ЕКОНОМІКО-МАТЕМАТИЧНЕ МОДЕЛЮВАННЯ БІЗНЕСОВИХ ПРОЦЕСІВ

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ANALYTICS AND MODELING OF INVESTMENT ACTIVITY OF ENTERPRISES IN THE FIELD OF CAPITAL EXPENDITURES

АНАЛІТИКА ТА МОДЕЛЮВАННЯ ІНВЕСТИЦІЙНОЇ ДІЯЛЬНОСТІ ПІДПРИЄМСТВ У СФЕРІ КАПІТАЛЬНИХ ВКЛАДЕНЬ

This article explores the investment activity of Ukrainian enterprises, focusing on capital expenditures and their impact on asset value and net income. The study analyzes the dynamics of net cash flow from investment activities during wartime uncertainty. Emphasis is placed on time series models (SARIMA, Holt) and multifactor regression with lag variables to reflect delayed investment effects. Results show that standard models may be unstable under limited data or structural shifts, while lagged regressions offer more realistic insights. The article also examines fixed asset structure, addresses multicollinearity, and applies centering to improve model performance. Overall, the research demonstrates the effectiveness of economic-mathematical tools in investment assessment and provides a foundation for strategy adjustments in unstable economic conditions.

Keywords: *investment activity, fixed assets, capital expenditures, net income, time series models, regression models.*

У статті представлено комплексне дослідження інвестиційної діяльності українських підприємств у розрізі капітальних вкладень та їх впливу на ключові фінансово-економічні показники, зокрема вартість активів і чистий дохід. Авторами проаналізовано динаміку «чистого руху коштів від інвестиційної діяльності» на прикладі підприємств обраних для дослідження, включно з періодом суттєвої невизначеності в умовах воєнного часу. Особлива увага приділяється методам часових рядів (SARIMA, Holt) і багатофакторним регресійним моделям із лаговими змінними, що дозволяють враховувати відкладений вплив інвестицій на зростання активів і прибутків. Результати дослідження демонструють, що стандартні часові моделі можуть виявлятися нестабільними за умов обмеженої вибірки чи різких структурних зламів, характерних для української економіки останніх років. Приділена увага тестам на стаціонарність (ADF), перетворенням Бокса–Кокса, сезонній декомпозиції та підбору параметрів SARIMA. У більшості випадків метод Хольта й простіші експоненційні підходи дають кращу інтерпретацію поточних тенденцій, проте потребують обережного аналізу для реалістичного прогнозування. У статті наведено приклади застосування лагового регресійного моделювання, яке підтверджує, що капітальні вкладення здатні генерувати приріст вартості активів не миттєво, а з певним запізненням. Дослідження показало, що на одних підприємствах лаги складають один-два роки, на інших не зафіксовано суттєвого відкладеного впливу в межах дослідженого періоду. Додатково розглянуто детальну структуру необоротних активів, виявлено проблему мультиколінеарності при використанні багатофакторних регресій, на основі складових основних засобів і випробувано метод центрування змінних, який покращує інтерпретацію моделі. Таким чином, робота демонструє універсальність економіко-матема-

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тичного інструментарію (різні специфікації регресій, методи прогнозування часових рядів) у контексті оцінювання інвестицій. Узагальнені висновки можуть стати основою для коригування інвестиційних стратегій у складних ринкових умовах, визначення пріоритетів модернізації та формування збалансованої політики розподілу капіталу.

Ключові слова: *інвестиційна діяльність, основні засоби, капітальні вкладення, чистий дохід, моделі часових рядів, регресійні моделі.*

Problem statement. Prior to early 2022, Ukraine's investment climate had been gradually improving, driven by relative macroeconomic stability and market liberalization. However, the introduction of martial law led to the suspension or significant transformation of numerous projects due to supply chain disruptions, loss of production capacities, and heightened uncertainty. Despite these challenges, some enterprises succeeded in implementing reinvestment initiatives and even partially improved their financial performance.

The prevailing trends, rapidly changing conditions, and unfavorable economic environment necessitates a prudent and evidence-based approach to investment decision-making by enterprises, as such decisions ultimately affect asset valuation and financial outcomes. Given that these effects are not immediate, it is essential to investigate and model the lagged impact, spanning the period from the initial investment to the actual growth in assets and net income.

The object of this research is the financial and economic processes related to asset and income formation under the influence of investment activities. The subject concerns the dependence of these processes on the volume and structure of investments, including disaggregated data from balance sheet notes (e.g., land, buildings, equipment, software, etc.).

The study aims to refine the understanding of the role of individual components of non-current assets, thereby expanding the conceptual framework of enterprise investment behavior and financial performance formation in unstable environments, using more granular statistical data.

This approach enables a comprehensive evaluation of corporate investment policies under conditions of economic instability and facilitates the development of strategies to enhance capital allocation efficiency. Moreover, it provides a broader basis for forecasting by allowing future net income to be extrapolated based on detailed asset indicators shaped by investment decisions of varying scope and depth.

