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Applying forecasting methods to accrual-based and cash-based ratio analysis

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Abstract

Research Questions*:* Which of the forecasting methods (SMA, ARIMA, ES) is the most informative? Can forecasting methods be used to verify each other's results? How do the manipulations in historical data affect the forecasting of accrual and cash ratios?

Motivation: addressing the challenge of analytical precision in financial forecasting, the research proposes and empirically investigates the financial forecasting approach based on integrated cash-based and accrual-based ratio analysis in the dimensions of solvency, liquidity, efficiency and profitability.

Idea: The effectiveness of the forecasting methods based on ratio analysis is evaluated by determining the most informative approach while examining how data manipulations influence forecasting outcomes.

Data: Historical panel data for seven years (2015-2022) from financial statements of two production companies listed on the Baltic Stock Exchange was taken as a base for equally-weighted ratio calculations: solvency, liquidity, efficiency and profitability. Based on the ratio results, the forecasting for three years was done.

Tools: Quantitative forecasting methods included Simple Moving Average method implemented in Excel, and ARIMA and Exponential Smoothing done via R-Script.

Findings: Exponential Smoothing is the most informative method of forecasting for three years due to its sensitivity to data fluctuations, particularly in cash-based ratios. The forecasts

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based on accrual data show smoother trends when a company manipulates its data in accrual-based financial statements but does not manipulate the historical cash data. Volatility or conflicting results within the accrual-based and cash-based ratio pairs reveal the actual situation.
Contribution: The research contributes to knowledge and empirical research on financial forecasting by integrating accrual and cash-based ratios for enhanced precision and demonstrating superior capabilities of Exponential Smoothing for detecting anomalies and improving credit risk analysis frameworks.

Keywords: cash-based ratios, accrual-based ratios, ratio analysis, forecasting, financial health.

JEL Codes: G17; G33; C53

1. Introduction

Nowadays, the importance of the cash flow statement analysis in forecasting is widely discussed (Khansalar & Namazi, 2017; Jury, 2012; Carslaw & Mills, 1991) and it becomes clear for academics and practitioners that cash-flow-based forecasting is more trustworthy, as it is harder to manipulate the data in the cash flow statement compared to the forecasting based on the traditional financial statement (Jury, 2012). The important part of the present paper is the ratios used in forecasting. There are plenty of studies comparing the accrual-based to cash-based ratios in the financial analysis and proving the higher analytical precision of cash-based ratios (Litvinenko, 2023; Rujoub *et al.*, 1995; Carslaw & Mills, 1991). There is also an ongoing discussion about the combination of accrual-based and cash-based methods in financial analysis (Hu & Kim, 2019; Toma *et al.*, 2015; Shi *et al.*, 2014). However, the use of combined cash-based and accrual-based methods in forecasting still requires knowledge development (Noury *et al.*, 2020; Francis & Eason, 2012). The present work contributes to the knowledge and empirical research about the different methods of forecasting empowered with the combinations of accrual-based and cash-based ratios.

The aim of the present work is to explore the effectiveness of three commonly used methods for the conduction of forecasting based on accrual and cash-based ratios in four dimensions: solvency, liquidity, profitability and efficiency. The forecasting will serve to determine the financial health of the companies, their pre-bankruptcy state and their level of credit risk. There have been attempts to determine the financial health of the companies using different methods, however, they used numbers only from accrual statements (Karpac & Bartosova, 2021). There are three methods of forecasting used in the paper: Simple Moving Average (SMA), ARIMA and Exponential Smoothing (ES). They are compared and analyzed to find out which method provides more comprehensive forecasting of the financial health and the level of credit risk of the companies.

The authors used mixed methods of research. The data is obtained from the financial statements of two production companies from Eastern Europe publicly listed on the Baltic Stock Exchange. The quantitative method used for ratio calculations based on historical panel data, Simple Moving Average, is calculated in Excel and used the R-Script code for the conduction of ARIMA and ES forecasting methods performed in R Studio. The obtained quantitative result was analyzed with the help of qualitative methods where the managerial and auditors' reports were used to support the analysis and draw conclusions.

The present paper has the following research questions:

RQ1. *Which of the forecasting methods (SMA, ARIMA, ES) is the most informative?*
RQ2: *Can forecasting methods be used to verify each others' results?*
RQ3. *How do the manipulations in historical data affect the forecasting of accrual and cash ratios?*

In this paper, we apply the method elaborated by Litvinenko (2024), which was initially used to analyze historical data for determining the pre-bankruptcy state of the companies. In the present paper, the method will not only be applied to historical data but also extended to forecasting. This method divides ratios into four equally weighted groups ("dimensions") for both accrual and cash-based ratios, carefully selected to assess financial health. Each accrual-based ratio has a corresponding cash-based ratio, resulting in a total of 24 ratios (12 accrual-based and 12 cash-based), referred to as "equally weighted ratios". This method reveals potential discrepancies between accrual and cash-based measures, indicating possible manipulations.

The present paper consists of the following parts. The literature review in Chapter 2 creates the necessary theoretical base. The research design in Chapter 3 and the research method in Chapter 4 describe the methodology and present the R code in subchapter 4.1. Chapter 5 represents the analysis and discussion of the results of the empirical research. Chapter 6 concludes the study.

2. Literature review

This part of the paper presents the main theoretical standpoints, terms, and notions connected to the research topic and reviews it from different angles, presenting various opinions. Currently, the decision-makers within the companies pay more attention to accrual-based statements analysis and forecasting rather than cash-based sources, such as cash flow statements (Steinberga & Millere, 2016). The accrual-based elements are also used in the attempts to forecast the financial health of the enterprises (Karpac & Bartosova, 2021), even developing the formula with four elements (where stability, liquidity, activity & profitability are considered as the indicators of the financial health) without taking into account the cash flow statement data. A wide variety of models were analyzed without paying attention to the absence or presence of cash-based elements and their effect on the reliability of the model, yet many famous accrual-based models, including Z-Score, were classified as not reaching 80% reliability (Camska, 2019). However, with the growing importance of forecasting, as many industry players rely on frequently changing data sets and outputs (Timmermann, 2018), academics and practitioners will turn to cash-based forecasting or combined accrual-based and cash-based forecasting to gain higher precision.

2.1 Defining methods of forecasting

First, it is important to understand the notion of forecasting. Diebold and West (2001) note that in finance, forecasting predicts revenue streams and asset prices, while in economics, it anticipates economic conditions affecting investment and consumption. Krylov (2018) defines forecasting as generating future trend estimates based on historical data and emphasizes its role in analyzing financial statements to enhance company health. Jury (2012) highlights that forecasts, governed by Bayesian probability, represent one possible future among many, based on assumptions of certain circumstances. The Bayesian approach suggests that decision-makers update their beliefs probabilistically as new information emerges. It extends classical statistics by providing a flexible interpretation of probability, valuable in economic and financial modeling. Since the 1970s, Bayesian methods, as demonstrated by Zellner (1971) and Geweke (1999), have gained traction in forecasting, particularly in models like ARIMA, by combining prior knowledge with observed data. Forecasts are not predictions but tools for modeling various scenarios, allowing managers to explore potential outcomes and develop strategies (Shi *et al*., 2014; Jury, 2012). Quantitative forecasting methods, classified into time series and economic forecasting (Majid & Mir, 2018; Makridakis *et al*., 1979), analyze sequential observations over time (Chatfield, 2000). Data aggregation, approached either bottom-up or top-down, influences forecasting accuracy, with the bottom-up approach generally being more precise (Montgomery *et al*., 2012; Dangerfield & Morris, 1992). This work examines the quantitative approach to forecasting, which is often more effective than judgmental methods (Makridakis *et al*., 1979; Elton & Gruber, 1972). The popularity of the ARIMA time series model is noted, though no single econometric model is universally superior (Makridakis *et al*., 1979; McNees, 1978; Christ, 1975; Fromm & Klein, 1973; Cooper, 1972; Jorgenson *et al*., 1970; Leser, 1966).

2.1.1 Simple moving average method of forecasting

The simple moving average (SMA) method predicts future values by calculating the unweighted mean of a fixed number of preceding data points, using the following formula

$$F(t) = \frac{A(t-1)+A(t-2)+A(t-3)+\ldots+A(t-n)}{n} \quad (1)$$

Where F(t) is forecast for the coming period, A(t-n) is the past data, and n – number of periods considered (Droke, 2001). Although, some scientists argue (Armstrong, 2001; Makridakis *et al*., 1979) that this method is more suitable for short-term forecasting, it remains widely used despite its limitations in financial management forecasting and accounting forecasting both by academics and practitioners to identify stable trends in datasets and when simplicity and minimal computational requirements are priorities (Praekhaow, 2010; Economic Comission for Latin America, n.d.).

2.1.2 ARIMA method of forecasting

The ARIMA (Auto Regressive Integrated Moving Average) model is crucial in time series forecasting. It operates by differencing observations to produce a stationary series, capturing both upward and downward movements with equal probability (Cuellar & Sánchez, 2016). Mathematically represented as

$$Y_t - Y_{t-1} = \varepsilon_t$$
$$Y_t = Y_{t-1} + \varepsilon_t \quad (2)$$

where ε_t – represents white noise, ARIMA effectively smooths fluctuations yet struggles with fat-tails and volatility clustering in financial data (Petrică *et al*., 2016). Thanks to its flexibility the hybrid models are possible, such as ARIMA-ANN, which combine nonlinear and linear dynamics for enhanced accuracy (Wang *et al*., 2013). Moreover, the integration of algorithms like Hyndman-Khandakar further enhances predictive precision through optimizing the Akaike Information Criterion (AIC) through Maximum Likelihood Estimation (MLE) (Hyndman & Khandakar, 2008). The applicability of the method ranges across domains, including economic planning and GDP recovery post-disasters, demonstrating adaptability (Zhu *et al*., 2018; Dong-mei, 2010).

