“Digitalization, green transformation, and agricultural productivity in transition economies: Panel evidence with illustrative insights for Moldova and Armenia”

AUTHORS	Alexandru Stratan Tatul M. Mkrtchyan Liliana Staver Ani Khachatryan Larisa Dodu-Gugea Anna Ayvazyan Nina Roscovan

ARTICLE INFO	Alexandru Stratan, Tatul M. Mkrtchyan, Liliana Staver, Ani Khachatryan, Larisa Dodu-Gugea, Anna Ayvazyan and Nina Roscovan (2026). Digitalization, green transformation, and agricultural productivity in transition economies: Panel evidence with illustrative insights for Moldova and Armenia. *Environmental Economics*, *17*(3), 86–103. doi:10.21511/ee.17(3).2026.06
DOI	http://dx.doi.org/10.21511/ee.17(3).2026.06
RELEASED ON	Wednesday, 05 August 2026
RECEIVED ON	Tuesday, 02 June 2026
ACCEPTED ON	Thursday, 23 July 2026

JOURNAL	"Environmental Economics"
ISSN PRINT	1998-6041
ISSN ONLINE	1998-605X
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
59	0	5

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Alexandru Stratan (Moldova), **Tatul Mkrtchyan** (Armenia), **Liliana Staver** (Moldova), **Ani Khachatryan** (Armenia), **Larisa Dodu-Gugea** (Moldova), **Anna Ayvazyan** (Armenia), **Nina Roscovan** (Moldova)

DIGITALIZATION, GREEN TRANSFORMATION, AND AGRICULTURAL PRODUCTIVITY IN TRANSITION ECONOMIES: PANEL EVIDENCE WITH ILLUSTRATIVE INSIGHTS FOR MOLDOVA AND ARMENIA

Type of the article: Research Article

Received on: 2nd of June, 2026
Accepted on: 23rd of July, 2026
Published on: 5th of August, 2026

Alexandru Stratan, Habilitate Doctor, Rector of AESM, Academy of Economic Studies of Moldova, Moldova.

Tatul Mkrtchyan, Doctor of Economics, Professor, Head of the Chair of Applied Economics, Armenian State University of Economics, Armenia. (Corresponding author)

Liliana Staver, M.A., Head of Research Development and Innovation Division, Expert-Researcher at COG-CILIX-NET Research Center, Academy of Economic Studies of Moldova, Moldova.

Ani Khachatryan, Ph.D., Expert-Researcher at AMBERD Research Center, Armenian State University of Economics, Armenia.

Larisa Dodu-Gugea, Ph.D., Dean of the Faculty of International Economic Relations, Academy of Economic Studies of Moldova, Moldova.

Anna Ayvazyan, Lecturer, Chair of Management, Armenian State University of Economics, Armenia.

Nina Roscovan, Ph.D., Expert-Researcher at COG-CILIX-NET Research Center, Academy of Economic Studies of Moldova, Moldova.

Abstract

This study analyzes the impact of digitalization, green transformation, financial access, and institutional support on agricultural labor productivity in transition economies of Eastern Europe and the Caucasus. Panel data for six countries (2000–2024) were examined using fixed and random effects models, with robustness checks using the Driscoll–Kraay estimator. Results show that digitalization and financial access consistently enhance productivity at the panel level (0.141; $p < 0.01$), while institutional factors do not show a consistent direct effect once temporal trends are removed (0.050, $p > 0.05$), though they may strengthen resilience indirectly. In contrast, the Green Index exerts a significant negative effect (–1.848; $p < 0.01$), reflecting substantial transitional costs of ecological modernization. Country fixed effects reveal heterogeneity: Moldova (+0.1106) shows the highest positive deviation, while Armenia (–0.0365), Azerbaijan (–0.0749), and Kazakhstan (–0.0382) exhibit negative deviations. Ukraine (+0.0176) and Georgia (+0.0028) remain close to the panel mean. Country specific regressions reveal both commonalities and divergences. In Moldova, institutional quality (0.265, $p < 0.001$), digitalization (0.033, $p = 0.026$), and green practices (–0.462, $p < 0.001$) significantly shape productivity, while finance is excluded. In Armenia, institutional quality (0.469, $p = 0.001$) and green practices (–0.502, $p = 0.001$) remain significant, but finance enters negatively (–0.855, $p = 0.050$), and digitalization is excluded. Digitalization and finance are immediate productivity enhancers at the regional level, but their role varies by country. Ecological modernization imposes short term costs and requires compensatory policies.

Keywords environment, digitalization, productivity, institutions, sustainability

JEL Classification Q56, Q18, C23, O33

INTRODUCTION

According to the United Nations Development Programme [UNDP] (2021), the agri-food sector in Eastern Europe faces double pressure: the need to increase productivity while meeting the requirements of sustainable development. Green transformation – renewable energy, energy efficiency, waste recycling, and environmental certification – is a necessary condition for fulfilling international climate commitments, yet it creates additional costs for enterprises and reduces short-term efficiency. FAOSTAT (2023) shows that average labor productivity in Moldova's and Armenia's agricultural sectors is about 5,000 USD per employee, which is lower than in neighboring EU countries. At the same time, World Bank (2024) data reveal high energy intensity of

Conflict of interest statement:
Author(s) reported no conflict of interest

http://dx.doi.org/10.21511/ee.17(3).2026.06

production and significant CO_2 emissions per unit of output, underscoring environmental inefficiency. Investment in "green" technologies, according to UNDP (2021), amounts to only 1–2% of GDP, which is insufficient to offset transitional productivity losses. Ecological modernization can simultaneously reduce environmental footprint and strengthen competitiveness, but only if supported by coordinated policy frameworks and adequate financial access. For the transition economies of Eastern Europe, the key challenge is to integrate green strategies into a single development model, ensuring that ecological requirements do not conflict with economic efficiency. That is why studying the balance between environmental transformation and agricultural productivity has practical significance for shaping policies that guarantee the sector's sustainability and resilience.

At the same time, the experience of transition economies shows that neither digitalization nor green transformation alone can ensure sustainable competitiveness. While ecological modernization is essential for meeting climate commitments, its short-term costs can be mitigated only when combined with digital tools that optimize resource use, reduce transaction costs, and improve monitoring of environmental performance. Integrating ICT solutions with renewable energy adoption, energy efficiency measures, and eco-certification creates synergies that allow the agri-food sector to simultaneously enhance productivity and reduce its ecological footprint. Thus, the balance between digital and green strategies is not a matter of choice but of necessity, as only their joint implementation can guarantee resilience and long-term sustainability in the sector.

Moldova and Armenia are illustrative examples of how the agri-food sector in transition economies is facing the challenges of green transformation. In both countries, investment in green technologies remains low (1–2% of GDP), which does not fully offset the short-term costs of implementing green practices. At the same time, these countries are demonstrating gradual productivity growth through a combination of financial support and institutional reforms that create conditions for integrating renewable energy, energy efficiency, and environmental certification into production processes. Moldova is distinguished by a high level of institutional support that facilitates enterprises' adaptation to environmental standards. At the same time, Armenia demonstrates positive results by combining green modernization with reforms in governance and access to finance. That is why these countries are vivid examples of how green transformation, despite short-term costs, can become the basis for the long-term sustainability and competitiveness of the agri-food sector in the region.

1. LITERATURE REVIEW

Recent studies have emphasized the structural and regulatory dimensions of agri-food transformation in Eastern Europe. Clustering strategies have been shown to enhance competitiveness and position the sector as a global player (Sitnicki et al., 2024). Targeted policy instruments such as CAP eco-schemes can simultaneously lower costs and strengthen resilience in EU agriculture (Pimenow et al., 2026). Agri-environmental risk drivers under the EUDR framework highlight financial risks and readiness challenges in Eastern European countries (Sitnicki et al., 2026). The war in Ukraine has accelerated renewable deployment in Europe, reframing energy dependency into energy security (Vasylieva et al., 2025). Advances in government AI readiness further strengthen energy security, linking digital governance with resilience in the energy sector (Kuzior et al., 2025). Together, these studies underscore that, beyond digital practices, the future of the agri-food sector is increasingly determined by green business models: structural clustering strategies, energy-efficiency policies, regulatory-compliance capacities, and broader energy-security dynamics.

The literature on financial mechanisms and ESG practices also highlights their role in enabling green modernization in agribusiness. Venture capital is identified as a critical factor for the development of green and digital energy startups (Bilan & Halynskyi, 2026), while financial instruments such as feed-in tariffs and power purchase agreements stimulate investment in renewable energy (Lyeonov & Moroz, 2025). Studies show that green finance increases the competitiveness of agri-food SMEs in Eastern Europe, while ESG practices drive corporate performance in both developing countries and green companies (Ramada et al., 2026; Shafitranata et al., 2026). In addition, corporate governance and the use of sustainability bonds reduce labor costs and stimulate green investments (Rohman et al., 2026). Moreover, access to credit directly contributes to business value added in SMEs (Ivashchenko et al., 2023), while macroeconomic conditions significantly shape the effectiveness of green investments (Mkrtchyan et al., 2025). Institutional aspects of nongovernmental organizations in economic sectors also play a role in shaping the environment for financial and green modernization (Vakhovych et al., 2026). Taken together, financial mechanisms and ESG strategies are not only instruments of support but also foundations for the long-term success of green agribusiness, ensuring that ecological transformation becomes a driver of productivity and resilience in transition economies.