Analysis of recent research and publications. In his study, O. Zharun [1] systematizes types of investments and proposes strategic approaches tailored to agricultural enterprises. The article by H. Khioni [2] examines factors influencing the effectiveness of fixed asset modernization in the agricultural sector. The study presented in [3] refines legislative and accounting aspects of investments to enhance transparency in the post-war period. N. Chyryk in [4] explores the concept of "capital investment" within the context of globalization and economic integration. Publication [5] presents algorithms for the accounting treatment of investments and offers practical approaches to monitoring and control.

Formulating the purposes of the article. The primary objective of this article is to investigate the dynamics of enterprise investment activity before and during the period of martial law. This includes testing the stationarity of time series such as "net cash flow from investing activities" and applying various forecasting methods (SARIMA, Holt). Special emphasis is placed on multifactor econometric models with lagged variables to identify the delayed impact of capital investments on asset valuation and subsequent net income growth. The article also aims to develop recommendations for further improvement of the constructed models to enable their practical application in enterprises.

To achieve these objectives, the following research methods were employed: observation, generalization, comparison, formalization and classification, statistical analysis, econometric modeling, and performance forecasting.

Presentation of the main research material. This study focuses on two major representatives of Ukrainian business: ATB-Market, an extensive chain of grocery stores that serves as a sensitive indicator of the consumer market and primarily invests in logistics and retail network expansion; and Nova Poshta, a leading logistics operator that develops infrastructure solutions, such as transshipment centers, an expanded vehicle fleet, and digital services, that directly impact the speed and accessibility of deliveries. Another key market participant is the agro-industrial holding MHP (PJSC "MHP"), known for its specialization in poultry farming, meat production, and processing. The company continuously invests in expanding production capacities, upgrading equipment, enhancing logistics, and supporting technological innovations in the agro-industrial sector.

The analytical and modeling framework is based on financial statement indicators, including the balance sheet (total asset value), the income statement (net revenues, net profits), and the cash flow statement (investing activities). Integration of these variables enables an assessment of how capital investments translate into asset growth and impact profitability [6; 7]. This approach demonstrates how the selected enterprises can adapt to military-economic challenges and maintain stable development even admit adverse market conditions [6; 7].

A visual analysis of the net investment cash flow dynamics for the selected companies, particularly ATB-Market (Figure 1) and Nova Poshta (Figure 2), reveals the complexity of the period from 2020 to 2023. Until 2022, both companies demonstrated either stable or moderately growing investment activity. However, following the outbreak of military aggression in February 2022, a sharp decline in investment activity was observed. Both enterprises faced significant challenges related to security concerns, physical asset protection, the reconfiguration of logistics routes, and overall economic uncertainty.

Simultaneously, the chart depicting the net cash flow from investing activities of PJSC MHP (Figure 3) indicates that the agroholding experienced significant wartime disruptions, particularly in export operations and the preservation of agricultural land. Prior to 2022, the company adhered to a consistent investment policy aimed

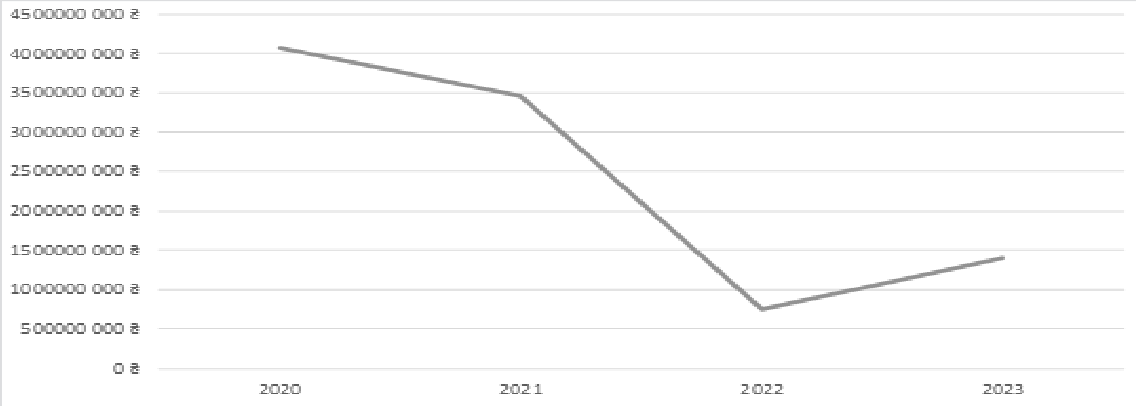

Figure 1. Time series of Net Cash Flow (Losses) from Investing Activities of ATB-Market LLC, 2020–2023, UAH

Source: prepared by the authors based on [6; 7]

