 to December 2022. The time series shows a slightly increasing trend. Based on White's test for heteroskedasticity, no significant evidence of heteroskedasticity was found (p-value = 0.4033).

Thus, the time series exhibits inhomogeneous behavior, making it challenging to model future revenue trends using only linear models. This issue has been addressed by selecting models that account for seasonality and fluctuations in the data. Due to ambiguous visual evidence of seasonality in the revenue time series, both non-seasonal and seasonal exponential smoothing models were examined. However, both non-seasonal ARIMA and exponential models tested failed to meet the basic assumptions required for their acceptance. Therefore, only seasonal models were considered. Suitable models were identified using SPSS, where we experimented with exponential models and linear ARIMA models. The parameters of the selected models are presented in Table 11.

Considering all criteria (e.g., MAPE, BIC, and Theil's U), the most suitable model for revenue forecasting using exponential smoothing is Holt–Winters' additive model (see Figure 11). This model was chosen for its balanced accuracy and ease of interpretation. It explains 75% of the variability in the time series. Holt–Winters' additive model achieves a BIC value of 25.568, the lowest among the models tested, suggesting that it offers an optimal balance between simplicity and accuracy in predicting revenue.

Considering Box–Jenkins methodology, among several tested autoregressive models with moving averages, the ARIMA(0,1,1)(0,1,1) model with a constant was selected (see Figure 11). This model was chosen for its ability to capture the underlying trend dynamics and seasonal fluctuations in the data, which were not adequately captured by the other models tested. It explains only 60% of the variability in the time series.

Subsequently, outliers were detected (see Table 12), and other models that account for these outliers were also tested. These outliers may be due to specific economic factors or unusual events during certain periods that significantly impacted the company's revenues. The choice of a ARIMA(0,1,1)(0,1,1) model without a constant, which accounts for these outliers, was supported by diagnosing the outliers and fitting models to address these specific fluctuations. Taking all criteria into account (e.g., MAPE, BIC, Theil's U, and autocorrelation of residuals), the ARIMA(0,1,1)(0,1,1) model without a constant was selected as the most appropriate model. This model explains 96.9% of the variability in the time series. It was found to be the most accurate, achieving the lowest MAPE value (9.765) and the highest R-squared and Theil's *U* coefficient values, providing a reliable prediction of revenues. In all models, autocorrelations and partial autocorrelations of residuals are not significant, and the requirement for normality of the residuals was fulfilled. In Figure 11, we see both the observed (red line) and expected (blue line) values of revenues, along with 95% confidence intervals (upper confidence limit—UCL, lower confidence limit—LCL). The confidence interval indicates the range within which we expect the actual revenue values to fall, providing important information about the reliability of the model.

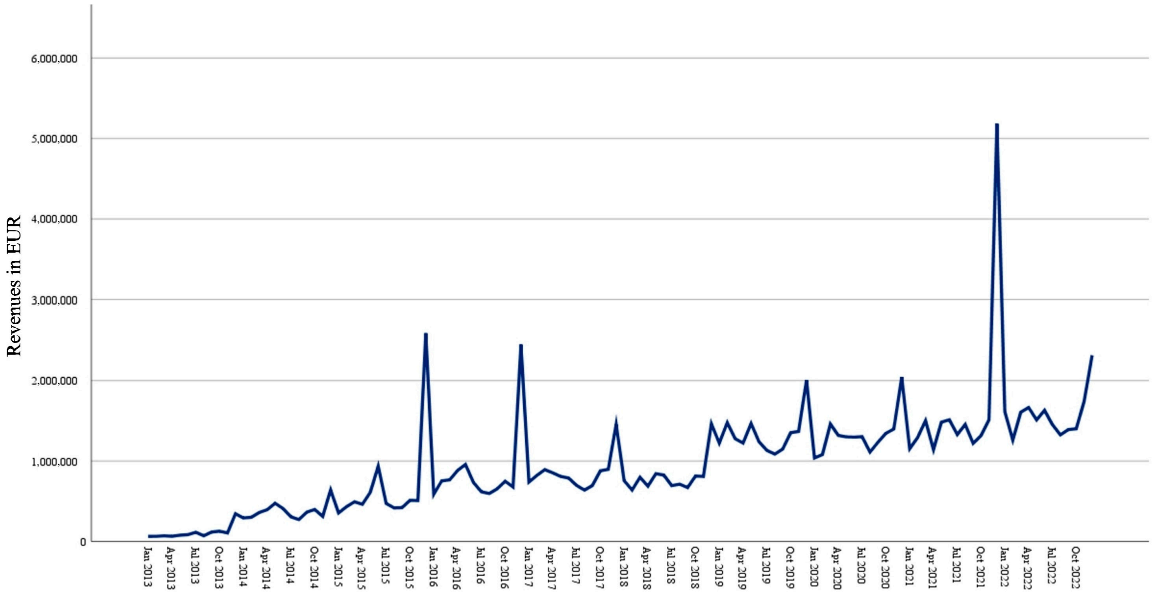

Figure 10. Development of revenues for HORTI, Ltd. Source: own processing in SPSS.

Table 11. Parameters of time series models of revenues for HORTI, Ltd. Source: own processing in SPSS.

	Holt–Winters' Additive Model	**ARIMA (0,1,1)(0,1,1)**	**ARIMA (0,1,1)(0,1,1): Outliers**
L (Level)	0.093		
b (Trend)	3.872×10^{-8}		
S (Season)	5.518×10^{-5}		
Constant		–0.009	
θ(1)		0.518	0.732
Θ(1)		0.822	0.692
Forecast accuracy			
MAPE	24.969	19.551	9.765
BIC	25.568	25.936	23.633
L-B Q' (Sign.)	5.930 (0.981)	11.043 (0.807)	17.160 (0.375)
R_S^2	0.684	0.330	0.967
R^2	0.750	0.600	0.969
U	0.7165	0.7361	0.2058