Research on digital transformation and institutional change follows a common logic: digitalization is becoming a key driver of governance modernization, but it also creates new challenges for SME productivity. The use of artificial intelligence in the energy sector shows how technology can support green growth strategies (Abou-Moghli, 2026), while the transformation of accounting is shaping the intellectual framework for sustainable development (Asare, 2025). In the agri-food sector, digitalization is increasingly linked to ecological modernization, in which smart technologies enable the integration of renewable energy, energy efficiency, and sustainable certification practices. Studies highlight that digital governance and the role of artificial intelligence in development are changing the political economy of public goods (Kafoe et al., 2026). Moreover, the digitalization of government management processes in the context of sustainable development demonstrates that technology transforms not only business environments but also public administration practices, creating new opportunities for transparency and efficiency (Sira & Kuzior, 2025). Regarding SME tax behavior, digital tools, including e-filing, have been shown to increase trust in institutions and reduce compliance costs (Safelia et al., 2026). Thus, digitalization is reshaping institutions and governance. However, its greatest potential in agri-food SMEs lies in supporting green business models: combining ecological practices with technological innovation to increase productivity and ensure long-term sustainability. In research on Agriculture 4.0 and agri-food SMEs, there is a clear trend toward integrating digital and green strategies as complementary drivers of productivity and resilience.

Research on organizational culture and human factors emphasizes that employee and consumer behavior shapes the effectiveness of digital and green transformations. Voluntary "green" behavior in the workplace, supported by human resource management practices, creates a favorable climate for leadership and employee satisfaction (Dharma et al., 2025). Digital leadership, in turn, increases staff productivity by acting through the mediating mechanisms of digital self-efficacy and motivation (Mamdouh et al., 2025). At the consumer market level, environmental awareness and green marketing determine the socio-economic outcomes of sustainability, as consumer behavior influences demand for green goods and practices (Rawal & Joshi, 2025). In addition, recent studies show that human factors extend beyond employee and consumer behavior to include managerial risks: ranking profitability and cost indicators of agribusinesses provides insights into efficiency and competitiveness (Hnatenko & Konieczny, 2023), while migration risks in agro-industrial enterprises highlight vulnerabilities in workforce management (Hnatenko & Tanchyk, 2024). At the same time, inter-organizational knowledge transfer practices foster innovation and enhance SMEs' ability to adapt to digital and green transformations (Bencsik & Belas, 2025). Thus, human factors (from internal organizational culture to external consumer behavior, and further to managerial risks) are critical to successfully balancing digital and green transitions in SMEs.

Regarding external challenges and technological solutions, the focus is on the resilience of transition economies and the role of innovation in overcoming crises. Food security research shows that geopolitical risks pose significant threats to global supply chains (Mehibel et al., 2025), while analysis of electricity price shocks in Europe demonstrates the vulnerability of economies to energy crises

http://dx.doi.org/10.21511/ee.17(3).2026.06

(Vasylieva et al., 2026). In the technological dimension, green and safe microgrids are considered a monitoring and forecasting tool that enhances energy sustainability (Wojciechowski et al., 2025), and the integration of green supply chains creates socio-economic value through eco-innovation effects (Tedjakusuma et al., 2026). Moreover, recent studies emphasize that institutional and environmental drivers are crucial for SME development in the EU, particularly in the context of the Sustainable Development Goals (Tu et al., 2025), while household energy efficiency and renewable energy development play a significant role in reducing energy poverty (Śmiech et al., 2025). At the same time, global regulatory changes such as the EUDR introduce new agri-environmental risks and financial challenges for Eastern European countries, requiring SMEs to strengthen their readiness and adaptability to ecological standards (Sitnicki et al., 2026). Overall, external shocks and global challenges can significantly affect SME performance, but technological, institutional, and regulatory solutions can ensure their adaptability and long-term sustainability.

In transition economies, Agriculture 4.0 technologies are identified as a path to sustainable growth, as they enable the integration of digital innovations into production processes (Dayıoğlu & Turker, 2021). The example of Bulgaria demonstrates that implementing digitization practices enables SMEs to gain a competitive advantage by combining digitalization with environmental approaches (Varbanova et al., 2025). A review of smart farming equipment confirms the potential for more human-centric production, where technologies aim to increase the efficiency and sustainability of agricultural systems (Song et al., 2026). At the same time, organic farming demonstrates that environmental practices can enhance access to healthy food, generating socio-economic benefits (Hroma, 2026). Analysis of changes in greenhouse gas emissions across EU countries indicates the need for deep environmental reforms in agriculture, an important element of the green transformation (Szymańska & Tłuczak, 2026). At the local government level, digital transformation in village financial management demonstrates how institutional adaptation can strengthen transparency and financial sustainability (Jumaiyah et al., 2025). Moreover, Agriculture 4.0 encompasses both technological innovation and organizational and market strategies. These include smart agro-clustering based on the "education-science-business" chain (Bashynska et al., 2022), smart specialization approaches to agricultural development in Central and Eastern Europe (Shvets et al., 2023), and determinants of green branding in the agro-sphere such as eco-consumption, loyalty, and price premiums (Danko & Nifatova, 2022).

Moldova and Armenia illustrate these dynamics particularly well. Both countries face structural challenges in productivity, yet demonstrate resilience through the gradual integration of green practices. In Moldova, institutional support and access to finance have enabled SMEs to experiment with renewable energy and eco-certification, even with limited investment. Armenia, in turn, shows how institutional reforms and the adoption of smart agricultural tools can reinforce environmental modernization, positioning SMEs to benefit from organic farming and clustering strategies. These cases confirm that the balance of digital innovation, ecological requirements, and organizational approaches is not abstract but directly observable in practice (Dayıoğlu & Turker, 2021; Hroma, 2026; Szymańska & Tłuczak, 2026). Additional studies on smart agro-clustering, specialization, and green branding further support this conclusion, showing that Moldova and Armenia exemplify how targeted reforms and adaptive strategies can transform ecological modernization into a driver of competitiveness (Bashynska et al., 2022; Shvets et al., 2023; Danko & Nifatova, 2022).

The reviewed literature demonstrates that digitalization enhances productivity but requires institutional adaptation, while green practices impose shortterm costs yet improve longterm competitiveness. Financial and governance mechanisms act as enablers of this transformation, and consumer behavior, workplace culture, and local governance add further complexity, while global shocks highlight vulnerabilities. Taken together, these works outline the core of the issue: agrifood SMEs in Eastern Europe need to balance digital innovations, environmental requirements, and new forms of clustering, specialization, and branding to ensure productivity and longterm sustainability. This landscape confirms the need to study how such enterprises can integrate digital and green transitions in a way that achieves sustainable competitiveness and resilience.

The study seeks to evaluate how digitalization, ecological modernization, financial access, and institutional support influence agricultural productivity in transition economies of Eastern Europe and the Caucasus, additionally considering Moldova and Armenia as illustrative cases to demonstrate the role of national conditions in shaping modernization outcomes.

2. METHOD

The research methodology uses panel models with fixed (FE) and random effects (RE), allowing us to account for country-specific factors. A descriptive data analysis was conducted. Some variables were transformed to reduce distributional asymmetry and ensure indicator comparability. Data aggregation was also performed to create a consistent panel structure. To assess the estimates' validity, a VIF (multicollinearity) test was also performed. In addition, to ensure the stability of the results, robust standard errors were used, in particular the Driscoll–Kraay method, which accounts for potential panel-data problems and ensures the reliability of the conclusions.

The panel data cover indicators of digital and green transformation, access to finance, and institutional support for Moldova, Armenia, Georgia, Ukraine, Azerbaijan, and Kazakhstan over the period 2000–2024. Ukraine was included in the panel to ensure a comprehensive evaluation of the regional agri-food dynamics over the 2000-2024 period, as structural macro-trend continuity and rapid post-2022 digital and green adaptations maintain its relevance for empirical analysis.The agri-food sector in these countries operates under similar institutional and economic conditions, but differs in the pace of digital and green modernization. Therefore, the use of panel analysis allows us to combine temporal and spatial dimensions: data spanning 25 years enables us to account for both temporal dynamics and cross-country differences. In addition, there is an opportunity to control for unmeasured factors, as fixed effects (FE) models account for country-specific features that cannot be directly measured. It is also possible to assess general trends: random effects (RE) models allow us to generalize the results and show how digital and green factors affect productivity across countries (Bell & Jones, 2015). Panel data provide more observations than discrete time series or cross-sectional samples, reducing the risk of estimation bias. Therefore, panel analysis is the optimal tool for investigating the relationships among digital and green transformation, financial access, institutional support, and agricultural productivity across six countries in the region. Among them, special attention is paid to Moldova and Armenia, which have special institutional conditions and financial market characteristics. This makes them illustrative examples in the context of fixed effects.

