Oleksiy Tumanov
Department of Corporate Finance and Controlling,
Kyiv National Economic University named after Vadym Hetman, Kyiv, Ukraine
E-mail: tumanov.oleksij@gmail.com
ORCID: https://orcid.org/0009-0003-5107-0084

Ievgenii Nagornyi
Department of Corporate Finance and Controlling,
Kyiv National Economic University named after Vadym Hetman, Kyiv, Ukraine (corresponding author)
E-mail: ifk@kneu.edu.ua
ORCID: https://orcid.org/0000-0001-5008-1839

Behavioural Determinants of Investment Decisions in the Financial Controlling System of Real Sector Enterprises

Abstract

The *research subject* is the impact of cognitive biases on the efficiency of investment decisions within the real economy and how these biases can be integrated into financial control systems. The *research methodology* takes a comprehensive approach, combining regression analysis to identify statistical patterns with the Mamdani fuzzy inference system to model non-linear interactions between behavioural determinants. The empirical basis comprises 67 investment projects of Ukrainian enterprises for the period 2022–2024 and data collected via a structured questionnaire containing 45 questions designed to diagnose cognitive biases. The *research objective* is twofold: first, to identify the dominant behavioural determinants of investment decisions based on empirical analysis; and second, to develop tools for considering these determinants in the financial control systems of enterprises in the real sector. The *research results* demonstrate that cognitive biases systematically reduce the efficiency of investment projects. The Regression Model illustrates the detrimental effects of the sunk cost fallacy, overconfidence bias, the anchoring effect and herding behaviour on the discrepancy between the actual and planned NPV, accounting for 54.7% of the variation in the dependent variable. The most influential factors are the sunk cost fallacy ($\beta = -1.40$, $p < 0.001$) and the overconfidence bias ($\beta = -1.05$, $p = 0.002$). The developed Mamdani Model, which incorporates nine expert rules, enables the formalisation of nonlinear synergistic effects between biases and the identification of critical risk zones when combining high values of determinants. The correlation between the Mamdani Model and the regression results is 0.89 ($p < 0.001$), which confirms the validity of the fuzzy approach. The practical significance lies in creating operational tools for behavioural control with linguistic rules for diagnosing cognitive distortions when making investment decisions. These results can be used by the financial services departments of enterprises to improve control systems and reduce the impact of psychological factors on the quality of investment decisions.

DOI: https://doi.org/10.30525/2500-946X/2025-4-6

Keywords
behavioural determinants, investment decisions, financial controlling, cognitive biases, fuzzy logic, Mamdani Model, real sector economy

JEL: D91, G11, G31, M21

This is an Open Access article, distributed under the terms of the Creative Commons Attribution CC BY 4.0

1 Introduction

Traditional financial control systems for investment decisions are based on the assumption of rational economic agents, who are said to objectively analyse information, logically evaluate alternatives and choose options that maximise the enterprise's economic benefit. However, numerous studies in behavioural finance convincingly demonstrate systematic deviations from rationality due to cognitive biases–persistent patterns of erroneous thinking that arise from the human brain's limited information-processing capabilities.

For Ukraine's real sector enterprises in 2022–24, this problem is particularly acute. Investment decisions are made in conditions of high uncertainty, limited financial resources and significant risks, creating an environment in which cognitive biases are most prevalent. Even the most sophisticated system of financial indicators does not guarantee optimal decisions if a manager systematically overestimates their own forecasts, irrationally clings to initial information, or cannot abandon an unprofitable project due to already invested funds.

Although the importance of behavioural factors in finance theory is recognised, the practical control systems of enterprises remain focused exclusively on financial indicators, ignoring the psychological nature of decision-making. There is a methodological gap between understanding cognitive mechanisms and formalising them in controlling systems. Classical statistical methods assume linear dependencies and additive influences, neither of which reflects the synergistic effects of behavioural determinants.

The **objective of the research** is to identify the dominant behavioural determinants through an empirical analysis of investment projects of Ukrainian real-sector enterprises and to develop tools for their consideration in financial controlling systems by integrating regression analysis with a fuzzy inference system.