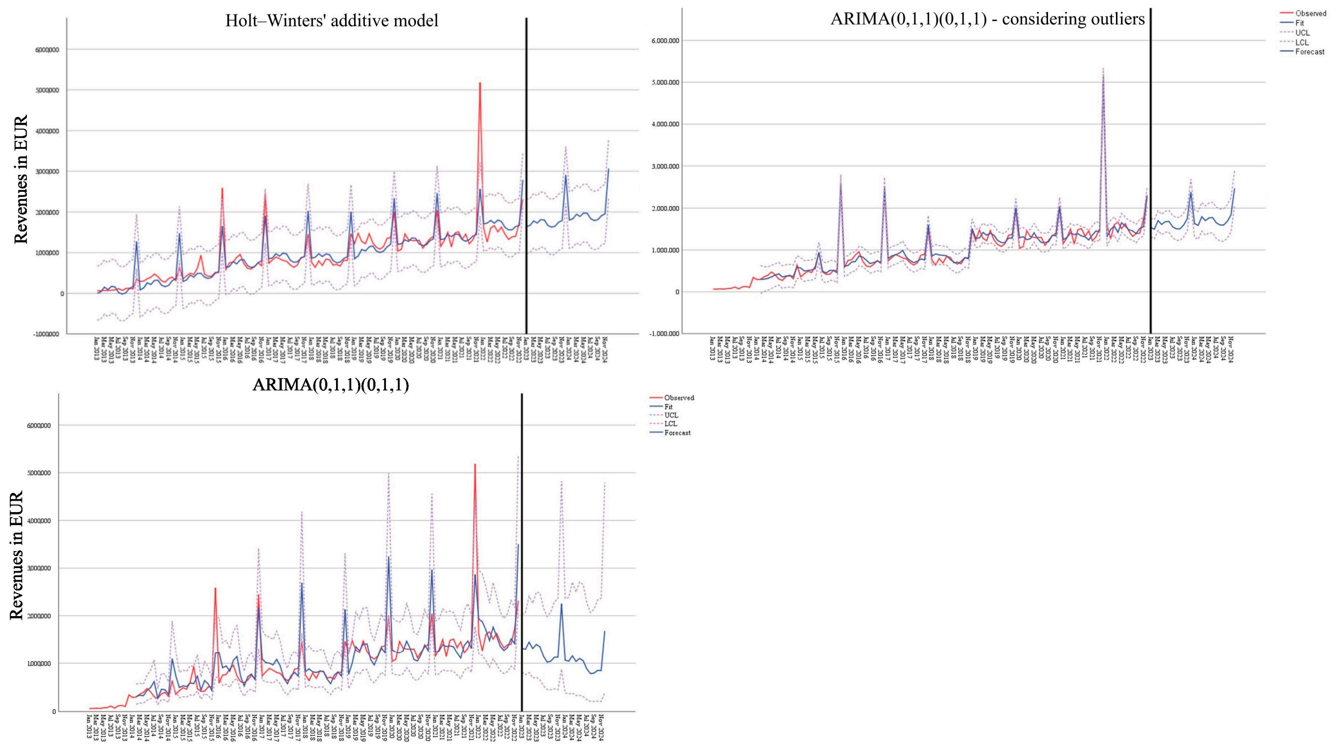

Figure 11. Time series models of revenues for HORTI, Ltd. Source: own processing in SPSS.

Table 12. Outliers of the model ARIMA(0,1,1)(0,1,1) of revenues for HORTI, Ltd. Source: own processing in SPSS.

Outliers—Revenues ARIMA(0,1,1)(0,1,1)		**Estimate**	**SE**	**t**	**Sig.**
2015/06	Additive	407,841.866	97,433.999	4.186	0.000
2015/12	Additive	1,271,452.212	111,726.334	11.380	0.000
	Seasonal Additive	527,083.537	99,361.508	5.305	0.000
2016/12	Additive	990,087.951	105,858.095	9.353	0.000
2019/01	Level Shift	488,365.441	71,987.466	6.784	0.000
2021/12	Additive	2,998,617.246	101,283.608	29.606	0.000

Note: SE denotes standard error, *t* is test statistics, and Sig. represents significance.

Table 13 compares the revenue forecasts for these models (from January 2023 to December 2024). All forecasts fall within the 95% confidence interval, supporting the stability and accuracy of the selected models. The results in Table 13 and Figure 11 show that Holt–Winters' additive model and the ARIMA(0,1,1)(0,1,1) model without a constant (taking into account outliers) predict stable revenue growth. On the other hand, the ARIMA(0,1,1)(0,1,1) model predicts a decrease in revenues. These models were chosen from a range of reviewed options as the most comparable and satisfactory, both in terms of forecast accuracy and adherence to all assumptions (e.g., normality of residuals and absence of autocorrelation in the residuals). Among all the forecasting models proposed, ARIMA(0,1,1)(0,1,1) without a constant (taking into account outliers) is the most accurate in estimating the revenues of HORTI, Ltd. This model has proven to be the most effective in capturing fluctuations caused by outliers and seasonal factors. On the other hand, Holt–Winters' additive model and the ARIMA(0,1,1)(0,1,1) model with a constant are also reliable, offering good predictions, though with slightly lower accuracy. Based on the Theil's inequality coefficient U (see Table 11), which is less than 1 for all proposed models, all the models can be considered satisfactory. For high prediction accuracy, MAPE values below 10% and Theil's U-values below 1 are considered good benchmarks, which holds true for the selected models.

Table 13. Comparison of the revenue forecasts using different models for HORTI, Ltd. Source: own processing in SPSS.

	Holt–Winters' Additive Model			ARIMA(0,1,1)(0,1,1)			ARIMA(0,1,1)(0,1,1): Outliers		
Period	**Forecast**	**LCL**	**UCL**	**Forecast**	**LCL**	**UCL**	**Forecast**	**LCL**	**UCL**
2023/01	1,639,725.36	974,661.47	2,304,789.25	1,314,554.08	814,541.83	2,013,826.89	1,538,818.87	1,317,155.53	1,760,482.20
2023/02	1,670,126.55	1,002,181.45	2,338,071.65	1,299,216.65	761,366.56	2,079,231.60	1,496,958.09	1,267,480.88	1,726,435.29
2023/03	1,780,673.39	1,109,859.45	2,451,487.33	1,448,476.86	806,408.40	2,410,773.88	1,702,803.37	1,465,769.75	1,939,837.00
2023/04	1,727,344.49	1,053,673.94	2,401,015.05	1,311,669.70	696,150.05	2,262,504.29	1,611,334.55	1,366,978.06	1,855,691.03
2023/05	1,811,552.25	1,135,037.14	2,488,067.36	1,399,378.98	709,989.88	2,494,690.80	1,676,806.19	1,425,340.00	1,928,272.38
2023/06	1,803,725.57	1,124,377.81	2,483,073.33	1,348,982.52	655,772.64	2,479,775.89	1,682,390.10	1,424,009.76	1,940,770.44
2023/07	1,669,976.03	987,807.39	2,352,144.67	1,141,685.67	532,793.93	2,159,940.65	1,556,214.80	1,291,100.58	1,821,329.03
2023/08	1,626,737.55	941,759.63	2,311,715.46	1,020,896.61	458,117.39	1,984,493.25	1,505,577.17	1,233,895.92	1,777,258.43
2023/09	1,649,717.10	961,941.39	2,337,492.80	1,041,701.03	450,136.03	2,077,591.62	1,504,880.06	1,226,786.80	1,782,973.31
2023/10	1,747,426.73	1,056,864.57	2,437,988.90	1,123,122.66	467,931.54	2,295,327.84	1,592,742.08	1,308,381.37	1,877,102.78
2023/11	1,791,438.92	1,098,101.49	2,484,776.34	1,1254,70.11	452,617.69	2,354,311.74	1,746,067.23	1,455,574.26	2,036,560.19
2023/12	2,906,872.64	2,210,771.02	3,602,974.26	2,253,764.29	875,762.04	4,820,735.73	2,385,398.70	2,088,900.27	2,681,897.13
2024/01	1,802,494.19	1,103,636.36	2,501,352.03	1,061,062.57	386,886.17	2,363,119.69	1,629,999.70	1,307,118.04	1,952,881.36
2024/02	1,832,895.38	1,131,295.10	2,534,495.67	1,041,337.71	363,205.06	2,383,904.15	1,588,138.92	1,256,042.08	1,920,235.76
2024/03	1,943,442.22	1,239,110.17	2,647,774.27	1,152,771.46	385,236.11	2,708,564.44	1,793,984.21	1,452,926.68	2,135,041.73
2024/04	1,890,113.32	1,183,060.05	2,597,166.59	1,036,534.62	332,254.39	2,496,817.45	1,702,515.38	1,352,727.65	2,052,303.11
2024/05	1,974,321.08	1,264,557.03	2,684,085.13	1,098,068.76	337,945.86	2,708,929.08	1,767,987.03	1,409,681.16	2,126,292.89
2024/06	1,966,494.40	1,254,029.88	2,678,958.92	1,051,090.87	310,876.23	2,653,167.71	1,773,570.93	1,406,943.82	2,140,198.05
2024/07	1,832,744.86	1,117,590.07	2,547,899.65	883,330.66	251,288.81	2,279,423.57	1,647,395.63	1,272,631.06	2,022,160.21
2024/08	1,789,506.37	1,071,671.39	2,507,341.36	784,339.63	214,783.13	2,067,444.96	1,596,758.01	1,214,026.52	1,979,489.49
2024/09	1,812,485.93	1,091,980.73	2,532,991.13	794,714.88	209,643.79	2,138,160.45	1,596,060.89	1,205,525.25	1,986,596.53
2024/10	1,910,195.56	1,187,030.00	2,633,361.12	850,827.91	216,366.80	2,334,884.41	1,683,922.91	1,285,736.08	2,082,109.74
2024/11	1,954,207.75	1,228,391.57	2,680,023.92	846,632.98	207,684.88	2,368,264.39	1,837,248.06	1,431,554.25	2,242,941.87
2024/12	3,069,641.47	2,341,184.34	3,798,098.61	1,683,513.78	398,612.93	4,797,315.23	2,476,579.53	2,063,515.03	2,889,644.03

Note: LCL denotes lower confidence limit, UCL denotes upper confidence limit.