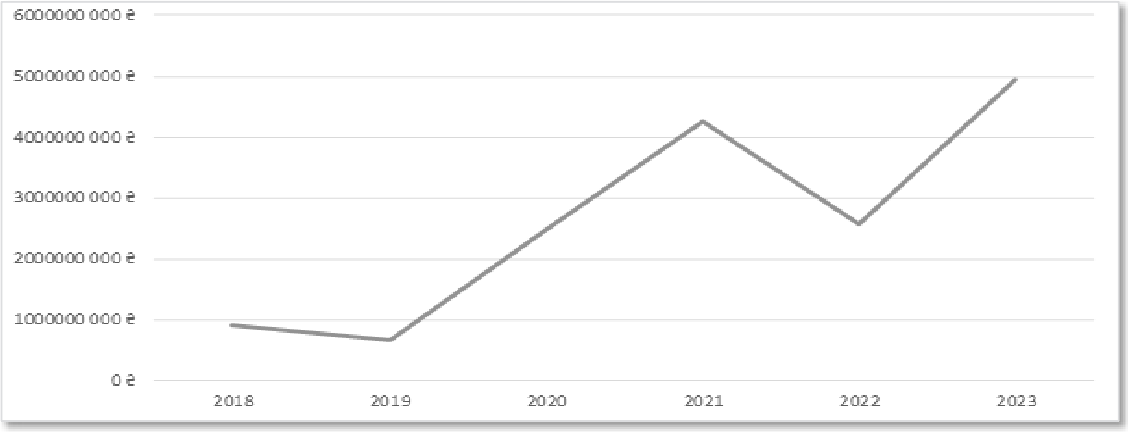

Figure 2. Time series of Net Cash Flow (Losses) from Investing Activities of Nova Poshta LLC, 2020–2023, UAH

Source: prepared by the authors based on [6; 7]

at expanding poultry production complexes, developing meat processing lines, and implementing modern agricultural technologies. However, following February 2022, MHP redirected its investment efforts toward ensuring production continuity and maintaining logistics routes for the domestic market. Despite a noticeable decline in investment activity at the onset of the invasion, the company demonstrated a recovery of investment flows in 2023, indicating its adaptation to the challenging conditions of the agricultural sector.

In 2023, a gradual adaptation of the analyzed enterprises to the new realities became evident. ATB-Market LLC showed signs of stabilizing its investment flows, although pre-war levels were not fully restored. Meanwhile, Nova Poshta LLC demonstrated a substantial recovery and even growth in investment activity, highlighting a high degree

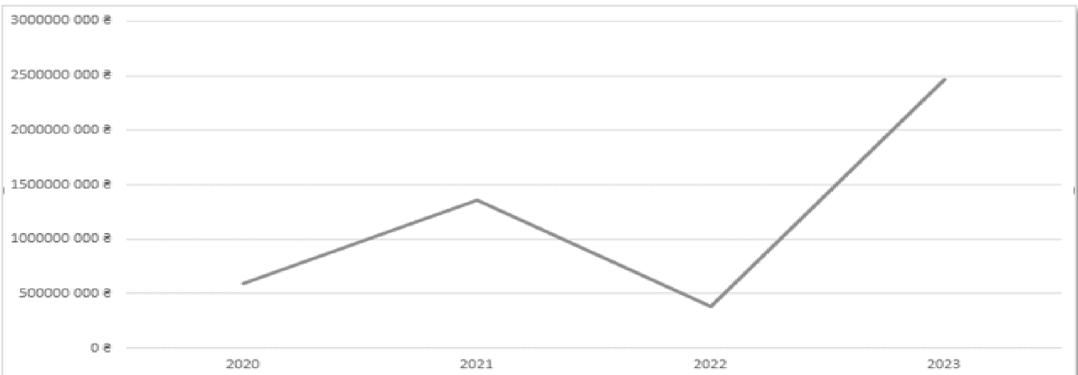

Figure 3. Time Series of Net Cash Flow (Losses) from Investing Activities of MHP PJSC, 2020–2023, UAH

Source: prepared by the authors based on [6; 7] of flexibility and the ability to respond rapidly to external changes. PJSC MHP also exhibited signs of investment revitalization, primarily focused on modernizing production capacities and expanding its agro-industrial base. This strategic direction enables the company not only to maintain its competitiveness but also to contribute positively to the international reputation of Ukraine's agricultural sector.

This divergence in the dynamics of individual companies highlights that, under martial law, the effectiveness of investment activity depends not only on the size of the business or industry sector, but also on the quality of managerial decision-making, the robustness of logistical infrastructure, and the enterprise's capacity for innovation.

Thus, despite unprecedented challenges, all analyzed companies remain pivotal in shaping Ukraine's investment climate. Their experience and adaptive strategies may serve as valuable case studies for understanding economic patterns and development dynamics in contexts marked by high uncertainty and instability [6, 7].

To forecast the time series representing the net cash flow from investing activities, a suite of statistical and econometric models was employed, which allow for the generation of future values based on historical observations. These included the SARIMA model and Holt's linear trend model. Each of these models has its characteristics, approaches to trend and seasonality modeling, as well as requirements regarding the stationarity of the series. The use of multiple models enables a comparative evaluation of their predictive capabilities, the stability of the results, and supports more informed conclusions regarding the behavior of the indicator under study.

The SARIMA model is one of the most widely used and time-tested approaches for forecasting time series data. It applies to stationary time series or those that can be transformed into stationary form through differencing [10]. Its advantages include capturing both the autocorrelation data structure and random shocks. However, SARIMA can be complex to calibrate, notably when the series exhibits seasonality or implicit trend components [10].

