Evaluating the effects of digitalization on the financial security of the corporate sector: Multivariate econometric analysis

Yuliia Kovalenko[1,†], Sergii Krynytsia[1,*,†], Alina Osipchuk[1,†], Tetiana Koliada[1,†], Alla Ivashchenko[2,†] and Volodymyr Osmyatchenko[3,†]

[1]*State University "Kyiv Aviation Institute", Liubomyra Huzara Ave., 1, Kyiv, 03058, Ukraine*
[2]*Kyiv National Economic University named after Vadym Hetman, Beresteiskyi Ave., 54/1, Kyiv, 03057, Ukraine*
[3]*State University of Information and Communication Technologies, Solomyanska Str., 7, Kyiv, 03110, Ukraine*

Abstract

This paper investigates the nature and intensity of digitalization's impact on the corporate sector's financial security in the context of digital transformation. The study aims to comprehensively assess this impact using multidimensional econometric tools to develop well-founded scientific and practical recommendations for enhancing financial resilience at the enterprise level. The research addresses several key tasks: adapting methodological approaches for quantifying financial security levels considering digital economy transformation processes; constructing classical OLS regression models to identify the basic relationships between digitalization and financial security; applying panel econometric models that account for spatial and temporal heterogeneity; and implementing a Bayesian modeling approach to obtain robust estimates under data limitations and potential violations of classical assumptions. Empirical results reveal a statistically significant negative relationship between the level of digitalization and financial security indicators of the corporate sector. This relationship is more pronounced among enterprises with higher levels of financial stability. The identified negative association should not be interpreted as an argument against digitalization, but rather as evidence of the need for a comprehensive approach to managing digital transformation, with attention to potential financial risks. The study proposes recommendations for adapting business models, improving financial monitoring systems, and strengthening the capacity of enterprises to address emerging challenges in the digital age.

Keywords

digitalization, financial security, financial analysis, corporate sector, econometric analysis, panel models, Bayesian regression, digital transformation, financial risks

1. Introduction

The rapid development of digital technologies over the past decades has transformed production and consumption processes and fundamentally altered the financial relations structure at all economic system levels. Digitalization, acting as a catalyst for structural changes in business models, data processing and analysis technologies, and forms of interaction with clients and investors, creates fundamentally new conditions for the functioning of the corporate sector. In this context, ensuring financial security becomes particularly relevant as a fundamental basis for the sustainable development of corporate structures amid the digital transformation of the economy.

CH&CMiGIN'25: Fourth International Conference on Cyber Hygiene & Conflict Management in Global Information Networks, June 20–22, 2025, Kyiv, Ukraine

*Corresponding author.
†These authors contributed equally.
kovalenko.iuliia@npp.kai.edu.ua (Y. Kovalenko); serge.krinitsa@gmail.com (S. Krynytsia); alina.osipchuk2012@gmail.comĐś (A. Osipchuk); tetiana.koliada@npp.kai.edu.ua (T. Koliada); alla.ivashchenko@kneu.edu.ua (A. Ivashchenko); osmatchenkov@gmail.com (V. Osmyatchenko)
0000-0002-5678-3185 (Y. Kovalenko); 0000-0002-5569-4682 (S. Krynytsia); 0000-0002-9053-2072 (A. Osipchuk); 0000-0002-1574-4446 (T. Koliada); 0000-0002-4599-7137 (A. Ivashchenko); 0000-0002-4174-2188 (V. Osmyatchenko)

2. Literature review

Digitalization, as a pivotal phase of the Fourth Industrial Revolution, is fundamentally reshaping all dimensions of corporate operations, including the financial security management system. In recent years, there has been a notable increase in scholarly attention to the implications of digital technologies for the financial resilience and safeguarding of enterprises operating under volatile external conditions.

Researchers emphasize several key dimensions through which digitalization influences corporate financial security. Among the most frequently cited positive effects are enhanced operational efficiency and cost optimization. Automation and digital tools significantly streamline financial processes, minimize human-induced errors, and reduce transaction costs, enabling corporations to operate more efficiently and strategically allocate resources [1]. Furthermore, advanced data analytics and artificial intelligence contribute to more accurate and expedited credit assessments, improving access to capital and facilitating business expansion, particularly for small and medium-sized enterprises and industries highly dependent on intangible assets [2].

Digitalization also plays a critical role in expanding access to finance and promoting financial inclusion. Digital platforms and fintech innovations facilitate broader access to financial services, particularly for firms historically facing funding constraints, enabling them to secure financing and manage liquidity more effectively [3]. By reducing financial barriers, digitalization supports adopting innovative business models and accelerates corporate growth [4].

Another significant contribution of digitalization lies in strengthening risk management and auditing practices. Integrating digital tools provides deeper insights into corporate operations, enhances audit quality, and enables real-time monitoring of financial transactions, reinforcing internal controls and increasing transparency. Artificial intelligence and machine learning support advanced risk modeling and fraud detection, contributing to developing more robust financial security systems [5].

Emerging empirical evidence also suggests that digital transformation may mitigate excessive corporate financialization by incentivizing productive investments over speculative financial activities. This shift potentially fosters more sustainable and resilient financial structures in the long term [6, 7].

Ultimately, existing research supports the hypothesis that digitalization contributes to the resilience of financial systems under crisis conditions [8].

At the same time, scholars increasingly highlight the risks and challenges associated with digital transformation, which may, in some cases, undermine financial security. Chief among these are cybersecurity risks. The expansion of digital connectivity and the exponential growth of data volumes increase the potential attack surface for cybercriminals, thereby exposing corporations to greater risks of data breaches, fraud, and other cyber threats [9].

Digitalization also introduces regulatory complexities and compliance costs, as corporations must continuously adapt to evolving data protection, privacy, and financial reporting standards. Meeting these requirements often demands substantial financial and human capital, which may divert resources from innovation and transformational initiatives [10]. Moreover, the success of digital transformation hinges on the availability of high-quality, integrated, and secure data. Inadequate data governance can significantly compromise decision-making processes, risk assessments, and compliance efforts [11].