4.5. Forecasting Costs for HORTI, Ltd.

In this part, we provide time series cost analysis for HORTI, Ltd. Both ARIMA and exponential smoothing models were applied.

Figure 12 shows the development of costs in HORTI, Ltd. from January 2013 to December 2022. Cost development follows a similar pattern to revenue development, with a slightly increasing trend. Since 2015, extreme fluctuations in costs, as well as revenues, have been regularly observed from October to January. The most significant changes occurred in 2015, 2016, and 2021, which saw decreases in crop yields compared to previous years. Based on White's test for heteroskedasticity, no significant presence of heteroskedasticity was found (p-value = 0.3567). Fluctuations in cost and revenue values can be attributed to external factors such as market changes, weather conditions, and shifts in demand, which may have caused seasonal variations in the data. Although the heteroskedasticity test did not indicate a significant problem, further analysis may be required to confirm the absence of other forms of heterogeneity in the residuals.

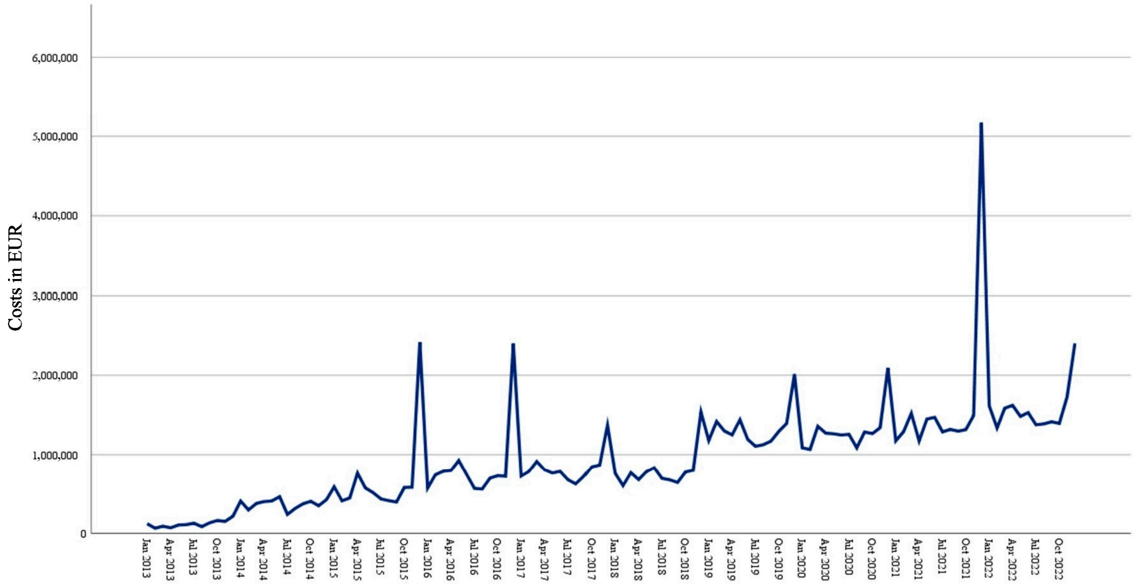

Figure 12. Development of costs for HORTI, Ltd. Source: own processing in SPSS.

Given the ambiguous visual evidence of seasonality in the cost time series, both non-seasonal and seasonal exponential smoothing models were examined. Seasonal exponential smoothing models were selected for their ability to capture potential periodic fluctuations, while non-seasonal models were used as a benchmark for comparison. The purpose of testing both types of models was to more thoroughly assess the presence of seasonal components. Both the non-seasonal ARIMA and exponential models tested did not meet the basic assumptions required for their acceptance. Specifically, these models violated assumptions regarding autocorrelation and the normality of residuals. The non-seasonal ARIMA models failed to address these issues, leading to a more focused evaluation of seasonal models, which better captured the observed patterns. The parameters of the models are presented in Table 14.

Considering all criteria (e.g., MAPE, BIC, and Theil's *U*), the most suitable model for cost forecasting using exponential smoothing is Holt–Winters' additive model (see Figure 13). This model explains 74.1% of the variability in the time series. However, the trend and seasonal components are not statistically significant. Holt–Winters' additive model was chosen for its ability to capture both trend and seasonality, although it was noted that the seasonal and trend components were not statistically significant in this case. It suggests that, while the model is suitable in terms of forecast accuracy, its underlying assumptions about seasonality and trend were weak, which may require further evaluation using ARIMA models.

Considering Box–Jenkins methodology, among several tested autoregressive models with moving averages, the ARIMA(0,1,1)(0,1,1) model with a constant was selected (see Figure 13). This approach was considered the most appropriate because it best fits the observed data, unlike other autoregressive models that either overfit or underfit the data. However, this model explains only 58.5% of the variability in the time series. The lower explanatory power of this ARIMA model suggests that it may not fully capture the complexity of the data, including seasonal effects or unobserved shocks. This finding highlights the need for further refinement and testing of other models to enhance prediction accuracy.

Table 14. Parameters of time series models of costs for HORTI, Ltd. Source: own processing in SPSS.

	Holt–Winters' Additive Model	**ARIMA (0,1,1)(0,1,1)**	**ARIMA (2,1,0)(0,1,1): Outliers**
L (Level)	0.086		
b (Trend)	4.973×10^{-7}		
S (Season)	0.0000		
Constant		–0.008	–0.008
$\Theta(1)$		0.805	0.444
$\theta(1)$		0.649	$\theta_1 = -0.747$ $\theta_2 = -0.434$
Forecast accuracy			
MAPE	24.954	20.628	9.057
BIC	25.565	25.956	24.243
L-B Q′ (Sign.)	3.192 (0.999)	21.178 (0.172)	20.119 (0.167)
R_S^2	0.677	0.379	0.897
R^2	0.741	0.585	0.897
U	0.8186	0.8299	0.2575

