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LEVERAGING DYNAMIC PRICING AS A COMPETITIVE ADVANTAGE FOR SUPPLIERS IN TENDER PROCESSES

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Annotation. *This study develops a dynamic pricing model to minimize unearned revenue in public procurement processes. The research focuses on suppliers' participation in public tenders to establish a fair lot price. By combining quantitative and qualitative methods, the study analyzes data from the public procurement portal, companies' financial statements, and insights from in-depth interviews. Using the Altman model, the analysis investigates how additional revenue from dynamic pricing impacts short-term (1–2 years) bankruptcy risks. Results indicate that optimal dynamic pricing-achieving an effect of 14–16% - can enhance a company's financial stability by reducing bankruptcy likelihood. The study also assesses suppliers' responsiveness to recommended prices, finding that suppliers raise their prices by approximately 55–60% in line with recommendations. Suppliers consider this approach ethical, as profit remains a key business objective. The research concludes with a linear model capable of achieving a 65% success rate in tenders and reducing unearned revenue by 83.9%.*

Keywords: *dynamic pricing, public procurement, unearned revenue, Altman model, financial stability*.

Main provisions. This study develops a dynamic pricing model to minimize unearned revenue in public procurement, significantly improving suppliers' financial stability. Results indicate that reallocating additional revenue from dynamic pricing into current assets and liabilities can enhance financial stability, with a 14-16% increase sufficient to reduce bankruptcy risks based on Altman's Z-score model. Suppliers demonstrated responsiveness to recommended prices, with adjustments aligning to recommendations by 55-60%, suggesting the effectiveness and ethical acceptance of dynamic pricing strategies. The proposed linear model reduces unearned revenue by 83.9% and increases the success rate in tenders to 65%, showcasing its practical application in optimizing procurement strategies. Insights from interviews reinforce the impact of knowledge on suppliers' pricing behavior, emphasizing the value of strategic awareness in achieving financial resilience.

Introduction. The number of companies going bankrupt in Kazakhstan has been increasing for three consecutive years, particularly affecting small and medium-sized enterprises (SMEs). Nearly 35% of these companies go bankrupt within their first two years

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of operation, indicating significant issues with the financial stability in the business sector. Effective participation in public procurement can significantly enhance a supplier's financial stability. In 2022 alone, suppliers in Kazakhstan missed out on 64.5 billion tenge in potential profits from public procurement. This amount could sustain at least 70 medium-sized or 500+ small companies for another year without additional revenues. Furthermore, this missed profit has increased yearly, with a growth rate of 1.48 times from 2022 to 2023.

The missed revenue for suppliers in 2022 and 2023 is considerable. In 2022, the planned procurement amount was 1,662,275,344,077 tenge, while the actual contract amount was 1,415,363,942,604 tenge, resulting in 64,551,556,429 tenge of unearned revenue. In 2023, the planned amount increased to 2,823,137,063,357 tenge, with actual contracts amounting to 2,417,041,271,168 tenge, leading to 94,937,814,644 tenge in unearned revenue.

Despite the overall unearned revenue being 64.5 billion tenge, representing only 4.56% of the total completed procurement amount, the unearned revenue in lots valued up to 50,000 tenge constitutes 51,93%, up to 100,000 tenge – 28,25%, and up to 2 million tenge – 11,60%.

Aim of the study is to explore these issues in greater depth and identify potential solutions to enhance the financial stability of companies. Effective participation in public procurements could be vital to achieving this goal. Our objectives are:

- to identify the impact of dynamic pricing on financial stability of companies;
- to analyze the perception level of suppliers towards recommended price;
- to identify the significance of the model towards unearned revenue;
- to develop recommendations for banks to integrate dynamic pricing models into the current process of issuing supplier guarantees and usage guidelines.

Dynamic pricing is crucial for suppliers to gain a competitive advantage in tenders and achieve financial stability. Based on our aim and objectives, we identified the following hypothesis to test our ideas of dynamic pricing:

H0: It is not feasible to influence a company's financial stability within a 1-2 year timeframe by utilizing dynamic pricing and appropriately allocating the acquired funds.

H1: It is feasible to influence a company's financial stability within a 1-2 year timeframe by utilizing dynamic pricing and appropriately allocating the acquired funds.

A more financially stable company has a better chance of avoiding bankruptcy, a critical issue in the current Kazakhstani market. To test this hypothesis, we will use computer modeling and Altman's Z-score model with modifications.

Literature review. In the intricate and evolving landscape of public procurement, the necessity for a comprehensive understanding of its dynamics and the factors influencing its strategies cannot be overstated. This part of the project delves into the multifaceted realm of public procurement, highlighting the significance of a literature review, the implications of dynamic pricing, and the critical insights provided by the theory of companies. Firstly, we explore the benefits of literature review in public procurement, emphasizing its role in synthesizing existing knowledge and identifying gaps for future research, thereby enhancing the efficiency and effectiveness of procurement practices. Secondly, we examine the impact of dynamic pricing on public procurement strategies, a phenomenon that introduces both challenges and opportunities in achieving value for money and ensuring fair competition. Lastly, we analyze the role of the theory of companies in public procurement practices, which offers a foundational understanding of the behavior and strategies of companies that engage in public procurement. Through this holistic approach, this essay aims to shed light on the complexities of public procurement, advocating for informed strategies that can adapt to changing market conditions and regulatory environments, ultimately contributing to more transparent, competitive, and efficient procurement systems.