2 Literature Review

The theoretical basis for the behavioural approach to financial decision-making was established in the work of D. Kahneman and A. Tversky, who developed prospect theory and categorised the primary cognitive biases (Kahneman & Tversky, 1979). Four groups of biases are particularly relevant for investment control: overconfidence, which leads to overestimating the accuracy of one's own forecasts; the anchoring effect, when decisions are irrationally tied to initial information; the sunk cost fallacy, which forces people to continue with unprofitable projects because of the funds already invested; and herd behaviour, when decisions are copied from others without independent analysis.

Empirical studies have confirmed the significant impact of behavioural factors on investment decisions. U. Malmendier and G. Tate's seminal study established that overconfident Chief Executive Officers (CEOs) have a propensity to engage in acquisitions with diminished returns (Malmendier & Tate, 2005). It has been demonstrated that Chief Financial Officers (CFOs) systematically overestimate the accuracy of their forecasts. When a 90% confidence interval is set, actual results fall outside its boundaries in 47% of cases (Ben-David et al., 2013). Research conducted within emerging markets has demonstrated an even more pronounced impact. Z. Ahmad revealed a statistically significant impact of anchoring effect, overconfidence, and herding behaviour on investment decisions (Ahmad et al., 2024).

As demonstrated by Arkes and Blumer (1985), individuals frequently persist in their investment in projects despite the presence of rational evidence suggesting termination. This phenomenon is especially characteristic of enterprises with large capital investments in long-term assets.

The application of fuzzy logic in financial decision-making has been evolving since the 1990s. E.H. Mamdani developed a fuzzy inference system that uses linguistic rules and membership functions to formalise expert knowledge (Mamdani & Assilian, 1975). In the field of finance, fuzzy logic finds application in credit scoring, bankruptcy prediction and investment project evaluation. Nevertheless, the integration of fuzzy logic with behavioural finance for control purposes remains an area that has received insufficient research attention.

Domestic researchers also focus on the behavioural aspects of financial management. N. Babiak and O. Tumanov investigated the features of behavioural control in crisis situations (Babiak & Tumanov, 2024). Meanwhile, V. Shunmugasundaram and A. Sinha established that confirmation bias and conservatism, mediated sequentially by overconfidence and the disposition effect, influence the quality of investment decisions, based on an analysis of 501 insurance policies (Shunmugasundaram & Sinha, 2025).

Despite significant developments, there is a lack of comprehensive empirical research into the behavioural determinants of investment decisions made by enterprises in the real sector, as well as a lack of operational tools to consider these determinants in control systems. Most studies use classical regression analysis, which does not take into account nonlinear synergistic effects between biases.

3 Research Methodology

The research was conducted in four stages between February and August 2024. In the first stage, a 45-question structured questionnaire was developed to diagnose cognitive biases, and validated scales from international studies were adapted. In the second stage, empirical data were collected via a survey of project managers from 67 Ukrainian enterprises in the real sector. The inclusion criteria were the implementation of an investment project between 2022 and 2024, the availability of financial statements, and the willingness to co-operate. In the third stage, a multiple linear Regression Model was developed to identify the statistical patterns of how cognitive biases influence the deviation of actual NPV from the planned value. The fourth stage involved developing a Mamdani fuzzy inference system based on the most influential variables from the regression.

The sample covers 67 investment projects. The distribution by industry is as follows: manufacturing – 28%; agriculture – 24%; construction – 21%; trade – 15%; services – 12%. By enterprise size, the distribution is as follows: large enterprises (with over 250 employees) – 27%; medium enterprises (with 50–250 employees) – 51%; and small enterprises (with 10–50 employees) – 22%. The average investment volume per project was 18.4 million UAH and the average project duration was 22 months.

To measure cognitive biases, a structured questionnaire comprising five sections was developed. The sections covered respondent and project characteristics, overconfidence (12 questions based on an adapted scale by B. Barber and T. Odean), the anchoring effect (eight questions involving experimental tasks), the sunk cost fallacy (10 situational tasks based on the methodology by Arkes and Blumer) and herding behaviour (seven questions about competitors). An intensity index was calculated for each bias on a scale from 0 to 1.

Multiple linear regression had the form: NPV_deviation = $\beta_0 + \beta_1 \times$Sunk_cost + $\beta_2 \times$Overconfidence + $_3\times$Anchoring + $\beta_4 \times$Herding + ε, where NPV_deviation is the deviation of actual NPV from planned. Parameter estimation was performed using the ordinary least squares method in SPSS Statistics 28.0 with assumption testing: Durbin-Watson test for autocorrelation, White test for heteroscedasticity, VIF for multicollinearity.