In addition to the technological and operational dimensions of financial security, scholars emphasize the importance of institutional factors in shaping the financial sustainability of the corporate sector. The institutional quality of the financial system, including regulatory efficiency, transparency, and the degree of institutionalization, directly influences firms' ability to adapt to digital transformation and maintain financial stability. As highlighted by Y. Kovalenko, an institutional approach allows for a more comprehensive assessment of financial sector efficiency, particularly in environments undergoing systemic change [12]. Further research underscores that the institutionalization of the financial sector is a critical enabler of digitalization's positive effects, as it ensures predictability, reduces transaction costs, and enhances trust in financial interactions [13]. Recent findings also indicate that countries with more mature institutional frameworks and digital governance systems are better positioned to harness digital tools for strengthening corporate financial resilience [14].

Despite substantial scholarly contributions to the study of digitalization and financial security, their interrelationship remains underexplored, particularly in empirical validation regarding the nature and intensity of digital transformation's impact on the corporate sector's financial security indicators. Most existing studies either focus on qualitative aspects of this interaction or examine isolated sector-specific case studies. This fragmented approach hinders the development of a comprehensive understanding of the phenomenon and limits the identification of broader patterns and trends.

3. Aims and objectives

The primary objective of this study is to conduct a comprehensive assessment of the nature and intensity of the impact of digitalization processes on the financial security of the corporate sector. This is achieved by applying multidimensional econometric tools to formulate evidence-based scientific and practical recommendations to strengthen financial security under conditions of digital transformation.

To achieve this objective, the following scientific and practical tasks have been identified and implemented:

- To select methodological approaches for the quantitative assessment of the financial security level of the corporate sector, taking into account the transformational dynamics of the digital economy
- To construct and evaluate classical Ordinary Least Squares (OLS) regression models of the impact of digitalization on corporate financial security, to determine the baseline characteristics of the relationship between the relevant indicators
- To develop and implement panel econometric models that incorporate the spatial and temporal heterogeneity of the examined processes, thereby enabling a more nuanced analysis of digitalization's influence on financial security
- To apply a Bayesian modeling approach to assess the impact of digitalization on corporate financial security, providing robust estimations under data limitations and potential violations of classical econometric assumptions
- To formulate evidence-based scientific and policy recommendations for ensuring the financial security of the corporate sector in the context of intensified digitalization processes at both macro and micro levels, based on the identified empirical regularities.

4. Materials and methods

4.1. Data sources and sample construction

To ensure the study's representativeness, panel data were collected from all 27 EU member states over 2016–2023, resulting in sufficient observations (n = 214) to support robust statistical analysis.

To assess the level of digitalization, the study employed the Digital Economy and Society Index (DESI) for the years 2017 to 2024. Compiled by the European Commission [15], DESI is a composite indicator that measures the progress of EU countries in advancing toward a digital economy and society.

It is important to note that the DESI methodology was revised in 2023, after which the European Commission discontinued the publication of the composite index and shifted its focus to disaggregated sub-indices. To preserve temporal comparability and maintain methodological consistency, this study recalculated the composite DESI scores for 2023 and 2024 using the 2022 methodology [16].

Given the structure of DESI reporting, where each year's index reflects data from the previous calendar year (e.g., DESI 2024 reflects statistics from 2023), the study applied a temporal adjustment by shifting DESI values by one year relative to financial security indicators. Thus, for instance, the DESI 2024 index is aligned with financial security indicators for 2023, ensuring accurate temporal synchronization of the analyzed data.

To measure the financial security of the corporate sector, official statistics from Eurostat for the period 2016–2023 were utilized. The analysis incorporated two distinct groups of indicators:

1. Financial assets and liabilities indicators (dataset NASA_10_F_BS) [17], including:
    - F - Total financial assets/liabilities
    - F2 - Currency and deposits
    - F31 - Short-term debt securities
    - F41 - Short-term loans
    - F8 - Other accounts receivable/payable
2. Non-financial transactions indicators (dataset NASA_10_NF_TR) [18], including:
    - B9 - Net lending (+)/net borrowing (-)
    - P1 - Output
    - B86 - Saving, gross
    - B8A36 - Operating surplus and mixed income, gross

For both indicator groups, the analysis focused on sector S11 – Non-financial corporations, which is in line with the study's objective of evaluating the financial security of the corporate sector of the economy. The methodology proposed by Y. Pavlyuk and O. Laktyonova [19] was employed to construct the composite financial security index. The integrated financial security indicator (FSR) was calculated using the following formula:

$$FSR = I_R \cdot \beta_R + I_A \cdot \beta_A + I_L \cdot \beta_L + I_S \cdot \beta_S + I_I \cdot \beta_I, \tag{1}$$

where FSR – composite financial security index,

I_R, I_A, I_L, I_S, I_I represent the composite sub-indices of profitability, business activity, liquidity and solvency, financial stability, and investment appeal, respectively.

β_R, β_A, β_L, β_S, β_I are the weighting coefficients assigned to each respective subcomponent in the integrated assessment.

Each sub-index (e.g., profitability, liquidity) was in turn calculated as a weighted average of selected individual indicators using the following formula:

$$I_j = \sum_{i=1}^{n} x_{ij} \cdot \alpha_{ij}, \tag{2}$$

where I_j denotes the composite value of the j-th component of financial security,

x_{ij} is the i-th indicator within the j-th component,

α_{ij} represents the weight of the i-th indicator in evaluating the j-th component;

n is the number of indicators comprising the j-th component.

The structure of the financial security index and the corresponding weighting coefficients for each component and indicator are presented in Table 1.

Unlike the original methodology [19], in our calculation of the composite financial security indicator, we employed an inverse indicator of the Debt-to-Equity Ratio, as the traditional Debt-to-Equity Ratio acts as a destimulant in the context of financial security (i.e., higher values indicate lower financial resilience).

4.2. Specification of Econometric Models

A comprehensive set of econometric models of varying complexity and assumptions was applied to assess digitalization's impact on the financial security of the corporate sector. This approach ensured the robustness of the results and enabled the exploration of different dimensions of the relationship between variables:

1. Classical Linear Regression (OLS):

$$FSR_i = \beta_0 + \beta_1 \cdot DESI_i + \varepsilon_i, \tag{3}$$

where β_0 is intercept, β_1 is DESI coefficient (main parameter of interest), $\varepsilon_i \sim \mathcal{N}(0;\, \sigma^2)$, σ^2 is error variance.