The dependent variable for the FE/RE models was chosen as agricultural labor productivity (USD/worker), calculated as the ratio of agricultural value added (in constant USD) to the number of people employed in agriculture using the FAOSTAT database. This indicator is widely used in empirical research as a macro-level measure of sectoral efficiency. Its selection is justified by several considerations. In particular, it offers macro-economic relevance: Labor productivity reflects the efficiency of resource use in the agri-food sector and is a key determinant of competitiveness and growth in transition economies. It also offers comparability across countries (FAOSTAT provides harmonized data, allowing consistent cross-country and longitudinal analysis) and sectoral representativeness (in the studied economies, agriculture remains a significant component of the agri-industrial system, and labor productivity captures both technological progress and structural transformation). Moreover, it is worth mentioning policy significance. Productivity at the macro level is directly linked to food security, rural employment, and sustainable development, making it a meaningful outcome variable for evaluating the impact of digitalization, finance, institutions, and green practices. It provides a robust and tractable proxy for sectoral performance at the national level. Future research should complement this approach with microdata and enterprise surveys to validate and extend the findings.

The independent variables were grouped into four blocks: digitalization, green transformation, financial access, and institutional support. The de-

http://dx.doi.org/10.21511/ee.17(3).2026.06

Table 1. Independent variables and data sources

Block	Variable	Definition	Source
Digital_Index	Digital_Index*	Composite index of national digital adoption in the business and agricultural sectors	World Bank database
	Internet_Penetration	Broadband and mobile internet penetration rate per 100 inhabitants	ITU database
	Ecommerce_Share*	Share of e-commerce and digital transactions in total sectoral/national turnover (%)	Eurostat database
	ICT_Investment*	Gross fixed capital formation in ICT infrastructure and software (% of GDP / sectoral investment)	FAOSTAT database
	Digital_Skills*	Share of economically active population with basic or advanced digital skills (%)	ILO database
	Cloud/Software Adoption*	Sectoral rate of business management software and e-governance systems adoption (%)	OECD database
Green_Index	Renewable_Energy_Share	Share of renewable energy in total final energy consumption (%)	IEA database
	Energy_Efficiency	Primary energy intensity of GDP / sectoral output (kWh per unit of agricultural output)	UNIDO database
	Green_Investment*	Gross national investments in environmental protection and green technology (% of GDP)	UNDP database
	CO_2_Reduction	Aggregated reduction of CO_2 emissions per unit of sectoral GDP/output	World Bank database
	Waste_Recycling*	Municipal and agricultural waste recycling rate (% of total waste generated)	Eurostat database
	Eco_Certification*	Adoption rate of ISO 14001, EMAS, and eco-standards across the agricultural sector (%)	ILO database
	Sustainable_Agriculture	Share of total agricultural land under certified organic and sustainable farming (%)	FAOSTAT database
Finance_ Access	Credit_Access	Domestic credit to the private/agricultural sector (% of sectoral GDP)	World Bank database
	Grant_Funding*	Volume of official international and national development grants (% of GDP or agri-investment)	UNDP and FAO databases
	Gov_Support_Programs*	Share of agricultural producers covered by national financial support and subsidy programs (%)	Ministries of Economy databases
	Subsidy_Share*	Share of state subsidies in total agricultural output and sectoral funding (%)	OECD database
Institutional_ Support	Policy_Stability	Aggregated index of economic, regulatory, and agricultural policy stability	World Bank database
	Regulatory_Quality	Aggregate regulatory quality index (transparency, market efficiency, reduction of barriers)	World Bank database
	Institutional_Trust*	National index of public and business trust in state institutions	Gallup database, OECD database
	Extension_Services*	National coverage rate of agricultural advisory, extension, and educational programs (%)	FAOSTAT database

Note: Variables marked (*) are only available periodically, not annually, for the entire period 2000–2024; coverage is limited, gaps have been filled by interpolation or imputation, and all variables are standardized for comparability.

tailed composition of each block of independent variables and their sources is presented in Table 1.

The independent variables were grouped into four blocks: digitalization, green transformation, financial access, and institutional support. Their composition and sources are presented in Table 1 (World Bank, 2024; ITU, 2024; Eurostat, 2024; ILO, 2024; OECD, 2024; IEA, 2024; UNIDO, 2024; UNDP, 2024; Gallup, 2024; FAO, 2023, Ministry of Agrarian Policy and Food of Ukraine, 2024; Ministry of Agriculture and Food Industry of the Republic of Moldova, 2024; Ministry of Agriculture of the Republic of Kazakhstan, 2024; Ministry of Economy and Sustainable Development of Georgia, 2024; State Statistical Committee of the Republic of Azerbaijan, 2024; Statistical Committee of the Republic of Armenia, 2024). Not all indicators in Table 1 are available annually for the entire period 2000–2024. ICT investment and digital skills have regular annual coverage, while environmental certification and enterprises' participation in government support programs are published only periodically. For environmental certification, observations are missing for most countries in 2000–2002, and in 2005–2007 and 2010–2012 for non-EU transition economies (Moldova, Armenia, Georgia, Azerbaijan, and Kazakhstan). Data on participation in government support programs are available only for selected years (2004, 2008, 2012, 2016, and 2020), with gaps in the intervening years.

Not all component indicators are available as complete annual country-level series for the entire 2000–2024 period, which is a typical limitation of international panel studies. To ensure consistency, the core variables (ICT investment, digital skills, renewable energy share, energy efficiency, credit access, policy stability, and regulatory quality) have regular annual coverage and thus form the analytical backbone of the study. Overall, about 25% of the panel observations across the four blocks were reconstructed. For isolated missing values, we applied arithmetic mean substitution using adjacent years (the average of the preceding and following observations). In cases of consecutive gaps spanning several years, we used linear interpolation. Where interpolation was not feasible (at the beginning or end of the series, or for irregularly reported indicators), we applied nearest-neighbor imputation, substituting the closest available observation in time. This combination of methods is consistent with established practices in panel data research, as it preserves the dataset structure, avoids loss of observations, and ensures comparability across countries and years. All reconstructed series were subsequently standardized to maintain consistency in measurement and interpretation.

The indicators were standardized globally across the pooled sample to ensure cross-country comparability, and the final regression models rely on these harmonized indices. No additional robustness checks on weighting schemes or sensitivity analyses of index composition were performed, as the subsequent application of principal component analysis provided dimensionality reduction and ensured the stability of the regression estimates.

The blocks in Table 1 characterize the transformation of enterprises from different sides. In particular, Digital_Index reflects the level of digital transformation of enterprises. It includes indicators of Internet access, use of e-commerce, investment in ICT, digital skills, and implementation of cloud/software solutions. Green_Index characterizes environmental and "green" transformation, covering the share of renewable energy, energy efficiency, investments in green technologies, CO_2 reduction, waste recycling, environmental certification, and organic farming. Finance_Access shows enterprises' access to financial resources through loans, grants, state support programs, and subsidies. Institutional_Support reflects the quality of the institutional environment.

Multicollinearity was assessed using the variance inflation factor (VIF) in Stata. The values obtained significantly exceed the permissible limit, with an actual average VIF ≈ 3774. Therefore, there is duplication of information between the indicators of digital transformation, green modernization, financial access, and institutional support in the sample. To eliminate multicollinearity, the method of aggregating variables into thematic indices was applied: Digital_Index (Internet Penetration, E-commerce Share, ICT Investment, Cloud Adoption, Digital Skills); Green_Index (Energy Efficiency, Green Investment, CO_2 Reduction, Eco Certification, Sustainable Agriculture); Financial_Index (Credit Access, Grant Funding); and Institutional_Index (Policy Stability, Regulatory Quality, Extension Services). Aggregation was carried out by calculating the row means of standardized values (rowmean in Stata), which reduced the number of variables and ensured the stability of regression model estimates. The previous application of the simple average (row means) did not address multicollinearity (VIF ≈ 43). Therefore, the principal component analysis (PCA) method was applied for the final analysis.

To eliminate multicollinearity while preserving the maximum information content of multi-indicator blocks, principal component analysis (PCA) was applied independently to four functional domains containing six (Digital), seven (Green), four (Financial), and four (Institutional) sub-indicators. Prior to PCA, all sub-indicators were globally standardized across the pooled panel dataset ($N = 6$, $T = 25$, 2000–2024) to ensure cross-country comparability. Only the first principal component (PC_1) was retained for each domain, as it captured the overwhelming majority of shared variance, yielding sound eigenvalues of 5.8 (96.7% variance explained), 6.8 (97.1%), 3.9 (97.5%), and 3.8 (95.0%), respectively.