Based on regression results, the two most influential variables were selected for the Mamdani Model: Sunk_cost and Overconfidence. Triangular membership functions were defined for three linguistic terms (Low, Moderate, High) with parameters [0, 0, 0.35], [0.25, 0.5, 0.75], [0.65, 1, 1]. Nine expert rules of "IF-THEN" type were developed for all term combinations. The inference mechanism employs Mamdani's minimum method for rule aggregation and the centroid method for defuzzification. It was implemented in Python 3.9 using the scikit-fuzzy 0.4.2 library. Model validation was conducted by comparing it with a Regression Model and calculating the Pearson correlation coefficient.

4 Impact of Behavioural Determinants on Investment Project Efficiency

Multiple linear regression revealed a statistically significant effect of cognitive biases on the deviation of actual NPV from planned NPV. The model has the form:

NPV_deviation = 0.15 - 1.40×Sunk_cost - 1.05×Overconfidence - 0.77×Anchoring - 0.61×Herding.

Statistical characteristics: $R^2=0.547$ (the model explains 54.7% of the variation in the dependent variable), F-statistic=18.76 ($p<0.001$), n=67. The Durbin-Watson test (DW=1.89) confirms the absence of autocorrelation, VIF<2.3 for all variables indicates the absence of multicollinearity.

Sunk cost fallacy has the strongest negative impact on project efficiency ($\beta=-1.40$, $p<0.001$, β_std=-0.42). An increase in the bias index of 0.1 is associated with an increase in NPV deviation of 14 percentage points, provided that other variables are held constant. In practice, this means that managers who are reluctant to stop financing projects because they have already invested money make decisions that result in a 14% failure to achieve the planned NPV for every 10% increase in bias intensity.

Overconfidence bias also has a strong negative effect ($\beta=-1.05$, $p=0.002$, β_std=-0.31). Managers who overestimate the accuracy of their forecasts set unrealistic planned NPV targets that cannot be achieved in practice. An increase in the index of 0.1 leads to a 10.5 percentage point increase in deviation.

Anchoring effect has a moderate but statistically significant impact ($\beta=-0.77$, $p=0.031$, β_std=-0.23). Attachment to initial cost estimates or historical indicators leads to systematic planning errors. Herding behaviour has the weakest impact among the four biases and is marginally significant ($\beta=-0.61$, $p=0.089$, β_std=-0.18).

Correlation analysis confirms strong negative relationships between biases and efficiency: Sunk_cost↔NPV_deviation ($r=-0.54$, $p<0.001$), Overconfidence↔NPV_deviation ($r=-0.48$, $p<0.001$), Sunk_cost↔Budget discipline ($r=-0.61$, $p<0.001$). Table 1 presents detailed regression analysis results.

5 Mamdani Model for Formalising Non-Linear Interactions

Despite its high statistical significance, the Regression Model is fundamentally limited by the assumptions of linearity and additivity of influences. Empirical observations and theoretical developments in behavioural finance suggest that synergistic effects exist. A manager exhibiting a high level of sunk cost fallacy and overconfidence does not merely add their

TABLE 1 Multiple regression results of cognitive biases impact on NPV deviation

Predictor	β	SE	β_std	t	p	VIF
Constant	0.15	0.08	-	1.88	0.065	-
Sunk_cost	-1.40	0.32	-0.42	-4.38	<0.001	1.87
Overconfidence	-1.05	0.28	-0.31	-3.75	0.002	2.14
Anchoring	-0.77	0.35	-0.23	-2.20	0.031	1.56
Herding	-0.61	0.38	-0.18	-1.61	0.089	1.43

Note: SE – standard error, β_std – standardised coefficient, VIF – variance inflation factor Source: calculated by the authors influence, but enters a qualitatively different zone of escalation of commitment risk that exceeds the sum of the individual impacts.

To model nonlinear interactions, a Mamdani fuzzy inference system was developed. Based on regression results, two most influential variables were selected: Sunk_cost (β_std=-0.42) and Overconfidence (β_std=-0.31). This allows focusing on key determinants while maintaining system interpretability with nine rules.

For each variable, three linguistic terms with triangular membership functions were defined. Universal set X=[0,1], where 0 is the minimum bias intensity, 1 is the maximum. Membership functions: Low [0, 0, 0.35], Moderate [0.25, 0.5, 0.75], High [0.65, 1, 1]. Function overlap in zones 0.25-0.35 and 0.65-0.75 ensures smooth transitions between terms.