Exploring the intricate landscape of public procurement reveals the indispensable role literature reviews play in enhancing the effectiveness and transparency of procurement processes. According to Adjei-Bamfo, Maloreh-Nyamekye, and their colleagues [1], a comprehensive review of existing literature on public procurement identifies critical gaps and benchmarks that can significantly improve procurement practices. This scholarly endeavor not only highlights the current state of procurement strategies but also provides a solid foundation for the development of innovative approaches aimed at optimizing resource allocation and conservation. By meticulously analyzing the findings from various studies, policymakers and procurement officials can draw upon evidence-based strategies to foster sustainable procurement practices that align with global sustainability goals. Furthermore, literature reviews serve as a crucial tool in advocating for policy reforms by showcasing the tangible benefits of adopting efficient and transparent procurement mechanisms. As such, the act of conducting a literature review transcends mere academic exercise; it becomes a pivotal mechanism for instigating positive change within the realm of public procurement, ensuring that resources are utilized in a manner that maximizes social, economic, and environmental benefits.

Dynamic pricing strategies have significantly impacted public procurement processes, introducing both challenges and opportunities for government entities. According to İ.G. Özbilgin and M.Y. Imamoğlu in their 2011 study published in Procedia Computer Science by Elsevier, dynamic pricing can greatly influence the efficiency and effectiveness of public procurement by allowing for more flexible and responsive pricing mechanisms [2]. This flexibility can lead to cost savings for public entities, as they can take advantage of market price fluctuations to purchase goods and services at lower costs. However, the adoption of dynamic pricing also requires a sophisticated understanding of market trends and a high level of coordination within procurement strategies to effectively leverage these price fluctuations without compromising the quality or timely delivery of goods and services. As Özbilgin and Imamoğlu highlight [2], the integration of dynamic pricing mechanisms into public procurement practices necessitates the development of advanced analytical tools and procurement policies that can accommodate the increased complexity and risk associated with market-driven pricing models. This evolution in procurement strategies underscores the need for public sector organizations to adapt and innovate in order to maximize the benefits of dynamic pricing while mitigating its potential drawbacks.

The integration of theoretical frameworks in the examination of public procurement practices provides a nuanced understanding of the complexities and dynamics involved. As highlighted by Malacina et al., the adoption of various theories of companies, such as agency theory, transaction cost economics, and resource-based views, offers invaluable insights into the decision-making processes, efficiency, and effectiveness of public procurement [3]. Agency theory, for instance, sheds light on the principal-agent dynamics, where public entities (principals) delegate procurement tasks to suppliers (agents), potentially leading to issues of information asymmetry and moral hazard. Furthermore, transaction cost economics provides a framework for understanding the costs associated with making and enforcing contracts in public procurement, emphasizing the importance of minimizing these costs for enhanced procurement performance. Lastly, the resource-based view assists in identifying the strategic resources and capabilities that public entities can leverage through procurement to achieve competitive advantage. Through the lens of these theories, Malacina et al. articulate that a theoretical grounding not only facilitates a deeper comprehension of public procurement mechanisms but also enables the identification of strategies to optimize procurement outcomes [3]. This theoretical approach underscores the significance of aligning procurement practices with broader organizational goals and strategies, thereby contributing to the overall efficiency and effectiveness of public sector operations.

Altman model. To achieve aim and test our hypothesis we used the Altman model, as famous techniques implementing by global consulting firms. The Altman model from 1968 [4] for public manufacturing companies and its modifications from 1983 and 1995 for public and non-manufacturing companies was chosen to assess the financial stability of companies. This model has been widely recognized for its accuracy and applicability across various sizes and industries.

The Altman model is simple yet effective, incorporating only five independent variables:

$$X1 = \frac{\text{Working Capital}}{\text{Total Assets}} \qquad 1)$$

$$X2 = \frac{\text{Retained Earnings}}{\text{Total Assets}} \qquad 2)$$

$$X3 = \frac{\text{Earnings Before Income Tax (EBIT)}}{\text{Total Assets}} \qquad 3)$$

$$X4 = \frac{\text{Equity Value}}{\text{Total Liabilities}} \qquad 4)$$

$$X5 = \frac{\text{Sales}}{\text{Total Assets}} \qquad 5)$$

For our calculations, we use standard formulas based on IFRS. The general form of the Altman equation is:

$$Z - \text{score} = A * X1 + B * X2 + C * X3 + D * X4 + E * X5 \qquad (6)$$

The Z-score serves as an indicator of a company's probability of bankruptcy and is interpreted as follows:

- safe zone ($Z > 2.99$): the company is considered financially stable with a low probability of bankruptcy.
- grey zone ($1.81 < Z < 2.99$): the company's condition raises some concerns, with uncertainty regarding its financial future.
- distress zone ($Z < 1.81$): the company is at high risk of bankruptcy within the next two years.

These threshold values, however, vary depending on whether the company is public or private and whether it is manufacturing or non-manufacturing, as shown in Table 1. The coefficients for the predictors (A, B, C, D, E) also change accordingly, as shown in the Table 2.