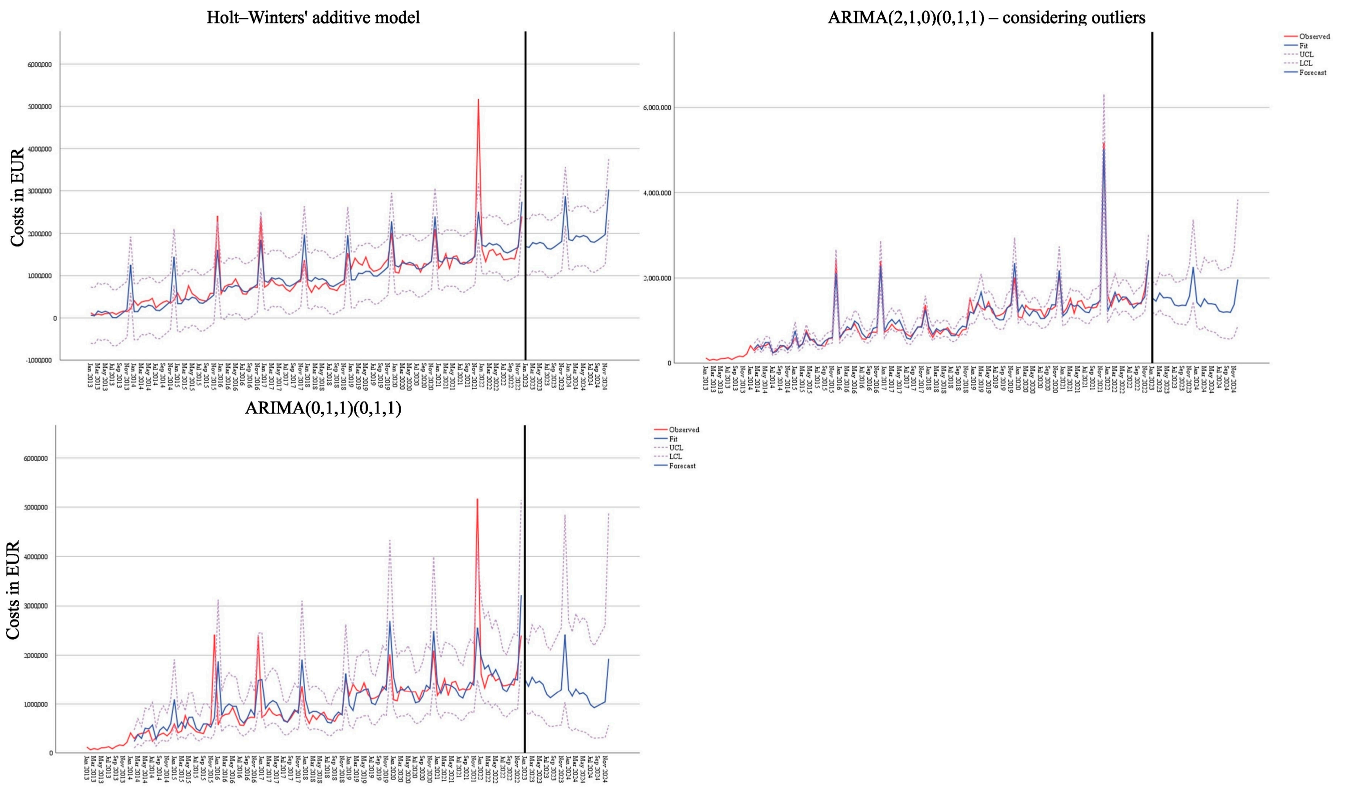

Figure 13. Time series models of costs for HORTI, Ltd. Source: own processing in SPSS.

Subsequently, outliers were detected (see Table 15), and models that account for these anomalies were also checked. The fluctuations identified as significant deviations from the overall trend were addressed by applying models specifically designed to handle such outliers. These fluctuations can arise from factors such as industry disruptions, policy changes, or extreme market events. Adjusting for these factors helps enhance the robustness of forecasting models. Taking all criteria into account, the ARIMA(2,1,0)(0,1,1) model with a constant was selected as the most appropriate model. This model was chosen due to its lower BIC value, indicating a better fit and greater efficiency compared to the other models tested. The BIC criterion was preferred because it penalizes model complexity, helping to identify the most efficient model without overfitting. The BIC value of 24.243 confirms that this model strikes the best balance between accuracy and complexity. This low BIC value supports the selection of this model as the most reliable for predicting costs in the company, though other models also provided reasonable predictions. Additionally, the Theil's U was less than 1, indicating satisfactory model accuracy across all models tested. The ARIMA(2,1,0)(0,1,1) model with a constant explains 89.7% of the variability in the time series. In all models, autocorrelations and partial autocorrelations of residuals are not significant, and the requirement of normality of the residuals is fulfilled. The absence of significant autocorrelations in the residuals suggests that the models have effectively captured the underlying patterns in the data. Moreover, the normality of the residuals, confirmed by statistical tests, ensures that the model assumptions are met, supporting the reliability of the predictions. In Figure 13, both the observed (red line) and expected (blue line) revenue values are shown, along with 95% confidence intervals (upper confidence limit–UCL, lower confidence limit–LCL). The small gaps between the actual and predicted values suggest that the chosen models are robust, though minor deviations may be due to unforeseen market changes or external factors.

Table 15. Outliers of the model ARIMA (2,1,0)(0,1,1) of costs for HORTI, Ltd. Source: own processing in SPSS.

Outliers—Costs ARIMA(2,1,0)(0,1,1)		Estimate	SE	t	Sig.
2014/02	Transient Magnitude	0.422	0.086	4.893	0.000
	Transient Decay factor	0.989	0.049	20.080	0.000
2014/07	Innovational	−0.899	0.139	−6.457	0.000
2014/11	Level Shift	−0.376	0.088	−4.278	0.000
2015/04	Additive	0.548	0.092	5.967	0.000
2015/12	Additive	1.075	0.096	11.213	0.000
2016/01	Seasonal Additive	−0.706	0.100	−7.035	0.000
2016/12	Additive	0.714	0.094	7.595	0.000
2018/02	Transient Magnitude	−0.361	0.083	−4.349	0.000
	Transient Decay factor	0.732	0.137	5.340	0.000
2019/01	Level Shift	0.412	0.082	5.026	0.000
2021/12	Additive	0.826	0.093	8.891	0.000

Note: SE denotes standard error, t is test statistics, and Sig. represents significance.

Table 16 compares the cost forecasts for these models (from January 2023 to December 2024). The lower (LCL) and upper (UCL) confidence limits indicate the expected range of results. By examining these intervals, we can assess the level of uncertainty associated with each prediction and evaluate the relative performance of the models in forecasting. All forecasts fall within the 95% confidence interval. The results in Table 15 and Figure 11 show that Holt–Winters' additive model predicts slight cost growth. In contrast, the ARIMA(0,1,1)(0,1,1) model and the ARIMA(0,1,1)(0,1,1) model without a constant (taking into account outliers) predict decrease in costs. The predicted cost increase in Holt–Winters' model may be explained by underlying seasonal trends or market factors that were not fully captured by the other models. On the other hand, the ARIMA models predict a decline in costs, which may reflect the model's ability to capture underlying noise and adjust for fluctuations or shifts in data patterns. These models were chosen from a range of reviewed options as the most comparable and satisfactory, both in terms of forecast accuracy and adherence to all assumptions. The selection of these models was based on their ability to balance model complexity, prediction accuracy, and adherence to key assumptions, such as normality of residuals and the absence of autocorrelation. The use of multiple accuracy measures (e.g., MAPE, BIC, and Theil's U) supported the selection process by quantifying the reliability of the models. Based on the Theil's inequality coefficient U (see Table 14), which is less than 1 for all proposed models, all the presented models can be considered satisfactory. This indicator, along with MAPE and BIC, strengthens the robustness of the selected models.

Table 16. Comparison of the cost forecasts using different models for HORTI, Ltd. Source: own processing in SPSS.