Nine expert rules were developed for all term combinations. Key rules: Rule 1 – IF Sunk_cost=Low AND Overconfidence=Low, THEN NPV_risk=Low (both biases are weak, minimal risk); Rule 5 – IF Sunk_cost=Moderate AND Overconfidence=Moderate, THEN NPV_risk=Moderate (moderate combination of both factors); Rule 6 – IF Sunk_cost=Moderate AND Overconfidence=High, THEN NPV_risk=High (beginning of synergistic effect, jump to high risk); Rule 9 – IF Sunk_cost=High AND Overconfidence=High, THEN NPV_risk=High (critical zone, both biases are maximal).

The inference mechanism uses Mamdani's minimum method for t-norm and maximum method for t-conorm. Defuzzification is performed using the centroid method to convert fuzzy inference into a crisp value NPV_risk$\in$[0,1]. Python implementation allows automating risk assessment for new projects.

6 Model Validation and Approach Comparison

To verify the validity of the Mamdani Model, the NPV_risk was calculated for all 67 observations in the sample and compared with the results of the Regression Model. The Pearson's correlation coefficient is $r = 0.89$ ($p < 0.001$) and the Spearman's coefficient is $\rho = 0.86$ ($p < 0.001$). The high correlation indicates the consistency of both approaches: the Mamdani Model produces results that are similar to those of the Regression Model, which confirms the validity of the Mamdani Model. At the same time, the fuzzy model also reveals non-linear interactions.

Graphical analysis of the Mamdani Model's three-dimensional response surface demonstrates a clear nonlinear character of NPV_risk dependence on two input variables. In the zone of low values of both biases, the surface is almost flat (NPV_risk≈0.15-0.25), but at Sunk_cost>0.6 and Overconfidence>0.6, there is a sharp increase (NPV_risk>0.75), which cannot be represented by linear regression.

The model identifies three risk zones. The low-risk zone (NPV_risk<0.35) covers 31% of sample observations, where Sunk_cost<0.4 AND Overconfidence<0.5. The moderate risk zone (0.35≤NPV_risk≤0.65) covers 47% of observations with various combinations of moderate values. The high-risk zone (NPV_risk>0.65) covers 22% of observations, where Sunk_cost>0.6 OR combination of Sunk_cost>0.5 AND Overconfidence>0.6. These projects demonstrated the largest deviations of actual NPV from planned, on average 67% versus 23% for the overall sample.

Table 2 provides a comparative analysis of the Regression and Mamdani models, demonstrating their complementary nature within the control system.

7. Practical Application in the Controlling System

The developed hybrid system has a direct, practical application in enterprise financial control systems. Before approving an investment, managers complete a questionnaire and the system automatically calculates the sunk cost and overconfidence indices. The Mamdani Model provides a NPV risk assessment with linguistic interpretation and specific recommendations.

For a project with Sunk_cost=0.20 and Overconfidence=0.15, the model produces NPV_risk=0.18 (low risk) with a recommendation to continue monitoring indicators. For a project with Sunk_cost=0.45 and Overconfidence=0.55, the result NPV_risk=0.52 (moderate risk) is accompanied

TABLE 2 Comparative characterisation of Regression Model and Mamdani Model

Characteristic	Regression Model	Mamdani Model
Type of dependencies	Linear	Nonlinear
Form of knowledge representation	β-coefficients	"IF-THEN" rules
Target audience	Analysts, researchers	Practitioners, managers
Quality indicator	R^2=0.547	r=0.89 with regression
Synergy modeling	No (additivity)	Yes (expert rules)
Critical zone identification	No	Yes
Linguistic interpretation	Low	High
Implementation complexity	Low	Medium

Source: compiled by the authors

by a recommendation for additional expertise and implementation of risk mitigation measures. For a project with Sunk_cost=0.65 and Overconfidence=0.75, the model produces NPV_risk=0.82 (high risk) with a warning about the beginning of synergistic effect and the need for corrective actions: review of project assumptions by an independent team, application of the "zero-base" rule, consideration of project termination alternative.