Table 1 - Z-score boundaries for different types of companies

	public		private	
	grey	safe	grey	safe
manufacturing	1,81	2,99	1,23	2,90
non-manufacturing			1,10	2,60
Note: prepared by the authors				

Table 2 - Independent variables coefficients of the Altman model

		A	B	C	D	E
public	manufacturing	1,200	1,400	3,3000	0,6000	0,999
	non-manufacturing					
private	manufacturing	0,717	0,847	3,107	0,420	0,998
	non-manufacturing	6,560	3,260	6,720	1,050	0,000
Note: prepared by the authors						

Even large firms such as McKinsey use the Altman model and emphasize its relevance, especially under conditions of uncertainty and crisis [5].To enhance our understanding of how variations in the Altman model's independent variables influence the Z-score, we developed a directed weighted dependency graph [6]. In these graphs, entities or variables are represented as nodes, while directed, weighted edges illustrate dependencies between them, allowing visualization of both the direction and intensity of their interactions. Adjusting the Z-score in response to changes in independent variable values involves a complex process. Thus, we applied a brute-force approach to bypass manual calculations. This method leverages computational power to explore all possible solutions; however, as complexity rises, this can lead to combinatorial explosion, making the process both resource-intensive and time-consuming. Yet, given the relatively small scale of our dependency graph, the brute-force method proved efficient within our timeframe. For program validation, we employed mutation testing [7], attaining a mutation score of 100%. Mutation testing involves introducing small modifications (mutations) to parts of the source code, examining the effects on automated unit tests. When tests pass despite code mutations, it may suggest gaps in test coverage or test limitations. The Mutation Score Indicator (MSI) quantifies test suite effectiveness. Studies, such as those by Just et al., suggest mutation testing often yields superior results to unit tests.

Despite brute-force efficiency in our study, we incorporated lower and upper bounds to enhance real-world applicability. Evidence from existing research indicates that dynamic pricing can increase revenue by up to 25% [8]. Accordingly, we established bounds of 0% (lower) and 25% (upper) for our brute-force algorithm.

To validate the second hypothesis, we conducted structured interviews with suppliers, guided by the funnel approach [9]. This method progresses through five question types in the following sequence:

- Screening questions – to assess respondent suitability;
- Open questions – to obtain general information about participants;
- Probing questions – to explore details in-depth;
- Fact-finding questions – to identify specific facts and needs;
- Confirmatory questions – to validate previously identified facts or needs.

To determine the optimal number of interviews, we employed data saturation methods [10].

After reviewing insights on the illusion of predictability [11], we eliminated future-oriented questions, focusing instead on participants' past experiences. We also simplified questions with multiple sub-questions, taking into account the edge effect [12], which suggests that people often recall items at the beginning and end of a sequence.

All data presented in this study and used for testing the second hypothesis stems directly from actual responses obtained during interviews. Recognizing the role of causal attribution, responses that were ambiguous were either excluded or clarified through follow-up questions.

Methods and Materials. Our research design employs both qualitative and quantitative methodologies. The sample includes 48,000 completed lots and 2,000 suppliers. In-depth interviews were conducted with 20 suppliers, using a structure of two screening questions, five open questions, and up to 27 closed questions.

To validate our model's results, we applied several data analysis techniques:

- The Altman model and computer modeling to assess suppliers' financial stability;
- In-depth interviews, guided by the funnel approach;
- Silhouette analysis through K-Means clustering;
- Regression analysis using metrics such as AIC/BIC, Durbin-Watson, F-statistic, R/Adjusted R square, and VIF.

Our study focuses on suppliers from small, medium, and large enterprises in Kazakhstan involved in public procurement. Primary data was sourced from the public procurement portal, which enables numerous procurements through a transparent, automated system aimed at preventing collusion and corruption.

For the first hypothesis, we required data on companies participating in government procurement, including their activity levels and general financial information. To identify active companies, we developed scripts to extract data from the government procurement portal for 2022. This extraction yielded over 100,000 lots, after which we excluded unsuccessful procurements and those with fewer than two suppliers, setting a minimum price threshold of 20,000. The result was a dataset of 44,468 lots with over 2,000 suppliers. We used GraphQL and Python to manage data collection effectively, utilizing these tools to obtain a significant amount of information.

For the second hypothesis, we collected data directly from suppliers via qualitative interviews. Each interview included two screening questions, five open-ended questions, and up to 27 closed-ended questions.

The Altman model was used to assess companies' financial stability in relation to the first hypothesis. This investigation required us to address the following:

- Can additional revenue generated from dynamic pricing enhance a company’s financial stability?
- If so, what is the minimum dynamic pricing threshold that positively impacts resilience and lowers bankruptcy risk?
- Is this threshold within a manageable range influenced by dynamic pricing?

Once interdependencies were identified and the graph constructed, we encoded the data model and created a function to generate values (k, n, m) within a specified range. For each campaign, the dynamic pricing adjustments, ranging from 0% to 25%, triggered corresponding actions in the analysis.

1. Calculate the delta free cash flow:

$$\text{delta free cash flow} = \text{company sales} * \left(\frac{\text{increase rate}}{100}\right) \quad (7)$$

2. For each value (k, n, m) calculate df(n), df(k) and df(m) according to the formula:

$$\text{df(n)} = \text{delta free cash flow} * \frac{n}{100} \quad (8)$$

$$\text{df(k)} = \text{delta free cash flow} * \frac{k}{100} \quad (9)$$

$$\text{df(m)} = \text{delta free cash flow} * \frac{m}{100} \quad (10)$$

3. Update values in the data model.
a. Increase EBIT by df(n).
b. Increase current assets by df(k).
c. Decrease current liabilities by df(m).
d. Other values will be recalculated dynamically based on the data model described above.
4. Calculate the Z-score and save data for further analysis and detailed study.

If, after analysis, we find an increase rate (in percentage) for most of the sample within the range up to 25% that, according to the Z-score, makes the suppliers more financially stable, then the first hypothesis can be considered confirmed. It means that using dynamic pricing and appropriately allocated funds can make suppliers more financially stable.