Table 1
Components of the Integral Indicator of Financial Security and the Size of the Weighting Coefficients

Financial security components (I_j)	Weight (β_j)	Financial security component indicator (x_{ij})	Weight (α_{ij})
Profitability (I_R)	0.24	Return on Equity (ROE)	0.35
		Return on Assets (ROA)	0.45
		Return on Sales (ROS)	0.20
Business Activity (I_A)	0.18	Asset Turnover Ratio	0.50
		Fixed Asset Turnover Ratio	0.30
		Equity Turnover Ratio	0.20
Liquidity (I_L)	0.22	Current Ratio	0.50
		Quick Ratio	0.20
		Receivable to Payable Ratio	0.30
Financial Stability (I_S)	0.26	1 / Debt to Equity Ratio	0.50
		Financial Sustainability Ratio	0.15
		Working Capital Ratio	0.35
Investment Appeal (I_I)	0.10	Net Profit Margin	0.55
		Profit Retention Ratio	0.45

2. Robust Linear Regression with Adjusted Standard Errors: Estimation was conducted with heteroskedasticity-consistent (HC1) robust standard errors to correct for potential heteroskedasticity in the residuals.
3. Robust Regression (M-estimation): The Huber M-estimator was applied to mitigate the influence of outliers on coefficient estimation, enhancing model reliability in the presence of non-normal disturbances.
4. Polynomial Regression: Non-linear specifications were introduced to capture possible curvilinear effects of digitalisation on financial security:
$$FSR_i = \beta_0 + \beta_1 \cdot DESI_i + \beta_2 \cdot DESI_i^2 + \varepsilon_i. \tag{4}$$
5. Quantile Regression: The model was estimated at various quantiles of the dependent variable distribution (τ = 0.25, 0.50, 0.75) to explore heterogeneous effects of digitalisation across different levels of financial security [20].
6. Panel Data Models: Both the Fixed Effects (FE) and Random Effects (RE) models were employed to account for country-specific unobservable heterogeneity over time:
$$FSR_{it} = \beta_0 + \beta_1 \cdot DESI_{it} + \alpha_i + \varepsilon_{it}, \tag{5}$$
where α_i denotes the country-specific effect [21].
7. Bayesian Regression: A Bayesian approach was adopted to generate robust estimates under data limitations and potential violations of classical assumptions. Informative priors were specified for the model coefficients as follows:
Prior distribution for $\beta_0, \beta_1, \ldots$:
$$\beta_j \sim \mathcal{N}(\mu_j;\, \tau_j^2), j = 0, 1, ... \tag{6}$$
Prior distribution for σ^2:
$$\sigma^2 \sim InvGamma(a; b), \tag{7}$$
where a, b are hyperparameters reflecting prior knowledge about the variance.
Posterior distribution forβ_1:
$$\beta_1 | y, \mathbf{X} \sim N(\mu_{post}, \tau_{post}^2), \tag{8}$$
where:
$$\mu_{post} = \frac{\left(\frac{\sum DESI_i \cdot FSR_i}{\sigma^2} + \frac{\mu_1}{\tau_1^2}\right)}{\left(\frac{\sum DESI_i^2}{\sigma^2} + \frac{1}{\tau_1^2}\right)}, \quad \tau_{post}^2 = \left(\frac{\sum DESI_i^2}{\sigma^2} + \frac{1}{\tau_1^2}\right)^{-1} \tag{9}$$

was obtained using the No-U-Turn Sampler (NUTS), an efficient implementation of the Hamiltonian Monte Carlo (HMC) method [22].

The model was estimated using four independent Markov chains, each comprising 4000 iterations with a 2000-iteration warm-up period, yielding 8000 valid posterior samples for inference.

4.3. Diagnostic methods for econometric models

A comprehensive set of diagnostic tests was applied to evaluate the model quality and ensure the results' robustness. These diagnostics allowed for the validation of model assumptions and the appropriateness of the panel data structure.

The Breusch-Pagan Lagrange Multiplier (LM) Test was employed to determine the presence of random effects, thereby evaluating the suitability of the panel data framework [23]. The null hypothesis (H_0) states that no significant cross-sectional variation exists, which would justify using a pooled OLS model. In contrast, the alternative hypothesis suggests significant individual-specific effects, thus motivating the application of panel models.

The Shapiro-Wilk Normality Test was used to test for normality of residuals. The assumption of normally distributed residuals is central to classical linear regression models, particularly for the validity of standard errors, confidence intervals, and significance tests. The null hypothesis (H_0) posits that the residuals follow a normal distribution.

The Studentized Breusch-Pagan Test was applied to check for heteroskedasticity - i.e., non-constant variance of residuals across observations. Heteroskedasticity can lead to inefficient estimates and biased standard errors. The null hypothesis (H_0) assumes homoskedasticity, whereas the alternative hypothesis (H_1) indicates the presence of heteroskedasticity in the model.

The Pesaran CD Test was implemented to test for cross-sectional dependence. This test determines whether residuals are correlated across cross-sectional units (e.g., countries or regions) at a given point in time. The null hypothesis (H_0) states that no cross-sectional dependence exists (i.e., residuals are uncorrelated between units). In contrast, the alternative hypothesis (H_1) indicates that residuals are correlated, implying the existence of interdependence between countries.

To detect the presence of serial correlation in idiosyncratic errors, the Breusch-Godfrey/Wooldridge Test was used. Serial correlation implies that residuals from one time period are correlated with those from another. This violates a key assumption of classical regression models: residuals should be independently distributed. The null hypothesis (H_0) assumes no serial correlation in the idiosyncratic errors [24].

The Hausman Test was employed to decide between Fixed Effects (FE) and Random Effects (RE) panel models. The null hypothesis (H_0) states that individual-specific effects are uncorrelated with the regressors, making the RE model both consistent and efficient. If the null is rejected, the FE model is preferred due to potential endogeneity between individual effects and explanatory variables [25].

Finally, the F-test for Two-Way Effects was applied to assess the significance of both individual and time-specific effects in the panel dataset. This test aims to determine whether cross-sectional (country-specific) and temporal effects should be incorporated into the model. The null hypothesis (H_0) states that there are no significant individual or time effects, supporting using a simpler pooled model. However, the alternative hypothesis (H_1) implies that a two-way effects model provides a more accurate specification by accounting for unobserved heterogeneity across both dimensions.