2.1.3 Exponential Smoothing method of forecasting

Exponential Smoothing (ES) is also a widely applied forecasting technique in finance and accounting, especially effective for trend analysis, inventory control, and seasonality adjustments (Gardner, 2006). The method adjusts forecasts by weighting recent data more strongly using the equation

$$S_t = \alpha X_t + (1 - \alpha) S_{t-1} \quad (3)$$

where S_t – is the smoothed value; X_t the actual observation, and α – is the smoothing constant (Gardner, 1985). The method is known for adaptability in capturing stochastic changes and noise reduction that enhances accuracy in demand prediction, income analysis, and socioeconomic indicators (Shvaiba, 2019; Aljandali, 2017; Tratar *et al*., 2016; Jun & Oliver, 1985). Moreover, its integration into quality function deployment and sales forecasting demonstrates its flexibility across different domains (Lin & Koo, 2007; Taylor, 2004; Snyder *et al*., 2002). ES is considered to be a robust tool for financial and operational planning despite its reliance on initial parameters (Billah *et al.*, 2006).

2.2 Cash flow ratios forecasting

This section explores cash flow forecasting, its objectives, and its characteristics. Early studies from the 1980s and 1990s focused on accrual-based predictions for future cash flows, but later critiques deemed these findings more descriptive than empirical. Arimany and Viladecans linked a company's lifecycle stages to its cash flow activities, supported by research from the US and EU, while the predictive power of cash flow statements remains debated (Ball & Nikolaev, 2022; Hajiannejad *et al*., 2020). Rajendra (2013) emphasized the importance of cash flow forecasting, which is often overlooked in operations. Business practices (Campbell, 2017; Jury, 2012) confirm its significance for financial stability, highlighting the need for forecasts to align with an enterprise's specific needs, crucial for strategic planning (Foley & Khavkin, 2019). The proper allocation of cash for investments, dividends, or debt repayments should match managerial expectations and obligations (Hendriksen & Van Breda, 1992). A well-constructed forecast is key for financial decision-making, optimizing returns, reducing costs, and ensuring liquidity (Rajendra, 2013). Cash flow ratios, which are more effective than traditional ratios in assessing financial health (Rujoub *et al*., 1995), can enhance forecasting accuracy and help evaluate a company's cash generation and decision impacts (Carslaw & Mills, 1991). These ratios also identify inaccuracies in accrual-based forecasts (Litvinenko, 2019) and predict business failures by linking cash movements to performance (Rujoub *et al*., 1995). Thus, using cash flow statements for analysis and forecasting is crucial for tracking profitability and solvency. This paper underscores the critical role of cash flow ratios in measuring a company's solvency, liquidity, and profitability, indicators vital for its sustained success. More explicitly, the ratio analysis and pairing of the ratios through four dimensions (solvency, liquidity, profitability and efficiency) are explained in the paper about the method (Litvinenko, 2024).

3. Research design

The research design of this paper aligns with the research questions and problem. To answer the research questions, we focused on two Eastern European production companies listed on the Baltic Stock Exchange: Linas Agro Group and Auga Group.

These two companies were selected to illustrate the applicability and features of a novel compound method of financial analysis and forecasting. Linas Agro and Auga Group are the two production companies operating in the Baltic agricultural sector. Both have shares outstanding in the Baltic Stock exchange and are comparable in terms of size, markets and operations. At the same time, they have different financial strategies, which represents the perfect characteristic feature to illustrate the application of the novel method. Another relevant factor is that these two companies and their financial behaviour have been studied for almost a decade, resulting in a number of publications that allow us to double-test the precision of the newly developed method.

The research design comprised four steps:

1. We analyzed the companies' annual reports and calculated comparable accrual-based and cash-based ratios in the dimensions of solvency, liquidity, efficiency, and profitability.
2. We applied the Simple Moving Average forecasting method to these ratios.
3. We wrote R code and implemented two additional forecasting methods, ARIMA and ES, based on the primary data.
4. Finally, we analyzed and compared the forecasting results.

We used mixed methods for our empirical study. The calculation of ratios, forecasting, and R code represent the quantitative methods, which focus on deriving future insights from historical financial data. This approach aligns with our objectives and the numerical format of the data, facilitating machine interpretation (Chatfield, 2000). Qualitative methods involved analyzing managerial and auditors' reports from Linas Agro and Auga Group in the analytical part of the study.

4. Research method

To conduct the analysis in the first step of the empirical study, we used historical panel data for seven years obtained from the financial statements of Linas Agro and Auga Group. We used this data for the calculation of ratios to generate the primary data for further analysis. The absolute values were used for calculations. It is important to explain the choice of the ratios in step 1. We extended the application of the ratio analysis method developed by Litvinenko (2024). This method categorizes ratios into four equally weighted groups ("dimensions") for both accrual and cash-based ratios, specifically selected to determine financial health. Each accrual-based ratio has a corresponding cash-based counterpart close by the meaning, totaling 24 ratios (12 accrual-based and 12 cash-based), referred to as "equally weighted ratios" in this study. The ratio pairs are presented in Table 1.

Table 1. Cash-based ratios and their accrual-based counterparts for solvency, liquidity, profitability and efficiency analysis. Source: Litvinenko (2024)

Accrual-based ratios	Cash-based ratios
Solvency	
Interest Coverage Ratio	Cash Interest Coverage
Debt to Equity Ratio	Total Debt (Cash flow-to-debt ratio)
Equity to Assets Ratio	Capital Expenditure
Liquidity	
Current Ratio	Operating Cash Flow (OCF)
Quick Ratio	Cash Debt Coverage
Equity Multiplier	Investment to Finance Ratio (I/F)
Profitability	
Return on Equity	Cash Return on Stockholders' Equity
Return on Assets	Cash Return on Assets
Return on Capital	Cash Return on Debt, Equity
Efficiency	
Assets Turnover	Quality of Sales
Capital Turnover	Cash Flow Per Share (CFpS)
Cash Turnover	Quality of Income

Source: developed by Litvinenko (2024)

Based on the data calculated with the use of the method explained above, we conducted Steps 2 and 3, performing the forecasting with the use of SMA, ARIMA and ES. The forecasting was done for 3 years because the present dynamic development of the economic environment and the numerous dynamic factors affecting forecasting make the conventional 5-year horizon irrelevant in this case. SMA results were calculated in Excel. ARIMA and ES methods were conducted in R Studio. The results of SMA calculations in Excel and the R Script code are presented via the link below for the convenience of the readers: https://www.scidb.cn/en/anonymous/WW55SWZl.

The R Script code written for the performance of the forecasting is discussed in the following subchapter.

4.1 R Script code in forecasting

First, we used the package Dplyr, which is a combination of multiple other packages that belong to the Tidyverse ecosystem (Wickham *et al.*, 2019). These packages aim to provide tools for cleaning and preprocessing data before constructing time series for forecasting. Secondly, we used the ggplot2 package, which equipped us with the tools needed to visualize our results graphically. We chose ggplot2 because it offers the widest variety of options for presenting data in graphical form.

In addition, the lubridate package is employed because our dataset contains variables in date and time formats, as visible between lines 14 and 28 in the code provided via links. Being a part of the Tidyverse ecosystem, lubridate is used to standardize the formatting of these time variables across all datasets, ensuring consistency and eliminating any errors or timeline mismatches (Wickham *et al*., 2019). In order to generate forecasts, the data must be formatted into time series variables. A time series variable consists of a sequence of numerical data points in sequential order. This formatting step is essential to ensure that the data is accessible in later phases when producing forecasts using the ARIMA method. The transformation is performed using the 'TS' function. This function involves selecting the data and its corresponding columns. In the 'frequency' clause, we specified that the data is annual by setting the value to 365. Additionally, in the 'start' clause, we indicated that the starting point is the year 2017, with day number 1. This is visible between lines 112 and 136 in the code. The Arima forecast is started by decomposing the different elements (trend, variance, seasonality) out from the time series. This is done by the decompose function. Then, these variables are inserted into the auto.arima function that would construct the optimal model for the forecasting. The forecast itself was done by the forecast function from the forecast package, which applies the model given by the auto.arima function into the time series. This is visible between lines 138 and 286 in the code.

In the case of ARIMA and ES regression forecasting, the graphs were produced by using the GGPLOT2 function package. For ARIMA, this is visible between lines 291 and 465 in the code. The data used for the ES is the same as for ARIMA, which enabled us to use the same time series formed between lines 55 and 79. Since it is cleaned and the time series is formed, the ES forecast can be done. The code shows it between lines 84 and 250. The ARIMA model decomposes the time series into three components: trend, seasonality, and frequency component using the decompose() function. Before that, the dataset was ensured to be stationary through calculating the difference between two different points by the diff() function, and the outcome was determined by the unit root test through auto.arima() function. The quality of forecasting was ensured by the Akaike information criterion (AIC), where we measured the amount of data that has been lost when making new points of forecasting with stationary data (normally, y-1). To make sure that three data points would be enough for forecasting, we split them into three different components, meaning that instead of three forecasting points, we actually had nine. The dataset was made stationary by differencing and confirmed by a unit root test. The best outcome from all the possible outcomes has been picked by AIC which is built into the forecast() function.

The ES forecast is done by the ses function from the xts package. The first variable inside the function is the data used for forecasting. The alpha parameter specifies the smoothing constant, which controls how much weight is given to recent observations (where a higher alpha means more weight is given to recent data, reflecting strong fluctuations expected). The h variable is set to 10, indicating that the forecast will cover 10 time periods, including the years 2015 to 2022 and 3 additional years into the future, making a total of 10 forecast points. In the next step, we formed the outcome from the list variables into a dataframe with the use of the data.frame function. After that, we selected the first 3 rows from this dataset, which correspond to the forecasts for the years 2023, 2024, and 2025. Then, we used as.numeric function to convert the values in these rows from character strings to a numeric format. The final step in the process is presenting the results graphically. The graph is structured similarly to the one presented in the ARIMA section, ensuring a consistent comparison. This is visible in the lines between 264 and 456.