The following interview questions were designed to gather insights on supplier perceptions:

(Screening question) – Are you currently participating in procurement as a supplier?

(Screening question) – How long and to what extent have you been involved in procurement activities?

Could you describe your experience in procurement as a supplier? Additionally, we would like to capture insights based on the following:

What types of goods and services do you provide?

How seamless has the procurement process been for you?

What criteria do you consider when selecting which procurements or lots to participate in?

Which factors influence your decision when setting a price for your goods or services?

What is the highest-value procurement in which you have participated, and what was its approximate value? Please describe this procurement and its specifics.

There is an assumptions of pre-determined budget. Companies have submitted a proposal as a supplier with a specific price. However, companies recently discovered that competitors provided similar goods - possibly to the same customer at a different price.

As support material for the seventh question, we used the price adjustment data shown in Table 3.

Table 3 – Supplier price adjustments based on previous winning prices

Planned lot amount	Price you offered / plan to offer	Previous winning price by a competitor for a similar lot	New price you will offer
69 200	34 200	51 900	
106 800	75 000	90 000	
203 600	146 000	170 000	
304 200	224 000	251 000	
391 700	276 000	320 000	
454 400	340 000	380 000	
609 400	434 000	493 000	
872 600	622 000	707 000	
1 164 600	868 000	970 000	
1 501 700	1 122 000	1 249 000	
1 720 400	1 343 000	1 465 000	
1 947 800	1 532 000	1 673 000	
2 423 100	1 821 000	2 015 000	
2 914 700	2 249 000	2 461 000	
3 585 000	2 742 000	2 991 000	
4 553 700	3 483 000	3 800 000	
5 850 200	4 487 000	4 862 000	
9 360 300	7 155 000	7 745 000	
18 790 200	14 306 000	15 447 000	
28 736 100	22 314 000	23 887 000	
Note: prepared by the authors			

For each interview, we calculated the amount of new information in percentage relative to all information conducted during the interview. This increased with each interview, especially rapidly at the beginning and very slowly towards the final interviews. Given the limited number of available suppliers, we stopped at a data saturation level of 87.25%.

After conducting the interviews and reaching an acceptable level of saturation, we shifted our focus to a more detailed analysis of our data. Our primary goal was to assess whether the knowledge of their probability of winning with a given price offer influences the price suppliers propose for a lot, procurement.

By obtaining the perception level, we estimate the potential profit from unearned revenue that we could realistically expect if the model performs well. Incorporating the results into the model, the formula for further evaluating the model will be based on how much from unearned revenue our model helps us earn:

$$\text{could earn} = \text{unearned revenue} * \text{model efficiency }\% \\ * \text{perception level }\% \tag{11}$$

If most suppliers decide to increase their prices following our recommendations, it will indicate that through awareness and recommendations, suppliers can independently positively impact their financial stability. Furthermore, integrating the recommended price into existing products, such as obtaining a bank guarantee, could also benefit the bank, typically by 1.5%-2%. This percentage might seem small, but considering an unearned revenue of 64 billion, these two percent translate to 1.28 billion, a significant amount.

Our main objective in the second hypothesis is to identify a phenomenon in which knowledge of the recommended price positively impacts the supplier. If we find that phenomenon, the second hypothesis will be confirmed.

Results and Discussion. After testing two hypotheses, it is time to build a model recommending prices to maximize the profit-to-win ratio.

We chose $\mathrm{Y} = \text{second lowest price} - 1$ as the dependent variable. The rationale is simple – by raising our price to just below the second-lowest bid, we can still win the tender while maximizing our profit.

For potential independent variables, we extracted categorical, textual, binary and numerical variables, including:

- Initial customer price – the maximum price the customer is willing to pay for a product, service, or work;
- Winner price (lowest price) – the best bid;
- Second price – the second-best bid;
- Quantity – the quantity of items in lot;
- Union lots – united lot indicator;
- Dumping – dumping indicator;
- Psd sign – indicator of work type (1 for work with feasibility study, 2 for development of feasibility study);
- Consulting service indicator;
- Is light industry – procurement of light and furniture industry;
- Is construction work – procurement characteristics of construction and installation works;
- For disabled person – procurement among organizations of disabled people;
- Total sum – total advertisement cost;
- Count lots – number of lots in the advertisement;
- Start date – tender start date;
- End date – tender end date;
- Publish date – tender publication date;
- Kato – delivery address;
- Ref trade methods name – planned procurement method;
- Ref subject type name – type of procurement item;
- Ref type trade name – type of procurement (first, repeat).

We selectively built our model without incorporating all available variables, as not all are appropriate for use. The analytical process was proceed as follows:

1. Conduct a preliminary review of each variable to determine which to retain and which to exclude.
2. Transform each variable into a format compatible with algorithmic application, ensuring categorical and textual variables are appropriately prepared.
3. Execute silhouette analysis and apply clustering to the dataset.
4. Construct a model tailored to each cluster.

After an initial study, we decided to exclude the features described in Table 4.

Table 4 - Excluded fields from the model

Field	*Reason*
Is Light Industry	The field wasn’t populated. Only 16 records had any value, all of which were 0
Is Construction Work	Data in this field didn’t match official documentation. Although only values 0 and 1 are permissible, other values like 4 were present, which we couldn’t interpret. There were 16 records with this field filled
For Disable Person	The field wasn’t populated as of 2022, with updates starting only in 2023
Note: prepared by the authors	

Encoding categorical variables is essential, as algorithms cannot process text directly. We opted for one-hot encoding to prepare these columns in our dataset. This approach creates a binary column for each category, where each observation is assigned a 1 in the column representing its category and 0 in all other columns. This method is particularly effective for nominal categorical variables that lack an inherent order, as is the case with our data.