4.4. Software

The econometric analysis was conducted using custom scripts developed by the authors [26] in the R statistical programming environment (version 4.4.2). The following R packages were employed for specific analytical tasks:

- $lmtest$ - for conducting diagnostic hypothesis testing, including tests for heteroskedasticity, serial correlation, and model specification

- $sandwich$ - for calculating robust standard errors, particularly under the presence of heteroskedasticity or autocorrelation
- $MASS$ - for performing robust M-estimation, allowing the analysis to reduce the influence of outliers using Huber-type loss functions
- $quantreg$ - for implementing quantile regression, enabling the estimation of heterogeneous effects across different points of the conditional distribution of the dependent variable
- plm - for estimating panel data models, including Fixed Effects (FE), Random Effects (RE), and diagnostic testing relevant to longitudinal data
- $ggplot2$ - for producing high-quality data visualizations, including coefficient plots and diagnostic graphics.

For the specification and estimation of the Bayesian regression models, the brms package was utilized [27]. This package serves as a high-level interface to Stan, a state-of-the-art platform for Bayesian probabilistic programming that enables efficient posterior sampling using the No-U-Turn Sampler (NUTS), an adaptive form of Hamiltonian Monte Carlo.

5. Result

Applying the aforementioned econometric modelling techniques, a comprehensive analysis was conducted to examine the relationship between the level of digitalization, measured by the Digital Economy and Society Index (DESI), and financial security indicators of the corporate sector. The results reveal a statistically significant negative association between these variables, consistently observed across most employed models.

5.1. Analysis of empirical results

5.1.1. Key findings from linear modelling

The classical linear regression model (Ordinary Least Squares, OLS) yields a coefficient of digitalization on corporate financial security equal to −0.028 (p < 0.01). This suggests that a one-unit increase in the DESI score is associated with an average decrease of 0.028 units in the financial security indicator (see Table 2).

Although the model demonstrates statistical significance ($F = 9.515, p = 0.002$), the coefficient of determination R^2 is only 0.043, indicating that digitalization explains approximately 4.3% of the variation in financial security across the corporate sector. However, the primary objective of this analysis is not to construct a predictive model for corporate financial security. It is evident a priori that digitalization is not the sole determinant of financial resilience. Instead, the purpose is to evaluate the presence and direction of the effect of digitalization on financial security.

Overall, the linear regression model representing the impact of digitalization on corporate financial security in EU countries can be expressed by the following general equation:

$$FSR_i = 2.122 - 0.028 \cdot DESI_i + \beta_2 \cdot \mathbf{X_i} + \varepsilon_i, \tag{10}$$

where $\mathbf{X_i}$ denotes the covariates (a vector of control variables accounting for heterogeneity in financial security outcomes).

The Breusch–Pagan Lagrange Multiplier test for random individual effects (Table 4) yields a test statistic of $\chi^2 = 0.254$ ($p = 0.6146$). Thus, the null hypothesis of no significant individual effects cannot be rejected. This finding implies that a pooled regression model may be sufficient for the analysis, and incorporating country-specific effects is not critically necessary in this specification.

Model diagnostics revealed a violation of the normality assumption for the residuals, as indicated by the Shapiro–Wilk test ($W = 0.700, p < 0.001$), suggesting a departure from one of the key assumptions of classical linear regression. On the other hand, the Breusch–Pagan test did not detect heteroskedasticity ($BP = 0.448, p = 0.503$), which represents a positive aspect of the model's specification.

Table 2
Comparative Analysis of Models of the Impact of Digitalization on the Financial Security of the Corporate Sector

Model	DESI coefficient	Standard error	p-value	R^2	Interpretation
Classical linear regression (OLS)	-0.028	0.009	0.002	0.043	An increase in DESI by 1 point is associated with a decrease in the financial security indicator by 0.028 units
OLS with robust standard errors	-0.028	0.012	0.015	0.043	When taking into account data heterogeneity, the significance of the effect remains, but with a lower level of confidence
Robust regression (M-estimation)	-0.017	0.004	<0.001	-	As the impact of emissions decreases, the coefficient decreases but remains statistically significant
Polynomial regression (linear term)	0.011	0.058	0.851	0.045	The nonlinear nature of the relationship is not confirmed
Polynomial regression (quadratic term)	-0.0004	0.0006	0.492	-	The nonlinear nature of the relationship is not confirmed
Quantile regression (25%)	-0.014	-	>0.05	-	For the bottom quartile, the impact is statistically insignificant
Quantile regression (50%)	-0.017	-	<0.05	-	The median of the distribution has a significant impact
Quantile regression (75%)	-0.026	-	<0.05	-	For the top quartile, the impact is significant and stronger

Table 4
Results of Diagnostic Tests of the Linear Regression Model of the Relationship between Digitalization (DESI) and Financial Security of the Corporate Sector

Test	Statistics	p-value	Interpretation
Breusch-Pagan Lagrange test (pooled vs. panel)	$\chi^2 = 0.254$	0.6146	Lack of significant individual effects
Shapiro-Wilk test	W=0.700	<0.001	The residuals are not normally distributed
Breusch-Pagan test	BP=0.448	0.503	Heteroscedasticity absent

Robust regression techniques were employed to account for potential issues arising from the residual distribution and the presence of outliers. The model estimated using heteroskedasticity-consistent standard errors (HC1) confirmed the negative effect of digitalization (−0.028), albeit with a slightly higher standard error (0.012) and reduced statistical significance ($p = 0.015$) (see Table 2).

Further robustness checks using Huber's M-estimation yielded a coefficient of −0.017, indicating a somewhat weaker magnitude of the effect, although it remained statistically significant. Notably, the standard error decreased to 0.004, enhancing the estimate's reliability. The use of robust estimation methods is particularly justified in light of the observed deviations from the normality assumption, reinforcing the robustness of the obtained results (Table 2).

An assessment of nonlinearity by including a quadratic term in the model did not indicate any statistically significant improvement in fit ($F = 0.474$, $p = 0.492$). The coefficient on the squared DESI term (−0.0004) was statistically insignificant ($p = 0.492$), suggesting no evidence of a parabolic (nonlinear) relationship between digitalization and corporate financial security. This finding supports the conclusion that the relationship between the investigated variables is predominantly linear in nature.

A comparison of linear and polynomial regression models is presented in Figure 1.