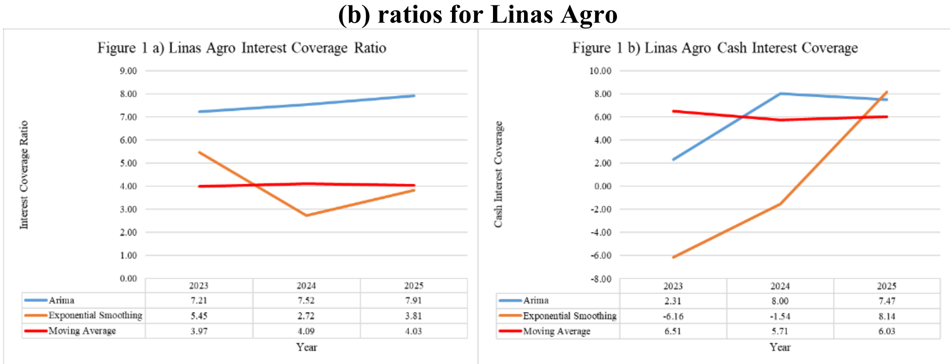
5. Results and discussion

This chapter presents the results of empirical research, analyzing Linas Agro and Auga Group the four dimensions (solvency, liquidity, profitability, efficiency) via three methods of forecasting: Simple Moving Average, ARIMA, and ES. For each of the three dimensions, there are three pairs of ratios, and each ratio is calculated with three methods. We will review each pair for both companies. The results of forecasting are represented in Figures for convenient analysis. In every pair, the accrual-based ratio is on the left side, and its cash-based ratio counterpart is close by the meaning it is on the right side. First, we compare the accrual-based and cash-based ratio pair calculated with three methods for Linas Agro Group, then for Auga Group. After that, we will compare the results between companies as well.

5.1 Solvency ratios

The first pair is the Interest Coverage Ratio and Cash Interest Coverage for Linas Agro Group. Comparing the accrual Interest Coverage ratio and Cash Interest Coverage ratio in Figure 1, forecasting results for the first pair at Linas Agro, SMA probes the most stable for both ratios.

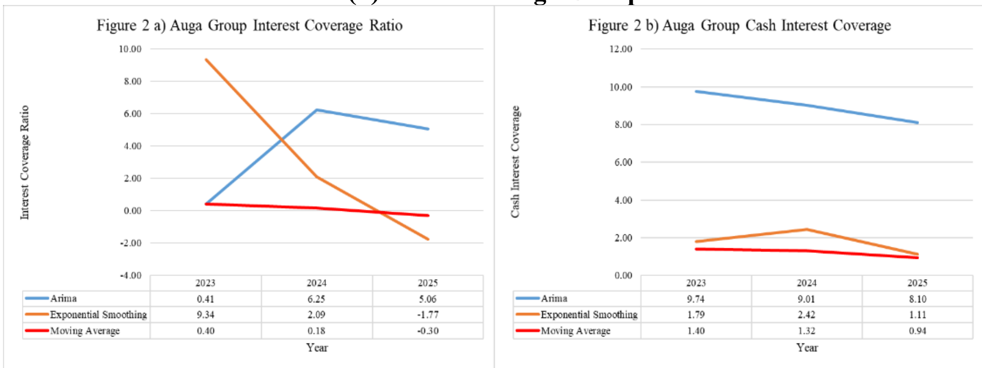
Figure 1. Accrual Interest Coverage (a) and Cash Interest Coverage (b) ratios for Linas Agro



Source: created by the authors

ARIMA captures growth effectively but shows greater variability in cash forecasts compared to accrual. ES is highly reactive to data shifts, highlighting short-term fluctuations, which might seem as a lack of consistency for the adepts of traditional forecasting, but in fact more informative about the potential historical data manipulations. The contrasting trajectories of accrual and cash ES forecasts indicate that data manipulation significantly impacts its projections. The same pair for Auga Group in Figure 2 reveals that accrual forecasts show greater variability compared to cash forecasts.

Figure 2. Accrual Interest Coverage (a) and Cash Interest Coverage (b) ratios for Auga Group



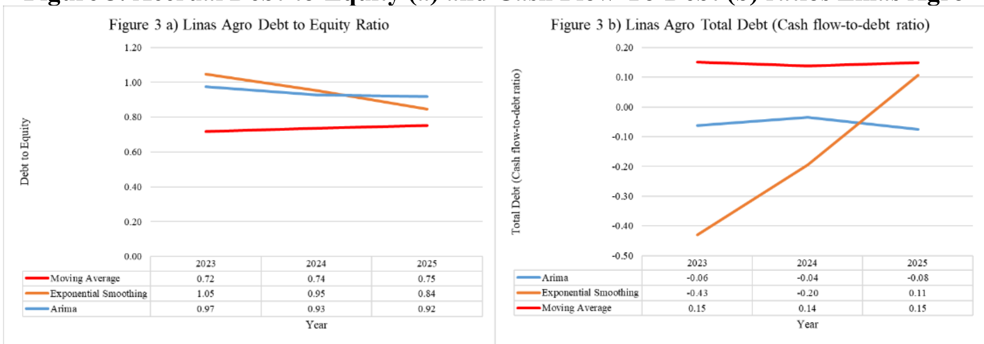
Source: created by the authors

SMA of the Auga Group is the most consistent for both ratios, offering reliable baseline predictions. ARIMA provides more insights into capturing dynamic trends, especially in accrual data, where it highlights significant peaks. ES is highly reactive to fluctuations, resulting in extreme variability in accrual forecasts and moderate instability in cash forecasts, indicating a potential sign of data betterment attempts from the company's side.

Comparing Linas Agro (Figure 1) to Auga Group (Figure 2), we see completely different pictures in forecasting patterns, techniques and reliability in the first ratio pair. Linas Agro shows steadier accrual-based forecasting, while its cash-based projections demonstrate significant volatility, expressing sensitivity to data irregularities. On the contrary, Auga Group shows a reverse trend where its relatively stable cash-based forecasts are contradicted by highly variable accrual-based predictions. This divergence underlines how historical data manipulation impacts forecasting outcomes, with ES being the most affected method due to its precision. ARIMA consistently stands out for capturing dynamic trends for both companies, particularly in contexts with fluctuating data, while SMA provides robust and reliable predictions for stable and long-term analysis.

The next pair is the accrual debt-to-equity ratio and cash total debt ratio (cash flow-to-debt) represented in Figure 3. The analysis of Linas Agro for this ratio pair highlights significant differences in accuracy and sensitivity to data manipulation between the ratios and across three forecasting methods.

Figure 3. Accrual Debt-to-Equity (a) and Cash Flow-To-Debt (b) ratios Linas Agro

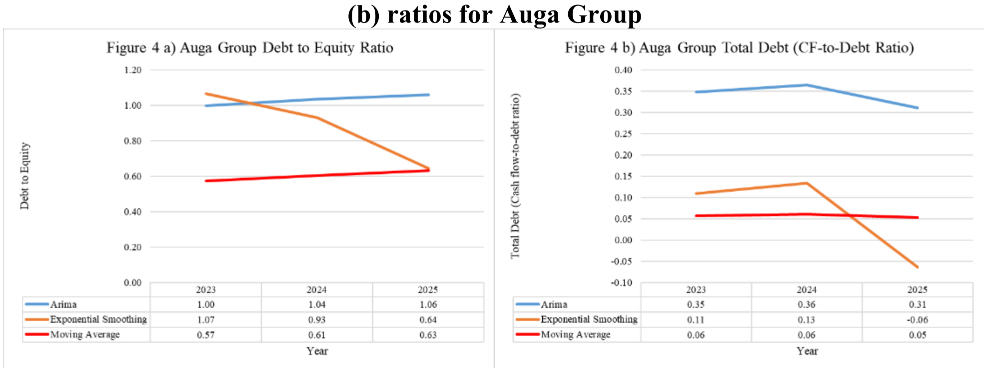


Source: created by the authors

SMA and ARIMA show consistent and stable results in both accrual and cash-based forecasts. In contrast, ES in the accrual ratio shows a sharper decline than other methods, suggesting that it is more reactive to historical data trends. A high volatility of ES may question the data integrity in scenarios with radically different forecasting between accrual and cash ratios.

The same pair for the Auga Group is shown in Figure 4. From the comparison of forecasting methods for accrual-based and cash-based ratios, it becomes evident that SMA represents the most consistent and reliable method for both accrual-based and cash-based forecasting due to its stability and resistance to historical data manipulations.

Figure 4. Accrual Debt to Equity (a) and Cash Flow-to-debt (b) ratios for Auga Group



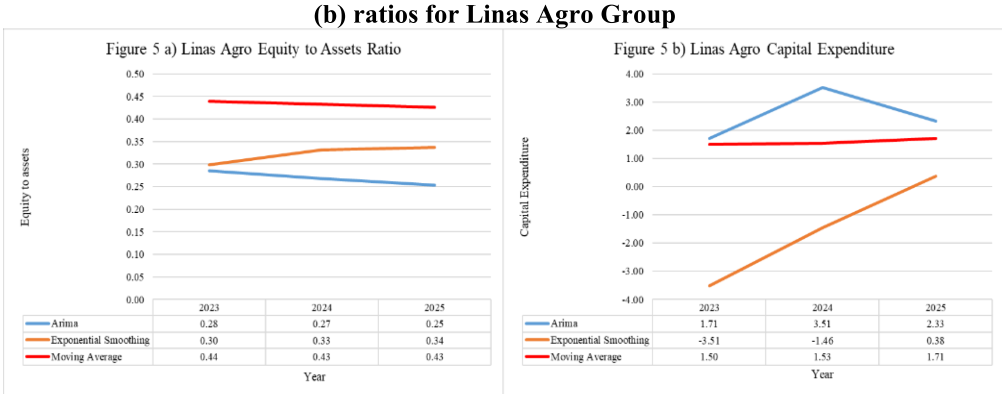
Source: created by the author

ARIMA shows good performance in capturing minor trends, yet suggests that it needs a context-dependent application, as it shows contradictions in upward accrual and downward cash-based forecasting. ES, with its responsiveness, is volatile, which makes it a strong indicator that further investigation in the data is needed if its projections are radically different from other methods.