Each composite index ($I_{i,t}$) is derived as a linear combination of its globally standardized sub-indicators ($Z_{k,i,t}$) weighted by their PC_1 factor loadings (w_k):

$$I_{i,t} = \sum_{k=1}^{n} w_k \cdot Z_{k,i,t}. \quad (1)$$

For the Digital Index (n = 6, λ = 5.8), the extracted loadings w_k are 0.4316 (InternetPenetration), 0.4073 (ICTDevelopmentIndex), 0.4247 (EcommerceShare), 0.4266 (ICTInvestmentGDP), 0.3892 (CloudSoftwareAdoption), and 0.3660 (DigitalSkills). For the Green Index (n = 7, λ = 6.8), the weights are 0.4119 (RenewableEnergyShare), –0.3671 (EnergyEfficiency), 0.3329 (GreenInvestmentGDP), –0.3667 (CO2EmissionsGDP), 0.3971 (WasteRecycling), 0.3658 (EcoCertification), and 0.3985 (OrganicFarmingShare). For the Financial Index (n = 4, λ = 3.9), the weights correspond to 0.5040 (CreditAccess), 0.4725 (GrantFunding), 0.5209 (GovSupportProgram), and 0.5014 (SubsidyShare). Finally, for the Institutional Index (n = 4, λ = 3.8), the loadings are 0.5109 (PolicyStability010), 0.4696 (RegulatoryQuality010), 0.5142 (InstitutionalTrust), and 0.5040 (EnterpriseDevelopment). This explicit mathematical specification ensures complete empirical transparency and exact reproducibility of all composite indices.

Preliminary aggregation of variables by row means was tested but not retained in the final models, as it did not reduce multicollinearity. The regression analysis was ultimately conducted using the first principal component from each block (digitalization, green transformation, financial access, and institutional support). These components explained between 97–99% of the variance and were selected to preserve the information content of the blocks while ensuring stability and interpretability of regression estimates.

To ensure the correctness of the econometric analysis, a preliminary descriptive data analysis was conducted (the summarize function in Stata), the main results of which are presented in Table 2.

According to Table 2, Moldova exhibits the highest mean agricultural labor productivity in the sample (5531.9), followed closely by Ukraine (5456.6). This strong performance is noteworthy given Moldova's moderate financial development (Financial Index mean of 0.28) and a negative institutional score (Institutional Index mean of –0.15). While its institutional index is negative, it remains more favorable than those of Armenia (–0.22) and Azerbaijan (–0.48), suggesting that relative institutional stability within this localized sub-group may help mitigate structural financial barriers. Armenia, on the other hand, displays a lower mean productivity (4939.3) but demonstrates a pronounced focus on ecological modernization with a high Green Index mean of 0.25, which is surpassed only by Kazakhstan (0.30). Concurrently, Armenia shows a relatively low digital footprint (Digital Index mean of –0.21) and a lower institutional average (–0.22).

The remaining nations in the panel provide critical contextual divergence. Kazakhstan and Ukraine emerge as the structural leaders in modernization: Kazakhstan records the highest scores in both the Green Index (0.30) and Digital Index (0.41), while Ukraine leads the sample in financial

Table 2. Descriptive statistics of raw/standardized indicators before PCA transformation

Country	Productivity (Mean, SD)	Green Index (Mean, SD)	Digital Index (Mean, SD)	Financial Index (Mean, SD)	Institutional Index (Mean, SD)
Moldova	5531.9 (2032.2)	0.12 (0.98)	–0.34 (1.05)	0.28 (0.87)	–0.15 (0.92)
Armenia	4939.3 (1841.5)	0.25 (1.02)	–0.21 (1.08)	0.19 (0.90)	–0.22 (0.95)
Georgia	5212.9 (2094.3)	–0.08 (0.95)	–0.29 (0.99)	0.31 (0.85)	–0.10 (0.91)
Ukraine	5456.6 (1849.7)	–0.14 (0.93)	0.05 (0.97)	0.42 (0.88)	0.02 (0.89)
Azerbaijan	4441.1 (1565.4)	–0.45 (0.92)	–0.62 (0.94)	–0.31 (0.86)	–0.48 (0.88)
Kazakhstan	5054.0 (2051.8)	0.30 (1.01)	0.41 (1.02)	0.39 (0.89)	0.25 (0.93)

Note: Mean – arithmetic mean, SD – standard deviation.

depth (Financial Index mean of 0.42) and institutional quality (Institutional Index mean of 0.02). Azerbaijan lags across all dimensions, reporting the lowest values for all four explanatory indices.

Consequently, at the descriptive level, Moldova and Armenia present highly compelling, contrasting developmental configurations: Moldova balancing peak productivity against institutional and financial constraints, and Armenia prioritizing ecological transitions despite lower aggregate efficiency and digital adoption. This distinct juxtaposition justifies their selection as the specific focus cases for the subsequent country-specific econometric modeling.

To avoid spurious regression, a formal stationarity check of the variables was conducted. For this purpose, the panel unit root tests of Levin–Lin–Chu (LLC) and Im–Pesaran–Shin (IPS) were applied; according to the results, the data were found to be non-stationary(p-value > 0.05). Therefore, logarithms were taken of the productivity indicator (Productivity) and the financial index (FinIndex). For institutional index (InstitInd) and green index (GreenIndex), first differences were used. After the transformation, the LLC and IPS tests were repeated; according to the results, the stationarity of the time series was achieved.

At the next stage, panel models with fixed (FE) and random effects (RE) were formalized. The FE (2) model allows for the individual characteristics of countries that do not change over time, while the RE (3) model assumes a random distribution of these effects. Formally, the models have the form:

$$\begin{aligned}\ln Productivity_{it} &= \alpha_i + \beta_1 Digital\ Index_{it} \\ &+ \beta_2 \Delta Green\ Index_{it} + \beta_3 \ln Financial\ Index_{it} \\ &+ \beta_4 \Delta Institutional\ Index_{it} + u_{it},\end{aligned} \tag{2}$$

$$\begin{aligned}\ln Productivity_{it} &= \alpha + \beta_1 Digital\ Index_{it} \\ &+ \beta_2 \Delta Green\ Index_{it} + \beta_3 \ln Financial\ Index_{it} \\ &+ \beta_4 \Delta Institutional\ Index_{it} + \mu_i + u_{it},\end{aligned} \tag{3}$$

where $Productivity_{it}$ – labor productivity in country i at time t (USD/worker), α_i – individual effect for country i, accounting for its time-invariant characteristics (in the FE model), α – common constant for the entire sample (in the RE model), $\beta_1, \beta_2, \beta_3, \beta_4$ – regression coefficients reflecting the impact of the respective indices (Digital, Green, Financial, Institutional) on productivity, u_{it} – random error term varying across time and countries, μ_i – random effect for country i (in the RE model), assumed to be uncorrelated with the independent variables, i – country index: 1 – Moldova, 2 – Armenia, 3 – Georgia, 4 – Ukraine, 5 – Azerbaijan, 6 – Kazakhstan, t – time index (year), 2000–2024.

The Hausman test ($\chi^2(4)$ = 0.59, Prob = 0.9645) did not detect systematic differences between the fixedeffects and randomeffects estimators. This result confirms that the randomeffects specification is consistent and more efficient, and therefore was selected as the preferred model for further interpretation.

Moldova and Armenia were selected as focal illustrative cases due to their contrasting structural configurations within the region. While both share the typical institutional and economic characteristics of non-EU transition economies – such as modest financial depth and low green investment (1-2% of GDP) – they represent distinct development pathways. Moldova reflects a high-productivity baseline driven by institutional support and digital integration, whereas Armenia illustrates a pronounced focus on ecological modernization constrained by financial misallocation and lower digital adoption. Comparing these two nations allows the study to highlight critical country-level heterogeneity that would otherwise remain masked by aggregate panel estimations.

To further specify the panel model and illustrate country-level heterogeneity, separate regression estimations were conducted for Moldova and Armenia. For each case, a stepwise exclusion procedure was applied to identify the most influential explanatory variables and to assess the robustness of results. These country-specific regressions serve as illustrative examples, complementing the panel analysis by highlighting structural characteristics that persist within individual transition economies. In addition, LASSO regularization with crossvalidation was employed as a supplementary robustness check, ensuring that variable selection was not overly sensitive to sample limitations and confirming the stability of the modeling approach.

http://dx.doi.org/10.21511/ee.17(3).2026.06

3. RESULTS

After controlling multicollinearity and formalizing panel models, the impact of aggregated indices on labor productivity in agriculture was assessed. The modeling results are presented in Table 3 for both models.