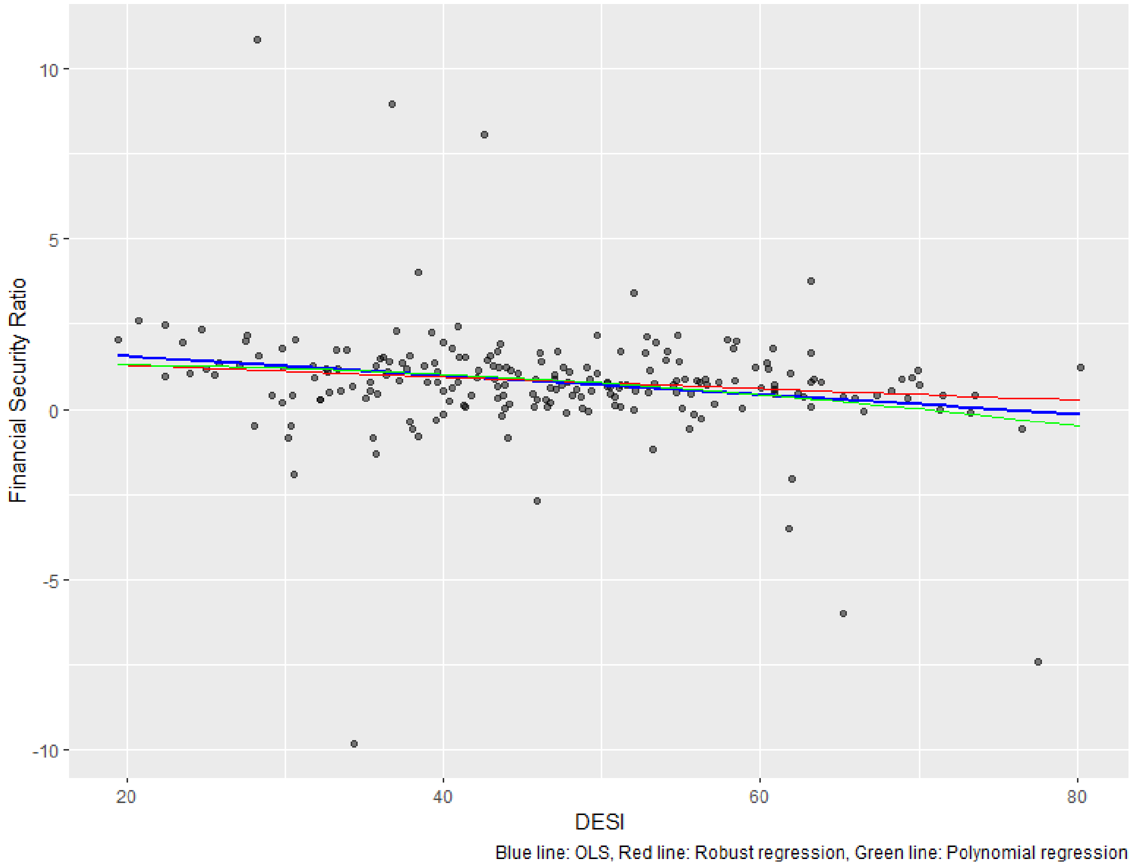

Figure 1: Comparison of regression models of the impact of DESI on financial security.

In addition, quantile regression was conducted to explore how the effect of digitalization varies across different points in the distribution of corporate financial security. The results indicate that the magnitude of the negative effect increases when moving from lower to higher quantiles:

- 25th percentile: −0.014 (not statistically significant)
- 50th percentile (median): −0.017 ($p < 0.05$)
- 75th percentile: −0.026 ($p < 0.05$)

These findings suggest a heterogeneous effect of digitalization: the negative impact is more pronounced among corporations with higher levels of financial security. In contrast, the effect is minor and statistically insignificant for those with lower financial security scores.

5.1.2. Results of panel data analysis

Although the Breusch–Pagan Lagrange Multiplier test failed to reject the null hypothesis of no significant individual effects, using panel data techniques remains justified due to theoretical considerations regarding unobserved heterogeneity across countries. The Hausman test (Table 5) rejected the null hypothesis at the 5% significance level, indicating that the fixed effects model is preferable to the random effects specification. This result suggests that the individual country effects are likely correlated with the explanatory variables, and thus, the fixed effects model provides more consistent estimates.

Table 5
Results of Diagnostic Tests of the Panel Model of the Relationship between Digitalization (DESI) and Financial Security of the Corporate Sector

Test	Statistics	p-value	Interpretation
Hausman test (FE vs. RE)	$\chi^2 = 4.331$	0.0374	The fixed effects model is consistent
F-test for twoways effects	F = 1.128	0.3474	No significant time effects
Pesaran CD test	z = 8.520	<0.0001	The presence of cross-sectional dependence
Breusch-Godfrey/Wooldridge test	$\chi^2 = 11.879$	0.1046	No serial correlation at the 0.05 level
Shapiro-Wilk test	W=0.700	<0.0001	The residuals are not normally distributed
Breusch-Pagan test	BP=0.448	0.503	Heteroscedasticity absent

The F-test for two-way effects did not reject the null hypothesis of no significant time effects, implying that including time-fixed effects is unnecessary, and a model with only individual effects is sufficient for the analysis.

The Pesaran test for cross-sectional dependence revealed statistically significant dependence across country-level observations. This finding underscores the importance of accounting for spatial correlation when estimating standard errors of the coefficients.

The Breusch–Godfrey/Wooldridge test for serial correlation showed no evidence of statistically significant autocorrelation in the residuals at the 5% level. This suggests the absence of systematic temporal patterns in the model's residuals.

Similarly, the Breusch–Pagan test for heteroskedasticity did not detect significant heteroskedasticity, supporting the assumption of homoskedasticity.

In contrast, the Shapiro–Wilk test for normality indicated that the residuals do not follow a normal distribution, which may affect the precision of interval estimates and test statistics, particularly in small samples.

A comparison of the estimation results from the fixed and random effects models is presented in Table 6.