The comparison of the forecasting results between Linas Agro (Figure 3) and Auga Group (Figure 4) reveals significant differences in forecasting performance across the three methods. For Linas Agro, in both ratios, SMA and ARIMA express consistency and reliability, where SMA shows more stable results in the long run, while ARIMA captures nuances in trends. ES shows volatility for both ratios, with dramatic declines in accrual ratios and convincing increases in cash ratios, indicating that it might be prone to data manipulation. Auga Group displays similar patterns with SMA and ARIMA, indicating stability and capturing trends, respectively. ES in the Auga Group underlines its limitations, particularly with peaks and declines in cash ratios compromising its reliability for stable financial forecasting. It is clear that the ES expresses notable discrepancies for both companies compared to SMA and ARIMA.

The final pair of solvency ratios are the accrual equity to assets and capital expenditure cash ratio. As evident from Figure 5, there are different patterns and reliability across three forecasting methods in Linas Agro's equity-to-assets accrual ratio and capital expenditure cash ratio.

Figure 5. Equity to Assets (a) and Capital Expenditure Cash (b) ratios for Linas Agro Group



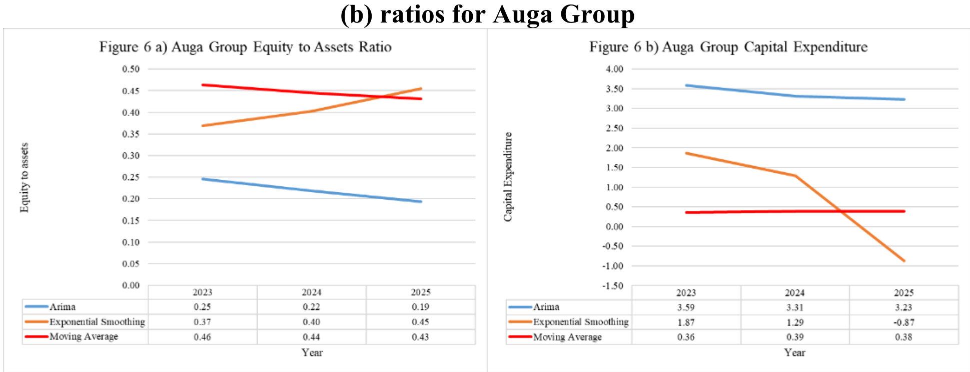
	2023	2024	2025
Arima	0.28	0.27	0.25
Exponential Smoothing	0.30	0.33	0.34
Moving Average	0.44	0.43	0.43

	2023	2024	2025
Arima	1.71	3.51	2.33
Exponential Smoothing	-3.51	-1.46	0.38
Moving Average	1.50	1.53	1.71

Source: created by the authors

SMA appears as the most consistent forecasting method, indicating stable results for both accrual and cash ratios. ARIMA shows a general downward sloping trend in the accrual ratio but indicates volatility with a single peak in the cash ratio. ES, on one hand, expresses growth trends in both metrics, has a steeper slope in cash ratio, which might be a sign of high responsiveness to recent changes in case when historical data is volatile. Figure 6 shows the same pair of ratios for the Auga Group. The analysis indicated that there are distinctions among forecasting methods in terms of sensitivity, responsiveness and stability.

Figure 6. Equity to Assets (a) and Capital Expenditure Cash (b) ratios for Auga Group



Source: created by the authors

SMA for both ratios show almost a straight line highlighting minimal data variability, however, the decline in the accrual ratio contradicts the slight increase in the cash ratio. ARIMA in this pair shows almost straight lines with similar trends for both ratios, which is a potential sign of its limited adaptability. ES moves in different directions for these ratios. Thus, for the accrual ratio, the ES line increases steadily, while for the cash ratio, it falls dramatically, reaching a negative value. Comparing the pair of ratios for Linas Agro (Figure 5) and Auga Group (Figure 6) we see that for the accrual ratio for both companies, the SMA and ARIMA show a similar trend to decrease, where SMA provides stable projections and is the most resistant to data manipulation, and ARIMA effectively captures general trends and is capable of expressing volatility as visible from the contradiction of cash to accrual ratio. On the contrary, ES shows a similar trend to increase for both companies in accrual ratios, yes indicating significant volatility for their cash-based counterpart. For Linas Agro, it shows a strong growth from negative values to positive, while for Auga Group, it shows a fall from positive values to negative, which speaks of the reactive nature of ES method of forecasting and a potential to point at data manipulations.

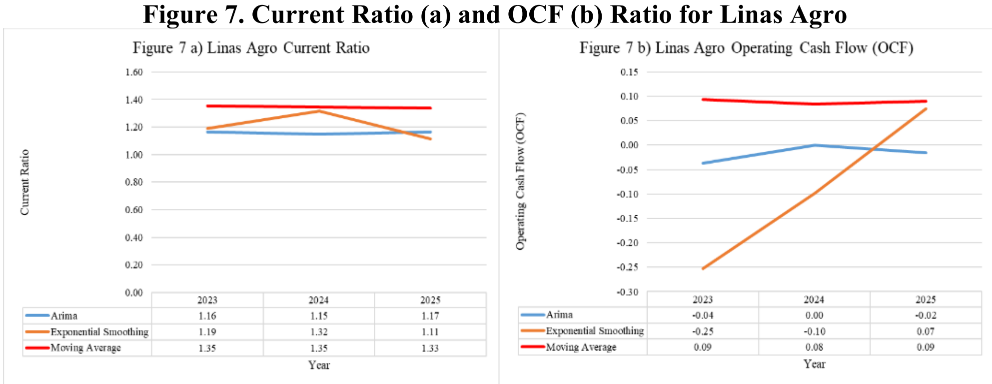
As it is evident from solvency analysis, the above-presented ARIMA and ES methods are able to predict changes in the trend and variance of the ratios. In most cases, ARIMA shows optimistic figures exceeding the result of the SMA, while the ES shows more pessimistic results. With a slightly higher optimistic approach without the pre-given limitations, ARIMA is a faster method to start tracking the variance and trend of the data, while ES offers insights into volatile, rapidly changing scenarios and adds value in identifying volatile patterns. The high responsiveness makes ES more reactive in environments with fluctuating historical data, while SMA is the least sensitive to data volatility and manipulation. To choose the most suitable method of forecasting, in this case, it is important to estimate the quality of the data and vice versa; the quality of data can be estimated based on the behavior of forecasting methods.

5.2 Liquidity

This subchapter is dedicated to the analysis of the results of liquidity ratios for the accrual and cash financial statements of Linas Agro and Auga Group. The first pair is the accrual current ratio and operating cash flow ratio (OCF). Figure 7 shows the first pair for Linas Agro Group.

As it is evident from Figure 7, there are distinctions between cash and accrual ratios in the results of ARIMA and ES forecasting methods where the operating cash flow ratio demonstrates more negative values in these methods and a stronger volatility for ES. ES captures dynamic shifts for cash ratio, expressing its sensitivity and adaptability to recent data and trends, which highlights the influence of historical data manipulation on forecasting outcomes. On the contrary, SMA and ARIMA do not reflect this. ES again proves to be the most informative method due to its ability to highlight significant directional changes, while SMA and ARIMA are more suitable for accrual-based forecasting where stability is essential.

Figure 7. Current Ratio (a) and OCF (b) Ratio for Linas Agro



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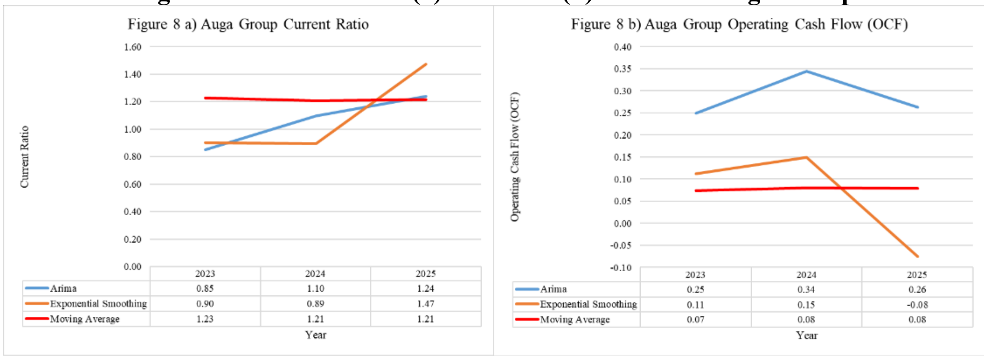
In Figure 8, all three methods of forecasting in the accrual Current Ratio at Auga Group contradict the results in the Operating Cash Flow ratio, each method in its own amplitude. While SMA shows nearly a straight line in both ratios providing a stable baseline suitable for settings with minimal variation, ARIMA displays moderate shifts suitable for identification of gradual trends, as shown in accrual ratio and reflected stronger in cash ratio, and ES strives in totally different directions: upward in accrual, downwards in cash ratio highlighting nuances and volatility effectively.

Figure 8. Current Ratio (a) and OCF (b) ratios for Auga Group



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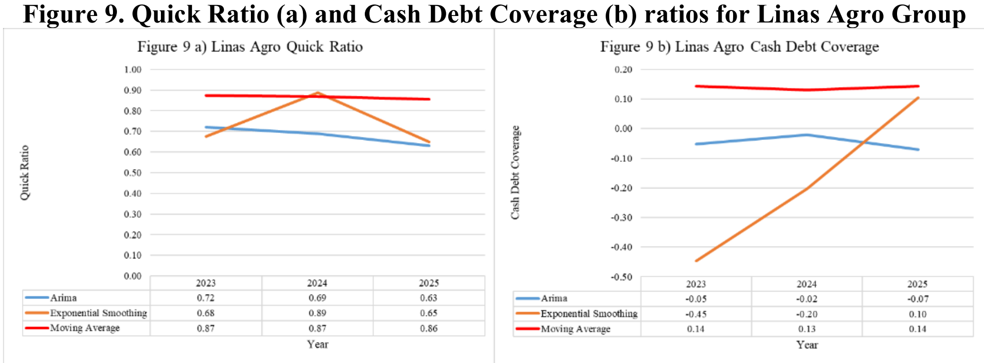
Comparing Linas Agro (Figure 7) and Auga Group (Figure 8) for this pair of ratios, a clear distinction between accrual and cash ratios is evident, with cash ratios reflecting higher volatility, especially under ES forecasting. The findings from this ratio pair show that SMA is more suitable for stable environments, ARIMA is capable of gradual trend identification, while ES offers valuable insights into dynamic shifts.

