MODELING THE DETERMINANTS OF CORPORATE CAPITAL INVESTMENT EFFICIENCY IN THE PRE-WAR AND WARTIME PERIODS

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Modern macroeconomic shocks and the ongoing war in Ukraine have severely disrupted investment activity in the real sector. According to industry analysts, the war has effectively wiped out the equivalent of five years of capital investment in the country's primary production subsector. In addition, more than 95% of total investment by production and resource-oriented enterprises is financed from internal funds [1], indicating limited access to external capital and making the optimization of firms' investment behavior especially pressing. The purpose of this study is to develop economic and mathematical models to assess and forecast how financial and economic determinants affect net revenue in production and resource-oriented enterprises of different scales under macroeconomic instability, and to formulate practical recommendations for improving the effectiveness of capital investment decisions.

To achieve this objective, a representative dataset of financial statements of Ukrainian production and resource-oriented enterprises was compiled for 2020 (the pre-war period) and 2023 (the period under martial law). The sample includes 12,294 enterprises for 2020 and 10,690 for 2023 [2]. All balance sheet and income statement indicators were converted into constant 2020 prices and transformed into relative structural ratios (standardized with respect to total assets) to ensure comparability over time. During initial data preparation (ETL), MS Excel Power Query was used to clean, reconcile, and aggregate raw data. To obtain homogeneous groups by scale, enterprises were ranked by total balance sheet assets and then split into three equal-sized groups (approximately the same number of firms in each), forming "large", "medium", and "small" clusters. This approach keeps the clusters comparable and analytically consistent. By contrast, dividing firms into clusters by equal asset-value intervals would be misleading: due to the strongly skewed distribution of assets, most firms would fall into the smallest interval, while the "large" cluster would contain only a few outliers ("titans"), biasing the results.

The core modeling tool was a multivariate regression specified in a double-log (log–log) form. Log-transforming both the dependent and independent variables makes the estimated coefficients interpretable as elasticities and typically mitigates heteroskedasticity while bringing distributions closer to normality. Given the high dimensionality of the model, multicollinearity among regressors was diagnosed and addressed using the Farrar–Glauber approach, which relies on a system of χ^2, F, and t criteria to evaluate correlation structure and detect problematic dependencies. Heteroskedasticity was tested using White's general test, which does not require a priori assumptions about the functional form of the error variance. Econometric computations were performed in Python using pandas, statsmodels, scikit-learn, and SciPy [2]. A full search over all possible combinations of explanatory variables was implemented – i.e., up to 2^n candidate specifications for each cluster and year—evaluating each model using R^2 and RMSE while simultaneously tracking the outcomes of diagnostic tests. For each specification, an integral quality measure (W-score) was computed as a weighted aggregation of model fit and diagnostic indicators, enabling the selection of the optimal models for each cluster-year setting:

$$W\_score_{index} = R^2\_train\_norm_{index} * R^2\_train\_weight + R^2\_test\_norm_{index} * R^2\_test\_weight + RMSE\_norm_{index} * RMSE\_weight + White\%\_norm_{index} * White\%\_weight + Chi2\%\_norm_{index} * Chi2\%\_weight + F\%\_norm_{index} * F\%\_weight, \quad (1)$$

where $R^2\_train\_norm_{index}$ – the normalized coefficient of determination (R^2) on the training set for the model with index *index*, $R^2\_test\_norm_{index}$ – the normalized coefficient of determination (R^2) on the test set for the model with index *index*, $RMSE\_norm_{index}$ – the normalized root mean square error (RMSE) for the model with index *index*, $White\%\_norm_{index}$ – the normalized White% statistic for the model with index *index*, $Chi2\%\_norm_{index}$ – the normalized Chi^2% statistic for the model with index *index*, $F\%\_norm_{index}$ – the normalized F% statistic for the model with index *index*.