As observed, we can safely remove one of the new features without affecting the model’s structure. In fact, this step is recommended, as "extra" features can introduce issues like overfitting, multicollinearity, or potentially disrupt model stability. Thus, omitting the feature associated with one of the categories is beneficial. In our case, for example, the final matrix for the subject type variable would appear as shown in Figure 1.

	lot_id	ref_subject_type_name_ru_product	ref_subject_type_name_ru_service
0	17249802	1	0
1	17249803	1	0
2	17249804	1	0
3	17230427	0	0
4	17230431	0	0
...	...	...	...
44463	23238882	0	0
44464	23239219	0	1
44465	23246945	0	0
44466	23275664	0	0
44467	23275673	0	0

Figure 1 - Independent variables after one-hot encoding and optimization.

Note: prepared by the authors

After obtaining tender duration variable and examining our data carefully, we discovered a few anomalies – some tender durations were negative. Since the number of such records was small (only 17), we decided to exclude these records from our dataset.

Having completed the preliminary transformations of the critical variables, we determined the number of clusters in our data to understand how many models we would need to build. To do this, we clustered our data using the K-Means algorithm and measured the silhouette score for each cluster.

Since the optimal number of clusters is determined by trial, we used a range of values from 2 to 100 and passed this as an input parameter to the K-Means algorithm. We utilized the Python programming language for all of this.

One of the best scores we achieved was 0.98 with 2 clusters. As the number of clusters increased, the silhouette scores began to fall, as shown in Table 5.

Table 5 - Sharp decrease in average silhouette score with an increased number of clusters

Number of clusters	**average silhouette score**	**silhouette scores per sample**
2	0,9847	0,986; 0,275
4	0,9506	0,96; x3 ~ 0,31
8	0,9354	0,947; x2 ~ 0,20; x5 ~ 0,5
16	0,7593	x2 ~ 0,83; 0,71; 0,20 – 0,51
32	0,6502	0,26 – 0,95
64	0,5805	0,02 – 0,94
Note: prepared by the authors		

Here, despite the high average score, clusters were imbalanced, with silhouette scores for some samples being less than 0,20. So unbalanced that some clusters are not even visible on the graph, as shown in Figure 2.

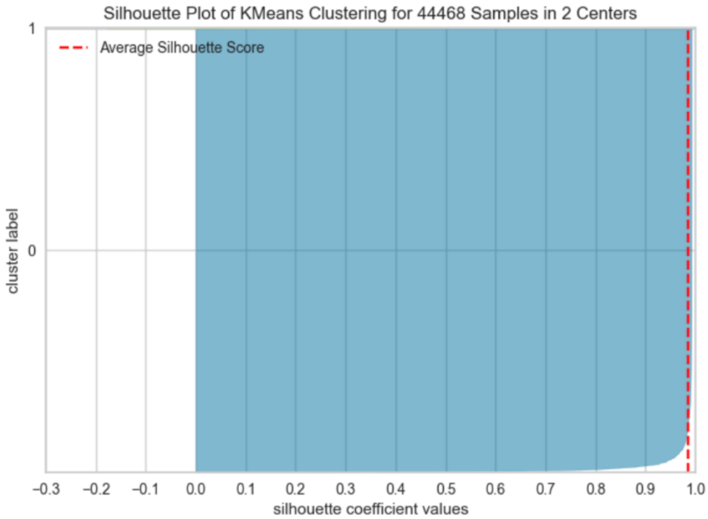

Figure 2 - Silhouette plot in 2 centers

Note: prepared by the authors

The same is true even if we divide our dataset into a bigger number of clusters, as you can see from Figure 3.

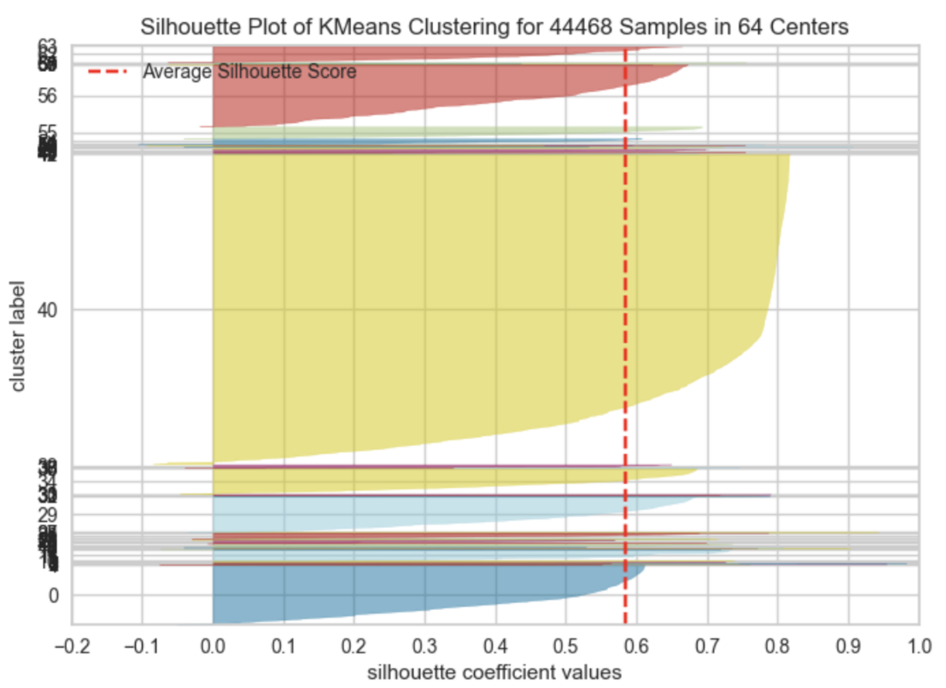

Figure 3 - Silhouette plot in 64 centers

Note: prepared by the authors

Overall, imbalanced clusters negatively impact silhouette analysis because of:

- *skewed average score* - the silhouette score measures how similar an object is to its cluster (cohesion) compared to other clusters (separation). in imbalanced clusters, the score can be misleading because smaller clusters may have artificially high silhouette scores due to fewer points and less variance, while larger clusters may have lower scores due to more points and higher variance;
- *bias towards larger clusters* – larger clusters can dominate the silhouette score, masking the performance of smaller clusters. this makes assessing the clustering quality for smaller clusters complex since the larger clusters heavily influence the overall score. and we see precisely that behavior in our table above.

Considering the above information, it became clear that clustering our data and building a model for each sample is unnecessary. Instead, focusing on building one model for the entire dataset would be better. Therefore, we continue analyzing the variables and will build a single model. In addition to the variables, we have already partially prepared, we were also concerned with other variables related to costs:

- total advertisement sum;
- initial customer price;
- winner price (lowest price);
- second price (second lowest price).

Referring to the properties of linear regression, it is essential to note that this algorithm performs well and produces representative results when the data follows a normal distribution. While it is not prohibited to perform regression on variables that do not follow a normal distribution, the variance of the errors (residuals) should be constant across all levels of the independent variables. If the independent variables are not normally distributed, it can sometimes indicate heteroscedasticity (non-constant variance of errors), which is detrimental to our model because it can result in:

- inefficiency of estimators - one of the critical assumptions of ols is that the residuals have constant variance (homoscedasticity). when heteroscedasticity is present, the ols estimators are still unbiased but no longer the best linear unbiased estimators (blue). this means that the ols estimators do not have the minimum variance among all unbiased estimators, leading to inefficiency;
- another significant implication of heteroscedasticity is the potential for biased standard errors. this directly affects hypothesis testing and the construction of confidence intervals, as these procedures rely on accurate standard error estimates. this highlights the importance of addressing heteroscedasticity to ensure the validity of our model's results.

Normalization can help address this issue, and we tested several methods to find the most suitable one. Square root and cube root transformations were not appropriate due to the extreme right-skewness of the data. Ultimately,we chose between the Box-Cox transformation and the logarithmic transformation, opting for the logarithmic transformation. Primarily, the logarithmic function is more straightforward and allows for easy recovery of the original values. In other words, log transformation is straightforward to implement and interpret, and it helped us. Thus, Box-Cox was not necessary

After transformation, we get a much better distribution, as shown in Figure 4.

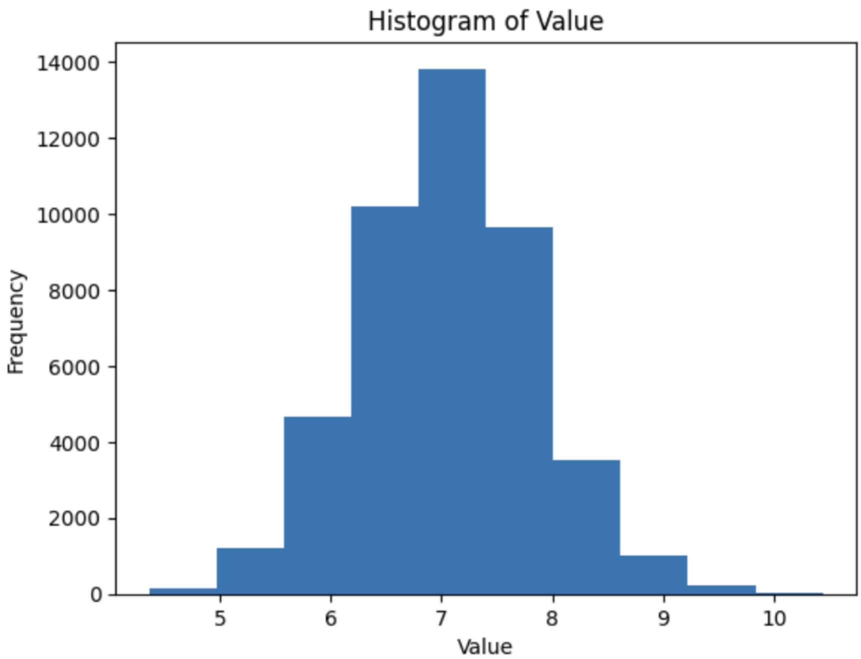

Figure 4 - Pricing variables after normalization

Note: prepared by the authors

The next step was to fit and predict the model using the OLS method for optimization and hyperparameter tuning. The modeling showed that not all variables were statistically significant. To determine significance, we use p-values and make the following assumptions:

- If the p-value is less than 0.05, the coefficient is considered statistically significant at the 95% confidence level;

- If the p-value is greater than 0.05, the coefficient is not statistically significant at the 95% confidence level, suggesting that the variable may not contribute meaningfully to the model.

Regarding other metrics by which we evaluated the model, they are presented in Table 6.