The Holt model, also known as Holt's linear trend method, is an extension of simple exponential smoothing that accounts for both the base level of the series and the trend component [11]. Unlike the Holt-Winters model, the classical Holt model uses only two smoothing constants: α and β. As such, it models the current level and the trend without incorporating seasonality parameters [11]. This model is well suited for series with a clear trend but no pronounced seasonality. With only two parameters, the Holt model remains relatively simple and interpretable, offering more flexibility than simple exponential smoothing [11].

At the forecasting stage, the time series of net cash flow from investing activities for Nova Poshta LLC during 2005–2023 was analyzed. The initial dataset provided a foundation for assessing the stationarity of the series and suitability for further modeling.

At the initial stage, a time series analysis was conducted using the Augmented Dickey-Fuller (ADF) test to assess stationarity. The test results indicated that the *p*-value was close to 1, and the computed ADF statistic suggested the presence of a unit root. This implies that the original "Investments" series is non-stationary. Non-stationarity is reflected in time-varying mean and variance and may also include trends or structural breaks. To transform the series into a stationary form, the Box-Cox transformation was first applied. This transformation is commonly used to stabilize variance when the variability of a time series depends on the level of the series itself. After the transformation, the stationarity was reassessed using the ADF test. However, the results showed that even after applying the Box-Cox transformation, the p-value remained high (close to 1), indicating that the transformation did not improve the series' stationarity to an acceptable level.

In the next stage, seasonal decomposition was employed. An attempt was made to seasonally difference the series and apply a periodic shift of three time steps in order to eliminate potential cyclical fluctuations. This shift, along with seasonal differencing, significantly reduced the *p*-value in the ADF test to 0,0006, which is below the commonly accepted significance level of 0,05. This indicated that, following a series of transformations, the series became stationary according to the Dickey-Fuller criteria.

The next stage involved the automatic selection of parameters for the SARIMA (p, d, q) model. The SARIMA model is a linear model that represents the current value of a time series as a linear combination of its past values (the autoregressive component, AR) and past forecast errors (the moving average component, MA), after transforming the series to a stationary state (through the integration operator, I). The automatic selection of parameters was conducted using information criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which allow for comparison across models with different (p, d, q) configurations and help identify the optimal model by balancing goodness of fit and model complexity.

The optimal model selected automatically was SARIMA(2,0,0)(1,1,0)[9]. The interpretation of these parameters is as follows: $p = 2$ indicates the presence of two autoregressive terms; d=0 means that, following seasonal and other transformations, no further (non-seasonal) differencing is required; $q = 0$ implies that there are no moving average terms in the non-seasonal component. The seasonal part (1,1,0)[9] signifies that the model includes a seasonal autoregressive term of order 1 and seasonal differencing of order 1, with a seasonal period of 3. In essence, the model assumes the presence of a first-order seasonal autoregressive component and first-order seasonal differencing with a periodicity of 3.

However, it is important to note that the statistical indicators and coefficient estimates of the model suggest a poor overall model fit. Despite SARIMA models being widely used for forecasting financial and economic time series, in this case the results indicated their inadequacy. First, the original time series was relatively short and unstable, and achieving stationarity required multiple transformations. Second, the parameters selected by the automated algorithm were found to be weakly significant. Third, diagnostic tests revealed heteroscedasticity and non-normality of the residuals, which raises concerns about the model's predictive validity. In practice, the SARIMA model in this study largely "fit" the historical data without capturing it accurately or reproducing the underlying patterns necessary for reliable future forecasts. The main reasons for this could be the limited number of observations, the absence of clearly defined patterns, or the presence of strong structural breaks in the time series caused by external factors such as war or other macroeconomic shocks.

During the modeling process, a two-parameter Holt's linear trend method (without seasonality) was employed. This model allows for the consideration of both the level of the time series and its trend component. By specifying the smoothing parameters α and β, it is possible to control the model's sensitivity to new data: higher values of these parameters increase the model's responsiveness to recent fluctuations, while reducing the overall smoothness of the series.

In our example, the parameters were set to α = 0,4 and β = 0,6 (Figure 4). With these values, the model responds relatively quickly to changes, placing greater emphasis on recent observations in determining both the level and the trend. By iteratively computing the level and trend values for each period, new forecasted values were generated step by step. The first period corresponds to the year 2005.

The visualization of the obtained results enabled an assessment of the model's performance not only through numerical metrics but also in terms of the overall shape of the time series. On the graph displaying the actual investment time series values alongside the forecast generated by Holt's method, one could clearly observe the model's degree of approximation to the real data, as well as instances where the model failed to "respond" in time to abrupt or unpredictable changes.

Ultimately, the analysis of the computed results and the graphical representation provides insight into the suitability of Holt's model for forecasting the selected investment time series. If the forecast errors are excessively large and the model fails to capture key dynamics, it may be necessary to consider alternative methods or incorporate additional data to enhance forecast accuracy.

The next stage of the study involves the construction of dynamic models that allow for an analysis of the impact of investments on the value of enterprise assets, taking into account potential time lags. Capital expenditures in production capacities, logistics, technologies, or other equipment may enhance asset value or generate added value for the company only after a particular time interval.