	Holt–Winters' Additive Model			ARIMA(0,1,1)(0,1,1)			ARIMA(2,1,0)(0,1,1): Outliers		
Period	**Forecast**	**LCL**	**UCL**	**Forecast**	**LCL**	**UCL**	**Forecast**	**LCL**	**UCL**
2023/01	1,691,684.20	1,027,593.34	2,355,775.06	1,515,502.91	888,330.67	2,424,913.93	1,531,132.36	1,200,130.85	1,925,932.45
2023/02	1,669,958.24	1,003,429.65	2,336,486.83	1,369,600.28	776,007.95	2,249,321.92	1,456,465.48	1,132,643.50	1,844,839.14
2023/03	1,783,513.37	1,114,555.94	2,452,470.80	1,554,547.20	852,761.05	2,616,274.15	1,647,701.40	1,260,031.54	2,118,128.39
2023/04	1,752,240.01	1,080,862.51	2,423,617.50	1,437,821.66	764,672.00	2,476,340.19	1,534,810.44	1,127,861.86	2,042,444.91
2023/05	1,788,534.33	1,114,745.47	2,462,323.20	1,475,207.08	761,529.49	2,596,972.59	1,543,874.56	1,118,264.55	2,080,081.96
2023/06	1,757,880.56	1,081,688.92	2,434,072.20	1,407,311.88	705,897.64	2,529,646.08	1,528,248.05	1,085,865.25	2,092,968.84
2023/07	1,645,982.46	967,396.55	2,324,568.37	1,198,197.54	584,521.48	2,197,100.03	1,367,997.83	950,646.69	1,908,880.33
2023/08	1,628,259.69	947,287.93	2,309,231.45	1,128,446.10	535,839.17	2,109,081.22	1,343,800.60	918,991.93	1,900,350.80
2023/09	1,682,235.55	998,886.27	2,365,584.84	1,185,160.46	548,198.74	2,256,083.01	1,362,903.27	915,892.98	1,955,484.86
2023/10	1,745,846.58	1,060,128.01	2,431,565.15	1,243,535.56	560,689.08	2,409,382.69	1,354,970.69	894,889.12	1,972,023.93
2023/11	1,811,712.61	1,123,632.90	2,499,792.31	1,298,063.76	570,864.64	2,558,250.35	1,574,932.56	1,024,128.76	2,321,362.85
2023/12	2,872,554.87	2,182,122.11	3,562,987.63	2,418,534.43	1,038,032.03	4,845,633.88	2,257,921.65	1,445,331.57	3,370,695.69
2024/01	1,852,938.30	1,160,148.67	2,545,727.93	1,294,593.75	524,277.99	2,695,755.06	1,425,077.38	849,811.18	2,250,391.32
2024/02	1,831,212.34	1,136,085.59	2,526,339.08	1,162,771.63	455,869.55	2,472,889.47	1,328,543.26	774,581.87	2,134,995.63
2024/03	1,944,767.47	1,247,311.43	2,642,223.50	1,311,642.26	498,319.45	2,846,339.60	1,513,179.66	858,482.16	2,483,175.36
2024/04	1,913,494.10	1,213,716.53	2,613,271.68	1,205,666.61	444,211.09	2,667,696.87	1,397,697.73	764,166.49	2,358,750.97
2024/05	1,949,788.43	1,247,696.99	2,651,879.87	1,229,386.92	439,544.24	2,771,713.39	1,393,824.12	743,210.69	2,396,538.45
2024/06	1,919,134.65	1,214,736.95	2,623,532.36	1,165,579.90	404,638.99	2,676,005.68	1,377,186.86	714,680.20	2,415,772.11
2024/07	1,807,236.56	1,100,540.11	2,513,933.00	986,275.76	332,643.46	2,304,522.85	1,224,441.45	617,763.53	2,192,338.77
2024/08	1,789,513.79	1,080,526.05	2,498,501.52	923,150.85	302,640.21	2,194,154.86	1,195,536.31	588,481.60	2,178,914.50
2024/09	1,843,489.65	1,132,218.00	2,554,761.30	963,586.28	307,213.91	2,328,492.28	1,207,149.17	579,467.65	2,239,723.62
2024/10	1,907,100.68	1,193,552.42	2,620,648.93	1,004,831.85	311,706.92	2,467,518.71	1,192,988.74	558,697.87	2,252,255.45
2024/11	1,972,966.70	1,257,149.08	2,688,784.32	1,042,445.22	314,776.24	2,600,217.65	1,379,012.95	630,856.07	2,646,275.42
2024/12	3,033,808.97	2,315,729.15	3,751,888.78	1,930,331.41	567,619.65	4,888,727.50	1,966,787.94	879,053.87	3,835,174.44

Note: LCL denotes lower confidence limit, UCL denotes upper confidence limit.

4.6. Forecasting EAT for HORTI, Ltd.

In this section, we present time series analyses of EAT for HORTI, Ltd. Both ARIMA and exponential smoothing models were applied.

Figure 14 shows the development of EAT in HORTI, Ltd. from January 2013 to December 2022. The time series is stationary, with no trend present, and no significant seasonal fluctuations are evident. Individual fluctuations do not occur consistently in the same months each year, thus cannot be attributed to seasonality. The presence of cycles is difficult to identify because of the short time span of the data. Based on White's test for heteroskedasticity, its presence was not confirmed (p-value = 0.2892). To evaluate the models, we use criteria such as the BIC and MAPE, which were selected to assess their predictive performance. The BIC is important because it balances model accuracy and complexity, favoring models with lower BIC values that reflect a better trade-off between the two. MAPE represents the average percentage deviation between actual and predicted values, with a lower MAPE indicating higher prediction accuracy.

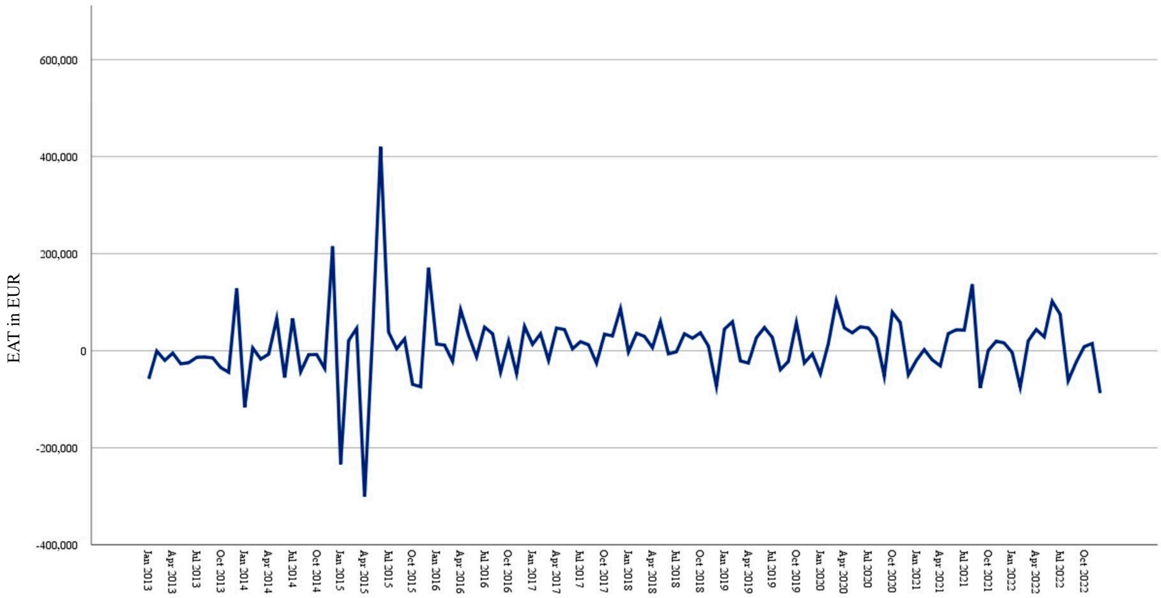

Figure 14. Development of EAT for HORTI, Ltd. Source: own processing in SPSS.