Table 6
Results of the Evaluation of Panel Models of the Relationship between Digitalization and Financial Security of the Corporate Sector

Parameter	Fixed effects model (FE)	Random effects model (RE)	Random effects model (robust standard errors)	Random effects model (Driscoll-Kraay standard errors)
Sample	27x8	27x8	27x8	27x8
Intercept	-	2,122*** (0,444)	2,122*** (0,467)	2,122*** (0,412)
DESI (value)	-0,010 (0,013)	-0,028** (0,009)	-0,028** (0,010)	-0,028*** (0,007)
R^2	0,003	0,043	0,043	0,043
Adjusted R^2	-0,141	0,038	0,038	0,038

*Note: Standard errors are shown in parentheses. Significance levels: *** p < 0.001, ** p < 0.01, * p < 0.05*

The random effects model suggests that a one-unit increase in the Digital Economy and Society Index (DESI) is associated with a 0.028-unit decrease in the corporate financial security index ($p < 0.01$). This result is statistically significant using conventional, robust, and Driscoll–Kraay standard errors, accounting for cross-sectional dependence. Notably, this estimate fully aligns with the findings from the classical linear regression model.

In contrast, the fixed effects model yields a weaker negative relationship ($coefficient =$ ˘0.010), which is not statistically significant ($p = 0.433$). The considerable difference between the estimates obtained from the fixed and random effects models confirms the Hausman test results, indicating a potential misspecification of the random effects model.

These findings reveal several methodological challenges, highlighting the need for more flexible and robust modeling approaches, such as Bayesian regression.

The results of the panel data analysis on the impact of digitalization on corporate financial security highlight several limitations of the classical approach-namely, violations of the normality assumption, the presence of cross-sectional dependence, and the sensitivity of results to model specification.

Bayesian regression offers a flexible methodological alternative that addresses these issues and enables more reliable and interpretable inferences. In particular, the Bayesian approach provides:

- Robustness to violations of classical assumptions
- A natural framework for incorporating estimation uncertainty
- The ability to integrate prior knowledge
- Greater flexibility in modeling complex relationships

Thus, applying Bayesian regression to assess the impact of digitalization on corporate financial security is feasible and necessary for obtaining reliable and theoretically grounded conclusions, particularly under data constraints and complex interdependencies.

5.1.3. Results of the Bayesian analysis

The results of the Bayesian regression analysis, conducted in conjunction with panel data methods to assess the relationship between digitalization and the financial security of the corporate sector, are presented in Table 7.

Table 7
Results of Bayesian Regression Analysis of the Relationship between Digitalization and Financial Security of the Corporate Sector

Parameter	Estimate	Est.Error	95% confidence interval (lower)	95% confidence interval (upper)	Rhat	Bulk-ESS	Tail-ESS
Intercept	2.07	0.46	1.16	2.97	1.00	9391	6134
DESI	-0.03	0.01	-0.05	-0.01	1.00	9335	6005
sd (Intercept for countries)	0.19	0.14	0.01	0.52	1.00	2918	3090
sigma	1.69	0.08	1.53	1.86	1.00	9737	5061

An assessment of the diagnostic metrics indicates the high quality of the Bayesian model estimation:

1. The Rhat statistic equals 1.00 for all model parameters, indicating excellent convergence of the Markov chains. Rhat values close to 1 confirm that the independent chains produce consistent parameter estimates, supporting the stability and reliability of the results.
2. The effective sample size (ESS) is high across all parameters (Intercept, DESI coefficient, sigma), further supporting the robustness of the posterior estimates.

Overall, the diagnostics confirm the reliability and stability of the parameter estimates generated by the Bayesian model.

The analysis reveals a statistically significant negative effect of the level of digitalization on the financial security of the corporate sector. The 95% credible interval does not include zero (Figure 2), confirming the credibility of the identified effect. A one-unit increase in the DESI index is associated with an average reduction of 0.03 units in the financial security index, all else equal. This result is