The application of lagged variables in modeling makes it possible to empirically assess how many periods after the implementation of investment inflows one can expect positive (or negative) changes in the company's assets.

The basic model can be represented as follows [13]:

$$Assets_t = \alpha + \beta \cdot Investment_{t-n}, \qquad (1)$$

where α represents the baseline asset value in the absence of investment influence; β is the coefficient indicating the impact of investments in the previous period on assets in the current year; t is the current period; and n denotes the lag length.

The lag length n is selected empirically, based on the availability of data and the economic logic of enterprise development. In this study, various lag structures were tested for individual enterprises: no lag (n = 0), one-period lag (n = 1), two-period lag (n = 2), and, where possible, a three-period lag (n = 3).

For ATB-Market LLC, due to the limited availability of statistical data, only a one-period lag (n = 1) was tested. This implies that the constructed model assumes the influence of investments made in the previous period on the asset value in the current period. The resulting coefficients for this lag specification indicate that β is statistically significant and demonstrates a noticeable delayed effect of investment with a one-year lag:

$$Assets_t = 50\,000\,000\,000 \text{ ₴} + (-\,1{,}791732053) \cdot \cdot Investment_{t-1}. \qquad (2)$$

In contrast, for Nova Poshta LLC, a more comprehensive historical data set made it possible to test a broader range of lag structures. Specifically, lags of 1, 2, and 3 periods were examined. This extended analysis enabled a deeper understanding of whether the effect of investment appears as early as one period later, or whether a longer time frame is required for the full realization of investment outcomes.

The results indicated that for particular lag values, the coefficients for the variable Investment became statistically significant and economically interpretable. For instance, if the highest coefficient and the best explanatory power were obtained at a two-period lag, this may suggest that

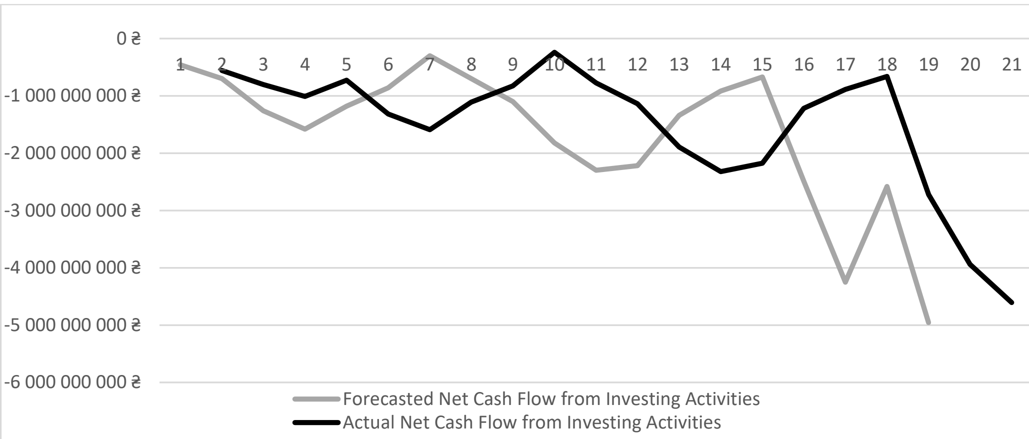

Figure 4. Overlay of forecasted and actual Net Cash Flow from Investing Activities by period using the Holt Method for Nova Poshta LLC, UAH

Source: prepared by the authors based on [6; 7] investments made two years prior have a substantial impact on asset value in the current period:

$$Assets_t = 9\,000\,000\,000 ₴ + 4{,}0399 \cdot Investment_{t-2}. \quad (3)$$

It is worth noting that at the initial stage, a similar correlation analysis was conducted for PJSC MHP, examining the relationship between net cash flow from investing activities and asset value (in nominal terms) over the period 2018–2023. Statistical testing (Pearson correlation coefficients calculated for various lags) revealed the highest correlation at a zero lag, indicating an absence of a delayed (lagged) effect of investments on assets within the given time frame. At other lag lengths (1, 2, or 3 years), the correlation coefficients were statistically insignificant and showed substantially lower coefficients of determination (R^2). This suggests that, based on correlation-regression analysis, the dynamics of asset growth at MHP closely align with the respective investment volumes in real time, without a notable time shift. While this does not diminish the MHP's analytical value in the context of investment activity, it does indicate that lag-based modeling approaches, as applied in this study, are not particularly relevant in this specific case.

In contrast, ATB-Market lacked sufficiently long time series data, which limited the analysis to a one-year lag. Even under this simplified structure, it became evident that capital injections do not immediately reflect on the balance sheet but begin to manifest after a particular delay. Nova Poshta, with a broader historical dataset, was able to test several lag structures and more clearly demonstrate the delayed nature of investment effects.

Net income, as a measure of efficiency, is logically associated with the size of a company's assets, as greater production capacity and access to resources typically contribute to higher sales volumes and profitability. To test this hypothesis, correlation coefficients were calculated and a linear regression model was developed to analyze the relationship between net income and asset value. If the correlation is statistically significant and the regression coefficients are stable, this confirms a strong linkage between income and the scale of the resource base.