Both non-seasonal and seasonal exponential models tested failed to meet the basic assumptions for their acceptance. Considering Box–Jenkins methodology, among several tested autoregressive models with moving averages, the seasonal ARIMA(0,0,2)(1,0,0) model without a constant was selected (see Figure 15 and Table 17). Only 9.7% of the variability in the time series is explained. The seasonal ARIMA(0,0,2)(1,0,0) model, selected based on Box–Jenkins methodology, achieves a BIC value of 22.373. This model was chosen because it had the lowest BIC value among the models tested, although it was not ideal. The parameter $\theta(1)$ in the model represents the autoregression coefficient, which shows how previous values influence the prediction. A value of 0.345 indicates that prior values have a moderate effect on future values. Additionally, the very low R-squared value (0.097) indicates that the model explains only a small portion of the variability in the data. This highlights the model's limited ability to capture the overall variability of the time series, and its limitations should be considered in practical applications.

Subsequently, outliers were detected (see Table 18), and other models that account for outliers were also examined. The model that accounts for outliers provides a better trade-off between accuracy and complexity but still does not satisfy the basic assumptions (BIC = 21.590). Taking all criteria (e.g., MAPE, BIC, and Theil's U) into account, the ARIMA(0,0,0)(1,0,0) model without a constant was selected as the most appropriate model. This model explains 66.0% of the variability in the time series. The parameters of the models are presented in Table 17. In all models, autocorrelations and partial autocorrelations of residuals are not significant, and the requirement for the normality of the residuals is fulfilled. In Figure 15, both the observed (red line) and expected (blue line) values of revenues are shown, along with 95% confidence intervals (upper confidence limit–UCL, lower confidence limit–LCL).

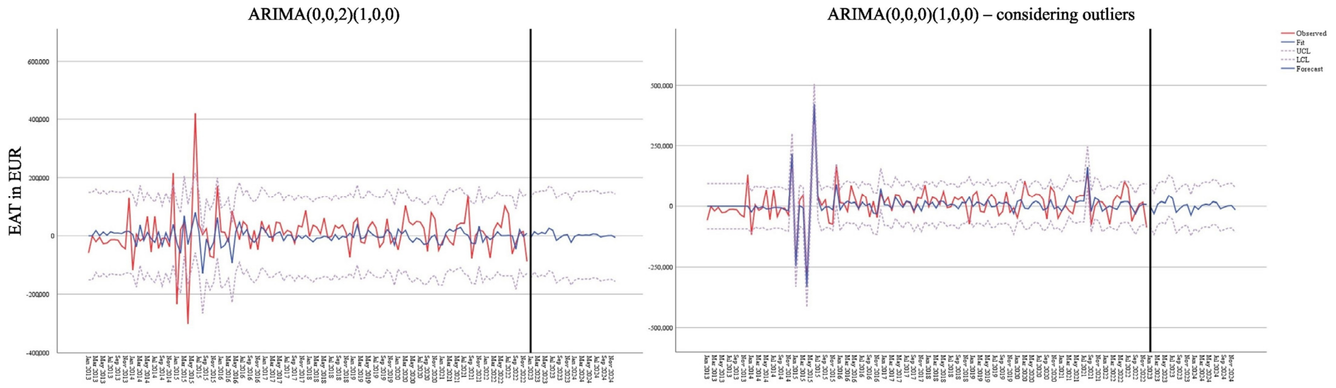

Figure 15. Time series models of EAT for HORTI, Ltd. Source: own processing in SPSS.

Table 17. Parameters of time series models of EAT for HORTI, Ltd. Source: own processing in SPSS.

	ARIMA (0,0,2)(1,0,0)	**ARIMA (0,0,0)(1,0,0): Outliers**
$\theta(1)$	0.345	
$\Theta(1)$	0.255	0.418
Forecast accuracy		
MAPE	209.93	159.446
BIC	22.373	21.590
L-B Q′ (Sign.)	17.534 (0.352)	21.076 (0.223)
R_S^2	0.097	0.660
R^2	0.097	0.660
U	0.9197	0.7693

Table 18. Outliers of the model ARIMA (0,0,0)(1,0,0) of EAT for HORTI, Ltd. Source: own processing in SPSS.

Outliers—EAT ARIMA(0,0,0)(1,0,0)		**Estimate**	**SE**	**t**	**Sig.**
2014/12	Innovational	161,420,608	44,260,628	3647	0.000
2015/01	Additive	−197,156,906	40,215,894	−4902	0.000
2015/04	Additive	−328,356,170	39,536,484	−8305	0.000
2015/06	Additive	444,117,526	39,653,459	11,200	0.000
2021/08	Additive	149,831,205	39,580,573	3785	0.000

Note: SE denotes standard error, *t* is test statistics, and Sig. represents significance.

Table 19 compares the EAT forecasts for these models (from January 2023 to December 2024). All forecasts fall within the 95% confidence interval. Considering all the criteria, especially for forecast accuracy, we have not found a sufficiently suitable and accurate EAT forecast model. Theil's U is an important criterion for assessing the quality of a model. This index measures the relative accuracy of the model compared to a simple random model, with lower values indicating higher prediction accuracy. Although all model predictions fall within the 95% confidence intervals, Theil's U and MAPE values remain high, indicating limited accuracy and the need for further improvement in the predictions.

Table 19. Comparison of the EAT forecasts using different models for HORTI, Ltd. Source: own processing in SPSS.

	ARIMA(0,1,1)(0,1,1)			ARIMA(2,1,0)(0,1,1): Outliers		
Period	**Forecast**	**LCL**	**UCL**	**Forecast**	**LCL**	**UCL**
2023/01	–6922.88	–143,929.35	130,083.60	–1575.15	–86,412.64	83,262.33
2023/02	13,891.79	–123,114.69	150,898.26	–31,406.55	–116,244.03	53,430.94
2023/03	5177.62	–139,747.33	150,102.58	8477.90	–76,359.59	93,315.39
2023/04	11,152.59	–133,772.36	156,077.55	18,261.38	–66,576.11	103,098.87
2023/05	7263.14	–137,661.82	152,188.09	11,892.74	–72,944.75	96,730.23
2023/06	25,961.39	–118,963.57	170,886.34	42,509.47	–42,328.02	127,346.96
2023/07	19,123.25	–125,801.70	164,048.21	31,312.64	–53,524.85	116,150.12
2023/08	–15,726.64	–160,651.60	129,198.31	–25,750.98	–110,588.47	59,086.51
2023/09	–5998.22	–150,923.18	138,926.73	–9821.55	–94,659.04	75,015.93
2023/10	2097.63	–142,827.32	147,022.59	3434.69	–81,402.80	88,272.18
2023/11	3793.10	–141,131.86	148,718.05	6210.86	–78,626.63	91,048.35
2023/12	–22,289.09	–167,214.05	122,635.86	–36,559.31	–121,396.80	48,278.18
2024/01	–1767.31	–150,853.01	147,318.39	–606.52	–92,557.61	91,344.56
2024/02	3546.37	–145,539.33	152,632.07	–13,128.17	–105,079.25	78,822.92
2024/03	1321.77	–148,251.08	150,894.62	3543.82	–88,407.26	95,494.91
2024/04	2847.09	–146,725.76	152,419.95	7633.39	–84,317.69	99,584.48
2024/05	1854.17	–147,718.68	151,427.02	4971.25	–86,979.83	96,922.34
2024/06	6627.56	–142,945.29	156,200.42	17,769.27	–74,181.81	109,720.36
2024/07	4881.89	–144,690.96	154,454.74	13,088.91	–78,862.17	105,040.00
2024/08	–4014.78	–153,587.63	145,558.07	–10,764.10	–102,715.18	81,186.99
2024/09	–1531.26	–151,104.11	148,041.59	–4105.48	–96,056.57	87,845.60
2024/10	535.50	–149,037.36	150,108.35	1435.73	–90,515.36	93,386.81
2024/11	968.32	–148,604.53	150,541.17	2596.18	–89,354.90	94,547.27
2024/12	–5690.08	–155,262.93	143,882.77	–15,282.06	–107,233.14	76,669.02

Note: LCL denotes lower confidence limit, UCL denotes upper confidence limit.