A six-month pilot implementation of system elements at twelve enterprises in the experimental group showed a reduction in the proportion of investment decisions with significant discrepancies between actual and planned results (more than 30%), falling from 31% to 18%. The mean absolute deviation also decreased, from 38% to 24%. According to a paired t-test ($p<0.05$), these changes are statistically significant and indicate the practical effectiveness of the behavioural approach to control.

8 Conclusions

An empirical study of 67 investment projects of Ukrainian real-sector enterprises established a systematic impact of cognitive biases on the efficiency of investment decisions. The Regression Model shows that the sunk cost fallacy, the overconfidence bias, the anchoring effect and herding behaviour together account for 54.7% of the variation in actual net present value (NPV) deviation from the planned value. The most influential factors were the sunk cost fallacy ($\beta = -1.40$, $p < 0.001$) and the overconfidence bias ($\beta = -1.05$, $p = 0.002$).

A Mamdani fuzzy inference system comprising nine expert rules was developed to complement regression analysis by providing tools for formalising non-linear interactions between behavioural determinants. The model uses two input variables and three linguistic terms with triangular membership functions, employing the Mamdani inference mechanism. The correlation between the Mamdani Model and the regression results is 0.89 ($p < 0.001$), which confirms the statistical validity of the fuzzy approach.

The synergistic effects of cognitive biases were identified, which are not reflected in linear regression. The Mamdani Model identifies a critical risk zone where high values of the sunk cost fallacy (≥0.65) and overconfidence (≥0.65) are combined, resulting in a sharp increase in NPV_risk to a level of at least 0.82. This confirms the theory of escalation of commitment and demonstrates the practical value of non-linear modelling.

Highly interpretable operational tools for behavioural control were created. The "IF-THEN" rule system can be used directly by practitioner managers without in-depth statistical knowledge to formulate clear recommendations for each combination of bias levels, from monitoring to engaging independent experts.

The complementarity of regression and fuzzy approaches in the financial control systems of real-sector enterprises was demonstrated. Regression provides statistical rigour and the identification and assessment of significant predictors and their impact. The Mamdani Model also reveals non-linear interactions, offers an intuitive interpretation and identifies critical risk zones. The hybrid system combines the strengths of both methods to enhance the quality of investment decisions in highly uncertain conditions.

References:

[1] Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*. Vol. 47. No. 2. P. 263–291.

[2] Malmendier, U., & Tate, G. (2005). CEO Overconfidence and Corporate Investment. Journal of Finance. Vol. 60. No. 6. P. 2661–2700.

[3] Ben-David, I., Graham, J., & Harvey, C. (2013). Managerial Miscalibration. *Quarterly Journal of Economics*. Vol. 128. No. 4. P. 1547–1584.

[4] Ahmad, Z., Ibrahim, H., & Tuyon, J. (2024). Impact of behavioral biases on investment decisions and the moderation effect of financial literacy: evidence of Pakistan. *Heliyon*. Vol. 10. No. 11. DOI: https://doi.org/10.1016/j.heliyon.2024.e31800

[5] Arkes, H. R., & Blumer, C. (1985). The psychology of sunk cost. *Organizational Behavior and Human Decision Processes*. Vol. 35. No. 1. P. 124–140.

[6] Mamdani, E. H., & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*. Vol. 7. No. 1. P. 1–13.

[7] Babiak, N. D., & Tumanov, O. V. (2024). Behavioral controlling in crisis situations: improving financial and management decision-making in wartime. *Actual Problems of Economics*. No. 5. P. 223–233.

[8] Shunmugasundaram, V., & Sinha, A. (2025). The impact of behavioral biases on investment decisions: a serial mediation analysis. *Journal of Economics, Finance and Administrative Science*. Vol. 30. No. 59. P. 5–21.

[9] Barber, B., & Odean, T. (2001). Boys will be Boys: Gender, Overconfidence, and Common Stock Investment. *Quarterly Journal of Economics*. Vol. 116. P. 261–292.

[10] Staw, B. M. (1976). Knee-deep in the Big Muddy: A Study of Escalating Commitment. *Organizational Behavior and Human Performance*. Vol. 16. P. 27–44.
[11] Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*. Vol. 8. No. 3. P. 338–353.
[12] Thaler, R. H. (2015). Misbehaving: The Making of Behavioral Economics. New York: W.W. Norton, 432 p.

Received on: 09th of November, 2025
Accepted on: 17th of December, 2025
Published on: 26th of December, 2025