The resulting equations allow for the incorporation of projected asset values (including those obtained from previous forecasting or lagged models) (Tables 1, 2) into formulas for estimating future income. This approach provides additional tools for managers and financial analysts: with data on potential asset expansion, they can extrapolate the expected impact on net income and adjust investment strategies accordingly. For instance, if a decline in the "Net Income / Assets" ratio is anticipated, the company may proactively enhance productivity, upgrade equipment, or optimize logistics.

Such regression models also assist in assessing the business model's resilience to various shocks, including changes in raw material prices or access to financing. With a quantitative foundation, enterprises can simulate different scenarios and evaluate how they might affect the income-to-assets relationship. In this way, the "obvious" link becomes statistically formalized and validated, enabling the integration of findings into strategic managerial decision-making. The corresponding results are presented in Tables 1 and 2.

Table 1

Modelling Net Income values in relation to Asset Value of Nova Poshta LLC

Year	Net Cash Flow from Investing Activities	Assets	Coefficients of Net Income Dependence on Assets	Net Income
2018	-916 337 000 ₴	4 988 253 000 ₴	2,11	10 515 739 000 ₴
2019	-671 136 000 ₴	6 927 368 000 ₴	2,31	16 010 832 000 ₴
2020	-2 487 469 000 ₴	9 533 558 000 ₴	2,16	20 621 616 000 ₴
2021	-4 248 936 000 ₴	15 365 128 000 ₴	1,66	25 549 607 000 ₴
2022	-2 579 746 000 ₴	19 515 221 000 ₴	1,46	28 461 964 000 ₴
2023	-4 955 381 000 ₴	26 752 062 000 ₴	1,63	43 645 219 000 ₴
2024	-3 940 815 311 ₴	45 377 869 092 ₴	1,50	68 066 803 638 ₴
2025	-4 606 132 539 ₴	41 121 443 862 ₴	1,60	65 794 310 180 ₴
2026		42 939 241 208 ₴	1,70	72 996 710 053 ₴
2027		41 747 192 331 ₴	1,80	75 144 946 195 ₴

Source: prepared by the authors using data from [6; 7]

Table 2

Modelling Net Income values in relation to Asset Value of ATB-Market LLC

Year	Net Cash Flow from Investing Activities	Assets	Coefficients of Net Income Dependence on Assets	Net Income
2018	-2 500 000 000 ₴	19 700 000 000 ₴	4,36	85 800 000 000 ₴
2019	-3 000 000 000 ₴	23 900 000 000 ₴	4,39	105 000 000 000 ₴
2020	-4 065 561 000 ₴	35 652 151 000 ₴	3,47	123 864 393 000 ₴
2021	-3 459 214 000 ₴	42 395 449 000 ₴	3,51	148 745 255 000 ₴
2022	-755 997 000 ₴	41 080 714 000 ₴	3,61	148 332 869 000 ₴
2023	-1 404 705 000 ₴	47 487 936 000 ₴	3,81	181 089 665 000 ₴
2024	-2 043 396 415 ₴	47 483 190 052 ₴	3,85	182 810 281 698 ₴
2025	-1 817 808 052 ₴	46 338 846 643 ₴	3,89	180 258 113 440 ₴
2026		46 743 033 313 ₴	3,93	183 700 120 919 ₴

Source: prepared by the authors using data from [6; 7]

Nova Poshta LLC prioritizes sustained development of logistics infrastructure, systematic expansion of its material-technical resources, and integration of advanced IT solutions as core pillars of its investment strategy. An analysis of the structure of non-current assets reveals a concentrated increase in land plots and buildings (for the construction and modernization of sorting centers), technical equipment and machinery (including conveyor systems and warehouse complexes), as well as vehicles (in line with the growth of transportation volumes). Significant investments in software, integrated ERP/CRM systems, and online services demonstrate an approach that accounts for tangible and intangible logistics components, consequently enhancing service speed and quality [8].

The notes to the financial statements also indicate a substantial share of construction-in-progress, reflecting the simultaneous execution of multiple large-scale projects. A year-by-year comparison revealed periods of accelerated growth in specific asset groups, for example, technical equipment in 2019–2020 and IT systems in 2021–2022. The most notable surge was observed in 2023, when all major fixed assets categories increased significantly, along with a sharp rise in construction-in-progress, underscoring the company's long-term commitment to expansion and modernization [8].

A logical preparatory step for constructing a multiple regression model is the analysis of the correlation matrix of all non-current asset components. Overall, the matrix shows that "Land and Buildings", "Technical Equipment and Machinery", and "Other Operational and Office Equipment" exhibit very high intercorrelations (0,8–0,99), suggesting that the company typically invests in these categories simultaneously, expanding its physical infrastructure comprehensively (e.g., new logistics centers, equipment for those centers, etc.). "Vehicles" also show strong correlations with the aforementioned categories, although their dynamics differ somewhat in specific years (resulting in slightly lower, yet still substantial, correlation values).