In conclusion, the presented results successfully demonstrate that both simple legacy forecasting methods, such as Holt–Winters' models and ARIMA models, are effective for predicting the financial indicators of the wholesale and retail trade sector, specifically for HORTI, Ltd. The analysis of revenues, costs, and EBT (EAT) indicates that these traditional models can provide reliable forecasts, suggesting that more complex approaches are unnecessary for achieving high accuracy in financial trend predictions. However, it is important to highlight the strengths and weaknesses of each model. Holt–Winters' models are particularly effective for data with strong seasonal patterns and stable trends, due to their ease of implementation and ability to quickly adapt to changes. On the other hand, ARIMA models offer greater flexibility in modeling various types of trends and seasonality, making them more suitable for complex data structures. While Holt–Winters' models are easier to implement and faster, ARIMA models can provide more stable and accurate forecasts, particularly when trends and seasonality are less pronounced. Therefore, for the current dataset, traditional models are sufficient, but more advanced models may be required for future analyses involving data with higher volatility or irregular patterns.

5. Discussion

The financial condition of a sector (industry) or company is continually influenced by various financial indicators that must be recognized and managed to sustain their long-term growth [71]. The results of this study suggest that identifying trends in these indicators through ARIMA and exponential smoothing models can effectively support long-term growth. These models have proven to be particularly well-suited for time series with consistent seasonal patterns. Time series analysis can be instrumental in identifying the development of financial indicators and understanding their trends over time. For example, for HORTI, Ltd., were fluctuations observed that may be attributed to the nature of the company's activities and the scope of its sales. The highest EAT is achieved in December, during the Christmas period, reflecting the cultural practices of the nation and region.

Our analysis revealed that Holt–Winters' model improved the accuracy of seasonal data predictions, particularly for revenue forecasts, where it achieved the lowest MAPE and BIC values (see Table 6). Thus, this model was more effective in capturing the dynamics of seasonality compared to ARIMA. The accuracy assessment showed that Holt–Winters' model performed better for seasonal data, likely due to its ability to model the seasonal component directly. In contrast, ARIMA models demonstrated lower MAPEs for data dominated by trend components with minimal seasonal effects. This variation in performance highlights the importance of selecting an appropriate model based on the characteristics of the time series.

This study contributes to the existing body of literature on financial indicators forecasting by examining approaches applied in the wholesale and retail trade sector and for HORTI, Ltd., the company which operates within the SK NACE 46.31 sector. It aids in analyzing revenues, costs, and EAT (EBT) while providing predictions for future values. The findings of this study add to the literature by demonstrating how simple models can achieve high predictive accuracy for relatively stable time series, such as revenues and costs, in the SK NACE Section G sector. For example, Holt–Winters' model proved to be the most accurate for predicting revenue, while the ARIMA(4,1,0) model excelled in predicting costs.

Retail revenue and cost data fall into a unique category of time series, often characterized by trends and seasonal patterns, which make it challenging to develop accurate forecasting models [7]. This study compares the forecasting performance of exponential smoothing models and ARIMA models. We demonstrate that seasonal models, such as Holt–Winters, provide robust predictions for these time series, while ARIMA models perform best for data with strong trend components and minimal seasonality. A comparable approach, contrasting ARIMA models with exponential smoothing models, was presented in [72,73]. The model comparison revealed that Holt–Winters' additive model was the most suitable for predicting revenue, while ARIMA(4,1,0) more accurately captured the historical evolution of costs. The accuracy of these models was assessed using MAPE, BIC, and Theil's U, with all models meeting the residual randomness requirements (see Tables 4 and 7).

Several prior studies have explored revenue forecasting methods, focusing on various areas. For instance, in the study by Ekmiş et al. [74], the ARIMA methods from Box–Jenkins methodology performed daily revenue prediction using data from 130 stores of a fashion retail chain. Liu and Wang [75] proposed a forecasting model using the ARIMA methodology to predict China's fiscal revenue, with data comprising 64 observations from 1950 to 2013. Using annual data obtained from 1980 to 2013, Urrutia et al. [76] developed the ARIMA model to estimate and forecast income tax revenue of the Philippines for the period 2014–2020. Nandi et al. [77] applied both the ARIMA model and Holt–Winters' additive model to predict monthly tax revenue in Bangladesh using data from July 2004 to November 2012. Micheni and Atitwa [78] employed similar research, employing both the ARIMA and Holt–Winters' time series forecasting models to estimate and forecast domestic tax revenue in Kenya, using data from January 2015 to December 2020. Research by Ayakeme et al. [79] examined time series ARIMA and exponential smoothing models to forecast internally generated revenue of Bayelsa State (Nigeria), using data from 2012 to 2018. In research by Ahmed et al. [80], the ARIMA model was applied to short-term forecasting of tourism receipts in Bangladesh, considering annual tourist receipts (revenues) from 1973 to 2017. Similarly, Çuhadar [81] used both the exponential smoothing multiplicative seasonal model and the Box–Jenkins seasonal ARIMA model to analyze Turkey's quarterly inbound tourism revenues from the first quarter of 2003 to the fourth quarter of 2019. Using yearly data from 1974 to 2010 of Iran's agricultural products export revenues, Mohaddes and Fahimifard [82] compared the ARIMA model with the Adaptive Neuro-Fuzzy Inference System (ANFIS) nonlinear model forecasts. Using the ARIMA model, Cho and Chang [83] forecasted the revenue of the G Hotel at Soul. They used the monthly revenue data from 2004 to 2008. Rahman et al. [84] forecasted the income and expenditure of Bangladesh Bimanc Airlines Limited for each year from 2018 to 2025, using data from the fiscal year 2006–2007 to 2017–2018. Ramos et al. [7] employed ARIMA models to forecast retail sales of women's footwear for the Portuguese retailer Foreva, drawing on monthly data from January 2007 to April 2011. Ghosh [85] modeled sales in Moroccan food manufacturing by the ARIMA model using data from January 2010 to December 2015. Tirkes et al. [86] used exponential smoothing when forecasting monthly sales for the sherbet and jam company 'Tarihi Yudumla'.

Other studies have explored cost (expenditure) forecasting models. Using yearly data from 1971 to 2015 on Iran's health expenditures, Ramezanian et al. [1] developed the ARIMA model and provided predictions for 2016–2020. A similar study was conducted by Dritsakis and Klazoglou [87] for the USA, using data from 1900 to 2017. The ARIMA and (or) exponential smoothing models were also used for forecasting construction costs [88], construction material prices [89], truck transportation prices [90], coking coal prices [91], potato prices [73], metal prices [92], the cost of a face drilling rig used in the Swedish mining industry [93], and warranty claim cost [94]. This study extends the insights of previous research by demonstrating how simple models can be effective even for sectoral time series, while highlighting their limitations, such as their inability to adapt to non-standard or unpredictable changes. One limitation of this study is that the data analyzed come from a relatively stable period and sector with predictable seasonal patterns. This stability may have contributed to the superior performance of traditional models; however, this does not imply that they would be equally effective in contexts involving high volatility or unpredictable economic changes. Potential bias may also stem from data selection, as the study did not account for external shocks that could affect the reliability of the predictions.