Table 6 - Metrics used to evaluate model

Metric	*Value*	*Interpretation*
Prob (F-statistic)	0.00	indicates that the overall model is statistically significant. At least one of the predictors is significantly related to the dependent variable
R-squared	0.983	indicates that 98.3% of the variance in the dependent variable is explained by the independent variables included in the model. Very good fit of the model to the data
Adjusted R-squared	0.983	value being close to the R-squared indicates that the included predictors are relevant and contribute to the model
Durbin-Watson	1.975	Close to 2, indicating no significant autocorrelation
Skew	-0.894	residuals are left-skewed, meaning there are more extreme values on the left side of the distribution than on the right
AIC/BIC	-82 870	In comparison with other built model very good fit model
Note: prepared by the authors		

Hypotheses Testing.

Hypothesis 1: Feasibility of Influencing Financial Stability through Dynamic Pricing.

To test this hypothesis, we used the Altman model, a well-recognized method for assessing financial stability. The model's five variables - working capital, retained earnings, EBIT, equity value, and sales - were analyzed using standard formulas based on IFRS. The goal was to determine if additional revenue from dynamic pricing could increase a company's financial stability.

Our approach involved allocating surplus free cash flow to current assets (cash and non-cash) and repaying current liabilities. We used a brute force to calculate the minimum percentage increase in revenue required to move companies to safer Z-score zones.

Hypothesis 2: Impact of Recommended Prices on Suppliers' Price Offers.

We conducted interviews with suppliers to assess whether the knowledge of their probability of winning with a given price offer influences the prices they propose. The interviews included screening, open and closed questions, focusing on suppliers with procurement experience of at least three years. The interviews aimed to capture the suppliers' reactions to new information about competitors' prices and subsequent price adjustment

After testing the hypotheses, we proceeded to build a model that recommends prices to maximize the profit-to-win ratio. The dependent variable chosen was Y (second lowest price - 1), with various independent variables including initial customer price, winner price, second price, quantity, and others. We performed a preliminary analysis to decide which variables to retain and transform into a format suitable for algorithms.

We conducted silhouette analysis and K-Means clustering to determine the number of clusters in our data, finding that two clusters provided the best scores. However, we built one model for the entire dataset due to imbalanced clusters. The regression analysis employed metrics like R^2, adjusted R^2, AIC, BIC, and the F-statistic to compare and evaluate the models.

Dynamic Pricing's Impact on Financial Stability.

Dynamic pricing could influence a company's financial stability positively. The Altman model analysis showed that reallocating free cash flow from dynamic pricing into current assets and liabilities improved the Z-scores of companies, thereby reducing their risk of bankruptcy. In most cases, the threshold increase rate for dynamic pricing proved sufficient at a level of 14-16% to move companies from the high-risk zone to the grey area, and from the grey zone to the safe zone.

Additional observations included:

- Keeping the delta free cash flow in cash or cash equivalents yielded the best effects.
- Allocating as much as possible to current assets (non-cash) like inventories proved to be one of the worst decisions for companies in highly vulnerable positions.
- Already financially stable companies benefit the most from additional income gained through dynamic pricing.

Suppliers' Price Adjustment Behavior.

The interview results confirmed the second hypothesis. A positive correlation exists between the recommended price and the supplier's price offer. The efficiency of the recommended price in terms of suppliers' perception was approximately 55-60%, with a data representativeness of 87.85%. Most suppliers consider price revisions and increases to be ethical. Additionally, it was found that the relative difference is more important for suppliers than the absolute difference. This indicates that through awareness and recommendations, suppliers can independently positively impact their financial stability and align with the objectives of the dynamic pricing model.

The regression model built using the entire dataset provided a robust mechanism for predicting optimal price recommendations. The analysis showed that the model's predictions aligned well with actual procurement outcomes, validating the effectiveness of our approach in real-world scenarios. Notably, the model indicated that suppliers' win rates could increase to 65% with the implementation of recommended prices, showcasing a significant improvement in competitive positioning. Meanwhile, the decrease in unearned revenue should be about 83,9% if we do not consider the perception level.

The analysis confirmed the feasibility of using dynamic pricing to enhance financial stability and demonstrated the impact of recommended prices on suppliers' pricing strategies. The regression model developed provides a practical tool for optimizing price offers in procurement processes, significantly reducing unearned revenue and increasing win rates.

The research conducted aimed to explore the impact of dynamic pricing on financial stability and the effect of recommended prices on supplier price offers in the context of public procurement in Kazakhstan. The study tested two primary hypotheses using qualitative and quantitative methods, including interviews with suppliers and data analysis from the public procurement portal.

Hypothesis 1: The feasibility of influencing financial stability through dynamic pricing

The Altman model analysis confirmed that dynamic pricing can positively influence a company's financial stability. Specifically, reallocating free cash flow from dynamic pricing into current assets and liabilities improved Z-scores, reducing the risk of bankruptcy. It was found that a threshold increase rate of 14-16% in dynamic pricing was sufficient to move companies out of the high-risk zone into the grey or safe zones. Additionally, already financially stable companies benefitted the most from dynamic pricing.

Hypothesis 2: The impact of recommended prices on suppliers' price offers.

Interviews with suppliers confirmed a positive correlation between the recommended price and the suppliers’ price offers. The efficiency of the recommended price in terms of suppliers' perception was approximately 55-60%, with a data representativeness of 87.85%. Most suppliers considered price revisions and increases to be ethical. The study also revealed that relative price differences were more important to suppliers than absolute differences.