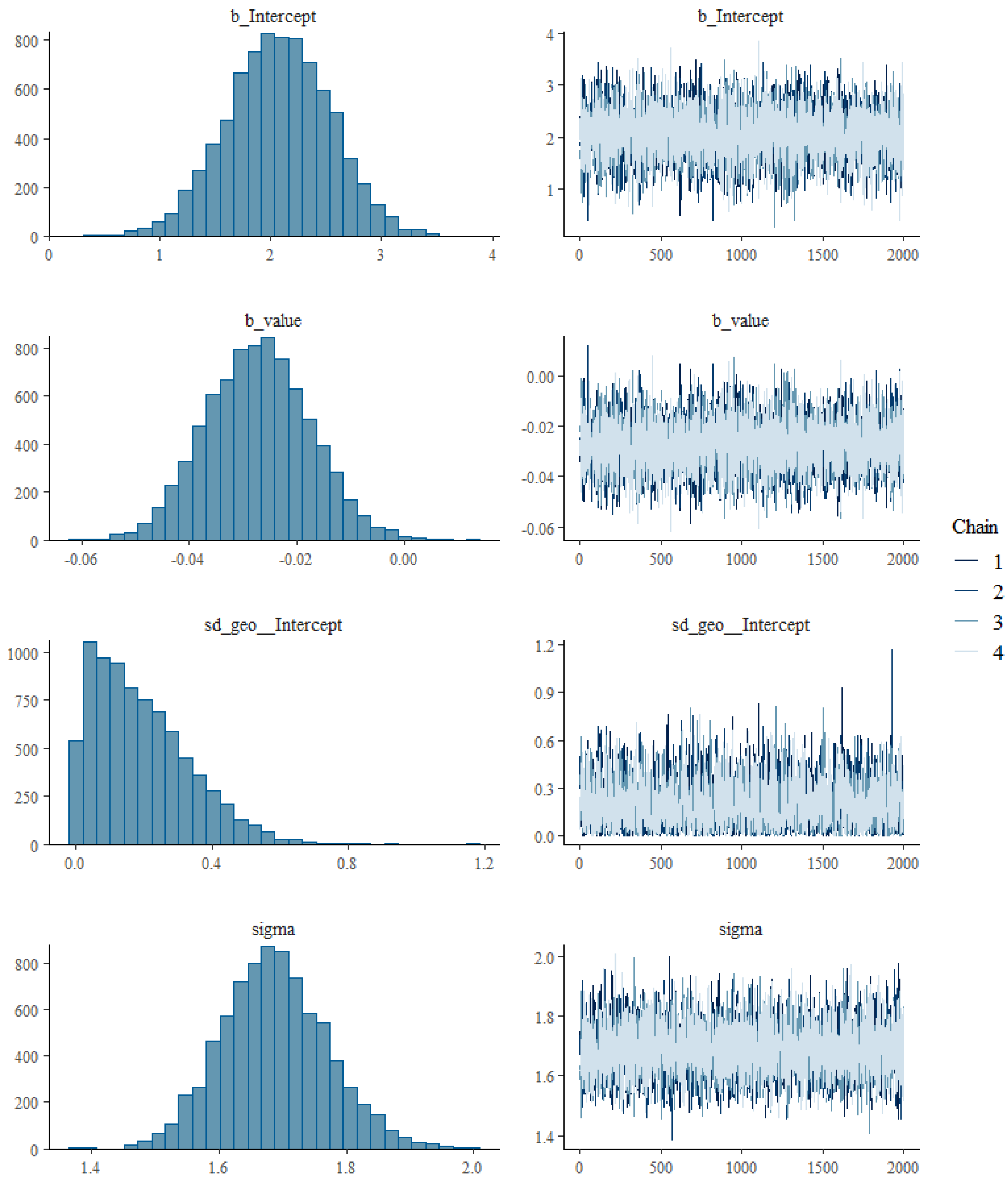

Figure 2: Results of Bayesian regression analysis of the relationship between digitalization and financial security of the corporate sector.

consistent with the findings of the classical regression analysis, which indicated a decrease of 0.028 units.

The standard deviation of the country-level random effects reflects the extent of heterogeneity in the baseline financial security level across countries after controlling for digitalization. The estimated standard deviation of the random effects (0.19) is relatively modest compared to the residual variance parameter (1.69), suggesting a moderate cross-country variation in baseline financial security. However, the wide credible interval [0.01, 0.52] indicates some uncertainty in this estimate.

The sigma parameter represents the unexplained variation in financial security not accounted for by the model. Its relatively high value (1.69) indicates substantial residual variability, likely due to the influence of unobserved factors not included in the model. This, again, aligns with the findings from the classical regression approach.

In general, the results of the Bayesian modeling are consistent with the direction of effects found in the classical panel data analysis but provide a more robust and informative estimation framework.

The formally derived model capturing the impact of digitalization on corporate sector financial security, based on Bayesian regression integrated with a panel data structure, can be expressed as follows:

$$FSR_{ij} \sim \mathcal{N}(\mu_{ij};\, 1.69^2), \mu_{ij} = 2.07 - 0.03 \cdot DESI_{ij} + u_j, u_j \sim \mathcal{N}(0; 0.19^2). \quad (11)$$

5.2. Interpretation of the results

The identified negative relationship between digitalization and the financial security of the corporate sector may be theoretically explained by several hypotheses:

- The Technological Risk Hypothesis. Adopting digital technologies is accompanied by new risks - cybersecurity threats, dependence on technological platforms, and data breaches - which may adversely affect financial stability. For instance, the Global Initiative Against Transnational Organized Crime, in its latest Global Organized Crime Index 2023, has for the first time included cyber-dependent crimes in the composition of the Organized Crime Index [28]
- The Investment Lag Effect. Substantial investments required for digital transformation may impose short-term financial burdens on enterprises. At the same time, the positive effects of digitalization may manifest with a time delay, resulting in a temporary deterioration of financial indicators
- The Structural Adaptation Hypothesis. The digital transformation process often necessitates significant changes in business models and organizational structures, which may temporarily undermine the financial resilience of enterprises during the transition phase
- The Digital Divide Effect. Variations in access to digital technologies and competencies across firms can lead to unequal competitive conditions, causing negative financial outcomes for less digitally advanced companies

Thus, the observed negative effect may stem from the transformational costs and emergent risks associated with the digitalization process. It is important to note that the presented findings reflect short- and medium-term effects, while the long-term consequences of digitalization for corporate financial security may differ significantly.

5.3. Practical recommendations

Based on the results of the conducted study, several practical recommendations can be formulated. For enterprises, it is advisable to:

- Develop comprehensive digital transformation strategies that explicitly incorporate risk management components
- Implement digital solutions in a phased manner, accompanied by regular assessments of their impact on financial performance
- Maintain a balanced approach to digital investment by aligning transformation efforts with the need to ensure financial stability

For investors, the following considerations are particularly relevant:

- Take into account the digital maturity indicators of companies when evaluating their investment attractiveness

- Conduct thorough analyses of the relationship between digital transformation expenditures and financial resilience indicators

From the perspective of regulators, it is recommended to:

- Foster an enabling regulatory environment for digital transformation that simultaneously accounts for potential financial security risks
- Develop monitoring tools and early warning systems aimed at identifying emerging threats to financial security arising from digitalization
- Promote advancing digital competencies and infrastructure to support sustainable and secure digital development

6. Discussion

When interpreting the findings of this study, it is essential to consider several methodological limitations that define the scope of generalizability and outline potential avenues for further scientific inquiry.

The primary limitation of this research lies in the relatively small panel dataset, which includes only 27 countries over an 8-year observation period. This characteristic of the sample imposes significant constraints on the statistical power of the analysis and reduces the robustness of the inferential procedures. In examining the relationship between digitalization and the financial security of the corporate sector, the limited temporal horizon is particularly critical, as it hampers the ability to assess potential lagged effects of digital transformation adequately.

By nature, digitalization represents a complex, long-term process, the outcomes of which may materialize over various time horizons. While short-term effects may reflect adverse outcomes due to the need for substantial upfront investments and transformation-related costs, medium- and long-term impacts are potentially positive, stemming from enhanced efficiency, streamlined business processes, and the emergence of new development opportunities. The available 8-year period - determined by changes in DESI methodology - appears insufficient to fully capture the entire spectrum of temporally distributed effects, particularly given the varying pace of digital transformation across countries.

Moreover, the limited cross-sectional dimension of the dataset (27 countries) reduces the capacity to identify and control for heterogeneity in the impact of digitalization across economies with different levels of development, institutional environments, and corporate sector structures. A larger sample size would enable more detailed segmentation and allow for cluster-based or differentiated analysis of countries, which might reveal divergent digitalization effects depending on specific national characteristics.

These identified limitations highlight the need to expand future research longitudinally, to account for lagged effects, and cross-sectionally, to increase the sample's representativeness and facilitate a more granular investigation of heterogeneity in the observed relationships.

7. Conclusions

The empirical findings of this study reveal a statistically significant negative association between the level of digitalization and indicators of financial security in the corporate sector. This relationship remains robust across different estimation methods and appears stronger for firms with higher baseline levels of financial security.