Table 3. The impact of digital and environmental transformation of agro-food sector (FE/RE models) for Moldova, Armenia, Georgia, Ukraine, Azerbaijan, and Kazakhstan

Variables	FE model(p-value)	RE model(p-value)
Digital_Index	0.141 (0.000)	0.140 (0.000)
ΔGreen_Index	–1.848 (0.000)	–1.830 (0.000)
Financial_Index (ln)	8 (0.002)	0.037 (0.001)
ΔInstitutional_Index	0.050 (0.849)	0.068 (0.794)
Const	9.100 (0.000)	9.087 (0.000)
Rsquared (Within)	0.9597	0.9597
Rsquared (Between)	0.3434	0.3248
Rsquared (Overall)	0.9024	0.9030
Ftest / Wald χ^2	F(4,89)=529.37	χ^2(4)=2144.61
Prob > F / Prob > χ^2	0.0000	0.0000
rho	0.629	0.686

The Digital_Index coefficient remains strongly positive and highly significant in both specifications (FE: 0.141, $p < 0.01$, RE: 0.140, $p < 0.01$). Given the log-level structure of the specification, this reflects a semi-elasticity relationship, confirming that a one-unit increase in the standardized digital score (reflecting ICT investment, internet penetration, digital skills, and e-commerce adoption) yields an approximate 14.1% increase in agri-food labor productivity. Conversely, the first-differenced $\Delta Green\_Index$ exhibits a statistically significant negative effect in both models (FE: –1.85, $p < 0.01$; RE: –1.83, $p < 0.01$). Rather than implying that static eco-friendly practices harm performance, this result specifically indicates that an acceleration in the annual rate of green adoption (e.g., rapid implementation of renewable energy, energy efficiency measures, certification, and organic production) imposes short-term structural adjustment and compliance costs, which temporarily dampen productivity growth. Because financial access enters the specification in logarithmic form $(\ln Financial\_Index)$, its estimated coefficient represents a constant elasticity. The positive and highly significant coefficient (FE: 0.037, $p < 0.01$; RE: 0.037, $p < 0.01$) confirms that a 1% expansion in financial access directly enhances agricultural labor productivity by 0.037%. In contrast, the first-differenced $\ddot{A}Institutional\_Index$ is statistically insignificant in both specifications (FE: 0.05, $p \approx 0.85$, RE: 0.07, $p \approx 0.79$). This indicates that short-term annual changes in institutional factors (such as trust, policy stability, and regulatory quality) do not exert an immediate measurable impact on productivity growth once within-country temporal trends are controlled for, though they may continue to influence long-term sectoral resilience indirectly.

Model quality is confirmed by the R^2 (within) values (0.96 in both FE and RE), which demonstrate strong explanatory power for within-country variation. The between R^2 is moderate (0.32–0.34), while the overall R^2 remains high (≈0.90), indicating good explanatory capacity across countries. Both models are highly significant (FE: F (4,89) = 529.37, Prob = 0.0000; RE: χ^2 (4) = 2144.61, Prob = 0.0000). The rho statistics show that country-specific effects explain a substantial share of variation ($\rho = 0.63$ in FE; $\rho = 0.69$ in RE), underscoring the importance of national contexts in shaping productivity outcomes. The high values of the within R^2 reflect the strong explanatory capacity of the selected indices, which capture most of the variation in productivity within countries. This outcome is consistent with the standardized construction of indicators and the application of principal component analysis, which reduced dimensionality and stabilized the estimates. At the same time, the moderate between R^2 highlights crosscountry heterogeneity, confirming that national contexts remain an important source of variation.

The next step is to estimate the country's fixed effects, i.e., the values that show how much the productivity of a particular country under study deviates from the average after considering the regressors (Table 4).

The estimated countryspecific fixed effects (ui) demonstrated in Table 4 reveal significant structural heterogeneity in agricultural labor productivity across the panel after controlling for digital, environmental, and financial factors. Moldova exhibits the strongest positive deviation (+0.1106) from the panel mean, while Ukraine (+0.0176) and Georgia (+0.0028) show small to nearly neu-

Table 4. Countryspecific fixed effects (FE model)

Country	Fixed Effect (u_i)	Interpretation
Moldova	+0.1106	Highest positive effect → productivity above the panel mean after controlling for digital, financial, and ecological factors
Armenia	–0.0365	Slight negative deviation → productivity slightly below the average
Georgia	+0.0028	Nearly neutral effect → productivity close to the panel mean
Ukraine	+0.0176	Small positive deviation → productivity slightly above the average
Azerbaijan	–0.0749	Noticeable negative deviation → productivity below the average
Kazakhstan	–0.0382	Negative deviation → productivity below the average

tral positive trajectories. Conversely, Azerbaijan (–0.0749), Kazakhstan (–0.0382), and Armenia (–0.0365) display negative deviations. These unobserved, time-invariant shifts highlight the critical role of country-specific contexts (such as deep-seated institutional legacies, geographic endowments, and historical structural trajectories) in establishing the baseline efficiency thresholds of national agricultural sectors.

To test the statistical robustness of the panel estimates against potential diagnostic violations, Driscoll–Kraay standard errors were applied to correct for heteroscedasticity, autocorrelation, and cross-sectional dependence. Under this robust inference framework, the core coefficients remain highly stable. The Digital_Index maintains its strong positive association (0.141, p = 0.001), indicating that digitalization trajectories are reliable co-determinants of productivity shifts within this sample. Similarly, the contemporary net cost of environmental compliance is validated by the stable negative coefficient of the Green_Index (–1.848, p < 0.001).

Furthermore, the macro-financial environment retains its positive and statistically significant link to productivity (Financial_Index (ln) = 0.037, p = 0.002), whereas the Institutional_Index remains statistically non-significant (0.050, p = 0.849), corroborating that short-run institutional variations do not capture direct contemporary shifts in aggregate productivity. The model baseline is captured by the highly significant constant (9.100, p < 0.001). Taken together, the robust estimations support the prominent roles of digital acceleration and financial depth, highlight the contemporary transitional burdens of ecological modernization, and indicate a limited direct impact of institutional variations within the limits of the examined panel dataset.

3.1. Case focus: Moldova and Armenia

To illustrate the countryspecific outcomes, separate regression estimations were conducted for Moldova and Armenia using a stepwise exclusion procedure. This approach allowed us to identify the most significant explanatory variables within each national context and to highlight structural heterogeneity across transition economies. The results are presented in Table 5. Due to the limited time horizon available for individual time-series estimations (T = 25, 2000–2024), country-specific regressions alongside Stepwise selection and LASSO regularization are implemented purely as exploratory, complementary robustness checks. These routines are designed to uncover signals of national trajectory and parameter heterogeneity rather than to establish strict asymptotic structural relationships.

Table 5. Comparative countryspecific regression results for Moldova and Armenia

Variable	Moldova (Country = 1)	Armenia (Country = 2)
lnFinance	Excluded (p = 0.947)	–0.8546 (p = 0.050)
ΔInstitutes	+0.2653 (p = 0.000)	+0.4686 (p = 0.001)
Digital	+0.0332 (p = 0.026)	Excluded (p = 0.616)
ΔGreen	–0.4621 (p = 0.000)	–0.5016 (p = 0.001)
Constant	6.0499	5.9493
R^2	0.8919	0.9261
Observations	25	25
Fstatistic	F(3,21) = 57,75 (p = 0.0000)	F(3,21) = 87,72 (p = 0.0000)

The countryspecific regressions for Moldova and Armenia reveal both commonalities and divergences in the determinants of productivity. In both cases, the institutional index emerges as a strong positive driver, underscoring the central role of governance quality and institutional support in shaping economic outcomes. Similarly,

http://dx.doi.org/10.21511/ee.17(3).2026.06

the green index exerts a significant negative effect in both countries, reflecting the transitional costs associated with adopting environmentally sustainable practices in agriculture and industry. However, the models diverge in terms of financial and digital factors. For Moldova, the stepwise procedure excluded the financial variable, indicating that access to finance does not independently explain productivity variations. Instead, digitalization remains significant, albeit with a modest coefficient, suggesting that technological penetration contributes positively to efficiency gains. This aligns with Moldova's relatively rapid adoption of digital tools in enterprise management and market access. In contrast, for Armenia, the financial variable is retained but with a negative coefficient. This counterintuitive result may point to structural inefficiencies in the financial system, where increased credit or financial flows do not translate into productivity improvements, possibly due to misallocation or high borrowing costs. At the same time, digitalization is excluded, implying that technological penetration has not yet reached a threshold where it significantly impacts productivity outcomes. The panel model averages effects across countries. However, the country regressions show structural heterogeneity: in Moldova and Armenia, institutional reforms had a breakthrough effect, whereas in other countries in the sample this effect was attenuated, resulting in a statistically insignificant indicator in the overall panel FE model.

The *F*statistics (57,75 for Moldova and 87,72 for Armenia, both highly significant) confirm the robustness of the models. The very high R^2 values (0.89 and 0.92 respectively) indicate that the selected variables explain nearly all observed variation in productivity within each country sample. Overall, these results illustrate structural heterogeneity across transition economies. Moldova's productivity gains are tied to institutional quality and digital adoption, whereas Armenia's are constrained by financial inefficiencies despite institutional progress. The consistent negative effect of the green index highlights the transitional burden of sustainability reforms, which may require targeted policy support to mitigate shortterm productivity losses.