IT systems, right-of-use assets, software, and other intangible assets also demonstrate considerable association with the "tangible" asset categories, as the development of IT infrastructure often accompanies large-scale logistics modernization projects.

In moving toward the construction of a multiple regression model using the ordinary least squares (OLS) method, it is advisable to first group certain elements (variable consolidation) to reduce multicollinearity among independent variables. The first grouping approach involves combining "Buildings" and "Vehicles" into a single category, and merging "IT Systems" with "Software and Licenses" into another while keeping "Operational Equipment" as an independent variable. This configuration makes clear economic sense, as buildings and vehicles are often viewed as core components of physical logistics infrastructure, when IT systems and software expenses typically go hand-in-hand as part of digital transformation efforts.

From a mathematical standpoint, such consolidation may help smooth out high correlations among the original asset items and mitigate multicollinearity. However, there is a risk of losing some granularity: for instance, if buildings grow faster than vehicles (or vice versa), this difference will be obscured in the aggregate indicator. As a result, the interpretation of each component's contribution becomes slightly more complex (Table 3).

The second combination retains "Land and Buildings", "Operational Equipment", and "Vehicles" as three separate variables, while individual IT components (such as IT systems and software) are either analyzed independently or excluded altogether. This approach offers greater granularity and allows for a more precise assessment of how each specific component affects net income. From an economic perspective, this is useful when it is important to understand, for example, the separate contribution of investments in buildings versus those in transportation. However, from a mathematical standpoint, this configuration may increase the risk of multicollinearity, as "Buildings" and "Vehicles" often grow in parallel, and "Operational Equipment" may also be strongly correlated with these components. As a result, the likelihood of obtaining unstable coefficient estimates in the multiple regression model increases (Table 4).

Table 3

First grouping of Non-Current Asset components to reduce the effect of multicollinearity (in thousands of UAH)

Year	Operational Equipment	Buildings and Vehicles	IT Systems	Software and Licenses
2018	294424	42114	61052	59159
2019	432457	3204	82444	143035
2020	1090173	3003	132333	135876
2021	1804768	8548	158051	153284
2022	3494143	475397	186336	159314
2023	4094820	1350918	168362	134590

Source: prepared by the authors using data from [8]

Table 4

Second grouping of Non-Current Asset components to reduce the Effect of multicollinearity (in thousands of UAH)

Year	Land and Buildings	Operational Equipment	Vehicles
2018	584	294424	41530
2019	753	432457	2451
2020	811	1090173	2192
2021	844	1804768	7704
2022	430800	3494143	44597
2023	1278146	4094820	72772

Source: prepared by the authors using data from [8]

The first grouping (with four variables: Operational Equipment, Buildings and Transport, IT Systems, and Software and Licenses) demonstrates a very high coefficient of determination ($R^2 \approx 0{,}987$), which implies a strong fit of the model to the available data. However, a deeper analysis of statistical indicators reveals several limitations. Most notably, the Significance F of this model exceeds the conventional 0,05 threshold (approximately 0,16–0,17), suggesting that at the standard significance level, we cannot confidently assert the overall statistical validity of the model. Additionally, the individual coefficients exhibit high p-values (none below 0,05), indicating that, given the current data volume, it is difficult to confirm any one variable as having a definitive effect on net income.

Meanwhile, the acutely high R^2 suggests that five out of six data points align "very well" with the regression surface, but this is likely driven by the small sample size: only six observations and four predictors [10].

The second grouping (with three variables: Land and Buildings, Operational Equipment, and Vehicles) yields similarly high R and R^2 values (above 0,97). However, in this case, the Significance F drops below 0,05 (approximately 0,038), meaning the model can be considered statistically significant overall. At the same time, the individual coefficients still fail to pass the 0,05 threshold in the t-tests, mainly due to the limited sample size and multicollinearity among non-current asset components. A positive aspect of this specification is that the intercept becomes statistically significant; however, interpreting its economic meaning remains challenging under such conditions [10].

Overall, both models should be regarded primarily as exploratory. Their value lies in demonstrating that even with a small data set, it is possible to build a multifactor regression and analyze the interaction between various components of non-current assets and net income.

Expanding the dataset by extending the time horizon or increasing the number of observations (e.g., through additional projects or organizational units) would enhance the reliability of estimating the influence of each investment category and reduce the sensitivity outliers, thereby improving the model robustness. In such a case, t-tests for the independent variables might yield low p-values, helping to identify which specific investments have a statistically significant impact on net income. Additionally, the risk of model overfitting would decrease, and the reliability of the conclusions would improve.

In constructing the regression model, centering of the independent variables was applied, i.e., subtracting the sample mean from each value. This technique is commonly used to reduce multicollinearity and improve the interpretability of the intercept. When predictor variables are highly correlated or have large absolute values, regression coefficients can become inflated, and the intercept may become statistically meaningless. Centering shifts variables closer to zero and helps to mitigate this issue [9].