The second pair is Quick Ratio accrual ratio and Cash Debt Coverage. In Figure 9, ARIMA captures a contradiction between accrual and cash ratio with a slightly declining trend with all positive values for accrual ratio and all negative values for cash ratio.

Figure 9. Quick Ratio (a) and Cash Debt Coverage (b) ratios for Linas Agro Group



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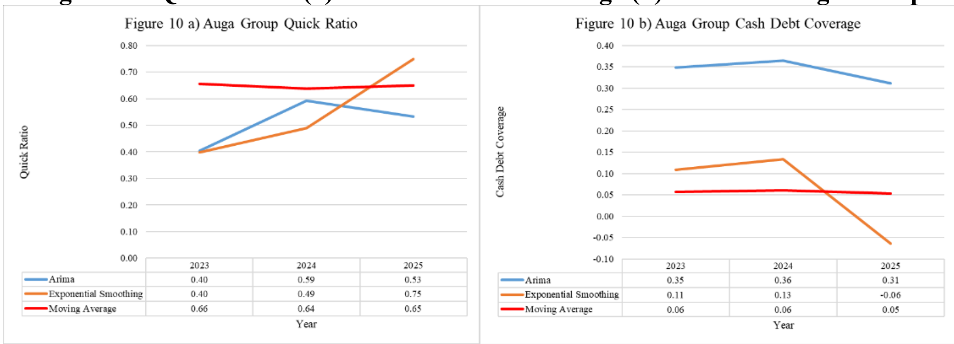
ES displays the most dynamic behavior and stands out for its sensitivity to changes reflected in significant volatility and shifts, particularly in cash ratio, where it transitions from negative to positive values, unlike its behavior in accrual. SMA remains stable, only capturing a slight, minimal trend with minimal variance.

Figure 10. Quick Ratio (a) and Cash Debt Coverage (b) ratios for Auga Group

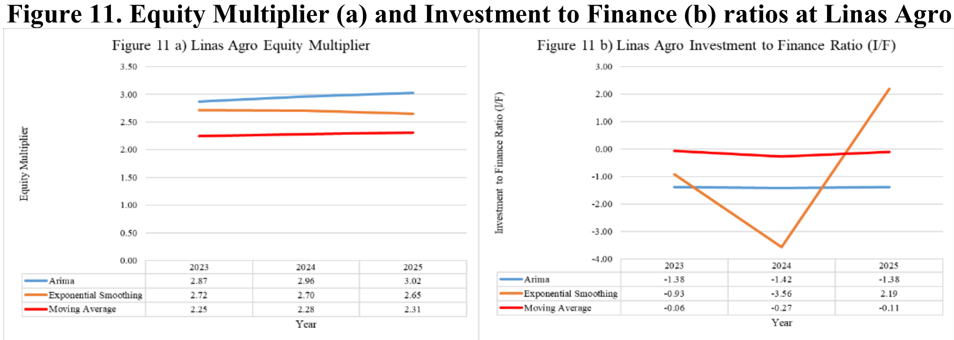


Source: created by the authors

The same pair for Auga Group shows interesting results as well in Figure 10. It is evident from Figure 10 that SMA and ARIMA in the accrual ratio coincide in pattern with its cash counterpart but with different amplitude of values. In contrast, ES again shows divergent directions and trends with positive accrual and negative cash ratio, which signals the necessity to pay more attention to historical data standing behind the forecast.

Comparing the pairs between Linas Agro (Figure 9) and Auga Group (Figure 10), SMA and ARIMA for the accrual Quick Ratio of both companies exhibit consistent patterns with low variability and slight downward trends, while these methods show slightly more dynamic behaviour in the cash ratio. ES indicates high sensitivity and volatility for both ratios and significantly differs between companies, showing a sharp decline for the cash ratio of Auga Group and its dramatic increase for Linas Agro.

Figure 11. Equity Multiplier (a) and Investment to Finance (b) ratios at Linas Agro



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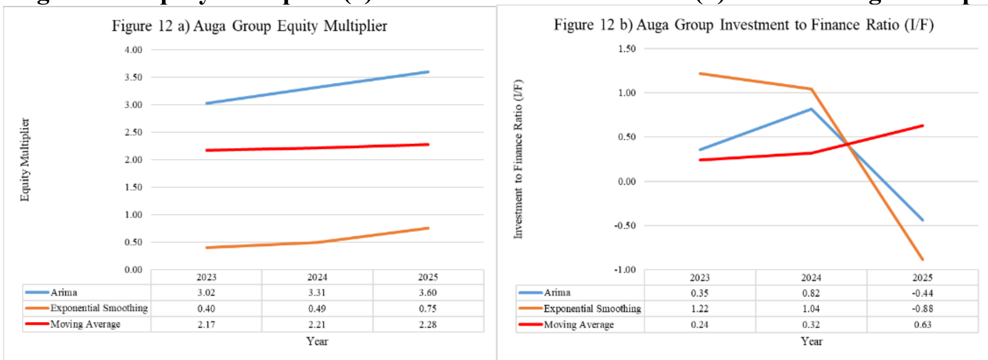
The third pair is the Equity Multiplier accrual ratio and Investment to Finance cash ratio as shown in Figure 11. As evident from Figure 11 for Linas Agro, all three methods exhibit consistency with minimal shifts and, therefore, limited dynamic insights for the accrual ratio. In the cash-based Investment-to-Finance ratio, ES captures substantial volatility with a sharp drop, not reflected by SMA and ARIMA.

Considering the same pair for the Auga Group, as shown in Figure 12, in the Equity Multiplier accrual ratio, all three forecasting methods show the same pattern of a slight growth in nearly a straight line with the lowest values in ES. In contrast, the cash ratio exhibits significant volatility in all three methods, with the strongest decline in ES.

SMA in cash ratio shows stable projection, and ARIMA exhibits growth with subsequent decline, expressing gradual trends. ES is the most informative, capturing dynamic shifts with its sensitivity to fluctuations.

Figure 12. Equity Multiplier (a) and Investment-to-Finance (b) ratios at Auga Group



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Comparing the pair of ratios between Linas Agro (Figure 11) and Auga Group (Figure 12), it is visible that there is a similar picture for the accrual ratio; the methods showed straight lines with a tendency to increase. For the cash ratio, the situation is different. Linas Agro SMA and ARIMA for cash ratio show similar results to accrual ratio, while ES is volatile resulting in a sharp increase. For the Auga Group, all methods show volatile results for the cash ratio, which contradicts its accrual counterpart. These results highlighted the greater sensitivity of cash ratios to data volatility and capabilities of ES in capturing dynamic shifts, making it more informative.

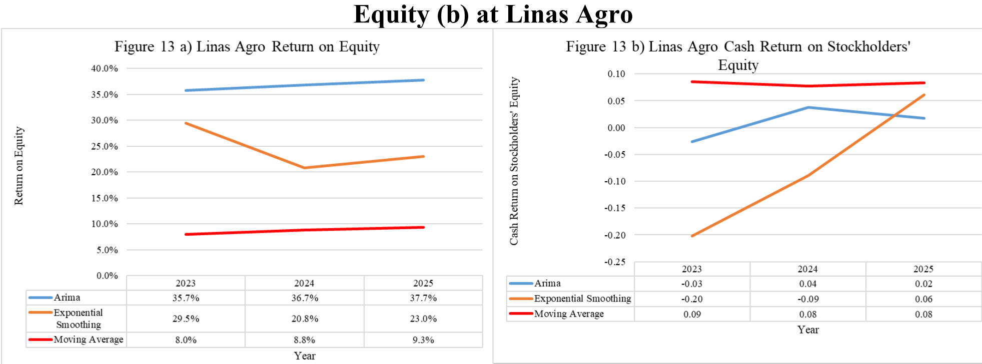
Comparatively, both companies exhibit significant volatility in cash-based ratios, especially under ES, however, Auga Group displays more fluctuations and differences between cash and accrual ratios, compared to Linas Agro which has closer relations between cash and accrual metrics, indicating greater sensitivity to dynamic changes in financial data and potential differences in cash flow management or historical data characteristics. ES highlights critical differences in cash flow strategies or financial conditions between companies, showing a strong increase in the cash-based Investment-to-Finance ratio for Linas Agro and a dramatic decline for Auga Group.

5.3 Profitability

This section is dedicated to the comparison of profitability analysis with the use of three methods of forecasting. The first pair of ratios is the accrual Return on Equity and Cash Return on Stockholders' Equity. Figure 13 shows the first pair for Linas Agro Group.

In the accrual Return on Equity ratio for Linas Agro (Figure 13a), there are notable differences in the dynamics across the three methods. While SMA and ARIMA show consistent and steady increases, ES demonstrates a declining trend in 2023 and 2024, with a slight recovery in 2025.