The model validation showed that the regression model developed was effective in predicting optimal price recommendations, aligning well with actual procurement outcomes.

Conclusion. The results of this study confirm the initial hypotheses to a significant extent. Dynamic pricing has been shown to enhance the financial stability of companies engaged in public procurement, mainly through the optimal allocation of additional revenue into current assets and repayment of current liabilities. This finding aligns with the expectations and suggests that strategic financial management, aided by dynamic pricing, can mitigate bankruptcy risks and improve financial health. Moreover, the positive correlation between recommended prices and supplier price offers indicates that suppliers are responsive to strategic pricing recommendations. This responsiveness can be leveraged to optimize procurement strategies, ensuring competitive yet profitable bids. Suppliers' ethical acceptance of price adjustments also supports the recommended pricing model's practical applicability.

The model's effectiveness in reducing unearned revenue is an important aspect to highlight. With a model quality of 83,9%, the model helped to decrease unearned revenue by 83,9%. When combined with the perception level of 55%, the overall reduction in unearned revenue can be calculated as 83,9% * 55% = 46.2%. Thus, implementing the model will help decrease unearned revenue by approximately 46.2%, demonstrating a significant improvement in financial outcomes. In conclusion, this study provides robust evidence supporting the strategic use of dynamic pricing and recommended pricing in public procurement to enhance financial stability and supplier competitiveness. These findings contribute to the broader understanding of procurement strategies and offer practical implications for policymakers and managers aiming to optimize public procurement processes. The demonstrated ability to reduce unearned revenue by approximately 46.2% underscores the practical value of the proposed model. Additionally, the potential increase in suppliers' win rates to 65% highlights the significant competitive advantage achievable through the implementation of the model.

The results and findings of the project are providing solutions that benefit not only suppliers but also other stakeholders, such as: banks - by earning more from issued guarantees, as higher lot values generate more income through interest; government - by helping to combat dumping practices.

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ТЕНДЕРЛІК ПРОЦЕСТЕРДЕГІ ЖЕТКІЗУШІЛЕР ҮШІН БӘСЕКЕЛЕСТІК АРТЫҚШЫЛЫҚ РЕТІНДЕ ДИНАМИКАЛЫҚ БАҒА БЕЛГІЛЕУДІ ПАЙДАЛАНУ

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Түйін. *Бұл зерттеу мемлекеттік сатып алуларда алынбаған табыстың үлесін азайту үшін динамикалық баға белгілеу моделін жасауға бағытталған. Зерттеу нысаны – лоттың әділ бағасын анықтау үшін мемлекеттік сатып алуларға жеткізушілердің қатысу процесі. Зерттеу мемлекеттік сатып алу порталының деректерін, компаниялардың қаржылық есептілігін және тереңдетілген сұхбаттарды қамтитын сандық және сапалық әдістерге негізделген. Альтман моделін пайдалана отырып, талдау қосымша кірістің қысқа мерзімде (1-2 жыл) компанияның банкроттыққа ұшырау ықтималдығына қалай әсер ететінін зерттейді. Нәтижелер динамикалық баға белгілеудің 14–16% деңгейіндегі тиімді қолданылуы компанияның қаржылық жағдайын жақсарта алатынын және банкроттық қаупін төмендететінін көрсетеді. Сондай-ақ, зерттеу барысында тендерлердегі ұсынылған бағалардың жеткізушілердің баға белгілеу шешімдеріне әсері бағаланды: жеткізушілер ұсынылған бағаларды шамамен 55–60%-ға ұлғайтады. Көптеген жеткізушілер бұл әрекетті этикалық деп санайды, өйткені бизнестің мақсаты – пайда табу. Зерттеу қорытындысы бойынша 65% сатып алуларды жеңіп алуға және алынбаған табысты 83,9%-ға азайтуға арналған сызықтық модель жасалды.*

Түйін сөздер: *динамикалық баға белгілеу, мемлекеттік сатып алу, алынбаған табыс, Альтман моделі, қаржылық тұрақтылық.*

ИСПОЛЬЗОВАНИЕ ДИНАМИЧЕСКОГО ЦЕНООБРАЗОВАНИЯ КАК КОНКУРЕНТНОГО ПРЕИМУЩЕСТВА ДЛЯ ПОСТАВЩИКОВ В ТЕНДЕРНЫХ ПРОЦЕССАХ

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Резюме. *Данное исследование направлено на разработку модели динамического ценообразования для сокращения доли нереализованного дохода в государственных закупках. Объектом исследования является участие поставщиков в госзакупках с целью определения справедливой цены лота. В исследовании использованы количественные и качественные методы, включая данные с портала госзакупок, финансовую отчетность компаний и глубинные интервью. С применением модели Альтмана проведен анализ влияния дополнительного дохода от динамического ценообразования на вероятность банкротства компании в краткосрочной перспективе (1–2 года). Результаты показывают, что оптимальное использование динамического ценообразования с эффектом 14–16% может улучшить финансовую устойчивость компании, снижая риск банкротства. Также исследуется влияние рекомендованных цен на решения поставщиков: поставщики в 55–60% случаев увеличивают цены относительно рекомендованных, считая это поведение этичным, поскольку целью бизнеса является получение прибыли. В заключение разработана линейная модель, позволяющая выигрывать 65% закупок и снижать нереализованный доход на 83,9% по сравнению с текущей ситуацией.*

Ключевые слова: *динамическое ценообразование, государственные закупки, нереализованный доход, модель Альтмана, финансовая устойчивость.*

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