However, this negative association should not be interpreted as an argument against digitalization. Instead, it should be viewed as evidence of the need for a comprehensive approach to managing digital transformation, which explicitly considers the potential risks to financial stability. Formulating effective digitalization strategies must incorporate mechanisms for monitoring and managing financial risks and adaptive changes in business models and organizational structures to ensure that the benefits of digital transformation do not come at the expense of corporate financial resilience.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

References

[1] Ernst & Young, How digital transformation impacts financial services companies and their audits, https://www.ey.com/en_gl/insights/assurance/how-digital-transformation-impacts-financial-services-companies-and-their-audits, 2024.

[2] OECD, Digitalisation of financial services: Access to finance and aggregate economic performance, 2024. URL: https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/08/digitalisation-of-financial-services-access-to-finance-and-aggregate-economic-performance_86d37dc7/10c7e583-en.pdf.

[3] O. Desyatnyuk, M. Naumenko, I. Lytovchenko, O. Beketov, Impact of digitalization on international financial security in conditions of sustainable development, Problemy Ekorozwoju 19 (2024). doi:10.35784/preko.5325.

[4] Prime Group, The future of finance: Digitalization in finance, 2023. URL: https://weareprimegroup.com/insights/the-future-of-finance-digitalization-in-finance/.

[5] F. Bernini, P. Ferretti, A. Angelini, The digitalization-reputation link: a multiple case-study on italian banking groups, Meditari Accountancy Research 30 (2022) 1210–1240. doi:10.1108/MEDAR-02-2021-1201.

[6] Z. Zhang, Z. Su, F. Tong, Does digital transformation restrain corporate financialization? evidence from china, Finance Research Letters 56 (2023). doi:10.1016/j.frl.2023.104152.

[7] R. Kostyrko, T. Kosova, L. Kostyrko, L. Zaitseva, O. Melnychenko, Ukrainian market of electrical energy: Reforming, financing, innovative investment, efficiency analysis, and audit, Energies 14 (2021) 5080. doi:10.3390/en14165080.

[8] I. Shkolnyk, S. Frolov, V. Orlov, V. Datsenko, Y. Kozmenko, The impact of financial digitalization on ensuring the economic security of a country at war: New measurement vectors, Investment Management and Financial Innovations 19 (2022) 119–138. doi:10.21511/imfi.19(3).2022.11.

[9] A. Krysovatyy, O. Desyatnyuk, O. Ptashchenko, Digital innovations and their ramifications for financial and state security, African Journal of Applied Research 10 (2024) 431–441. doi:10.26437/ajar.30.06.2024.26.

[10] Y. Samoilenko, I. Britchenko, I. Levchenko, P. Lošonczi, O. Bilichenko, O. Bodnar, Economic security of the enterprise within the conditions of digital transformation, Econ.Aff. 67 (2022) 619–629. doi:10.46852/0424-2513.4.2022.28.

[11] V. Biliavskyi, Y. Biliavska, Y. Umantsiv, Y. Shestack, O. Zhurba, A. Khavanov, Digital technologies in the financial sector of the economy, Financial and Credit Activity Problems of Theory and Practice 57 (2024) 171–183. doi:10.55643/fcaptp.4.57.2024.4444.

[12] Y. Kovalenko, Efficiency of financial sector of economy: Institutional approach, Actual Problems of Economics 120 (2011) 11–17.

[13] Y. Kovalenko, S. Onyshko, O. Akilina, O. Tanchyk, Institutialization features of the financial sector of the economy, in: Proceedings of the 33rd International Business Information Management Association Conference (IBIMA), Granada, Spain, 2019, pp. 1759–1766. URL: https://www.scopus.com/record/display.uri?eid=2-s2.0-85074099970&origin=recordpage.

[14] S. Smerichevskyi, Strategic aspects of adaptive management of the economic security of enterprises, Ukrainian Journal of Applied Economics and Technology 2 (2023) 37–44. doi:10.36887/2415-8453-2023-2-5.

[15] European Commission, Digital economy and society index (desi), 2024. URL: https://digital-strategy.ec.europa.eu/en/policies/desi.

[16] European Commission, Digital Economy and Society Index (DESI) 2022, Methodological Note, Technical Report, 2022. URL: https://ec.europa.eu/newsroom/dae/redirection/document/88557.

[17] Eurostat, Financial balance sheets - annual data, n.d.. doi:10.2908/NASA_10_F_BS.

[18] Eurostat, Non-financial transactions - annual data, n.d.. doi:10.2908/NASA_10_NF_TR.

[19] S. Krynytsia, J. Tryhub, Methodical approaches to diagnosis of financial security of enterprise taking into account the factor of competitiveness, Socio-economic Relations in the Digital Society 3 (2020) 79–84. doi:10.18371/2221-755X3(39)2020225583.

[20] T. S. Morrison, Comparing Various Robust Estimation Techniques in Regression Analysis, Master's thesis, Minnesota State University, Mankato, USA, 2021.

[21] A. Bell, K. Jones, Explaining fixed effects: Random effects modeling of time-series cross-sectional and panel data, Political Science Research and Methods 3 (2015) 133–153. doi:10.1017/psrm.2014.7.

[22] A. Gelman, A. Vehtari, D. Simpson, C. Margossian, Bayesian workflow, 2020. doi:10.48550/arXiv.2011.01808.

[23] T. Breusch, A. Pagan, The lagrange multiplier test and its applications to model specification in econometrics, The Review of Economic Studies 47 (1980) 239–253. doi:10.2307/2297111.

[24] D. Hoechle, Robust standard errors for panel regressions with cross-sectional dependence, Stata Journal 7 (2007) 281–312. doi:10.1177/1536867X0700700301.

[25] J. Hausman, Specification tests in econometrics, Econometrica 46 (1978) 1251–1271. doi:10.2307/1913827.

[26] S. Krynytsia, Software to evaluate the effect of digitalization on the financial security of the corporate sector, GitHub, 2025. URL: https://github.com/Haidamac/desi_finsec.git.

[27] P.-C. Burkner, Advanced bayesian multilevel modeling with the r package brms, The R Journal 10 (2018) 395–411. doi:10.32614/RJ-2018-017.

[28] Global Initiative Against Transnational Organized Crime, The global organized crime index 2023, 2023. URL: https://globalinitiative.net/wp-content/uploads/2023/09/Global-organized-crime-index-2023-web-compressed-compressed.pdf.