Figure 13. Return on Equity (a) and Cash Return on Stockholders' Equity (b) at Linas Agro

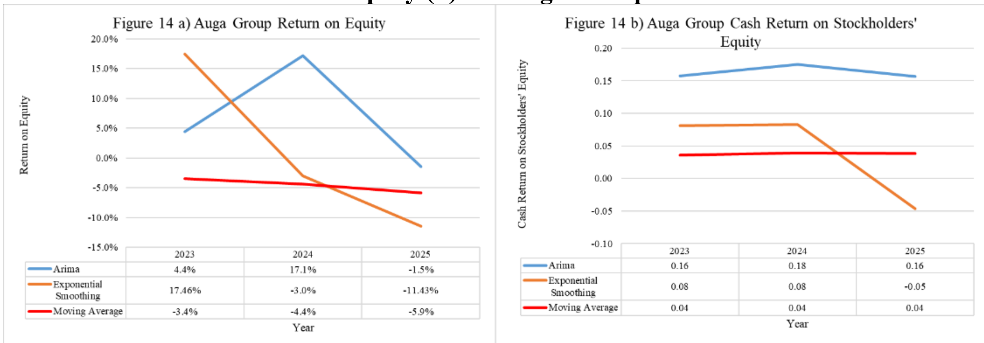


Source: created by the authors

In Cash Return on Stockholders' Equity in Figure 13b, methods diverge further with SMA showing a minor decrease, ARIMA indicating an increase in 2024 before tapering to 0.02 in 2025, and ES rising from a significant negative in 2023 to a positive value in 2025. Thus, it is evident that the behaviour of ES in cash ratio contrasts its behaviour in accrual, reflecting high sensitivity to data volatility and effectively capturing dynamic shifts in cash-based ratio.

The same pair is shown in Figure 14 for the Auga Group. It is evident from Figure 14a that the three forecasting methods contradict each other in the accrual Return on Equity where SMA consistently declines with all negative values, ARIMA is highly volatile with tremendous difference between years, while ES reflects a sharpest drop.

Figure 14. Return on Equity (a) and Cash Return on Stockholders' Equity (b) for Auga Group



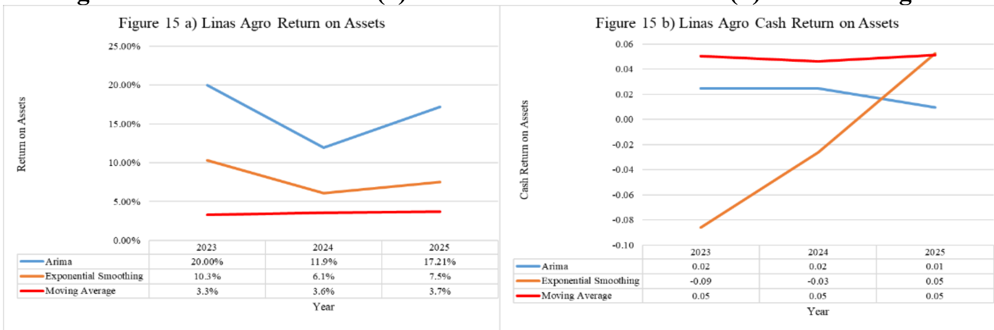
Source: created by the authors

The cash-based ratio in Figure 14b shows that in 2023 and 2024, methods reflect almost no change, followed by a drop in ARIMA and ES, where ES depicts a sharper decline reaching negative values. Thus, it is clear that ES is more reactive in both ratios within the pair and that all three methods in the cash-based ratio are more aligned than in the accrual one. Comparing the ratio pairs between Linas Agro (Figure 13) and Auga Group (Figure 14), it is visible that SMA shows a straight line with insignificant shifts, meaning that it cannot adequately capture dynamic shifts in the financial performance of volatile environments. ARIMA for Auga Group in this ratio pair managed to identify broader patterns where growth is followed by decline, however, its results differ within the pair for Linas Agro, indicating sensitivity to input data variations. ES is highly sensitive to fluctuations of data, reflecting both short-term movements and general trend shifts where contradictions within pairs for both companies reflect possible manipulations.

Figure 15 shows the second pair of profitability ratios for Linas Agro Group. In the accrual Return on Assets at Figure 15a for Linas Agro, the SMA is a straight line with an insignificant tendency to increase. ARIMA and ES are similar to each other, yet the ES forecast is less optimistic. In Cash Return in Assets at Figure 15b for Linas Agro, SMA and ARIMA show stability in 2023 and 2024 while striving in opposite directions in 2025. ES contrasts their moderate behaviour with a dramatic upward trajectory, aligning with SMA in the final year.

A comparison of both ratios in Figure 15 shows a dichotomy, where ARIMA and ES align in the accrual ratio, while SMA and ARIMA are more aligned in their behaviour in the cash ratio. ES in cash ratio is more reactive than in the accrual ratio forecast.

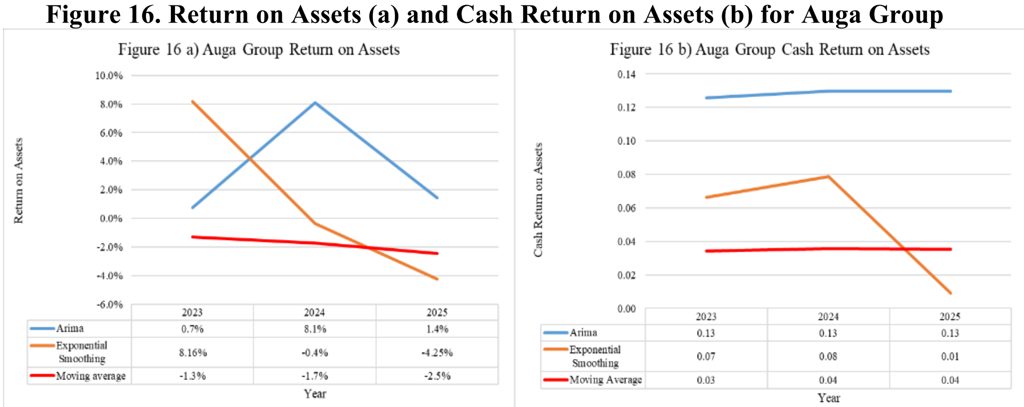
Figure 15. Return on Assets (a) and Cash Return on Assets (b) for Linas Agro



Source: created by the authors

The same pair for Auga Groups is represented in Figure 16. In the accrual Return on Assets from Figure 16a, the methods show distinct behavior. While SMA is stable in negative values, ARIMA is volatile with a peak followed by a drop, and ES indicates a dramatic decline.

Figure 16. Return on Assets (a) and Cash Return on Assets (b) for Auga Group



Source: created by the authors

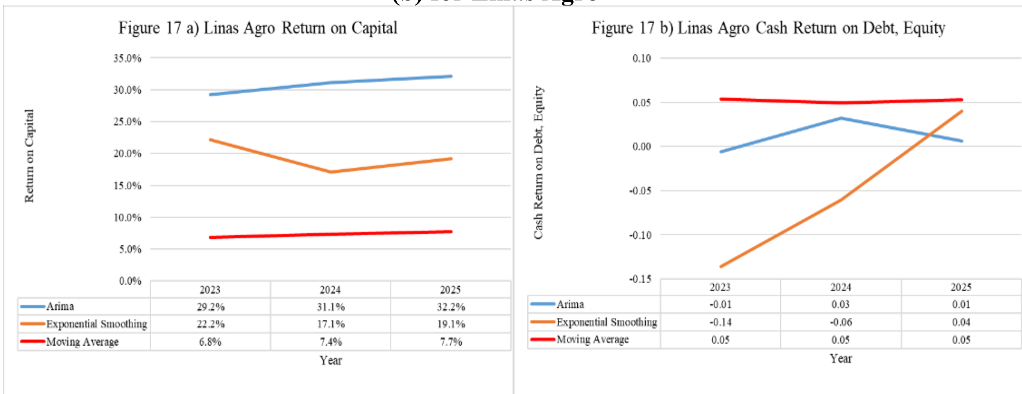
In Cash Return on Assets for Auga Group, SMA and ARIMA show positive straight lines yet with different values, while ES contradicts them with volatility. Comparing this pair of ratios from Figure 16, it is clear that SMA is consistent in both ratios, while ARIMA and ES show contrasting trends in cash and accrual ratio.

Comparing this pair of ratios for both Linas Agro (Figure 15) and Auga Group (Figure 16), it is visible that SMA in all cases has a straight line with insignificant shifts toward raise or decline. ARIMA shows stability in cash-based forecasts for both companies but is highly volatile in accrual-based forecasts, especially for Linas Agro. ES shows opposite trends for Linas Agro within the ratio pair, while it is aligned in declines of both metrics for Auga Group. Cash ratio forecasts for Linas Agro show more significant differences between methods and larger positive values in ARIMA for accrual ratios, while Auga Group maintains closer alignment for SMA and ARIMA, and with a slight difference in magnitudes for ES.

The third pair is represented in Figure 17. As it is visible from Figure 17a, in the accrual return on capital ratio, SMA and ARIMA are nearly straight lines, and ES indicates a slight volatility with a fall in 2024.

In the cash return on debt and equity ratio from Figure 17b, the three methods indicate different dynamics. SMA is a straight line with small positive results for all three years. ARIMA's growth from a negative in 2023 to a positive value in the year 2024 is followed by a drop in 2025. ES reflects a confident growth from negative to positive, effectively capturing a significant shift in cash flow dynamics.

Figure 17. Return on Capital (a) and Cash Return on Debt and Equity (b) for Linas Agro



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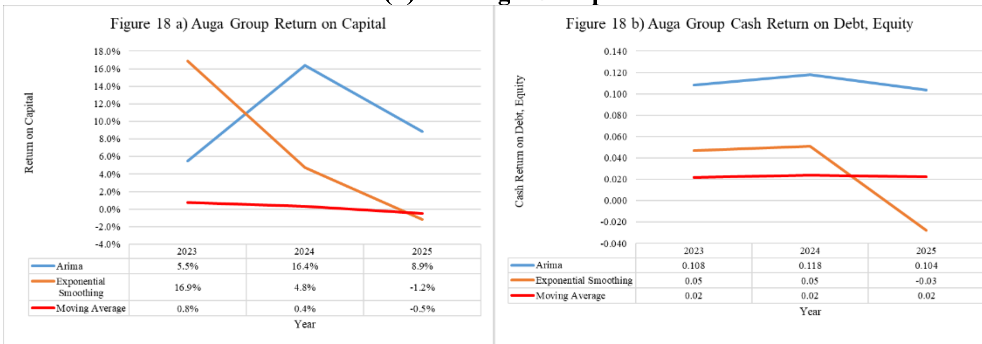
Comparing accrual and cash ratio analysis in Figure 17, SMA and ARIMA align closely, while ES captures fluctuations both in accrual and cash-based ratio, which other methods failed to reflect. Thus, ES is the most informative method for detecting changes or anomalies in financial trends, especially in cash-based forecasts.