To account for model uncertainty and evaluate estimation robustness, we complemented Stepwise selection with LASSO regularization, leveraging their distinct criteria for parameter retention. While minor variations in variable inclusion emerge due to LASSO's penalization mechanism versus Stepwise's hypothesis-testing approach, both methods consistently identified the primary structural drivers, confirming the overall stability of our core empirical findings.

In addition, LASSO regularization was applied to evaluate the robustness and stability of the country-specific model estimations. The use of LASSO is justified because, in small samples and under high correlation among variables, classical selection methods (such as stepwise regression) can yield overfitted and unstable predictors that lose significance when model constraints change. Instead of replicating the stepwise outcomes, LASSO introduces a penalization mechanism that discards weaker, less stable effects by shrinking their coefficients to absolute zero, thereby identifying a more parsimonious set of core predictors.

To test the stability of the results, LASSO regularization with cross-validation was applied. In the case of Moldova, the optimal lambda of 0.0088 left the institutional index (out-of-sample R^2 = 0.867) exclusively, dropping the digital and green indices that were previously retained by the stepwise procedure. This divergence implies that while digital and green transformations exhibit descriptive correlation, institutional quality stands out as the singular robust driver under penalized estimation. For Armenia, the optimal lambda of 0.0529 retained only two predictors, the institutional and financial indices (out-of-sample R^2 = 0.661), while excluding the green index. Consequently, the LASSO results do not confirm the stepwise specifications; rather, they refine the economic interpretation by filtering out potential overfitting and demonstrating that institutional governance is the only consistently stable factor across both national contexts under strict regularization constraints.

To account for model uncertainty and evaluate estimation robustness, we complemented Stepwise selection with LASSO regularization, leveraging their distinct criteria for parameter retention. While minor variations in variable inclusion emerge due to LASSO's penalization mechanism versus Stepwise's hypothesis-testing approach,

both methods consistently identified the primary structural drivers, confirming the overall stability of our core empirical findings.

4. DISCUSSION

The empirical results confirm that digitalization and financial access are consistent and significant drivers of agricultural productivity at the country level, while green transformation exerts a negative short-term effect and institutional factors remain statistically insignificant. This finding aligns with prior literature. Abou-Moghli (2026) and Asare (2025) emphasized that digital tools and AI training enhance efficiency and sustainability, while Pellegrini et al. (2023) and Ramada et al. (2026) demonstrated that financial and ESG practices strengthen agricultural sector competitiveness. The positive coefficients for Digital Index and Financial Index in both FE and RE models reinforce the argument that ICT adoption, e-commerce, and access to credit are immediate productivity enhancers, consistent with Varbanova et al. (2025) and Bilan and Halynskyi (2026).

At the same time, the negative and highly significant effect of Green Index highlights the transitional costs of ecological modernization. This result echoes Hroma (2026), who found affordability challenges in organic agriculture, and Szymańska and Tłuczak (2026), who documented persistent inefficiencies in EU agricultural emissions. The evidence indicates that environmental practices introduce immediate compliance and adjustment costs, imposing contemporary structural burdens on the agri-food sector as a whole and temporarily dampening aggregate productivity during the initial adoption phase. Tedjakusuma et al. (2026) similarly showed that green supply chain integration generates socio-economic value only when eco-innovation is embedded in broader sectoral and national strategies.

The Institutional Index is insignificant in both models, suggesting that institutional factors such as trust, policy stability, and regulatory quality do not exert a direct measurable influence once temporal trends are removed, though they may still play an indirect role in shaping national resilience. Country-specific fixed effects reveal structural heterogeneity across the panel. Moldova displays positive effects, which may reflect country-specific structural conditions and macro-financial frameworks that allow digital and green transitions to translate into sectoral productivity gains. While institutional factors are statistically insignificant in the overall panel model (where temporal trends dominate), the country-specific regressions reveal that institutional quality is a primary positive driver of productivity in both Moldova (beta = 0.265, $p < 0.001$) and Armenia (beta = 0.469, $p = 0.001$). This indicates that national institutional governance is critical for absorbing structural shocks at the macro level. Conversely, Azerbaijan, Kazakhstan, and Armenia exhibit negative deviations from the panel baseline, reflecting structural constraints or exposure to external shocks. Meanwhile, Ukraine and Georgia show small positive deviations, remaining close to the panel mean. These findings resonate with Bilan et al. (2026), who emphasized the role of institutional quality, and Vasylieva et al. (2026), who highlighted the destabilizing impact of energy price shocks. In Armenia, the country-specific model indicates that digital adoption has not yet reached a threshold level to directly boost aggregate productivity (leading to its exclusion in stepwise regression), while access to finance exerts a negative coefficient, pointing to macro-level credit misallocations or high borrowing costs across the economy. Moldova's strong positive fixed effect (+0.1106) is driven primarily by high institutional effectiveness and targeted digital adoption, whereas access to finance was excluded during model selection, showing that financial availability alone is not the main bottleneck for Moldovan agricultural productivity. Together, these two cases illustrate how targeted national policies and institutional frameworks can enable transition economies to leverage digital and green strategies for sustainable agricultural development.

The significant negative coefficient of the Green Index (–1.848, $p < 0.001$) points toward substantial transitional costs associated with ecological modernization. However, since the current panel specification relies on contemporaneous effects without an explicit lag structure or long-run dynamic modeling, this negative association should not be definitively categorized as a purely short-

http://dx.doi.org/10.21511/ee.17(3).2026.06

term phenomenon. Instead, it reflects the net contemporary burden of environmental compliance and green infrastructure investments over the analyzed period. Future research utilizing dynamic panel frameworks or distributed lag models is required to test whether these transitional costs eventually diminish and yield positive productivity returns in the long run.

In the context of Moldova and Armenia, the discussion highlights that both countries represent illustrative cases of how transition economies navigate the challenges of ecological modernization in the agri-food sector at the national level. Moldova's experience shows that macro-financial access and gradual digitalization enable the agricultural sector to adopt renewable energy and eco-certification, though institutional effects remain statistically insignificant in the panel analysis. Armenia, meanwhile, demonstrates that adoption of smart agricultural tools and ongoing reforms strengthen national resilience, though institutional effects remain statistically insignificant in the panel analysis. Despite the short-term costs reflected in the negative Green_Index, these two countries exemplify how targeted policies and adaptive governance can transform environmental practices into long-term drivers of sectoral competitiveness. Their trajectories confirm that green transformation in the agri-food sector is not only a matter of compliance with climate commitments but also a strategic pathway to sustainable productivity and resilience in transition economies. The individual country-level results should be interpreted with caution, given the small sample constraints (T = 25). To mitigate the risk of over-parameterization inherent in short time dimensions, the variable candidate space was constrained via PCA index aggregation and penalized with LASSO shrinkage. Consequently, these country-specific estimations serve as indicative insights into structural differences rather than baseline econometric proofs.

CONCLUSION

This study aimed to evaluate how digitalization, green transformation, financial access, and institutional support influence agricultural labor productivity across six transition economies (Moldova, Armenia, Georgia, Ukraine, Azerbaijan, and Kazakhstan) over the period 2000–2024, with illustrative case insights for Moldova and Armenia.

The empirical regression results confirm that the Digital Index exerts a strong positive effect on aggregate productivity, yielding a semi-elasticity coefficient of 0.141 (p = 0.001). Similarly, the log-transformed Financial Index demonstrates a positive and statistically significant elasticity of 0.037 (p = 0.002). Conversely, the first-differenced Green Index exhibits a significant negative association (–1.848, p < 0.001), reflecting contemporary structural adjustment and compliance costs associated with ecological modernization. The first-differenced Institutional Index remains statistically insignificant after robust corrections (0.050, p = 0.849), though country-level estimations confirm its underlying importance for national resilience. The statistically significant constant term (9.100, p< 0.001) establishes the baseline log-productivity level across the panel.

Country-specific fixed effects reveal substantial structural heterogeneity. Moldova (+0.1106 FE) consistently performs above the panel mean due to high institutional efficacy and targeted digital integration, whereas Armenia (–0.0365 FE) exhibits a negative deviation driven by financial allocation inefficiencies and limited digital depth. Ukraine (+0.0176) and Georgia (+0.0028) remain close to average, while Kazakhstan (–0.0382) and Azerbaijan (–0.0749) show negative deviations. Overall, the evidence indicates that while digitalization and finance act as immediate drivers of competitiveness, ecological transition policies impose short-term implementation burdens that require targeted support policies.

Several methodological limitations should be acknowledged. The sample of six countries (N = 6) limits out-of-sample generalizability, while data interpolation retains potential statistical noise. Furthermore, country-specific regressions operate on a constrained time horizon (T = 25) and serve as exploratory checks rather than strict asymptotic proofs. Finally, omitting year fixed effects to preserve degrees of freedom means captured impacts may partially reflect global macroeconomic trends rather than purely national dynamics. Future research should utilize expanded multi-country datasets and dynamic causal identification models to extend these findings.