Models with the highest W-scores were selected as optimal for each cluster and year, and their robustness was additionally validated using k-fold cross-validation. As a result, representative regression equations for net revenue were developed for small, medium, and large enterprises for 2020 and 2023, quantitatively capturing the impact of asset structure and financial ratios on performance outcomes. For instance, for the large-enterprise cluster in 2020, the estimated optimal multiplicative model takes the following form:

$$\textit{Net sales revenue} = 10{,}6777 * \textit{Number of employees}^{1{,}159} * \textit{Capital–labor ratio}^{0{,}7252} * \textit{Fixed assets}^{-0{,}5424} * \textit{Production capacity index of fixed assets}^{-0{,}001487} * \textit{Inventories (finished goods)}^{0{,}07433} * \textit{Accounts receivable for products, goods and services}^{0{,}06489} * \textit{Cash and cash equivalents}^{0{,}1011} * \textit{Accountspayable for goods, works and services}^{0{,}03206}. \quad (2)$$

The estimated coefficients can be interpreted as elasticities. In particular, a 1% increase in staff headcount is associated with an approximately 0.47% increase in net revenue, while the strongest effect among the determinants is observed for the index of productive capacity of fixed assets (elasticity of about 0,31) [2].

The regression results reveal substantial differences in investment behavior across enterprise size groups in the pre-war versus wartime periods. In 2020, net revenue growth among large production and resource-oriented enterprises was driven mainly by an expansion of labor resources (higher employment) and the maintenance of a balanced level of capital–labor intensity. In contrast, for small enterprises the key drivers were intensive modernization of fixed assets and the accumulation of sufficient liquidity buffers [2].

For the large-enterprise cluster in 2023, the estimated optimal multiplicative model takes the following form:

$$\textit{Net revenue from sales of products} = 10{,}5701 * \textit{Capital–labor ratio}^{-0{,}7642} * \textit{Production capacity index of fixed assets}^{0{,}7774} * \textit{Inventories (finished goods)}^{0{,}0984} * \textit{Cash and cash equivalents}^{0{,}1229}. \quad (3)$$

In the wartime environment of 2023, the focus shifted from extensive resource expansion toward improving the efficiency of resource utilization [2]. The productivity of existing fixed assets became a decisive factor, whereas excessive accumulation of low-efficiency tangible capital began to negatively affect financial outcomes. This change in the role of determinants reflects enterprises' adaptation to constrained access to labor and credit resources, as well as the growing importance of technological readiness of equipment and the availability of liquid reserves. Overall, across all clusters, the results indicate a gradual transition from an extensive growth model to an intensive one, which is consistent with contemporary perspectives on sustainable development in the agricultural sector [5].

A comparative analysis of the models confirmed that sensitivity to external shocks depends substantially on enterprise scale [1]. Large companies are able to partially offset workforce losses through faster technological upgrading and by maintaining a more optimal asset structure, whereas small enterprises are forced to shift toward targeted investments in critically important equipment and the accumulation of cash buffers. The developed economic and mathematical models formed the basis for practical recommendations aimed at improving investment efficiency under crisis conditions. For the wartime period, the most relevant measures include phased renewal of machinery and equipment, the use of leasing as an alternative to bank lending, optimization of asset structure, tighter control over accounts receivable, and maintaining sufficient liquidity – each of which supports stronger financial resilience [1]. Overall, combining a cluster-based approach with elasticity-oriented log–log models made it possible to identify how capital and liquidity factors affect performance across enterprises of different sizes, and the resulting conclusions and recommendations can be used to improve investment management in the primary production subsector.

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ARTIFICIAL INTELLIGENCE IN MODELING ECONOMIC PROCESSES

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In the context of a constantly changing market environment, artificial intelligence acts as a tool that fundamentally changes the approaches to analyzing and forecasting economic processes. The prospect of integrating modern machine learning algorithms into business models opens new horizons for increasing the accuracy, adaptability, and speed of decision-making, and optimizing their resources.

The use of methods such as machine learning, neural networks, deep learning, and evolutionary algorithms allows for modeling complex non-linear relationships, identifying hidden patterns and trends in economic data. We will systematize the directions of application for the main methodological approaches of artificial intelligence in the modeling of economic processes, which are currently gaining widespread use in fig. 1.

Among the technical aspects of applying artificial intelligence in modeling economic processes, several critical directions can be identified that highlight both methodological depth and practical applicability. First, the implementation of models on Python-based platforms such as TensorFlow, PyTorch, and Scikit-learn provides a flexible environment for constructing, training, and deploying machine learning algorithms, enabling researchers and practitioners to address complex economic problems with scalable solutions. Second, the application of Natural Language Processing (NLP)