Figure 18 shows the same pair of ratios for the Auga Group. In the accrual return on capital ratio at Figure 18a, the SMA shows a simplistic trend which does not account for volatility. ARIMA and ES reflect opposite trends in 2023-2024, followed by an aligned decline direction in 2024-2025.

In the cash-based ratio ARIMA and SMA, two methods are more aligned, yet reflect different levels of values. ES uncovers potential risks in later years while SMA and ARIMA are more stable, as visible in Figure 18b.

Comparing Linas Agro (Figure 17) to Auga Group (Figure 18) for this pair of ratios, it is visible that ARIMA stands out for its ability to reflect both growth and decline phases, while ES highlights dramatic downturns. Again, the accrual-based forecast with the ES method for Linas Agro contradicts the cash-based, while for Auga Group, they are more aligned. On the other hand, ARIMA is more volatile for the accrual-based forecast of the Auga Group than for its cash-based forecast. However, in general, forecasting methods for Auga Group indicate similar directions, while for Linas Agro, they are not that aligned.

Figure 18. Return on Capital (a) and Cash Return on Debt and Equity (b) for Auga Group



	2023	2024	2025
Arima	5.5%	16.4%	8.9%
Exponential Smoothing	16.9%	4.8%	-1.2%
Moving Average	0.8%	0.4%	-0.5%

	2023	2024	2025
Arima	0.108	0.118	0.104
Exponential Smoothing	0.05	0.05	-0.03
Moving Average	0.02	0.02	0.02

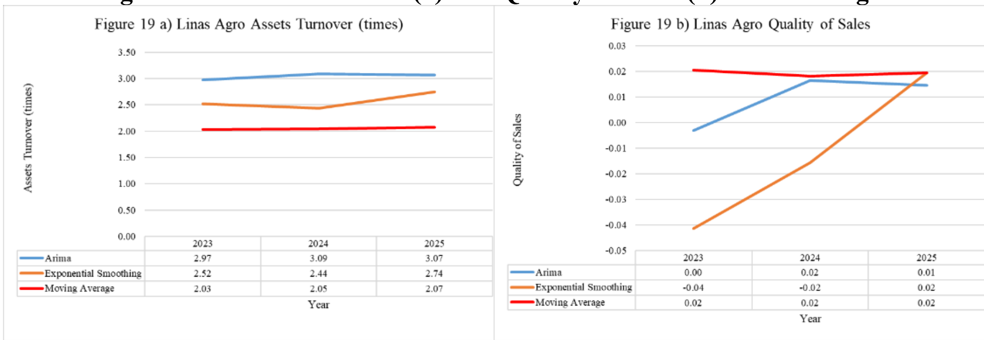
Source: created by the authors

From the analysis of profitability ratios, it is evident that forecasting methods exhibit divergent behavior within Linas Agro's ratio pairs compared to Auga Group's relatively aligned forecasting trends. SMA consistently provides stable projections, and ARIMA reflects moderate sensitivity, effectively capturing broader patterns like growth or decline and is more volatile in accrual-based forecasts for Auga Group. ES again proved itself as the most informative method due to its sensitivity to fluctuations and ability to reflect significant shifts, particularly in cash-based ratios. It reveals contradictions between accrual and cash-based ratios as well as potential anomalies and manipulations in historical data, while SMA and ARIMA are more suitable for general trend identification.

5.4 Efficiency

This section is dedicated to the analysis of forecasting for efficiency ratio pairs. The first pair is the accrual Assets Turnover ratio and Quality of Sales cash ratio. Figure 19 shows the first pair for Linas Agro. As evident from Figure 19a, in the accrual Assets Turnover for Linas Agro, the SMA, ARIMA, and ES show straight lines with an insignificant increase, indicating minimal variation and relatively consistent forecast.

Figure 19. Assets Turnover (a) and Quality of Sales (b) for Linas Agro



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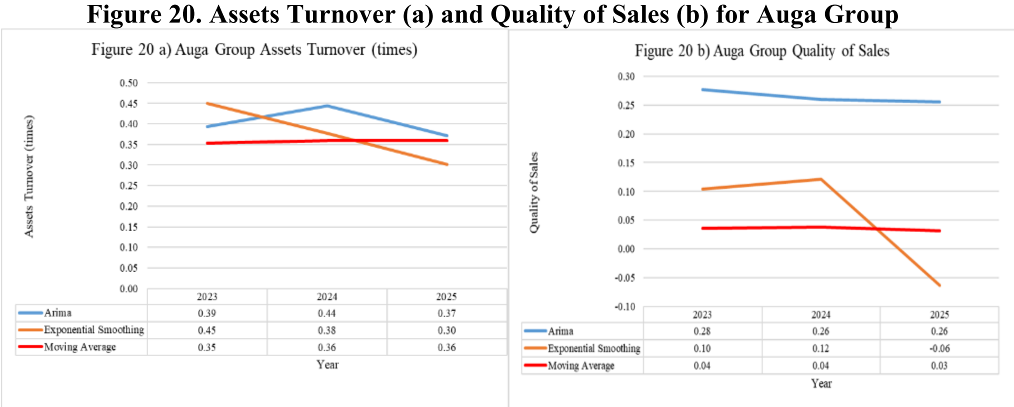
In the Quality of Sales cash ratios in Figure 19b, SMA remains flat, while ARIMA indicates a slight shift. In contrast, ES showed a dynamic and responsive cash-based forecast where manipulations in historical data affected the sharp trajectory of the method, making it the most informative compared to the other methods. The same pair for the Auga Group is represented in Figure 20.

Figure 20. Assets Turnover (a) and Quality of Sales (b) for Auga Group



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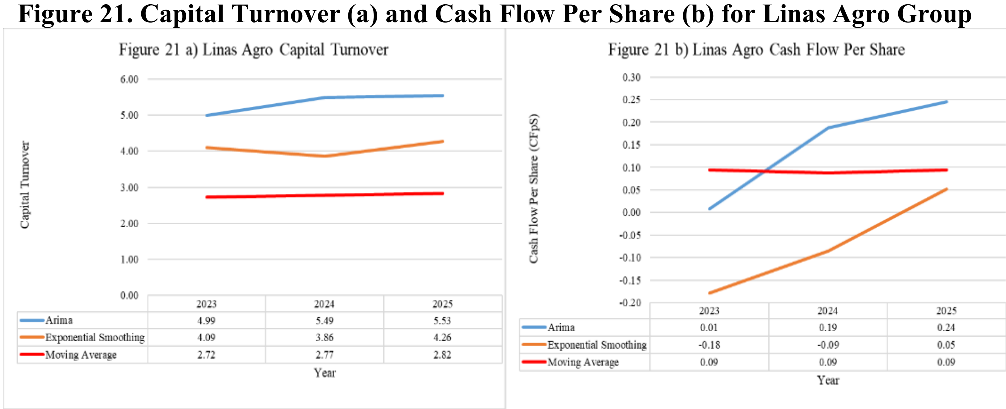
At Figure 20a in accrual Assets Turnover for Auga Group, SMA is a straight line with insignificant growth. ARIMA shows a slight volatility, while ES exhibits a confident decline as a straight line. For the Quality of Sales cash ratio for Auga Group, SMA and ARIMA show straight lines with an insignificant decline in values, as depicted at Figure 20b; however, ES is more volatile and striving to decline. Its volatility contrasts with the relative stability of SMA and ARIMA, and it appears to capture larger shifts in data, especially in the cash ratio.

Comparing the first pair of ratios between Linas Agro (Figure 19) and Auga Group (Figure 20), out of the total of 4 ratios and 12 lines, only 4 lines are volatile, and 8 lines are straight. Auga Group shows more volatility in both metrics than Linas Agro.

It is visible in ARIMA and ES, exhibiting their sensitivity to changes, especially in cash-based data.

The second pair of ratios is the accrual Capital Turnover and Cash Flow Per Share cash ratio shown in Figure 21. As visible from Figure 21a, in the accrual Capital Turnover ratio for Linas Agro, all three methods show straight lines with insignificant shifts to increase, keeping all values positive. In the Cash Flow Per Share ratio in Figure 21b, SMA is a straight line, ARIMA shows a growing trend, and ES shows a confident growth from a very negative -0.18 in the year 2023 to a positive 0.05 in the year 2025.

Figure 21. Capital Turnover (a) and Cash Flow Per Share (b) for Linas Agro Group



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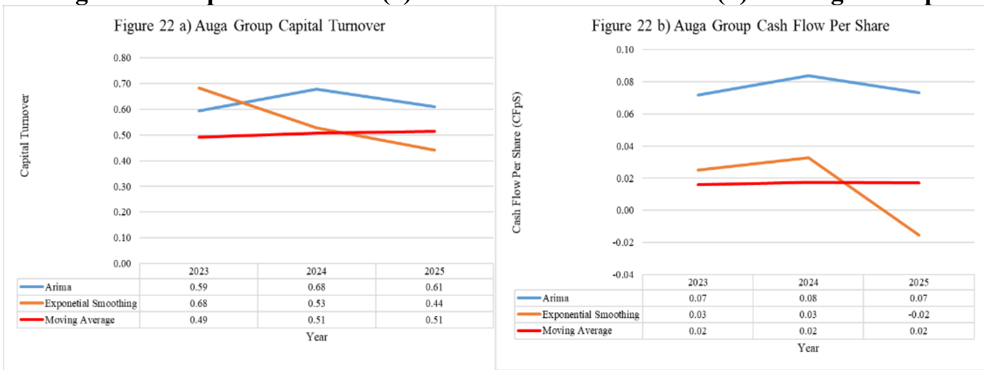
Comparing the ratios from Figure 21, it is clear that only ARIMA and ES for the Cash Flow Per Share ratio depict confident growth tendencies, while the same methods in accrual show straight lines with insignificant growth.