Profit analysis aids in comprehending sales, as well as the profits and losses incurred, while forecasting future values. In this paper, we examined and forecasted EAT and EBT. Previous studies have also concentrated on forecasting similar financial indicators using exponential smoothing and/or ARIMA models, such as forecasting profits (losses) [5], earnings of firms listed in Amman Stock Exchange [95], EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortization) in the fashion sector in Colombia [2], and earnings per share [96,97].

The limitations of traditional statistical methods in financial forecasting have been widely discussed in academic research [10]. Our findings confirm that while traditional models, such as exponential smoothing and ARIMA, are sufficient for stable time series, their limitations lie in their inability to capture unexpected changes caused by external factors. This is an area where more complex models could be beneficial, particularly in anticipating economic shocks. Some research shows that ARIMA models are ineffective for predicting market trends [98]. On the other hand, the results of this study demonstrate that even simple legacy forecasting methods, such as exponential smoothing and Box–Jenkins methodology, are both adequate and sufficient for predicting the development of financial indicators. These models have been proven to deliver high forecast accuracy, aligning with the objective of identifying an effective statistical model. Therefore, more complex models may not be necessary for achieving reliable financial forecasts, supporting the use of these traditional approaches in practical applications. Despite this, it is essential to note that more complex models, such as GARCH or machine learning methods, could be beneficial when involving high volatility or complex nonlinear patterns (see, e.g., [99]). Although the results suggest that simple models are adequate for the SK NACE Section G sector, their use should always be considered in the context of specific conditions. For example, for high-frequency data or data with nonlinear trends, more complex models may be more appropriate. At the same time, the computational efficiency and ease of implementation of these models offer practical advantages, making them attractive for corporate and sectoral forecasting in stable environments.

The results of this study show that simple models are effective forecasting tools for stable sectors with regular seasonal patterns. In contrast, their limitations in the context of unpredictable changes or highly variable data suggest that more complex models may be beneficial in other application domains. These findings highlight the importance of considering the nature of the data and the forecasting objectives when selecting an appropriate model.

6. Conclusions

Decision-making processes, such as a firm's investment decision, can be influenced by forecasts obtained by analyzing the associated financial time series. The estimated time series models (exponential smoothing and ARIMA) are reasonably accurate in estimating the ex post behavior of the financial indicators under study, which lends credibility to the forward-looking forecasts. The accuracy of these models was validated using several metrics, including MAPE, Theil's U, and BIC. For example, for the SK NACE Section G sector, Holt–Winters' multiplicative model achieved a MAPE of 3.497%, indicating excellent predictive performance. In the case of HORTI Ltd., the ARIMA(0,1,1)(0,1,1) model without a constant was the most accurate, achieving a MAPE of 8.706%, which meets the standard for good prediction (values below 10%). These results highlight the high effectiveness of the models used in estimating past developments and forecasting future trends.

In conclusion, the findings indicate a stable positive outlook for the operations of the wholesale and retail trade sector in Slovakia (SK NACE Section G). Revenue growth is anticipated, alongside an expected rise in costs. Additionally, the forecast for EBT demonstrates an increasing trend, reinforcing the expectation of continued positive development within the sector. When comparing the development of the financial indicators of HORTI, Ltd. with the sector development, we observe a similarity. Unfortunately, while we developed a significant model for predicting sector earnings (EBT), we were unable to identify an adequate model for the earnings (EAT) of HORTI, Ltd. The underperformance of HORTI Ltd.'s EAT prediction may be attributed to limitations in the available data, including the short time series and the presence of seasonal and one-time fluctuations. Additionally, specific company characteristics, such as dependence on seasonal market factors and demand volatility, increase the complexity of modeling this indicator. Further research could explore the use of advanced models, such as GARCH or Long Short-Term Memory (LSTM), to better address these challenges. Despite this, we note that Holt–Winters' and ARIMA models are highly effective tools for forecasting revenues, costs, and EBT, as well as identifying trends in analyzed areas. The effectiveness of Holt–Winters' and ARIMA models was especially evident in predicting revenues and costs. The ARIMA(4,1,0) model explained up to 85.2% of the variability in EBT for the SK NACE Section G sector, demonstrating its ability to predict this indicator accurately. The accuracy of the predictions was further validated using tests such as the Ljung–Box test, which confirmed the randomness of the residuals, with all predictions falling within 95% confidence intervals. Moreover, a comparison of sectoral and firm-level data confirms the robustness of the forecasts, as the models exhibited similar trends across both levels of analysis. This consistency supports the applicability of simple models in strategic decision-making.

Forecasting revenues, costs, and profit (loss) using time series methods is beneficial in management decisions in achieving set objectives. In the context of this research, the most appropriate forecasting models for selected financial indicators were developed, which can be beneficial for managers in the field of the wholesale and retail trade sector, as well as for the management of HORTI, Ltd. The financial indicator models derived from this study can help determine the strategic direction for improving the company's performance. Forecasting costs and revenues is particularly important for assessing profitability, which ultimately determines the overall financial performance of the company. HORTI, Ltd. can improve performance primarily by increasing return on sales or by accelerating the turnover of inventories and receivables. The presented forecasting models are applicable across sectors; however, each sector has its own specificities, making it essential to consider each sector individually. In the context of V4 countries, there is a notable lack of studies on forecasting financial absolute or ratio indicators specific to the wholesale and retail trade sectors. This study addressed this gap.

At HORTI, Ltd., the seasonality observed in the company's financial indicators is partly driven by its connection to the food processing industry. The characteristic behavior of the analyzed time series can be compared across the crisis, post-crisis, and the current periods of economic growth. HORTI, Ltd. successfully navigated the crisis and emerged stronger. In 2021, the company experienced a significant increase in net revenues, driven by growth in non-current assets, inventory, and accounts receivable. It also substantially increased its working capital. However, during the period under review, the cost of foreign capital rose. When comparing the evolution of its time series with that of the entire sector under study, several similarities can be observed.

The study conducted has several limitations. First, the available data covers a shorter period, and there is a lack of recent data to compare the forecasts with actual results. Second, the forecasts may not align with reality due to factors beyond the organization's control, such as regulatory changes, competition, or technological advancements, which can influence the accuracy of the forecasts. In addition to the limitations related to the time series length and the absence of actual data, it is important to note that Holt–Winters' and ARIMA models have inherent weaknesses, such as sensitivity to outliers and a limited ability to handle nonlinear patterns. These weaknesses can lead to inaccuracies, especially when predicting long-term trends or when significant market changes are not reflected in the historical data. However, simple models like Holt–Winters' and ARIMA were preferred for this research due to their low sample size requirements, ease of application, and interpretability of results, which are crucial for managerial decision-making. Given the stable nature of most of the time series analyzed, these models provided reasonably accurate and reliable predictions.

In future research, other, more advanced models may be utilized. Future studies might focus on using GARCH models to analyze the volatility of financial indicators or applying machine learning methods, such as LSTM, which can identify complex patterns in time series. For example, LSTM could be particularly useful in predicting seasonal and volatile indicators (e.g., EAT of HORTI, Ltd.) where traditional models have struggled. Additionally, we recommend monitoring the evolution of the variables under study for at least four more years and evaluating the new data using GARCH-type nonlinear models applied to the extended time series. Future studies could explore the application of machine learning algorithms to improve forecasting accuracy and uncover complex patterns in data. It would also be valuable to obtain more recent data and compare it with the resulting forecasts. Furthermore, a similar analysis could be conducted for a different sector (industry) or company.

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