AUTHOR CONTRIBUTIONS

Conceptualization: Alexandru Stratan, Tatul Mkrtchyan, Liliana Staver, Ani Khachatryan, Larisa Dodu-Gugea, Anna Ayvazyan, Nina Roscovan.
Data curation: Larisa Dodu-Gugea, Nina Roscovan.
Formal analysis: Anna Ayvazyan.
Funding acquisition: Alexandru Stratan, Ani Khachatryan.
Investigation: Tatul Mkrtchyan.
Methodology: Alexandru Stratan.
Project administration: Alexandru Stratan, Tatul Mkrtchyan.
Resources: Liliana Staver.
Software: Ani Khachatryan.
Supervision: Alexandru Stratan.
Validation: Liliana Staver, Anna Ayvazyan.
Visualization: Larisa Dodu-Gugea, Nina Roscovan.
Writing – original draft: Alexandru Stratan, Tatul Mkrtchyan, Liliana Staver, Ani Khachatryan, Larisa Dodu-Gugea, Anna Ayvazyan, Nina Roscovan.
Writing – review & editing: Alexandru Stratan, Tatul Mkrtchyan, Liliana Staver, Ani Khachatryan, Larisa Dodu-Gugea, Anna Ayvazyan, Nina Roscovan.

ACKNOWLEDGMENTS

The authors acknowledge the financial support received for the implementation of the project "Accelerating the Digital and Green Transformation of Agri-Food SMEs in Moldova and Armenia", funded by the National Agency for Research and Development of the Republic of Moldova (NARD) (Project No. 26.80013.0807.05ARM) and the Higher Education and Science Committee of the Ministry of Education, Science, Culture and Sports of the Republic of Armenia (Project No. 26NARD-1D007).

REFERENCES

1. AbouMoghli, A. (2026). Sustainable digital transformation in the energy sector: The role of artificial intelligence training in achieving Jordan's green growth strategy. *Environmental Economics, 17*(1), 1-11. https://doi.org/10.21511/ee.17(1).2026.01
2. Asare, K. N. (2025). Digital transformation in accounting for sustainable development: Mapping the intellectual structure. *Financial Markets, Institutions and Risks, 9*(4), 1-15. https://doi.org/10.61093/fmir.9(4).1-15.2025
3. Bashynska, I., Kichuk, Y., Danylyuk, S., Bessarab, A., Levytska, L., & Zaitsev, O. (2022). Smart agroclustering based on the chain «educationsciencebusiness» for sustainable development. *Journal of Agriculture and Crops, 8*(3), 208-215. https://doi.org/10.32861/jac.83.208.215
4. Bell, A., & Jones, K. (2015). Explaining fixed effects: Random effects modeling of time-series cross-sectional and panel data. *Political Science Research and Methods, 3*(1), 133-153. https://doi.org/10.1017/psrm.2014.7
5. Bencsik, A., & Belas, J. (2025). Interorganisational knowledge transfer practices for SMEs. *Economics & Sociology, 18*(4), 160-181. https://doi.org/10.14254/2071-789X.2025/18-4/8
6. Bilan, S., & Halynskyi, D. (2026). Financial market support for green and digital energy startups: The role of venture capital expenditures. *Financial Markets, Institutions and Risks, 10*(2), 1-21. https://doi.org/10.61093/fmir.10(2).1-21.2026
7. Bilan, S., Ibadov, A., Marci, A., Danileviča, A., & Podosynnikov, S. (2026). Ethical and transparent governance for sustainable innovation: Does institutional quality support green and digital

energy startup development? *Business Ethics and Leadership, 10*(2), 32-54. https://doi.org/10.61093/bel.10(2).32-54.2026

8. Danko, Y., & Nifatova, O. (2022). Agrosphere determinants of green branding: Ecoconsumption, loyalty, and price premium. *Humanities and Social Sciences Communications, 9*(1), Article 334. https://doi.org/10.1057/s41599-022-01077-9
9. Dayıoğlu, M., & Turker, U. (2021). Digital transformation for sustainable future - Agriculture 4.0: A review. *Tarım Bilimleri Dergisi, 27*(4). https://doi.org/10.15832/ankutbd.986431
10. Dharma, E., Hadikusumo, R. A., Butarbutar, M., Faris, S., & Lie, D. (2025). Driving business leadership through voluntary workplace green behavior: Evidence from green human resource management, green satisfaction, and green supportive climate. *Business Ethics and Leadership, 9*(4), 272-288. https://doi.org/10.61093/bel.9(4).272-288.2025
11. Eurostat. (2024). *Statistics on e-commerce, waste management, and environmental indicators* [Data set]. European Commission. Retrieved from https://ec.europa.eu/eurostat/data/database
12. Food and Agriculture Organization. (2023). *Statistical Yearbook: World Food and Agriculture 2023*. FAO. Retrieved from https://openknowledge.fao.org/server/api/core/bitstreams/28cfd24e-81a9-4ebc-b2b5-4095fe5b1dab/content/cc8166en.html
13. Gallup. (2024). *Institutional trust and confidence in institutions*. Gallup News. Retrieved from https://news.gallup.com/topic/category-institutions.aspx
14. Hnatenko, I., & Konieczny, G. (2023). Ranking of profitability and costs indicators of agribusinesses. *Smart Economy, Entrepreneurship and Security, 1*(1), 73-83. https://doi.org/10.60022/sis.1.(01).7
15. Hnatenko, I., & Tanchyk, O. (2024). Analysing migration risks in the management of agroindustrial enterprises in Europe. *Smart Economy, Entrepreneurship and Security, 2*(1), 7-16. https://doi.org/10.60022/sis.2.(01).1
16. Hroma, I. (2026). Organic agriculture and the affordability of healthy diets: Evidence from crosscountry panel analysis. *Health Economics and Management Review, 7*(1), 41-56. https://doi.org/10.61093/hem.2026.1-03
17. International Energy Agency. (2024). *World energy balances and renewable energy statistics* [Data set]. IEA. Retrieved from https://www.iea.org/data-and-statistics/data-product/world-energy-balances
18. International Labour Organization. (2024). *ILOSTAT database: Digital skills, employment, and occupational statistics* [Data set]. ILO. Retrieved from https://ilostat.ilo.org/data
19. International Telecommunication Union. (2024). *ITU DataHub: Global ICT statistics and indicators* [Data set]. ITU. Retrieved from https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx
20. Ivashchenko, A., Polishchuk, Y., Dubyna, M., Smerichevskyi, S., & Kornyliuk, A. (2023). Modelling the impact of SME lending on business value added. *Acta Innovations, 48,* 5-21. https://doi.org/10.32933/ActaInnovations.48.1
21. Jumaiyah, Andayani, W., Rosidi, R., & Purwanti, L. (2025). Digital transformation in village financial management: A bibliometric analysis of research evolution and contemporary challenges. *Public and Municipal Finance, 14*(2), 15-28. https://doi.org/10.21511/pmf.14(2).2025.02
22. Kafoe, A. S., Foh, B. M., & Kafoe, M. A. (2026). Beyond panacea: Digital governance, AI, and the political economy of public benefit in African development. *Public Governance, Regulation and Law, 2*(2), 1-20. https://doi.org/10.61093/pgrl.2(2).1-20.2026
23. Kuzior, A., Bielialov, T., Morozova, O., Vasiltsova, O., Rubanov, P., Holub, I., & Lyeonov, S. (2025). Does a country's energy security increase with advances in government AI readiness? An empirical panel study. *Environmental Economics, 16*(4), 182-196. https://doi.org/10.21511/EE.16(4).2025.12
24. Lyeonov, S., & Moroz, A. (2025). Financial instruments for renewable energy incentives: A clusterbased analysis of feedin tariffs and power purchase agreements. *Financial Markets, Institutions and Risks, 9*(1), 123-139. https://doi.org/10.61093/fmir.9(1).123-139.2025
25. Mamdouh, A., Adel, R., Khourshed, N., & Ragheb, M. A. (2025). Impact of digital leadership on employee performance with mediation roles of digital selfefficacy and employee motivation. *Business Ethics and Leadership, 9*(3), 109-129. https://doi.org/10.61093/bel.9(3).109-129.2025
26. Mehibel, S., Boudjana, R. H., ZambranoMonserrate, M. A., Bouzid, A., & Lazereg, M. (2025). Food security, prices, and geopolitical risk: A dynamic panel threshold model. *Geopolitics under Globalization, 6*(1), 30-44. https://doi.org/10.21511/gg.06(1).2025.04
27. Ministry of Agrarian Policy and Food of Ukraine. (2024). *Open data and statistical indicators of the agricultural sector* [Data set]. Government of Ukraine. Retrieved from https://minagro.gov.ua/gromadyanam/vidkryti-dani
28. Ministry of Agriculture and Food Industry of the Republic of Moldova. (2024). *Official reports on state support and agricultural subsidies for agri-food SMEs*. Government of Moldova. Retrieved from https://mded.gov.md/indicatori-economici/
29. Ministry of Agriculture of the Republic of Kazakhstan. (2024). *Official documents, regulatory acts, and statistical reporting of the agro-industrial complex* [Data set]. Government of Kazakhstan. Retrieved from https://www.gov.kz/memleket/entities/moa/documents/1?type=14&lang=en
30. Ministry of Economy and Sustainable Development of Georgia. (2024). *Economic review and main*

economic indicators [Data set]. Government of Georgia. Retrieved from https://www.economy.ge/?page=ecoreview&s=37&lang=en

31. Mkrtchyan, T. M., Pakhlyan, A., & Khachatryan, G. G. (2025). Interactions between macroeconomic factors and green investments. In *Advances in Science, Technology and Innovation* (pp. 359-364). Springer. https://doi.org/10.1007/978-3-031-91560-4_49

32. Organization for Economic Co-operation and Development. (2017). *OECD Guidelines on Measuring Trust.* Paris: OECD Publishing. https://doi.org/10.1787/9789264278219-en.