Figure 22 shows the second pair of efficiency ratios for the Auga Group. In the accrual Capital Turnover for Auga Group in Figure 22a, SMA shows a straight line with insignificant growth. ARIMA shows a slight increase followed by a decrease, and notably, its highest peak in the year 2024 equals the highest peak of ES forecasted in the year 2023.

As evident from Figure 22b, in the Cash Flow Per Share of Auga Group, SMA is a straight line, and ARIMA has a slight peak of 0.08 in the year 2024, agreeing with the accrual ratio. The pattern of the cash ratio of ES for the first two years contradicts its forecast for the accrual counterpart yet shows a tendency to fall in both.

Figure 22. Capital Turnover (a) and Cash Flow Per Share (b) for Auga Group



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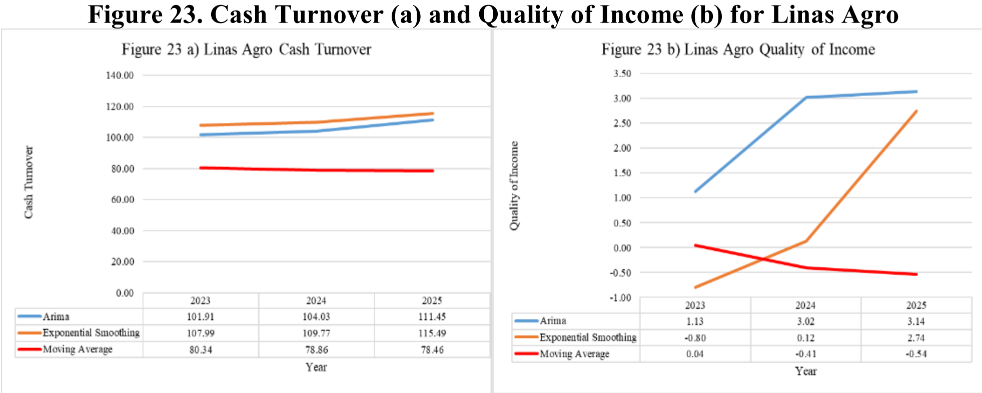
Comparing the pairs of ratios for both Linas Agro (Figure 21) and Auga Group (Figure 22), it is clear that out of all methods, ES suggests the most dynamic and informative forecast for both Capital turnover and Cash Flow Per Share revealing even the negative shifts in Auga Group's cash ratio or the recovery of Linas Agro.

The third pair of ratios is the accrual Cash Turnover and Quality of Income cash ratio, as Figure 23 shows the distinct differences below for Linas Agro.

Figure 23. Cash Turnover (a) and Quality of Income (b) for Linas Agro



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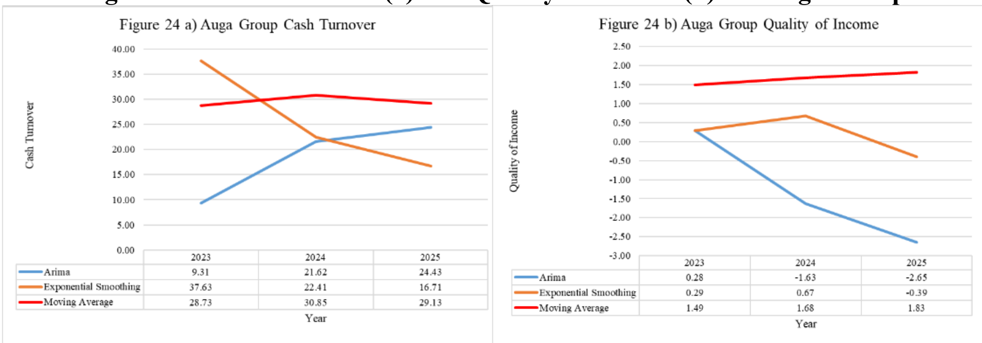
While all three forecasting methods show nearly straight lines in the accrual Cash Turnover ratio, the cash-based Quality of Income is more dynamic, where even SMA shows a steady decline from a positive 0.04 in the year 2023 to a negative -0.54 in the year 2025. ARIMA and ES exhibit steep growth where ES raises from a negative value. It is clear that the methods contradict each other for the accrual and cash ratio.

Figure 24 below shows the third pair for the Auga Group. As visible from Figure 24a, in the accrual Cash Turnover ratio for Auga Group, SMA shows insignificant volatility, while ARIMA exhibits a rapid growth. Unlike them, ES shows a tendency to a dramatic decline. Notably, in the year 2024, ARIMA and ES forecasts show nearly the same results.

Figure 24. Cash Turnover (a) and Quality of Income (b) for Auga Group



Source: created by the authors

In the Quality of Income cash ratio for Auga Group in Figure 24b, SMA shows a straight line with a tendency to grow. ARIMA indicates a significant decline, while ES exhibits a growth to 0.67 in the year 2024, followed by a decline to the negative -0.39 in the year 2025. Important to note that ARIMA begins its downturn one year earlier than ES, yet in the year 2023, both methods show very similar forecasts.
Comparing both ratios for Auga Group in Figure 24, SMA shows a stable forecast, while the results of ARIMA for accrual and cash-based ratio contradict each other. ES generally shows declining trends, which is more dramatic and negative in the Quality of Income cash ratio. For this pair, ES and ARIMA both informatively captured volatility, especially in cash forecasting.

Comparing the third pair of ratios between Linas Agro (Figure 23) and Auga Group (Figure 24), it is visible that SMA has steep growths or falls. ARIMA in three cases out of four shows growth; it falls only in the Quality of Income cash ratio of Auga Group reaching negative values. ES of Linas Agro, both for cash and accrual, shows a tendency to growth. In the case of Auga Group, both for accrual and cash ES method shows a decline. All three methods confirm each other only for the Cash Turnover accrual ratio in Linas Agro, while in the rest of the cases for the third pair of efficiency ratios, they show different results, sometimes contradicting each other.

Overall, while the SMA method provides a stable and less informative outlook due to its simplicity, ARIMA and ES offer more dynamic insights. ARIMA shows gradual changes, aligning with overall trends of growth or decline, and is therefore suitable for capturing both short-term fluctuations and long-term trends, as it proved both for accrual-based and cash-based forecasting of efficiency metrics. ES highlights more significant shifts, revealing potential growth areas for Linas Agro and suggesting possible challenges for Auga Group, especially visible in cash-based ratios with its high sensitivity. These differences underscore the importance of using multiple forecasting methods to gain a comprehensive understanding of financial performance and make informed strategic decisions.

6. Conclusion

The analysis in the present paper has found the answers to the research questions.

RQ1. *Which of the forecasting methods (SMA, ARIMA, ES) is the most informative?* The analysis showed that ES is the most informative forecasting method, followed by less informative ARIMA and the least informative SMA. Informativeness is shown by the volatility of the forecasting lines, which makes them similar in their volatility to the ratio analysis based on historical data presented in the paper „Using Combined Accrual And Cash Ratio Analysis To Determine Pre-Bankruptcy Status". In that paper, where the detailed ratio analysis based on the historical data was shown, all graphs were volatile and informative; therefore, the more volatile the lines of forecasting methods are, the more they are similar in their volatility to the historical aspect, and the more informative they are in forecasting. SMA is a straight line in the majority of the cases, ARIMA shows some moderate volatility, while ES is highly volatile in most cases, looking alike to the historical ratio analysis, which makes it a more trustworthy prediction.

RQ2: *Can forecasting methods be used to verify each others' results?*
The analysis has shown that SMA, ARIMA and ES cannot be used to verify each other's results because, in many cases, they show different results. SMA, in the vast majority of cases, shows a nearly straight line with insignificant shifts, which makes it less useful in forecasting. SMA shows much more positive and smoothed results of forecasting than the other two methods. Theoretically, it could be used to indicate the general trend of increase or decline to test the other forecasting methods, but practical application shows that it contradicts other forecasting methods even within the same ratio in many cases. Moreover, the shifts in values from year to year and volatility shown by SMA are so insignificant that they can hardly be compared to ARIMA and ES in the forecast horizon of 3 years. SMA might be used for a shorter period of forecasting.

If to consider each ratio for each company as a single case, then ARIMA strictly contradicts ES in this forecasting analysis in 5 out of 12 cases for Solvency ratios, 5 out of 12 cases for Liquidity, 4 out of 12 cases for Profitability, in 1 out of 12 for Efficiency. In total, these methods contradict each other in 15 out of 48 cases. Since the number of contradictions is nearly one-third of the total cases, the forecasting methods cannot be used to verify each other's results.
RQ3. *How do the manipulations in historical data affect the forecasting of accrual and cash ratios?*

The analysis revealed that if the company manipulated its data in accrual financial statements without manipulations in cash historical data, it has more smoothed lines in accrual forecasting and the actual picture is revealed by volatility or contradicting results in cash forecasting.

The research also revealed that forecasting methods can show different performances depending on the data type and quality. Thus, the method of forecasting can be chosen based on the quality of data and vice versa; the quality of data can be estimated based on the behavior of forecasting methods. With the present data and number of companies, ES is more precise than other methods. ARIMA will be more effective for a bigger amount of data with a bigger number of companies and more periods in the historical panel data (broken down to quarterly or monthly), resulting in more precise patterns of forecasting. SMA method has shown the unconvincingness and weakness of forecasting for the present research.

The novel method of ratio analysis (Litvinenko, 2024) was combined with three widely used forecasting methods to test their compatibility and illustrate their applicability and features of the in-depth analysis based on a case study of two production companies. Picked for clear illustration, the companies are comparable yet possess different financial strategies.

The present work is an interim, yet essential step for building the new credit risk model based on the equally-weighted simple and complex financial ratios. The authors hope that the present paper will serve as a decent base for future research directions in examining the power of combined ratio analysis and forecasting for a wider selection of companies and as an insight for practitioners for credit risk and investment decisions.

Disclosure statement: The authors report that there are no competing interests to declare.

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