In this case, after subtracting the means from each factor, several model indicators improved. Notably, the t-statistic and p-value for the intercept became more acceptable: whereas previously the p-value exceeded 0,05, making it statistically insignificant, it is now approximately 0,0024, indicating strong significance. This not only increases confidence in the model estimates but also facilitates the economic interpretation of the intercept, as the centered data reduce the influence of inter-variable correlations. This result demonstrates that even with a small sample size, mean-centering can meaningfully stabilize coefficient estimates and improve the statistical performance of a regression model.

The general form of the resulting multiple linear regression model is:

$$\begin{gathered} \textit{Net Income} = 24\ 134\ 162\ 833{,}33\ ₴ + 18\ 053{,}10 \cdot \\ \textit{Land and Buildings} + 4\ 185{,}85 \cdot \textit{Operational Equipment} + \\ +(-190\ 377{,}55) \cdot \textit{Vehicles}. \end{gathered} \tag{4}$$

By substituting the statistical values of the corresponding asset components into the regression equation, we obtain the modelled values, which are then compared with the actual net income figures of Nova Poshta LLC.

Furthermore, by analyzing the chart where the statistical (observed) and modelled values are overlaid, it becomes evident that the model captures the dynamics of Nova Poshta's net income with reasonable accuracy (Figure 5).

If a longer time series were available, the constructed multiple regression model would be better trained and possess greater predictive power for future net income values.

Conclusions. The analysis confirmed that purely time-series models (SARIMA, Holt) do not always perform reliably when applied to non-stationary series of net cash flow from investing activities and in the context of a limited sample size. After applying appropriate transformations (Dickey–Fuller test, Box-Cox transformation, seasonal decomposition), the forecasting accuracy improved to some range. However, external shocks and insufficient data continue to pose risks of significant forecasting errors. In contrast, incorporating lagged variables provided a more realistic representation: investments exhibit a delayed effect, contributing to asset growth not immediately, but after one or two years.

Table 5

Comparison of Actual and Modelled Net Income Values for Nova Poshta LLC

Year	Actual Net Income, UAH	Forecasted Net Income, UAH	Absolute Error, UAH	Relative Error, %
2018	10 515 739 000 ₴	9 932 223 684,17 ₴	583 515 315,83 ₴	-5,5%
2019	16 010 832 000 ₴	17 952 825 130,65 ₴	-1 941 993 130,65 ₴	12,1%
2020	20 621 616 000 ₴	20 756 283 353,34 ₴	-134 667 353,34 ₴	0,7%
2021	25 549 607 000 ₴	22 698 708 590,28 ₴	2 850 898 409,72 ₴	-11,2%
2022	28 461 964 000 ₴	30 508 626 732,26 ₴	-2 046 662 732,26 ₴	7,2%
2023	43 645 219 000 ₴	42 956 309 509,29 ₴	688 909 490,71 ₴	-1,6%

Source: prepared by the authors using data from [6; 7; 10]

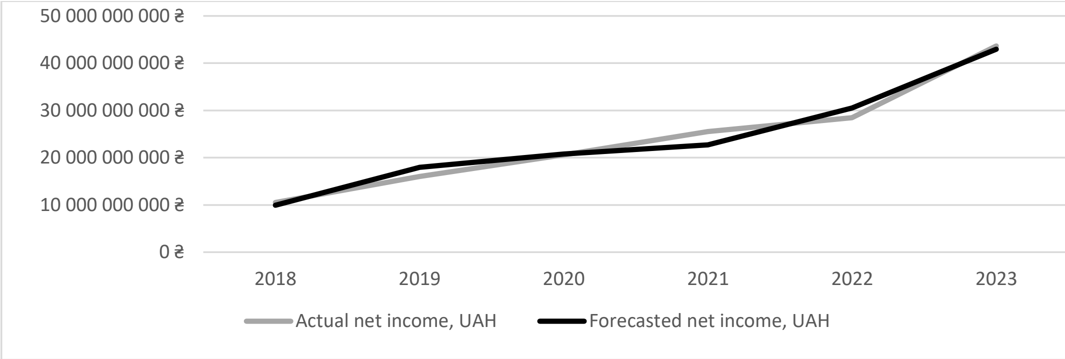

Fig. 5. Comparison Chart of Actual and Modelled Net Income Values for Nova Poshta LLC

Source: prepared by the authors based on [6; 7; 10]

The results of the study revealed a linear relationship between asset value and net income. These findings enabled, on the one hand, the extrapolation of forecasted asset values into equations for estimating future income and, on the other, the adjustment of managerial decisions in response to potential declines in asset utilization efficiency. Statistical validation (confidence intervals, t-tests, residual variance analysis) showed that model quality varied under different conditions. However, the refinement of modeling approaches, such as lagged regressions and alternative specifications, brought the results significantly closer to well-substantiated conclusions.

At the final stage, multiple linear regression models were applied using detailed categories of non-current assets. The presence of high multicollinearity, combined with limited data availability, complicated the individual assessment of each category's influence. The comparison of various specifications, such as grouping related asset types and applying mean-centering to variables, confirmed the effectiveness of these techniques. It showed that with a larger dataset and lower correlations between variables, multifactor modeling could be a powerful tool for income forecasting and investment planning.

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