33. Organization for Economic Co-operation and Development. (2024). *OECD Data Explorer: Economic, social, and environmental indicators* [Data set]. OECD. Retrieved from https://data-explorer.oecd.org

34. Pimenow, S., Pimenowa, O., Sitnicki, M. W., Dluhopolskyi, O., & Zieliński, M. (2026). Energy use, costs and economic resilience of EU agriculture: The role and potential of CAP ecoschemes in reducing energy intensity. *Energies, 19*(4), Article 1016. https://doi.org/10.3390/en19041016

35. Ramada, A., Shemeis, M.A., Aldabousi, A. M., & Awad, A. (2026). Green finance and ESG practices as drivers of multidimensional corporate performance: Evidence from UAElisted firms. *Investment Management and Financial Innovations, 23*(1), 243-252. https://doi.org/10.21511/imfi.23(1).2026.18

36. Rawal, D., & Joshi, P. R. (2025). Understanding socioeconomic challenges of environmental sustainability through consumer awareness, buying behaviour and green marketing. *SocioEconomic Challenges, 9*(4), 207-215. https://doi.org/10.61093/sec.9(4).207-215.2025

37. Rohman, F., Yanto, Y., Subadriyah, S., & Janah, H. (2026). Corporate governance, sustainability bonds, and labor costs in promoting green investment. *Investment Management and Financial Innovations, 23*(1), 82-94. https://doi.org/10.21511/imfi.23(1).2026.07

38. Safelia, N., Tiswiyanti, W., Olimsar, F., Hasanah, N., Hernando, R., & Putra, W. E. (2026). Taxpayer compliance among MSMEs in Indonesia: Moderating role of efiling on tax authority services, awareness, and tax sanctions. *Public and Municipal Finance, 15*(2), 68-79. https://doi.org/10.21511/pmf.15(2).2026.06

39. Shafitranata, Alvia, L., & Azizah, R. (2026). ESG implementation and its effect on financial performance: Focusing on sustainable financial strategies of green companies in Indonesia. *Environmental Economics, 17*(1), 12-24. https://doi.org/10.21511/ee.17(1).2026.02

40. Shvets, N., Shevtsova, H., Pidorycheva, I., Prokopenko, O., & Maslosh, O. (2023). Sustainable development of agriculture based on the smart specialization approach: Cases of the Central and Eastern European countries. *Agricultural and Resource Economics, 9*(1), 260-282. https://doi.org/10.51599/are.2023.09.01.12

41. Sira, M., & Kuzior, A. (2025). Digitalization of government management processes in the context of sustainable development. *Management Systems in Production Engineering, 33*(2), 289-310. https://doi.org/10.2478/mspe-2025-0029

42. Sitnicki, M. W., Kurinskyi, D., Pimenowa, O., Wasilewski, M., & Wasilewska, N. (2024). Strategic formation of agricultural market clusters in Ukraine: Emerging as a global player. *Sustainability, 16*(21), Article 9430. https://doi.org/10.3390/su16219430

43. Sitnicki, M. W., Prykaziuk, N., Stelmakh, D., Pimenowa, O., Pimenow, S., & Wigier, M. (2026). EUDR: Identification of agrienvironmental risk drivers of financial risks and implementation readiness in Eastern European countries. *Agriculture, 16*(9), Article 1014. https://doi.org/10.3390/agriculture16091014

44. Śmiech, L., Kurbatova, T., Kubatko, O., Sotnyk, I., Trypolska, G., & Perederii, T. (2025). Assessing the impact of household energy efficiency and renewable energy developments on energy poverty reduction. *Environmental Economics, 16*(4), 83-94. https://doi.org/10.21511/ee.16(4).2025.06

45. Song, W. K., Bird, E., McNerney, G., & Richardson, K. (2026). Categorizing smart farm equipment for sustainable and humancentric food production: A comprehensive review encompassing terrestrial agriculture and aquaculture. *Green Transition and Sustainable Development, 2*(1), 1-17. https://doi.org/10.61093/gtsd.2(1).1-17.2026

46. State Statistical Committee of the Republic of Azerbaijan. (2024). *Official statistical databases and open data indicators* [Data set]. Government of Azerbaijan. Retrieved from https://www.stat.gov.az/menu/7/?lang=en

47. Statistical Committee of the Republic of Armenia. (2024). *Official statistical databases: Agriculture and economic development indicators* [Data set]. Armstat. Retrieved from https://armstat.am/en/?nid=13

48. Szymańska, E. J., & Tłuczak, A. (2026). Changes in greenhouse gas emissions from agriculture in selected European Union countries. *Journal of International Studies, 19*(1), 185-206. https://doi.org/10.14254/2071-8330.2026/19-1/10

49. Tedjakusuma, A. P., Kulachai, W., & Rudenko, S. (2026). How green supply chain integration generates sustainable socioeconomic value: Economic and ecoinnovation effects in manufacturing firms. Equilibrium. *Quarterly Journal of Economics and Economic Policy, 21*(1), 321-371. https://doi.org/10.24136/eq.3983

50. Tu, Y.X., Kubatko, O., Melnyk, L., Li, R., Kovalov, B., & Yaremenko, A. (2025). Economic, institutional and environmental drivers of SMEs' development in the EU: Sustainable development goals perspective. *Environment,*

Development and Sustainability, 27(8), 20101-20119. https://doi.org/10.1007/s10668-024-05686-z

51. United Nations Development Programme. (2021). *UNDP annual report 2020: Turning the tide*. UNDP. Retrieved from https://annualreport.undp.org/2020/assets/UNDP-Annual-Report-2020-en.pdf
52. United Nations Industrial Development Organization. (2024). *INDSTAT: Industrial statistics database (ISIC Revision 4)* [Data set]. UNIDO Statistics Data Portal. Retrieved from https://stat.unido.org/data/table?dataset=indstat&revision=4#data-browser
53. Vakhovych, I. M., Al-Shirawi, T., & Smolych, D. (2026). Statistical visibility and identification of the non-governmental organizations in economic institutional sectors. *Journal of Statistics Applications and Probability, 15*(1), 11-21. https://doi.org/10.18576/jsap/150102
54. Varbanova, M., Dutra de Barcellos, M., Kirova, M., De Steur, H., & Gellynck, X. (2025). Sustainably implementing Agriculture 4.0 in SME manufacturing companies in Eastern Europe: A case study from Bulgaria. *International Food and Agribusiness Management Review, 28*(3), 421-439. https://doi.org/10.22434/ifamr.1267
55. Vasylieva, T., Derkacz, A., Popp, J., & Horsch, A. (2025). From energy dependency to energy security: How the war in Ukraine accelerated renewable deployment in Europe. *Economics & Sociology, 18*(3), 229-253. https://doi.org/10.14254/2071-789X.2025/18-3/13
56. Vasylieva, T., Oláh, J., Khouri, S., & Horsch, A. (2026). Electricity price shocks, renewable energy penetration, and macroeconomic stability in European countries: Evidence from the 2022 energy crisis. *Economics & Sociology, 19*(1), 250-275. https://doi.org/10.14254/2071-789X.2026/19-1/12
57. Wojciechowski, W., Niewiadomski, A., & Bilan, Y. (2025). Ecological and secure electricity microgrids – Monitoring and forecasting challenges. *Human Technology, 21*(3), 469-473. https://doi.org/10.14254/1795-6889.2024.21-3.0
58. World Bank. (2024). *Total greenhouse gas emissions (kt of CO2 equivalent)* (Indicator Code: EN.GHG.ALL.MT.CE.AR5) [Data set]. World Bank Open Data. Retrieved from https://data.worldbank.org/indicator/EN.GHG.ALL.MT.CE.AR5
59. World Bank. (2025). *Repurposing agricultural support: 2025 policy compendium* (FoodSystems2030 Multi-Donor Trust Fund Report). World Bank Group. Retrieved from https://thedocs.worldbank.org/en/doc/71abe8ae549793b1fc3061e05242c7c5-0320012025/original/FoodSystems2030-2025-Policy-Compendium.pdf